

When creativity meets artificial intelligence: a sequential path to smart learning and academic performance

Md. Kazi Hafizur Rahman

Department of Management, Rabindra University, Bangladesh,
Sirajganj, Bangladesh

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Abstract

Purpose – This study examines how the use of artificial intelligence (AI) and students' creative thinking (CT) contribute to smart learning (SL) and academic performance (AP) in higher education. It further examines whether AI use and SL mediate the relationship between CT and AP in a sequential manner.

Design/methodology/approach – A quantitative approach was adopted, and data were collected from 227 university students in Bangladesh. Structural equation modelling with SmartPLS was used to evaluate the proposed relationships.

Findings – The results show that both AI usage and CT are positively and significantly related to SL and AP. Beyond these direct associations, the data also point to a meaningful serial mediation pathway: students with stronger CT tend to report greater AI usage, which is in turn associated with higher SL engagement, and this heightened engagement is associated with better AP.

Originality/value – This study uniquely links CT, AI use, SL and AP in Bangladeshi higher education. It shows how CT affects academic achievement through sequential paths of AI usage and SL, clarifying how student talents convert into outcomes in digital learning environments. The findings suggest that institutions should promote CT and use AI-based learning tools to improve student performance.

Keywords Technology-enhanced learning, Artificial intelligence, Student performance, Creative thinking

Paper type Research article

1. Introduction

The education field is one of several industries that are being transformed by artificial intelligence (AI) (Al-Mamary *et al.*, 2024; Shahzad *et al.*, 2024). The advent of AI has resulted in a multitude of innovations that have entered various spheres of human life (Krishna, 2023; Rivas *et al.*, 2020). These developments have significantly improved the education sector and have been a driver of greater societal and individual change (Abulibdeh *et al.*, 2024). Currently, AI is introducing a new paradigm in education theory and practice, radically transforming the learning process of students, as well as the way they are taught (Bressane *et al.*, 2024; Dimitriadou and Lanitis, 2023).

Academic performance (AP) plays a major role in shaping students' academic paths by showing their highest achievements and growth over time (Al-Mamary *et al.*, 2024; Hudig *et al.*, 2022). Not only does it include knowledge of the curriculum, but it also quantifies the effectiveness with which students utilize their knowledge, time management and learning difficulties (Singh *et al.*, 2024; Hussain and Khan, 2021). Increased AP has many times been linked to increased self-esteem, improved workplace opportunities and increased personal fulfilment (Rodríguez-Ruiz *et al.*, 2024). With the further expansion of AI technologies, colleges and universities are increasingly adopting them to enhance learning and increase AP (Demartini *et al.*, 2024; Hooda *et al.*, 2022). Additionally, creative thinking (CT) has emerged

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as a critical concept in education (Chen *et al.*, 2020). Over the past several decades, CT has exerted a significant influence across multiple domains, including science, technology, economics and education (Yang and Zhao, 2021). CT equips professionals with the skills necessary to address complex problems, make informed decisions and adapt to the evolving demands of daily life (Karunaratne and Calma, 2023). Integrating AI into learning environments facilitates smart learning (SL) by enabling self-directed, technology-enhanced and efficient learning experiences. SL systems that utilize AI to customize and enhance educational content have demonstrated potential in delivering individualized educational support and resources (Dimitriadou and Lanitis, 2023). Yet, it is unclear what the impact of these technologies is on measurable learning gains and there is a need to explore that impact further. Recent advancements in AI, such as the development of ChatGPT, have resulted in increasingly powerful virtual assistants within the academic sector, signalling a transformative and disruptive trajectory for the field of AI (Dempere *et al.*, 2023; Holmström and Carroll, 2024). Given the numerous benefits associated with these AI systems, it is essential to rigorously assess their impact on the educational performance and overall learning experiences of university students (Demartini *et al.*, 2024). Previous studies such as, Al-Mamary *et al.* (2024) explored how task, technology and individual characteristics affect the effective use of ChatGPT among Saudi university students, demonstrating that task-technology fit significantly enhances AP. In a similar study, Shahzad *et al.* (2024) looked at how AI and social media affect students' mental health and AP in China. They found that SL was a factor that made a difference. Singh *et al.*'s (2024) study in North India, focussing on Gen Z students, highlighted that higher AI literacy leads to improved learning outcomes and AP.

Despite the growing adoption of AI in higher education, empirical evidence on its effectiveness in enhancing student learning outcomes remains limited, particularly in developing countries. Previous research has generally focused on the application of AI, creative cognition, or intelligent learning separately, without considering the interplay between these factors to determine their effects on education. In addition, the channels by which AI affects learning, namely, the effect it has on cognitive abilities like CT and consequent behavioural results like SL, have not been fully researched. In particular, the potential for serial mediation pathways linking AI usage, CT, SL and AP has received little attention. This gap highlights the need for research that integrates technological, cognitive and behavioural factors to better understand how AI adoption can enhance student achievement. To fill these gaps, the authors pose the following research questions to explore solutions to the issues raised: RQ1: Does AI usage and students' CT individually influence SL and AP in higher education? RQ2: Does SL mediate the relationship between students' AI usage and AP? RQ3: Does a sequential (serial) mediation pathway exist in which CT influences AI usage, which in turn affects SL, ultimately impacting AP?

This study advances research on technology-enhanced learning by examining how cognitive and technological factors work together to influence students' academic outcomes. Previous research has examined CT, AI usage, SL and AP largely as separate relationships, providing limited insight into the process through which students' cognitive capabilities are translated into improved learning outcomes in AI-supported environments. To address this gap, the present study proposes a serial mediation framework in which AI usage and SL explain the pathway through which CT contributes to AP. Rather than viewing AI as a direct determinant of academic success, this study conceptualizes AI as an enabling learning resource that allows students to apply their creative capabilities through more adaptive, intelligent and meaningful learning practices. The study further contributes to theory by bringing together constructivist learning theory (CLT) and social cognitive theory (SCT) to explain the interaction between students' cognitive capabilities, technology use and learning behaviours. This perspective can help to understand the interplay between CT and learning through the aid of AI. The study also gives practical suggestions to teachers and higher education institutions. It argues that the successful implementation of AI should go beyond

mere application, emphasizing the need for a learning ecosystem that fosters significant interaction with AI, creative problem-solving and autonomous learning. Furthermore, the study emphasizes the need for supportive policies to foster digital readiness, AI literacy and innovative pedagogical approaches, in order to enhance students' technological competencies and creative potential.

2. Review of literature and hypotheses development

2.1 Underpinning theory

The present study is grounded in CLT and SCT in order to explain the relationship between CT, AI usage, SL and AP. These theories offer a theoretical foundation to explain the relationship between cognitive abilities, interaction with the learning resources supported by AI and learning behaviour of students with AP.

CLT views learning as an active process, one where learners build knowledge through direct engagement with their educational environment. This study draws on two complementary strands of constructivist thought: Piaget's cognitive constructivism (Piaget and Inhelder, 1969) and Vygotsky's social constructivism (Vygotsky, 1978), which together offer a fuller picture of how knowledge is constructed in learning contexts (Pass, 2007). Piaget's contribution centres on the idea that learners don't just receive information passively – they actively interpret it and weave it into what they already understand. From this perspective, AI-powered learning tools can enhance knowledge building by providing customized support, personalized learning resources and dialogue-based learning experiences that encourage students to probe and delve into concepts. Vygotsky, on the other hand, places social interaction, collaboration and appropriately scaffolded support at the centre of learning. This is exactly what a SL environment wants to capture: an AI-powered platform that enables interaction, reflection, collaboration and adaptive learning experiences that are learner-centric. SCT (Bandura, 2001) explains learning as the result of reciprocal interactions among personal factors, behaviour and the learning environment. Within this framework, self-regulation, self-efficacy and observational learning are particularly relevant to AI-supported education. AI-based learning tools may support self-regulated learning by providing timely feedback, learning guidance and opportunities for students to monitor and evaluate their learning progress (Feng, 2024). Likewise, SL environments can support observational learning by enabling students to observe, practise and refine effective learning and problem-solving strategies through interactive learning activities (Ali et al., 2018).

Drawing on these theoretical perspectives, the proposed framework explains how CT, AI usage and SL are associated with AP. CLT explains how students actively engage with AI-supported learning resources to construct knowledge, whereas SCT explains how cognitive, behavioural and environmental factors interact throughout the learning process. Together, these theories provide the theoretical foundation for the proposed serial mediation model, in which CT is associated with AI usage, AI usage supports SL and SL is associated with AP.

2.2 Artificial intelligence (AI), academic performance (AP) and smart learning (SL)

SL refers to an advanced and technology-driven approach to education that leverages modern tools, digital resources and intelligent systems to enhance the learning experience. It is characterized by its focus on personalized, efficient and interactive methods that adapt to each student's requirements and interests (Biber et al., 2022). It allows learners to acquire knowledge with greater convenience. The term AP refers to the measurement of a student's academic achievements, which are usually evaluated through grades, test scores, assignments and general advancement in various areas or courses (Chan and Lee, 2023). It shows how well a student is learning the material, skills and information that are required in a certain educational setting. According to prior empirical evidence, AI tools are associated with gains in SL and AP through a range of tailored solutions (Shahzad et al., 2024; Yu and Guo, 2023).

The importance of the human aspect in the learning process must constantly be acknowledged. AI technology ought to serve as complements to, rather than replacements for, human instruction and mentorship.

One of the best things about current teaching is personalized learning. AI networks look closely at how each person learns and slowly improve the learning environment (Tapalova and Zhiyenbayeva, 2022). Intelligent tutoring systems also give students rapid feedback and help, which is like personalized education and helps them learn difficult concepts (D'Mello and Graesser, 2023). AI may also change learning materials to fit the needs of each student, giving them personalized, flexible learning experiences that help them understand difficult subjects better and may even boost their academic achievement (Li *et al.*, 2025; Dekker *et al.*, 2020; Gambo and Shakir, 2022). AI tools provide students with real-time access to a large pool of resources and information, thus enhancing their entire learning experience (Mutambik, 2024). AI-based platforms will be able to provide interactive simulations, practice exercises and immediate feedback, while enhancing engagement with dynamic tools and learning games, making the learning process more enjoyable and effective (Mallik and Gangopadhyay, 2023). According to the results of Dahri *et al.* (2024), performance expectancy, effort expectancy, information accuracy and pedagogical fit were the main factors that contributed to the adoption of AI tools among students in Pakistan and Malaysia, increasing the level of satisfaction and AP; engagement and innovativeness, in turn, did not affect the adoption statistically.

Moreover, AI significantly enhances accessibility for learners with disabilities by providing technologies such as speech-to-text and translation services (Mateos-Sanchez *et al.*, 2022). Predictive analytics will provide an opportunity for students who are likely to fall behind to receive early intervention, and AI-based suggestions of learning materials can be used to augment the instructional continuum. The implementation of collaborative tools based on AI will help in effective teamwork and communication, thus enhancing the interaction among peers. Finally, AI facilitates capacity-enhanced learning that provides a larger population with high-quality education without any geographic or economic limits. Besides technological competency, AI has the potential to change the AP by incorporating technology as well as customized, adaptive learning experiences (Dimitriadou and Lanitis, 2023). The previous studies show that prioritizing AI and adopting effective implementation strategies can materialize the inherent potential of AI in improving learning and AP among students (Shahzad *et al.*, 2024). Considering the above, we formulate the following hypotheses.

H1. AI positively influences AP.

H2. AI positively influences SL.

2.3 Creative thinking (CT), academic performance (AP) and smart learning (SL)

CT refers to the ability to generate original ideas, approach problems in novel ways and apply imaginative thinking in academic contexts (Eshet and Margaliot, 2022; Schoevers *et al.*, 2021). Students with higher CT abilities are more likely to engage in flexible cognitive processing and develop effective problem-solving strategies, which can enhance their academic outcomes. Prior empirical evidence also indicates a consistent positive relationship between CT and AP, suggesting that creativity contributes to improved learning achievement (Fan and Sun, 2024; Wei *et al.*, 2025; Akpur, 2020; Yang and Zhao, 2021). The use of AI in education facilitates intelligent learning by providing customized feedback, adaptive learning and improving engagement with the learner through intelligent systems (Embarak, 2022). The abilities enable students to engage better with the learning content and enhance their learning effectiveness. However, AI usage is more likely to influence AP indirectly by shaping how students learn rather than directly improving outcomes. Therefore, SL is proposed as a mediating mechanism through which AI usage enhances AP.

Moreover, students who are more creative in their thinking are more willing to use and explore AI tools in a more efficient way because they are more likely to test alternative

solutions and interact with learning technologies more. CT is conceptualized as a relatively stable cognitive disposition that precedes exploratory behaviour, consistent with trait-based accounts of creativity (Basadur and Basadur, 2011) and SCT's view that personal cognitive factors shape the initiation of behaviour (Bandura, 1986). This is reinforced by CLT, wherein learners' existing cognitive capabilities determine how they engage with new resources such as AI tools (Jonassen, 1999), which subsequently shapes downstream learning behaviours and outcomes. While an alternative ordering – AI usage shaping CT – is theoretically plausible and has some empirical support in both educational (Baek *et al.*, 2024) and organizational settings (Cai *et al.*, 2026), the present study positions CT as the entry point of the mediation chain because it precedes and enables the specific tool-engagement and learning-behaviour pathways that the model is designed to test. It is hoped that this increased involvement in the use of AI will result in the development of SL practices, including active exploration, adaptive learning strategies and enhanced knowledge processing, which will eventually translate into better AP. Accordingly, the mediation of CT on AP is likely to occur in a cascade with the use of AI and SL.

- H3. Students' CT has a positive effect on AP.
- H4. Students' CT has a positive effect on SL.
- H5. SL mediates the relationship between AI usage and AP.
- H6. CT influences academic performance through a sequential mediation pathway involving AI usage and SL.

Based on the above discussion, we proposed the following framework (see Figure 1):

3. Methodology

3.1 Sample selection

A convenience sampling technique was used to recruit Bangladeshi university students who met the study's eligibility criteria. This non-probability sampling method is commonly used in studies that focus on examining relationships between constructs rather than making population-wide generalizations.

A comprehensive and accessible sampling frame covering eligible university students across the target population was not available, which limited the feasibility of probability sampling. Although individual universities may maintain student records, no single sampling

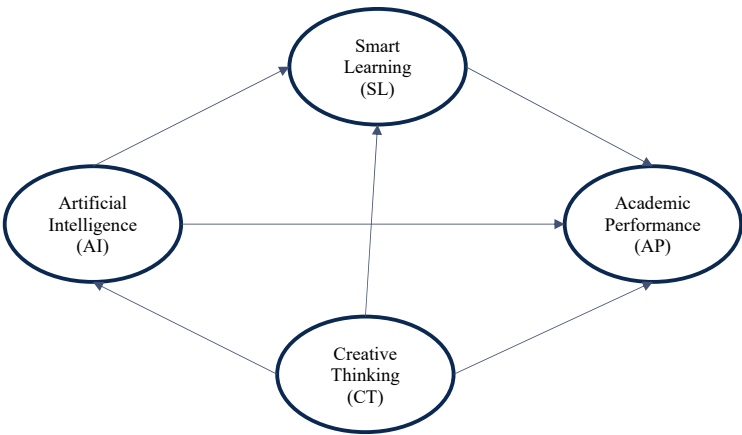


Figure 1. Conceptual framework

frame covering eligible students across the target population was accessible for the study. Structured self-administered questionnaire, both online and offline, were used to gather data. The questionnaire was developed to assess the constructs of the study using measurement items that are already available. Participation was voluntary, and the questionnaire was anonymous; no personal data were recorded for the participants. A total of 230 responses were received. The collected responses were screened before the main analysis to assess data completeness and response quality. During the screening process, three responses were identified as unsuitable for analysis due to extensive straight-line response patterns and/or missing data and were subsequently removed from the analysis. As a result, 227 valid responses were retained for the final analysis. The obtained sample size was considered adequate for the proposed Partial Least Squares Structural Equation Modeling (PLS-SEM) model and substantially exceeded the minimum threshold indicated by the 10-times rule (Hair *et al.*, 2022). The final sample therefore provided an adequate empirical basis for estimating the proposed relationships and examining the hypothesized direct and indirect effects within the PLS-SEM framework. The sample-size adequacy was evaluated with consideration of the model complexity and the statistical requirements of PLS-SEM rather than relying solely on the 10-times rule.

3.2 Measurement instruments

The questionnaire has been created in three steps. First, a comprehensive literature search was done to identify measurement scales that were previously developed and suitable items for each study construct. Second, the preliminary questionnaire was examined by researchers who had relevant expertise in the field of education for the relevance, clarity and contextual appropriateness of the items. Comments made by them were considered for reinforcing the content validity of the instrument. Third, a few words were changed in the questionnaire before it was administered to enhance the wording, clarity and readability of the instrument. All measurement items were adapted from previously validated scales. Items measuring AI usage were adapted from Gao *et al.* (2024), Shahzad *et al.* (2024) and Rodríguez-Ruiz *et al.* (2024). Items measuring SL and AP were adapted from Shahzad *et al.* (2024), Yang and Zhao (2021) and Ali *et al.* (2018), while items measuring CT were adapted from Yang and Zhao (2021), Eshet and Margaliot (2022) and Akpur (2020). Minor changes in wording and context where necessary were made to ensure that the items were appropriate for the study context but maintained the meaning of the original measures. Based on students' self-reported perceptions of their learning achievement, rather than on objective measures like grade-point average (GPA) or exam results, AP was operationalized. This operationalization corresponds with a self-administered questionnaire and reflects perceived academic results in the context of the study by students. The final questionnaire was preceded by a pilot test of the questionnaire with 35 students of universities who fulfilled the eligibility criteria of the study in Bangladesh. To evaluate the preliminary internal consistency of the measurement scales and the clarity and comprehensibility of the items, the pilot test was conducted. The results indicated that all constructs achieved Cronbach's alpha values above 0.70, suggesting acceptable internal consistency (Hair *et al.*, 2010). For the main survey, all measurement items were assessed using a seven-point Likert scale ranging from 1 = "strongly disagree" to 7 = "strongly agree."

3.3 Analysis overview

Analysis was done with PLS-SEM on SmartPLS. The two-step analytical method was used. Firstly, the measurement model was tested to determine the construct reliability and validity, such as internal consistency reliability, convergent validity and discriminant validity, through the criteria that were established. Second, the structural model was examined to test the proposed hypotheses by evaluating path coefficients, the coefficient of determination (R^2) and effect sizes (f^2). The significance of the hypothesized relationships was assessed using a bootstrapping procedure (Hair *et al.*, 2019; Podsakoff *et al.*, 2003).

4. Analysis and results

The data analysis findings are shown in this section. A summary of the respondents' demographics is given first, and then the measurement model's validity and reliability are evaluated. The proposed links are next examined by reporting the results of the structural model. The results of the mediation analysis are finally presented in this section.

4.1 Demographic profile

Table 1 shows the demographics of the 227 participants, such as their gender, age and level of education. The sample consists of 46.7% females (106 participants) and 53.3% males (121 individuals). Most of the people who took part, 76.2% (173), are between the ages of 21 and 25. The next largest group, 17.2% (39), is between the ages of 26 and 30. The smallest group, 6.6% (15), is between the ages of 16 and 20. In terms of their current academic status, 78.4% (178 participants) are undergraduates, whereas 21.6% (49 participants) are postgraduates.

4.2 Measurement model analysis

The measurement model demonstrated strong psychometric robustness across all latent constructs. Figure 2 illustrates the measurement model, while Table 2 presents the results of

Table 1. Demographic information ($n = 227$)

Construct	Items	Frequency	Percentage
Gender	Female	106	46.7
	Male	121	53.3
Age (years)	16–20	15	6.6
	21–25	173	76.2
	Above 25	39	17.2
Current academic position	Undergraduate	178	78.4
	Postgraduate Level	49	21.6

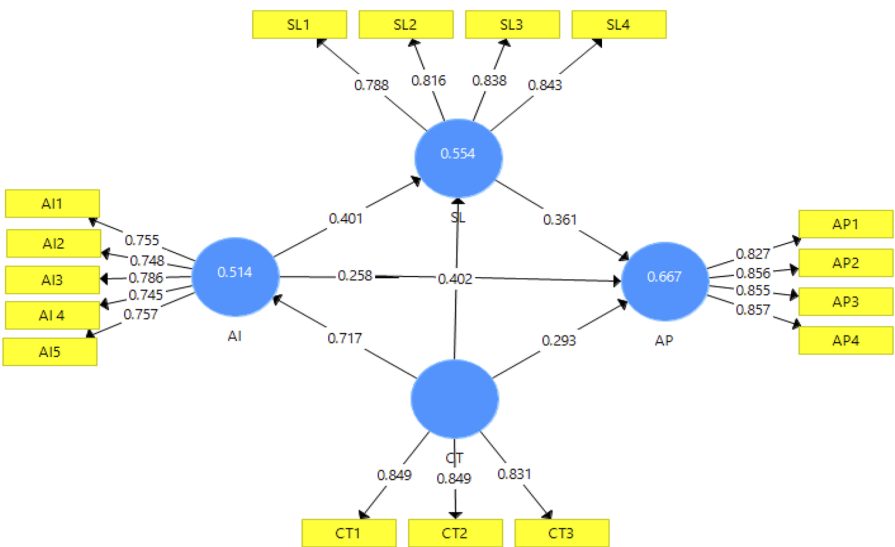


Figure 2. Measurement model

Table 2. Reliability and convergent validity results

Variable	Item	Loading	VIF	Cronbach's alpha	rho_A	CR	AVE
AI	AI1	0.755	1.623	0.816	0.821	0.871	0.575
	AI2	0.748	1.649				
	AI3	0.786	1.615				
	AI4	0.745	1.591				
	AI5	0.757	1.623				
SL	SL1	0.789	1.688	0.839	0.842	0.893	0.675
	SL2	0.816	1.774				
	SL3	0.837	1.995				
	SL4	0.845	1.976				
CT	CT1	0.848	1.733	0.796	0.796	0.881	0.711
	CT2	0.849	1.753				
	CT3	0.831	1.615				
AP	AP1	0.827	1.901	0.871	0.871	0.912	0.720
	AP2	0.856	2.174				
	AP3	0.855	2.240				
	AP4	0.857	2.211				

the reliability and convergent validity assessments, supporting the robustness of the measurement model across all latent constructs. The reliability of the indicators was initially confirmed, as all outer loadings surpassed the suggested minimum of 0.70, validating that each observed indicator effectively represented its foundational design. In addition, variance inflation factor values remained below the conservative cut-off value of 3.3, indicating the absence of problematic multicollinearity and suggesting that common method bias was unlikely to threaten the validity of the estimates. Internal consistency reliability was further supported, with Cronbach's alpha, rho_A and composite reliability values for all constructs exceeding the recommended minimum threshold of 0.70, thereby confirming satisfactory construct reliability (Hair *et al.*, 2022). Convergent validity was confirmed, too, with average variance extracted (AVE) values of 0.575–0.720 (surpassing the 0.50 suggested value) and each construct explained over half of its indicators' variance (Fornell and Larcker, 1981). The model showed an acceptable fit to the data. The Standardized Root Mean Square Residual (SRMR) value (0.062) was below the recommended threshold of 0.08, indicating a good model fit (Hu and Bentler, 1999; Hair *et al.*, 2022). The Normed Fit Index (NFI) value of 0.841 also indicated an acceptable level of model fit (Hair *et al.*, 2022).

Two approaches were employed to ascertain discriminant validity. First, the Fornell–Larcker criterion revealed that the square root of the AVE for each construct was greater than its correlations with other constructs, demonstrating construct distinctiveness (Table 3). Second, the HTMT ratios were below the suggested cutoff of 0.90 (Table 4), further establishing distinctiveness and helping to alleviate concerns about construct overlap among latent variables (Henseler *et al.*, 2015).

Table 3. Fornell-Larcker criterion

	AI	AP	CT	SL
AI	0.758			
AP	0.718	0.849		
CT	0.717	0.728	0.843	
SL	0.690	0.742	0.690	0.822

Table 4. Heterotrait-Monotrait ratio (HTMT)

	AI	AP	CT	SL
AI				
AP	0.843			
CT	0.881	0.873		
SL	0.824	0.866	0.842	

4.3 Structural equation model (SEM) analysis

After establishing measurement sufficiency and the overall model compatibility, the structural model was evaluated using bootstrapping methods to test the proposed relationships between constructs (Table 5). The results indicate that all proposed direct effects are positive and statistically significant. Specifically, AI usage exerted a significant positive effect on AP ($\beta = 0.258$, $t = 2.554$, $p = 0.011$), thereby supporting H1. Similarly, AI significantly influenced SL ($\beta = 0.401$, $t = 5.880$, $p < 0.001$), supporting H2. CT also demonstrated a significant positive effect on AP ($\beta = 0.293$, $t = 2.513$, $p = 0.012$), confirming H3, while its effect on SL was likewise positive and highly significant ($\beta = 0.402$, $t = 5.017$, $p < 0.001$), supporting H4. In addition, the direct paths underlying the indirect effects reported in Table 6 were both positive and significant: CT significantly predicted AI ($\beta = 0.717$, $t = 12.740$, $p < 0.001$), and SL significantly predicted AP ($\beta = 0.361$, $t = 5.202$, $p < 0.001$). In all cases, the t -values were over the critical value of 1.96 and p -values were less than 0.05, which validates statistical significance at the 5% level (Hair *et al.*, 2022).

Model explanatory power was evaluated using the coefficient of determination (R^2). AI, CT and SL together accounted for 66.7% of the variance in AP ($R^2 = 0.667$), demonstrating substantial explanatory power. The model explained 55.4% of the variation in SL ($R^2 = 0.554$).

Table 5. Hypotheses results

Hypotheses	Original sample (O)	Sample mean (M)	Standard deviation	t statistics	p values	Decision
H1: AI $\rightarrow$ AP	0.258	0.262	0.101	2.554	0.011	Accepted
H2: AI $\rightarrow$ SL	0.401	0.399	0.068	5.880	0.000	Accepted
H3: CT $\rightarrow$ AP	0.293	0.291	0.117	2.513	0.012	Accepted
H4: CT $\rightarrow$ SL	0.402	0.390	0.080	5.017	0.000	Accepted

Table 6. Indirect effect

Hypotheses	Original sample (O)	Sample mean (M)	Standard deviation	t statistics	p values
H5: AI $\rightarrow$ SL $\rightarrow$ AP	0.145	0.142	0.036	4.045	0.000
H6: CT $\rightarrow$ AI $\rightarrow$ SL $\rightarrow$ AP	0.104	0.102	0.030	3.462	0.001

Note(s): The component paths underlying the proposed serial mediation model that were not specified as separate hypotheses are reported here for completeness and transparency. Specifically, CT $\rightarrow$ AI ($\beta = 0.717$, $M = 0.711$, $STDEV = 0.056$, $t = 12.740$, $p < 0.001$) and SL $\rightarrow$ AP ($\beta = 0.361$, $M = 0.358$, $STDEV = 0.069$, $t = 5.202$, $p < 0.001$) were statistically significant

and 51.4% of the variance in AI ($R^2 = 0.514$). Following recognized guidelines for variance-based SEM, R^2 values above 0.50 indicate moderate-to-substantial explanatory power (Hair *et al.*, 2019; Sarstedt *et al.*, 2017); because no out-of-sample predictive assessment (e.g. PLSpredict) was conducted, these values are interpreted here as explanatory rather than predictive. The effect size analysis (f^2) revealed the relative contributions of each predictor. CT had a large effect on AI ($f^2 = 1.058$), showing a substantial practical contribution. AI and CT had minimal-to-moderate effects on AP ($f^2 = 0.083$ and 0.107 , respectively) and AI ($f^2 = 0.175$) and CT ($f^2 = 0.176$) had moderate effects on SL.

4.4 Mediation analysis

The bootstrapping process in PLS-SEM was used to do mediation analysis in order to investigate the indirect correlations suggested in the structural model (Figure 3). A mediator explains how an independent variable is associated with a dependent variable by transmitting its effect to the outcome variable (Baron and Kenny, 1986). The significance of the indirect effects was assessed using 5,000 bootstrap resamples in accordance with the recommendations of Hair *et al.* (2022). The findings indicate that SL plays a role in mediating the relationship between AI and AP ($0.145, t = 4.045, p = 0.001$). The positive and significant indirect effect indicates that AI usage is associated with AP in part through its association with SL, consistent with a mediation pattern. Moreover, the indirect pathway between CT and AP via AI and SL was also statistically significant ($0.104, 3.462, 0.001$). This finding suggests that CT is indirectly associated with AP through its association with AI usage, which is in turn associated with SL practices and, subsequently, with AP. The mediating role of SL in the explanatory framework as a whole is supported by both indirect effects being statistically significant. These findings suggest that cognitive and technology-related characteristics are associated with AP through layered learning-related pathways.

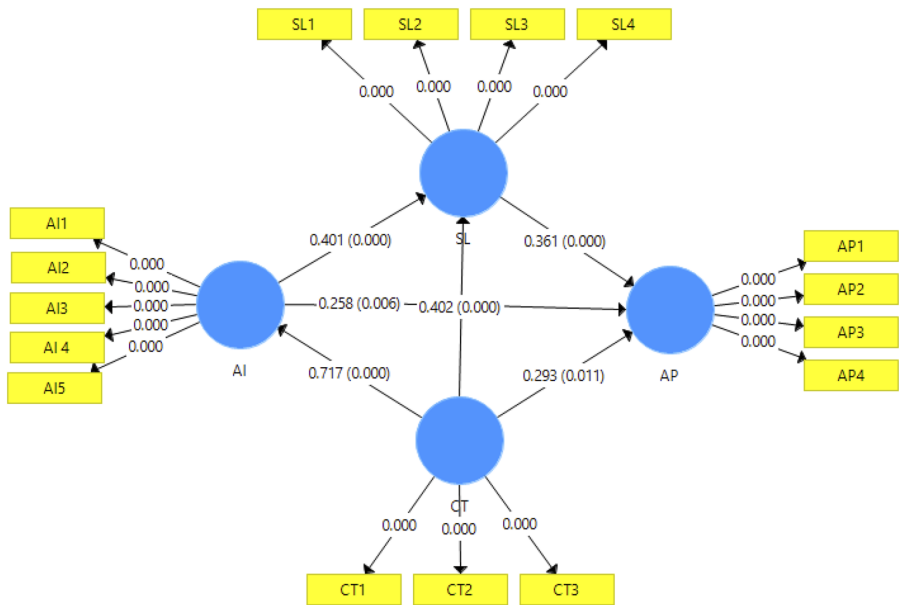


Figure 3. Structural model

5. Discussions

This study was guided by three research questions examining the direct, mediating and sequential relationships among AI usage, CT, SL and AP in higher education. The findings provide complete empirical information to address all research questions and contribute to the improved comprehension of the interplay between cognitive and technological conditions in order to influence AP.

To respond to RQ1, which compared the associations of AI use and CT with SL and AP separately, the data show that both constructs have a significant positive association with the two outcomes. In particular, there was a positive correlation between AI use and SL and AP, that is, taking advantage of more AI tools was associated with better learning experiences and academic outcomes. The findings are consistent with the literature, which has reported the potential of AI in education, such as benefits in personalized learning and provision of high-order academic support (Gao *et al.*, 2024; Shahzad *et al.*, 2024; Bressane *et al.*, 2024; Yang and Zhao, 2021). The H1 and H2 findings suggest that AI tools may be a useful component of course design. These technologies incorporated into the course setups assist in the establishment of inclusive, interactive and supportive learning environments. Correspondingly, CT was also positively associated with SL and AP, suggesting that students who reported more developed creative abilities also reported more adaptive learning and better self-reported academic outcomes. These results suggest that technological engagement and cognitive ability are independently associated with student achievement in higher education.

In terms of RQ2, which examined the mediating role of SL in the relationship between AI use and AP, the findings indicate that the mediation effect is statistically significant. This suggests that AI usage is associated with AP both directly and indirectly through SL: students who reported greater use of AI tools also tended to report more adaptive and structured learning behaviour, which was in turn associated with higher self-reported AP. These findings are consistent with previous studies (Shahzad *et al.*, 2024; Hu *et al.*, 2024). Regarding RQ3, which examined whether a serial mediation pathway links CT, AI usage, SL and AP, the findings support the presence of a statistically significant serial mediation pattern. This is consistent with a pathway in which CT is associated with greater engagement with AI tools, which is associated with greater use of SL practices, which is in turn associated with higher AP.

6. Conclusions

This paper has analyzed the direct, mediated and sequential correlations between higher education AI utilization, CT, SL and AP. The results indicate that AI utilization and CT have a positive impact on SL and AP, which is crucial in highlighting them as student success factors. The data further indicate that SL intermediates the relationship between AI use and AP, indicating that learning benefits of AI are achieved, in part, via better learning behaviours. The research indicates that there is a significant serial mediation, where CT facilitates AI use, SL and AP. The results suggest that the cognitive abilities and technological interaction interact with each other via organized learning to influence student achievement and that students who well-combine their cognitive abilities with technology-based learning techniques have better chances of succeeding in their schooling.

6.1 Theoretical contributions

This study makes several theoretical contributions to the body of existing literature. First, it extends existing research by developing a more integrated understanding of how cognitive and technological factors jointly influence academic outcomes. Previous studies have often examined CT, AI usage, SL and AP as separate relationships. This study, on the other hand, elucidates the interaction among these factors by demonstrating that students' CT can be transferred to better AP by applying AI and immersing in SL practices. Thus, the study moves

beyond asking whether AI contributes to learning outcomes and instead examines the process through which students' cognitive capabilities are converted into meaningful learning behaviours. Second, this study strengthens the theoretical understanding of AI-supported learning by integrating CLT and SCT. From a constructivist perspective, creative students actively construct knowledge by engaging with available learning resources, including AI-based tools. From a social cognitive perspective, AI provides an important learning environment that can support students' self-regulation, interaction and adaptive learning behaviours. By connecting these theoretical perspectives, the study provides a clearer explanation of why AI usage and SL may serve as important mechanisms linking student characteristics to AP. Third, the study extends the mediation literature by elucidating the mediation role of SL between AI usage and AP. Importantly, the results are consistent with a serial mediation model, where the effect of CT on AP is mediated by AI usage, then by subsequent SL engagement. This framework offers a more complex view of the interaction among students' personal capacities, technology-related behaviours and learning processes and their implications for academic outcomes in higher education.

6.2 Practical implications

The results have some practical implications for higher education institutions, teachers and students. First, universities can leverage AI-powered learning technologies into the teaching and learning process in a fashion that offers personalized learning support, timely feedback and further opportunities of engagement. Incorporating AI, however, should be viewed as a tool to support students' cognitive work, not as a replacement for it. Secondly, this study underscores the need for a comprehensive curriculum that fosters students' CT skills in tandem with the use of AI. Teachers may plan activities to promote creativity, problem-solving, critical thinking, generation of ideas and original responses. Then it is possible to assign students to tasks, give them tasks to complete in class, for which they are responsible for verifying the information and producing their own academic work, but using AI tools to explore and develop ideas. Third, the results indicate that universities should offer the proper guidance and training for teachers and students regarding the effective use of AI in learning. With careful and effective use of AI, these initiatives can help build students' AI skill sets and help educators design learning activities that incorporate AI tools and creatively engage students with rich and challenging experiences. Finally, pedagogical support for effective use of AI tools is an important consideration for academic administrators and policymakers, not only in the purchasing of the technologies but also in their use in the classroom. Institutions can analyze the use of AI tools for learning over time, and the impact on student learning and learning outcomes. This can include reflecting on student experiences, evaluations of teaching and the outcomes of learning to inform the responsible and appropriate use of AI in higher education.

6.3 Limitations and future research guidelines

Although this research yields useful insights, there are certain limitations. First, the cross-sectional design means that the findings cannot support conclusions about the causes and effects of the variables studied; the observed relationships should be interpreted as associations rather than evidence of a temporal or causal process. Longitudinal data would be more useful in establishing dynamic interrelations between AI use, CT and learning outcomes. Second, the sample was drawn from Bangladeshi universities using convenience sampling and it is not clear that the findings can be generalized to other nations with different cultures, education systems, technology infrastructures and pedagogies. Third, all constructs, including AP, were measured through self-report rather than objective indicators such as GPA or examination records, which may contribute to common method bias and subjectivity in the assessment of CT, SL and AP.

The limitations in the present studies can be addressed in future studies through longitudinal or experimental designs that determine causal relationships between AI use,

cognitive development and student performance. A cross-country or cross-system design would also be used to determine the sensitivity of the model to various settings. For future use, digital literacy or motivation or organizational support could be seen as a moderating variable that would further help explain the model. This would have been useful, too, with qualitative or mixed-method studies that could have brought in a deeper understanding of students' perceptions and experiences of using AI in learning, as well as the statistical models used in this study.

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Corresponding author

Md. Kazi Hafizur Rahman can be contacted at: mkazi.mgt@rub.ac.bd