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Research Article

Effect of AI Usage on Learning, Creativity, and Innovation: The Role of Mediating Self-Efficacy and Moderating Task Complexity

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ABSTRACT

The impact of artificial intelligence usage (AIU) on learning, creativity, and innovation (LCI) is a pressing concern in the digital transformation era, as it significantly alters educational systems. These insights are crucial for enhancing learning systems and fostering students' creativity and innovation. This study examines the factors by which AI usage (AIU) affects students' LCI and puts forward a comprehensive conceptual framework that incorporates perspectives from both students and instructors, which were validated by Social Cognitive Theory (SCT) and Cognitive Load Theory (CLT). To evaluate the hypotheses, 638 students from Bangladeshi public universities participated in a questionnaire survey conducted over nearly 5 months, along with a hierarchical regression analysis. Self-efficacy (SE) plays a significant mediating role between AI usage and LCI. Moreover, the association between AIU and SE is positively moderated by task complexity (TC), which promotes LCI. So, a mechanism of moderated mediation was found. The results of the study not only contribute to the theoretical understanding of how AI use affects students' LCI but also provide instructors and students with valuable guidance to utilize AI to promote LCI during the period of digital transformation.

Keywords: AIU (AI Usage); SE (Self-Efficacy); TC (Task Complexity), LCI (Learning, Creativity, Innovation).

INTRODUCTION

Artificial Intelligence, as the world moves quickly with technology, is a valuable companion in this era. AI has permeated every sphere of our lives, solving difficulties and enhancing self-efficacy (Jeilani & Abubakar, 2025). It significantly contributes to the modern educational system, providing ideas and materials to enhance learning and academic achievement (Vieriu & Petrea, 2025). The advancement of AI has identified a remarkable turning point in students' quest to perceive intelligence (Jan, 2023). AI signifies the impending transformation of power. – Andrew Ng, Co-founder of Google Brain. The progression of AI technology has revolutionized multiple sectors, including education (Aakanksha, 2025). AI in education rapidly transforms traditional classroom methodologies and learning experiences (Pham & Le, 2024). In the age of swift digital transformation, AI has been increasingly incorporated into the educational sector (Singh & Aziz, 2025), significantly impacting learning, creativity, and innovation (LCI). Aakanksha (2025) asserts that AI technologies are employed by students for educational purposes, learning, thinking, creative writing, and problem-solving tasks. Consequently, students are now focusing more on using AI, especially in terms of Task Complexity (Zhang et al., 2025). The effective collaboration of AI technology is essential for promoting student innovation inside educational systems and is a critical strategy for improving progression, differentiation, and complexities of learning (Celik et al., 2022; Wu et al., 2024). AI-driven technologies have been integrated into several aspects of education, encompassing individualization of learning, intelligent tutoring systems, automation of administrative tasks, and learning analytics (Alam, 2022; Chen et al., 2020). Analytical thinking is essential for addressing task difficulties and fostering self-efficacy (SE), as it entails the critical investigation and analysis of data (Pokkakillath & Suleri, 2023). To enhance educational and research outcomes, these qualities are crucial for learners' capacities to plan, assess, comprehend, and form conclusions (Ismail, 2023). Hasibuan and Azizah (2023) highlighted the ability of AI to provide specific instruction as a factor that fosters student creativity (Vidani, 2015).

Creativity is employed in everyday activities (Kaufman & Beghetto, 2009; Richards, 2007) where original thought is essential for innovation and creative endeavors. On the contrary, Singh & Aziz (2025) stated that AI can significantly enhance students' self-efficacy (SE), which refers to learners' confidence in their ability to perform tasks. Indeed, AI assistance substantially improves students' SE (Bation, 2024). Not only this, but also Artificial intelligence can enhance students' academic performance by assisting them with writing, examinations, and idea generation (Wang et al., 2023). In addition, Zhang et al. (2025) emphasized that LCI is facilitated when job complexity—the cognitive and physical requirements of the task—positively influences the relationship between SE and AIU. Despite the heightened interest in AI-enhanced learning environments, limited research has comprehensively investigated the interplay between learners' SE, TC, and AIU in shaping LCI. By examining the effect of AI use on LCI, mediated by SE and moderated by TC, this study aims to close this gap.

Students with constructive views on AI technologies are more likely to utilize them for learning, improving their critical thinking skills, and information retention (Hwang et al., 2020). Given the ramifications of AI utilization and the aforementioned scarcity of empirical evidence about AI's uses in LCI, it is demanding, and the researchers in this study were motivated to formulate the following inquiries. *Does the use of AI influence students' LCI, and to what extent do the difficulty of tasks and self-efficacy moderate and alter the relationship between students' opinions of AI-supported tools and the practical implications of AI in real-world scenarios?* This research uses quantitative and empirical methodologies to address these inquiries. The researchers analyzed the variables influencing these applications, drawing on established understandings to address the study's specific issues. This study examines the effect of AIU, SE, and TC on students' LCI. To explore the mediating and moderating influences of SE and TC on the link between students' perceptions of AI deployment. This study identified the aspects influencing AI's applications in LCI. Formulating AI regulations and measures to ensure ethical AI use, and educational sectors and institutions may find this information beneficial.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

AI Usage in Learning, Creativity, and Innovation (LCI)

AI has become a potent instrument in education, transforming teaching and learning (Kamenskih, 2022). Management of strategic objectives, operational decision-making, manufacturing processes, and R&D ecosystems are just a few organizational domains where artificial intelligence—autonomous systems with machine learning, reasoning, problem-solving, and decision-making capabilities—has become a disruptive force (Mariani & Dwivedi, 2024). According to Pham & Le (2024), the role of artificial intelligence in education has undergone significant changes. By providing learning opportunities and automating routine tasks, artificial intelligence (AI) has the potential to transform higher learning completely (Soeffner, 2023). To improve students' LCI, AI has been increasingly incorporated into educational systems (Holmes et al., 2019; Luckin et al., 2016). Additionally, AI can assist adaptive learning systems in creating more successful learning experiences and analyzing massive datasets to enhance student outcomes (Saleh, 2019) with creativity. Students' creativity increases when AI is used effectively in the classroom (Wu & Zhang, 2025). A collection of concepts considered to have unique value, application, or significance to different users is a commonly recognized definition of creativity (Chirico et al., 2018; Csikszentmihalyi, 1996; Guilford, 1950, 1967; Torrance, 1969, 1974; Collard & Looney, 2014). Originality and efficacy are also indicators of and linked to novelty (Runco, 2004; Runco & Acar, 2012). "Students think AI might contribute to cultivating their creativity by promoting self-sustaining, generating ideas, and providing numerous chances to be creative," as stated by Marrone et al. (2022). According to Vinchon et al. (2023), "a harmonious partnership that can benefit all parties, potentially leading to an entirely novel level of creative performance respecting ethical considerations and human values during the creative process, is the bright future of creativity and AI." Since it has a major impact on studying, learning, and the general efficacy of learning environments at all levels, comprehending student involvement is essential to research on learning (Aliyu et al., 2022). A support technology called artificial intelligence (AI) makes a variety of learning and troubleshooting tasks easier. Accordingly, when AI is included in the innovation environment, it has the potential to alter the way decisions about innovation are made, especially when it comes to the development and validation of new concepts (whether they be services, goods, or processes) (Zhang et al., 2025). In the words of Jaiswal and Dhar (2015), innovations can improve performance and offer competitive advantages. According to Ahn et al. (2025), views of AI service quality foster innovation. In a similar vein, Zheng et al. (2025) demonstrated that utilizing AI can foster creativity. According to Dong et al. (2025), the use of AI can both encourage and impede creative behavior.

H1: AI usage significantly influences LCI

Task Complexity (TC) as a Moderating Factor

The term "task complexity" refers to the intellectual and practical demands that are placed on a person to complete a specific task (Wood, 1986). Job complexity, which is defined as a combined assessment of the cognitive demands, the task diversity, and the degree of uncertainty that are inherent in various work activities, manifests itself through multiple task sequences, problem space insufficient clarity, information processing toughness, and autonomy in making decisions (Venkataramani & Tang, 2024; Verma & Singh, 2022). In environments that are supported by artificial intelligence (AI), the complexity of a task can either improve or hamper the outcomes, depending on the learner's ability to cope with the constraints. Although basic tasks may not fully leverage the potential of artificial intelligence, excessively complicated tasks may overwhelm students who lack sufficient support (Campbell, 1988). According to research, learners with a high level of self-efficacy and competence in situations of high complexity experience a greater impact of artificial intelligence (AI) on their creativity and invention (Zhou & George, 2001).

H2: Task complexity moderates the relationship between AI usage and LCI

Self-Efficacy (SE) as Mediating Factor

Self-efficacy has been identified as a key mediator in the interaction between the use of artificial intelligence (AI) and students' learning, creativity, and innovation, all of which are influenced by AI usage (Ahn et al., 2025). The evolution of SE started with Bandura's Social Learning Theory (SLT) in 1977, which eventually came to be called Social Cognitive Theory (SCT) in 1986. Self-efficacy, defined as the conviction that one can carry out the actions required to achieve specified results, is a central conceptual mediator in learning achievement (Bandura, 1997). In addition, the concept of general self-efficacy, defined as a person's confidence in their ability to carry out activities and achieve goals, has been the subject of substantial research in the university environment (Jia & Tu, 2024). By reinforcing students' overall self-efficacy and drive to learn, artificial intelligence capabilities indirectly improve students' intellectual awareness. Jia and Tu (2024). There is a correlation between self-efficacy and a variety of outcomes in higher learning, including academic achievement and ongoing achievement (Gore, 2006; Wright et al., 2012). The execution of AI has proven successful in enhancing the efficiency of both administrative and teaching tasks, which, in turn, may have a beneficial behavioral impact on students. This is partly because students who have access to AI feel stronger in their ability to manage task complexities, which in turn makes them feel more self-sufficient and confident. According to Weng et al. (2018), this is the case. Zawacki & Marín et al. (2019) also suggest that students' general self-efficacy may be improved by AI. Learners who possess a high degree of digital and analytical skills are more likely to leverage artificial intelligence (AI) tools to facilitate creative inquiry and more in-depth learning (Redecker, 2017). The influence that self-efficacy has on views toward artificial intelligence is particularly evident when considering its effect on one's willingness to learn (Balakrishnan et al., 2022). Learning is improved by the adoption of artificial intelligence (Mat Yusoff et al., 2025), as is creativity (Kim & Park, 2025), and invention, particularly through an increase in creative self-efficacy. When it comes to artificial intelligence in learning, self-efficacy has an impact on how easily and effectively students interact with intelligent belief systems (Ifenthaler & Yau, 2020).

H3: SE mediates the relationship between AIU and LCI.

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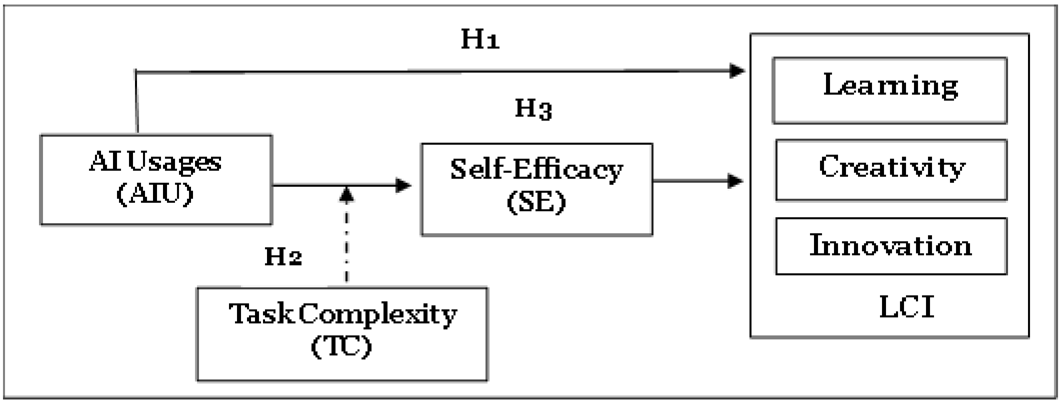

Figure: Research Model (Developed by Authors)

RESEARCH MATERIALS AND METHODS

Data Collection, Measurement, and Research Instrument

The relevance of the findings was enhanced by selecting individuals with direct expertise in AI uses through the use of purposeful, non-probabilistic sampling. To better understand the effect of AI on academic performance—particularly in learning, idea generation, creativity, and innovation—it is helpful to compare students' experiences before and after the implementation of AI. This is particularly true for students with a graduate business background who have had extensive exposure to new technologies and have a solid grasp of the basics. In their quantitative study, Tamanna & Sinha (2025), Zhou & Peng (2025), Zhang et al. (2025), Jeilani & Abubakar (2025), Vieriu & Petrea (2025), Haefner et al. (2021), Zawacki-Richter et al. (2019, Jung and Kellaris (2004), Wang and Lucianetti (2019), Ng and Lucianetti (2015), Amabile (1996), Medcof (1996), Bandura (1997), Zhou & George (2001), Pajares (2002), Schiuma & Lerro (2008), Snyder et al. (2019), used established measures of AI usage (AIU), task complexity (TC), and self-efficacy (SE), Learning, Creativity, and Innovation. All the measurements were chosen from earlier studies, where some of the propositions were slightly altered to fit the present situation. It is crucial to note that these types of modification displayed no validity issues during the pilot test. The respondents used a Likert-type response key with a range of 1 to 5 to rate 40 statements. The following is a summary of scales' sources:

Scale	Number	Sources
AI Usage (AIU)	7	Medcof (1996), Dwivedi et al. (2021)
Learning	8	Sweller (1988), Dixson (2015), Zhou & Peng (2025), Chaudhari et al., n.d.; Garcia et al. (2024)
Creativity	5	Amabile et al. (1996), Tierney & Farmer (2002), Zhou & Peng (2025)
Innovation	8	Jiménez-Jiménez & Sanz-Valle, (2011); Wang & Ahmed, (2004a, 2004b)
Self-Efficacy	5	Banoglu et al., (2015); Jia & Tu, (2024); Peng et al., (2024), Snyder et al. (2019)
Task Complexity	7	Campbell (1988), De Koning et al. (2008)

From mid-February to early June of 2025, the questionnaire poll was distributed. A small fraction of the questionnaire was sent using more conventional methods; the majority was delivered online using Google Form through email, messenger, WhatsApp, and Telegram.

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Sample

Students from Dhaka, Chittagong, and Cumilla in Bangladesh, who are currently pursuing postgraduate degrees in business at public universities, filled out the survey. Students with a background in business who have completed their degrees are in high demand because they bring a comparative perspective to the table and have come to rely on AI and AI tools for academic collaboration. A total of 1,110 surveys were distributed, and 717 samples were collected from the surveys. After 79 samples were excluded due to misinterpretation of information, 638 valid samples remained. None of these options will apply to the other majors or backgrounds at these schools. We need more comprehensive and diverse investigations to gain better insights.

Strategy of Data Analysis

For data analysis, statistical tools, namely, SPSS 25, Mplus 7.4, and AMOS 24, were used in this work. To eliminate invalid and illogical questions, data cleaning was done by descriptive statistics. Secondly, to examine the mediating effects with the Bootstrap method, hierarchical analysis of regression was used. However, to confirm the moderating effects, a component of interaction regression analysis was performed and used. This comprehensive approach to analyzing data confirmed the data's scientific and credible integrity, providing robust empirical support for understanding how students' learning, creativity, and invention are impacted by the use of AI.

RESULTS AND ANALYSIS,

Results

For data processing, this study uses SPSS 25.0 and PROCESS 3.4. With a 96.03% confidence level, 5000 samples were utilized to examine the regression coefficient of significance using the bias-corrected Bootstrap technique.

Reliability Analysis

This means that each set of items is reliable because all the variables in Table 1 have Cronbach's Alpha > 0.80. AI in Learning (0.921) and AI in Innovation (0.908) are the most reliable. CITC levels, on the other hand, are generally above 0.6, which is an optimal thing. Some, like Q1 = 0.521 or Q14 = 0.563, are lower but still satisfactory. More significantly, it doesn't appear that any of the items would substantially reduce the reliability if they were eliminated (i.e., no item exhibits a considerably higher alpha if it is removed).

Table 1: Variable Cronbach's Reliability Analysis (Based on the authors' own compilation)

Variable Name	***Items***	***Corrector Total Correlation (CITC)***	***Cronbach's Alpha coefficient with term deleted***	***Cronbach's Alpha Coefficie nt***
AI Usage	Q1	0.521	0.870	0.874
	Q2	0.645	0.857	
	Q3	0.639	0.858	
	Q4	0.629	0.859	
	Q5	0.639	0.858	
	Q6	0.615	0.861	
	Q7	0.632	0.859	
Task Complexity	Q8	0.574	0.836	0.849
	Q9	0.641	0.823	
	Q10	0.624	0.825	
	Q11	0.643	0.823	
	Q12	0.622	0.825	
	Q13	0.609	0.827	
	Q14	0.563	0.834	

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Self-Efficacy	Q15	0.578	0.763	0.807
	Q16	0.613	0.795	
	Q17	0.639	0.746	
	Q18	0.648	0.743	
	Q19	0.627	0.774	
AI in Learning	Q20	0.753	0.899	0.921
	Q21	0.734	0.910	
	Q22	0.763	0.907	
	Q23	0.762	0.908	
	Q24	0.775	0.906	
	Q25	0.726	0.910	
	Q26	0.781	0.906	
	Q27	0.629	0.918	
AI in Creativity	Q28	0.588	0.773	0.806
	Q29	0.606	0.764	
	Q30	0.642	0.746	
	Q31	0.648	0.744	
	Q32	0.649	0.739	
AI in Innovation	Q33	0.636	0.845	0.908
	Q34	0.760	0.897	
	Q35	0.759	0.902	
	Q36	0.768	0.899	
	Q37	0.727	0.907	
	Q38	0.781	0.906	
	Q39	0.627	0.915	
	Q40	0.701	0.913	

Table 1.1: At a glance, the Variable Cronbach Reliability Analysis (Based on the authors' own compilation)

Validity Analysis

Variable Name	Number of Items	Cronbach's Alpha	Interpretation
AI Usage	7 (Q1–Q7)	**0.874**	Good internal consistency
Task Complexity	7 (Q8–Q14)	**0.849**	Good internal consistency
Self-Efficacy	5 (Q15–Q19)	**0.807**	Acceptable consistency
AI in Learning	8 (Q20-Q27)	**0.921**	Excellent consistency
AI in Creativity	5 (Q28–Q32)	**0.806**	Acceptable consistency
AI in Innovation	8 (Q33–Q40)	**0.908**	Excellent consistency

When assessing a measuring model, Hair et al. (2017) recommended that convergent and construct validity be demonstrated. We employed the average variance extracted (AVE), composite reliability (CR), and the loading of each item on its associated variable to establish convergent validity (Hair et al., 2014). Table 2 shows that all

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constructs have AVE Values > 0.50, indicating appropriate convergent validity. AI usage has the greatest AVE, 0.610, and task complexity has the lowest, 0.501, but it is acceptable. All constructions have CRs above 0.80, indicating robust internal consistency; AI in learning has the highest CR, 0.921. This table indicates that all latent variables in this study meet the requirements of AVE ≥ 0.50 and CR ≥ 0.80.

Table 2: Variable Model AVE and CR Indicator Results (Based on the authors' own compilation)

Variables Name	***Average Variance Extraction (AVE Value)***	***Combination Reliability (CR Value)***	***Interpretation***
AI Usage	0.610	0.870	Excellent convergent validity and internal consistency
Task Complexity	0.501	0.850	Acceptable validity and good reliability
Self-Efficacy	0.517	0.808	Acceptable AVE and CR
AI in Learning	0.595	0.921	Excellent AVE and Stronger CR
AI in Creativity	0.589	0.807	Good AVE and acceptable CR
AI in Innovation	0.596	0.909	Excellent AVE and CR

Correlation Analysis

According to Table 3, on a scale likely ranging from 1 to 5, the average across all variables is 3.5, indicating moderate engagement. The standard deviation, or range, on the other hand, ranges from 0.773 to 0.895, showing considerable variability in responses. A greater correlation among all factors was identified in this study, specifically a strong connection between AI usage and innovation 618 (p <.01), meaning that the more AI is used, the more it fosters innovation. Additionally, a strong connection of.630 (p <.01) was found between AI in learning and AI in creativity. .626 (p <.01) also agreed that AI-driven creativity has a significant influence on innovation outcomes. However, this study found that LCI is significantly correlated with higher AI usage and self-efficacy (Confidence) with AI. For instance, the associations between AI usage and learning [.414 (p <.01)], AI usage & creativity [.449 (p <.01)], AI usage and self-efficacy [.320 (p <.01)], and self-efficacy and AI in innovation [.411 (p <.01)]. This study also looks into the relationship between task difficulty and AI in creativity, finding that it has no discernible effect on how AI is used to creativity or learning .038, indicating insignificance. Similarly, there was a negligible correlation (r = .092) between task difficulty and AI in learning.

Table 3: Mean, Standard Deviation (SD), and Correlation of Each Variable (N=638) (Based on the authors' own compilation)

Variables Name	Average	SD	1	2	3	4	5	6
1. AI Usage	3.567	0.773	-					
2. Task Complexity	3.464	0.839	.250**	-				
3. Self-Efficacy	3.528	0.847	.320**	.173**	-			
4. AI in Learning	3.387	0.879	.414**	**.092**	.387**	-		
5. AI in Creativity	3.516	0.782	**.449****	.038	.132*	**.630****	-	

6. AI in Innovation	3.672	0.895	.618**	.350**	.411**	**.573****	**.626****	-

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Regression and Hypothesis Testing

Here, the dependent variables are learning, creativity, and innovation (LCI); the independent variable is AI usage. Task complexity serves as an adjustment variable, and self-efficacy functions as a mediator variable.

The relationship between AI usage and LCI.

The regression equation is significant and has a rather acceptable goodness of fit, as indicated by Table 4's modified R^2 value of M2 (0.097), ΔR^2 / DR^2 (0.018), and F (9.954). With an independent coefficient β value of 0.163** for AI usage in M2, the impact is noteworthy, indicating that AI usage significantly affects LCI. Indeed, AI Usage significantly affects LCI, which means a **direct impact is visible**.

In fact, Hypothesis 1 (**H1**: AI usage significantly influences LCI) has been verified.

Table 4: LCI Regression Results (Based on the authors' own compilation)

Variables		**Learning, Creativity, and Innovation (LCI)**			
		M1 (CV only)	**M2** (CV+ AIU)	**M3** (CV+ AIU+ TC)	**M4** (CV+ AIU+ TC + SE)
Constant		1.847***	1.414***	0.572*	1.681**
Control Variable (CV)	Gender	0.185*	0.187*	0.166*	0.171*
	Age	0.041***	0.040***	0.037***	0.037***
	University	0.009	0.02	0.02	0.019
Independent Variable	AI Usage		**0.163****	**0.072**	- 0.273
Adjustment/ Moderator	Task Complexity			**0.381*****	0.029
Mediator	Self-efficacy				**0.099***
Regression Equation Fitting	**Adjust R^2**	0.086	0.097	0.178	0.180
	ΔR^2	0.093	0.018	0.081	0.008
	F-Statistics	22.407***	9.954**	**61.068*****	5.394*
	Comments based on F-statistics	Strong model with controls	The model is still significant with AI	***Best-fitting & Stronger Model- TC is key & matters a lot***	Slightly weakening mediation reduces AI's direct role.
	Comments based on **Adjust R^2**	CV explains 8.6% of LCI	The model improves slightly when AIU is added	***TC** adds significant explanatory power*	SE adds little more

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Note: CV = Control Variables, AIU= AI usage, TC= Task Complexity, SE= Self-efficacy; *p<0.05,**p<0.01,***p<0.001

The Moderating Effect of TC

From Table 4, in M3, TC is very favorable (0.381*) and AI usage becomes non-significant (0.072), resulting in the effect of AIU varying with task complexity. For example, high-complexity tasks may be more effectively supported by AI. The mediator item (SE) in M4 has an unstandardized coefficient value of 0.099, indicating a substantial impact and positive effect, after adding TC as an adjustment/moderator variable (Table 4). It also shows how TC moderates the effects of AI on LCI. Results demonstrate that LCI is significantly impacted by AI use, even when challenging assignments are controlled.

The proposed Hypothesis 2 (**H2**: Task complexity moderates the relationship between AI usage and LCI) is proven.

The Mediating Effect of SE

This section examines how SE impacts the utilization of AI and LCI. Table 4 shows that the effect of AI Usage decreases (from 0.072 in M3 to -0.273 in M4) when self-efficacy (SE) is included, suggesting that AI usage indirectly increases LCI by increasing SE rather than directly. It also reveals a significant *(p = 0.0998*) effect* of SE, indicating a mediation effect. Table 5 clearly shows that both the direct and indirect impact of AI on LCI are statistically significant (b=0.2013, p < 0.001, confidence interval, (2.677, 2.3722) and b=0.0613, confidence interval, [0.0624, 0.3140]). An examination of the mediation effect found that SE acted as a mediator between AI use and LIC. The bootstrapped 95% confidence interval (0.0624, 0.3140) does not contain 0, as shown in Table 5, for the indirect effect (0.0813). Consequently, this indirect effect is statistically significant, even though a traditional t-test and p-value are not reported here (as is typical in bootstrapping). Hence, there is substantial evidence to support Hypothesis 3 (H3: Self-efficacy mediates the relationship between AI usage and LCI).

Table 5: Analysis of the Mediating Effect of SE on LCI (Based on the authors' own compilation)

Effect	EV	SD/ Boot S.E.	T-Value	P-Value	LLCI/ Boot LLCI	ULCI/ Boot ULCI	Comments
Total (D+I)	0.2013	0.0577	9.3846	0.0401	2.677	3.4637	Overall effect of LCI
Direct (D)	0.1543	0.0661	4.4635	0.0397	0.0418	0.3848	Effect of AI usage without SE (AI usage → LCI)
Indirect (I)	0.0813	0.0418 (Bootstrapped)	_	_	**0.0624**	**0.3140**	Effect of AI usage through SE (AI usage → SE → LCI)

Note: EV= Estimated Value, SD= Standard Deviation, LLCI/ULCI = Lower/Upper Limit of Confidence Interval (the effect will be statistically significant when the interval doesn't include 0), Boot S.E. = Standard Error from Boot Strapping (Used for calculating indirect effects)

Additional observations regarding moderated mediating effects

It is clearly shown in Table 6, 6.1 & 6.2: we additionally evaluate indirect effects (0.0758 (95% CI: [0.0332, 0.1432]), which is significant) on LCI, the dependent variables, through SE when the adjustment variable is task complexity (TC), which can take on a range of values (e.g., 3.5746, 4.4134, and 5.4312). The findings are displayed in the table. Examining the results on the left side of the table, it is evident that the conditional indirect impact is substantial for various values of TC. This means that regardless of the value of the moderating variable (TC), there is an effect. A user's sense of SE is a key intermediary between AI use and the outcome variable LCI. Here, determining the presence or absence of a moderated mediating effect requires more than just examining conditional indirect effects. According to the data provided in the right section of Table 6, with a 95% confidence interval [-0.0662, 0.0024], including 0, the procedure gives an index of moderated mediation. Hence, there is no moderated mediating impact when uncertainty avoidance is the moderating variable, and the data demonstrate that the effect is not substantial.

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Table 6: Results of moderated mediation effect analysis (Based on the authors' own compilation)

Outcome Variable	Moderated Variable (Task Complexity)	**Conditional Indirect Effect**				**Moderated Mediating Effect**			
		Effect Size (Indirect Effect)	S.E. (Boot)	Boot LLCI	Boot ULCI	INDEX	S.E. Boot	Boot LLCI	Boot ULCI
Learning, Creativity, and Innovation	3.5746	0.0758	0.0351	0.0332	0.1432	-0.0236	0.044	-0.0662	0.0024
	4.4134	0.0786	0.0283	0.0151	0.0887				
	5.4312	0.0563	0.0294	0.0236	0.0971				

Table 6.1: Conditional Indirect Effects at Specific Levels of Task Complexity

Task Complexity	**Indirect Effect**	**Bootstrapped SE**	**95% CI (Boot LLCI – ULCI)**
3.5746	0.0758	0.0351	0.0332 – 0.1432
4.4134	0.0786	0.0283	0.0151 – 0.0887
5.4312	0.0563	0.0294	0.0236 – 0.0971

Table 6.2: Index of Moderated Mediation

Index	**Bootstrapped SE**	**95% CI (Boot LLCI – ULCI)**
−0.0236	0.044	−0.0662 – 0.0024

The index lacks statistical significance because its confidence interval includes zero. It can be inferred from this that the effect of mediation is unaffected by task difficulty.

DISCUSSION

Focusing on their perspectives and the challenges associated with AI use in LCI, this essay examines the impact of AI on LCI. A thorough literature review developed the conceptual framework and assumptions. Despite the variables passing the validity, reliability, and convergent validity tests, neither the independent nor the dependent variables showed a significant quadratic effect. According to the findings, nearly 90% of students utilize AI in some way to help them with their coursework. It is not clear how AIU affects LCI via SE when TC is the modified variable and relies on varied values, according to the results. In other words, neither the moderated nor the unmodified mediating effects are statistically significant, and this holds even when TC serves as the moderating factor. To begin, research has shown a positive relationship between students' AIU and their LCI; hence, the more AI students use, the more critical it is for them to enhance their LCI. Students high in TC should be cognizant of the validity and logic of utilizing AI technology to initiate LCI, since TC moderates the beneficial relationship between AIU and LCI. Therefore, LCI is enhanced by the magnifying effect of AIU. With a sense of self-efficacy and collaboration, pupils can effectively utilize AI in practical ways as needed. Those who are able can seek out low-TC course instructors for advice and assistance if they need a relatively high level of AIU. Lastly, AIU is influenced by self-efficacy. It plays a mediating role in the LCI process. Students who score higher on the self-efficacy theory's measures of future confidence, resilience in the brain, and behavioral activity are those attending AIU (Tang et al., 2010). Students' self-efficacy serves a significant role in influencing employees' LCI when they work within the framework of AIU.

THEORETICAL AND PRACTICAL CONTRIBUTIONS

This study importantly contributes to the literature on AIU, SE, TC, and LCI by addressing critical gaps and offering new perspectives.

The study magnifies theory and knowledge in different ways by providing unique empirical insights. First, this lightens knowledge concerning LCI gained when students use AI for academic purposes by positioning self-efficacy as a mediating mechanism. Second, the study adds integrated new dimensions to the Social Cognitive theory (Bandura, 1986) and Cognitive Load Theory (Sweller,1988), which empirically establishes that learning and performance result from the dynamic interaction among personal aspects, behavior, environmental influences, and task complexity to facilitate LCI resulting from AI uses. Social Cognitive Theory (SCT) increases students' capability to guide digital platforms, enhancing significant perceptions of their utility and relevance in academic contexts (Abubakar et al., 2024; Wang et al., 2022). The study enhances the application of SCT in AI-assisted LCI. This study also examined empirical evidence for the SCT, where self-efficacy (SE) and learning have a significant influence on LCI. SCT suggests that there is a mutually influential relationship among the individual, environment, and behavior (Jeilani & Abubakar, 2025). In learning and technology adoption, Bandura's SCT focuses on the necessities of personal factors, environment, and behavior. This study examines the psychological factors by which AI fosters LCI, where earlier studies have mostly focused on the significant influence of AI on academic development and performance. AI uses in learning offer students personalized support and problem-solving feedback, which strengthens students' SE. Students who exhibit higher SE prompted by AI are more likely to engage in intricate cognitive processes, persist in complex tasks, and show increased creativity and innovation. As a result, SE acts as a mediating factor connecting AIU to LCI.

On the other hand, the Componential Load Theory (CLT) explains the moderating impact of task complexity, which helps to understand how students absorb information in a classroom ambiance (Paas & Ayres, 2014) This study examines the impact of AI, which depends on the interaction between technological support & task complexity, while CLT traditionally focuses on instructional design & cognitive process. AI assists students in performing routine cognitive operations, promoting their focus on higher-order creativity and innovative problem-solving when tasks are difficult. Alternatively, cognitive overload may limit the significant influence of AI when tasks are highly complex. As a result, the moderating role of task complexity broadens CLT by demonstrating how AI tools interconnect with cognitive and task-based conditions to influence learning outcomes (Paas & Ayres, 2014; Rosak-Szyrocka et al., 2023; Sweller, 1988).

Finally, these theoretical contributions build a multifaceted understanding of how AI usage enhances learning, creativity, and innovation through the interplay of SE and task-based factors. Therefore, this study gives a new integrative framework that combines educational psychology and cognitive research, and innovation theory to describe technology-based learning, creative & innovative performance.

CONCLUSION

Learning, creativity, and innovation gained from AI access to educational resources are the advantages that AI has brought to the trendy academic landscape. It has been proven in our research. This study highlights several notable concerns: most students (67.87%) expressed that they generate ideas using AI, then rethink these ideas, and finally combine all they can create to innovate new solutions on specific issues, which expands their learning, creativity, and innovation (LCI). While the majority of students view AI in a positive light, praising its ability to enhance learning speed, achieve academic excellence, and increase creativity and innovation, there are still significant concerns to consider. Among them are the reliability of AI desirable outcomes, the likelihood of being too reliant on them, the ignorance of rethinking concerning the desired results, and the possibility that the capacity for critical thinking among students would be limited and diminished. Our recommendations for a smooth rollout of AI use are as follows.

Firstly, it may involve thorough instruction and the use of data protection measures (Săseanu et al.,2024). The most effective way for universities to ensure that their teachers and students are well-versed in using AI tools is to implement training programs and data protection measures. Secondly, outlined standards and procedures for validation. To avoid becoming overly reliant on technology, it is essential to establish robust standards for the deployment of AI. These standards should include procedures for regularly validating AI-generated information. Thirdly and finally, regarding privacy and ethics (Łodzikowski et al., 2023), we require rules to safeguard students' information and minimize the likelihood of bias in AI.

LIMITATIONS AND FUTURE RESEARCH

Consistent with other quantitative studies, this one has a few drawbacks. Dhaka (Capital of Bangladesh), Chittagong, and Cumilla are the only three regions of Bangladesh from which the data for this study came. In this study, students only from the public universities with a business background were included. Indeed, data from various locations and universities with different backgrounds in Bangladesh may be collected for further investigation. To further understand how public and private universities with different student backgrounds in Bangladesh differ in terms of students' learning, creativity, and innovation, it would be beneficial to compare data from both types of institutions and their respective student backgrounds. To synthesize the research findings, it will be helpful to conduct such evaluations from different universities. Only business background graduate students possessed the subjects of this study's data collection. Postgraduate students from diverse backgrounds can also be surveyed in future studies, allowing for comparisons between the two groups. Researchers may gain further insights into the mechanisms for improving students' learning, creativity, and innovation by comparing AI usage in academic performance with students' creativity and innovation in various countries. Additional findings from similar comparative studies can enhance the present work. Future research can build upon the limitations of this study and explore the potential positive and optimal effects of artificial intelligence on students' creativity, innovation, and learning.

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