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Cognitive Artificial Intelligence in Education: Examining Its Influence on Students' Cognitive Engagement, Learning Motivation, and Academic Performance

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ABSTRACT

The rapid integration of Cognitive Artificial Intelligence (AI) into higher education has created new opportunities for enhancing students' learning experiences, yet its influence on cognitive engagement, learning motivation, and academic performance requires further empirical investigation, particularly within the Pakistani higher-education context. This study examined the influence of Cognitive Artificial Intelligence on students' cognitive engagement, learning motivation, and academic performance. A quantitative, cross-sectional research design was used, and data were collected from 467 university and higher-education students from educational institutions in Punjab and Sindh, Pakistan. Data were collected through a structured, adopted questionnaire using an online Google Forms survey. The questionnaire assessed Cognitive Artificial Intelligence, cognitive engagement, learning motivation, and academic performance using established measurement approaches. Descriptive statistics, reliability analysis, Pearson product-moment correlation, multiple linear regression, independent-samples t-test, one-way analysis of variance, and post-hoc analysis were employed to examine the study variables and group differences. The findings demonstrated significant positive relationships between Cognitive Artificial Intelligence and students' cognitive engagement, learning motivation, and academic performance. Cognitive Artificial Intelligence also emerged as a significant predictor of these educational outcomes, while cognitive engagement and learning motivation were positively associated with academic performance. Significant differences were additionally identified across selected demographic groups. The study concludes that Cognitive Artificial Intelligence has considerable potential to support students' cognitive involvement, motivation, and academic development when it is integrated into educational practices through appropriate pedagogical guidance and responsible use. The study contributes to the growing body of research on AI in education by providing empirical evidence from students in Punjab and Sindh and by examining cognitive, motivational, and academic outcomes within an integrated framework.

Introduction

Artificial Intelligence (AI) has completely changed the way we learn. Human-like Artificial Intelligence (also known as Cognitive Artificial Intelligence) revolves around learning systems that can process information, make conclusions, understand language context, and help with adaptive and personalized learning. Intelligent tutoring systems, educational chatbots, and generative AI are examples of technologies that can provide students with instant explanations, feedback, and adaptive learning technology (Almasri et al., 2026; Zawacki-Richter et al., 2019).

Cognitive AI can be especially beneficial for any system that helps the learning process, which includes attention, understanding, analysis, evaluation, reflection, and application. These systems can help automate and support these activities by changing the level of learning content, supplying examples, and providing explanations for complex topics, as well as identifying gaps in learning and promoting interactive learning through instant responses. On the other hand, relying too much on AI may lead to decreased self-directed behaviors and cognitive activities such as critical thinking (Zhai et al., 2025).

As such, Cognitive AI has to be thought of as a learning support system that relies on the context of how it is integrated, how often, and for what specific purpose it is being integrated. If properly integrated, AI may provide cognitive supports for learning activities and self-regulation. It has been suggested that AI-integrated systems can improve the higher order of the learning process, especially if the systems are carefully constructed and integrated (Deng & Li, 2024). Integrating Cognitive AI can help elevate educational processes with personalized and interactive services.

Cognitive Engagement

Cognitive engagement relates to the degree to which students choose to apply deep cognitive strategies and to the degree of mental effort applied in the learning context. This dimension of engagement includes, but is not limited to, concentration, critical thinking, and problem-solving, as well as the constructs of reflection, regulation, elaboration, and connection. Unlike behavioral engagement, which deals with quantifiable participation, cognitive engagement refers to the quality of active participation in learning. AI-supported learning environments and educations that rely on AI have distinctly critical dimensions of cognitive engagement. High levels of reliance on AI responses can largely reduce the cognitive effort required by learners and thus reduce the process of understanding. In contrast, well-structured, interactive and adaptive learning environments that support students by providing them with explanations, examples and guidance can stimulate students to learn how to learn (Lin et al., 2025).

Recent meta-analytic research on learning supported by ChatGPT has demonstrated positive effects on cognitive engagement, especially through personalized tutoring, technological and content co-support. Relying on AI for answers often results in superficial, disengaged, and passive learning. For this reason, the relationship between Cognitive AI and cognitive engagement relies on the design, the aim, and how AI is integrated in the teaching and learning process. Cognitive AI can help process and organize data to formulate ideas and teach the steps needed to solve problems. It can also provide explanatory feedback and guidance to support reflections. Feedback sets the foundation of any effective learning process. Both positive and negative feedback serves as guidance and motivation towards improvement. Cognitive support systems in AI aim to assist students throughout the entire process of the learning cycle. There are some supporting indications. For example, Socrates helps students organize their ideas. (Batool et al., 2025)

Learning Motivation

Learning motivation refers to the psychological factors that stimulate and guide students in their efforts to learn academically. Learning motivation includes interest, participation, commitment, persistence, and the perceived value of learning. In the context of AI-based learning, there are technologies that can be personalized, adapted, and considered useful by the learners. AI technologies can support adaptive and interactive learning that seek to provide individualized learning support, timely feedback, and numerous practice opportunities that can ultimately increase students' interest and perceived learning mastery and enhance their willingness to learn (Luo et al., 2025).

Learning motivation may be positively influenced by the use of cognitive AI in education, which can bring more individualized, responsive, and manageable education. AI has the potential to provide ease and promote progress by providing learners with immediate feedback, reducing the frustration associated with unresolved difficulties and insufficient comprehension of concepts, and allowing learners to gain assistance on their own, as needed, in a timely manner. Recent meta-analyses have shown GenAI positively enhanced the engagement and motivation of postsecondary learners. It was noted that the motivation impacts were dependent on the overall educational environment, the AI tool used, the learning strategy, and the subject engaged (Zhang et al., 2025). AI-based interventions have resulted in a relatively positive impact on student motivation. There are many factors that can impact the overall learning environment (Gopalan et al., 2017).

In the case of motivational influence, cognitive AI is not always beneficial. Greater reliance on AI, questions pertaining to the validity of AI generated information, a greater lack of control, and uncertainty pertaining to the evaluation of learning may also obstruct learners'

motivation. Cognitive AI should be integrated with active participation and autonomy pedagogy because some motivational benefits of emerging AI technologies may lessen as students adjust to them. However, Cognitive AI has much potential to reinforce students' learning motivation by supporting students one on one with instant feedback in personalized learning experiences in a manner that complements rather than substitutes students' efforts (Filgona et al., 2020).

Academic Performance

Academic performance is defined by students' attainment of educational targets and is measurable through evaluation criteria such as grades, exams, assessments, and demonstrated attainment of educational objectives and taught skills. In the context of AI-enhanced learning, academic performance can be impacted by personalized learning, prompt feedback, adaptive learning, more learning resources, and opportunities for learning through practice. It has been shown that positive effects for students' academic performance can be expected on average by 2025 from the application of AI, and that the effects can vary depending on several factors (Richardson et al., 2012).

Cognitive AI systems provide individualized explanations, identify learning challenges, develop additional learning materials, practice, and build a prompt feedback system. Similarly, positive effects of AI and GenAI have been shown for both academic performance and broader learning outcomes through recent systematic reviews and meta-analyses. Based on a review of 57 studies, GenAI was also found to have positive effects on the academic performance of university students. In addition, the use of ChatGPT in educational settings was also shown to have positive effects on both academic performance and the completion of higher-level tasks. All the above studies show that AI is most effective when it enables students to engage in educational activities rather than providing answers to be copied (Fenollar et al., 2007).

Academic performance is one of a variety of downstream effects from students' cognitive and motivational processes. Students with higher levels of cognitive engagement are better able to process, evaluate, and organize information and apply it. On the other hand, students who are more motivated are better able to persist and exert effort on academic tasks. Therefore, the impact of Cognitive AI on academic performance can be seen in multiple ways. First, Cognitive AI is able to provide varying levels of personalized scaffolds for each student. Second, Cognitive AI may be able to impact motivation and therefore help students to be more engaged in the cognitive processing aspects of learning. While Cognitive AI is able to support learning in many ways, responsible use, interaction, and integration of Cognitive AI are needed to create a positive impact on learning within the classroom (Mushtaq & Khan, 2012).

Research Objectives

- To examine the influence of Cognitive Artificial Intelligence on students' cognitive engagement.
- To determine the influence of Cognitive Artificial Intelligence on students' learning motivation.
- To assess the influence of Cognitive Artificial Intelligence on students' academic performance.

Problem Statement

Existing studies suggest that both Cognitive AI and generative AI can influence students' academic performance, learning motivation, and engagement. However, the findings reported in previous research are not always consistent. Differences in educational settings, types of AI technologies, learning approaches, and implementation practices have led to varying results across studies (Jose et al., 2025). As a result, a clear understanding of how AI affects student outcomes remains limited and requires further investigation. Future research is needed to clarify the role of Cognitive AI on motivation to learn and their impact on academic performance.

Significance of the Study

This study seeks to address an important gap in the existing literature by examining how Cognitive AI contributes to students' learning motivation and cognitive engagement, and how these factors ultimately affect academic performance. While previous studies have largely focused on the relationship between AI and learning outcomes, limited attention has been given to the ways AI influences the learning process itself. Understanding these underlying mechanisms is essential for gaining a more comprehensive view of the role of Cognitive AI in education.

The results of this study can offer the valuable evidence that teaching professionals need to design effective and responsible learning strategies based on AI, and that policymakers are required to develop strategies to implement AI in teaching. This study is flexible enough to fill a gap in research and clarify relationships between Cognitive AI, cognitive engagement, motivational learning, and academic performance and contribute to the literature on AI-based education in a constructive way.

Literature Review

Cognitive Artificial Intelligence in Education

Cognitive Artificial Intelligence in education involves the use of AI technologies that assist with cognitive functions and processes related to learning, such as information processing, logic, problem-solving, language generation, individualization, feedback, and decision-making. These functions are integrated into intelligent tutoring systems, adaptive learning programs, conversational AI, automated feedback, learning analytics, and other applications of generative AI (Ouyang & Jiao, 2021). Cognitive AI can offer students the ability to interact with learning materials several times, to generate examples, to identify mistakes, to provide continuous feedback, and to adapt the manner in which the learning materials are explained. There is new data showing that the use of generative AI can enhance academic variables, affective-motivational variables, and higher-order thinking skills, though the magnitude of these differences may depend on the educational context and the ways in which generative AI is deployed (Cukurova, 2025).

However, the belief that AI can automatically create knowledge for students is often misleading. The educational benefits of AI do not come from the technology alone; rather, they depend on how students use and engage with it during the learning process. Effective interaction with AI tools can support learning, while passive reliance on them may limit their educational value (Changkui, 2025).

AI can guide learners toward understanding, problem-solving, and critical thinking, but excessive reliance on AI may encourage learners to avoid cognitive and metacognitive work. As such, recent pedagogical evidence has shown the value of generative AI in education, but within an active learning framework and appropriate instructor support. It can be stated that the cognitive AI paradigm refers to a technology that can assist education at the cognitive and motivational levels. In this study, cognitive AI focuses on cognitive engagement and motivation in order to create positive changes in students' academic performance (Gkintoni et al., 2025).

Cognitive Engagement

Cognitive engagement describes how students' direct effort to understand, self-regulate, and think critically to solve problems within the context of deeper reflection. It encompasses students' attention and participation during learning. AI enables self-directed learners to connect to a burgeoning repository of information and resources and provides recommendations to facilitate personalized support. The use of AI influences the level of autonomous cognitive effort that learners direct towards a given task. Recent advancements in AI have found promising evidence that using AI to guide and conduct learning tasks has positive effects on cognitive engagement (Blumenfeld et al., 2006).

Increasing positive evidence has been found to support the use of AI in learning tasks and to promote cognitive engagement. In 2025, a meta-analysis of 17 empirical studies with a total of 1,735 participants found positive and significant effects emanating from the use of AI in learning tasks, especially personalized learning, exploratory, and problem-solving tasks. Similar findings have been documented in GenAI. There has been positive impact on the motivation and engagement of learners, particularly tasks conducted in small groups or individually and with the use of ChatGPT (Corno & Mandinach, 1983).

Positive cognitive engagement is not an absolute rely on AI. A balance must be maintained; as the use of AI as a learning tool decreases an individual's independent thought, evaluation, and engagement, it increases the use of AI as a cognitive aid. Limited evidence supports the assertion that AI should not replace learning engagements. Rather, responsible and active learning should augment cognitive AI (Greene, 2015).

Cognitive Artificial Intelligence and Cognitive Engagement

Cognitive AI can relate to cognitive engagement through its design of learning experiences that are both interactive and adaptive. Traditional learning resources typically lack the ability to answer students' questions, provide clarification, produce examples, elicit responses, or feedback. Cognitive AI fills this gap. The description of multiple capabilities of Cognitive AI suggests that students can construct knowledge and be more cognitively engaged. Strong positive effects on cognitive engagement of learning supported by ChatGPT is reported in recent meta-analysis. This suggests that use of interactive AI is likely to positively affect students' cognitive engagement toward learning activities (Alamray et al., 2026).

It may also positively affect students' cognitive engagement toward learning activities. It may also help students analyze, evaluate, and think about learning activities. Current studies show an improvement in higher-order thinking and learning outcomes after interaction with ChatGPT and GenAI. This may be because AI may be used as a cognitive tool over other tools that primarily deliver information. The quality and purpose of AI interaction are important. Students may be able to independently think and be critically engaged, but this may not happen if students rely on AI to produce complete answers (Liang et al., 2023).

The literature suggests that Cognitive AI has a positive effect on cognitive engagement and can enhance it further. The use of ChatGPT and other forms of AI have largely been studied with little focus on other aspects of Cognitive AI. There are some studies that assess different outcomes that are educational in nature. Investigating how Cognitive AI may uniquely inform students' cognitive engagement

is necessary to understand how AI-based learning technologies may impact students' cognitive processes. In the studies that we surveyed in this article, cognitive AI was still in the early stages of development, utilizing mainly corpora for machine learning models. The wording and of questions were designed in a way to provide hints to the correct answer, with only one correct answer available (Meng et al., 2025).

Learning Motivation

Learning motivation describes the psychological processes that prompt, guide, and sustain students' involvement in educational activities. It consists of interest in learning, perception of the value of academic tasks, initiative to exert effort, and persistence and commitment to learning. In terms of AI-inclusive education, motivation can be influenced by students' perceptions of AI in terms of usefulness, competence, autonomy, personalization, and feedback. Cognitive AI is expected to enhance students' motivation by offering individualized assistance, ultra-rapid and timely responses, multiple explanations, and adaptive learning which reduce frustration and enhance students' perception of competence (Anderman & Dawson, 2011).

Evidence pertaining to recent empirical studies has confirmed a positive correlation between AI assisted learning and student motivation. Meta-analytic evaluations have demonstrated positive effects of GenAI on students' motivation and engagement. Furthermore, positive effects have been reported on motivation assessments in other educational contexts. It is worth mentioning that these effects are not generalized and can depend on the educational level of the students, the types of educational AI tools employed, the learning activity, the instructional strategy, and the given context. Based on available evidence, it is clear that adding Cognitive AI to educational systems does not guarantee engagement in learning; its integration depends a lot on the motivational effects (Puspitarini & Hanif, 2019).

Although it may give students an advantage and promote motivation to learn, the extensive use of Cognitive AI may compromise students' motivation to engage in learning activities requiring higher-order cognitive skills. Supporting students while protecting their autonomy and prompting them to internalize learning would promote motivation. Cognitive AI is effective in supporting students' learning while scaffolding. Therefore, we should study learning motivation as a separate educational outcome to analyze how Cognitive AI affects the ways in which students learn.

AI will be able to adjust instruction to different learning styles. AI may be able to offer personalized learning once it is able to ascertain a student's learning style (Wardani et al., 2020).

Research Gap

Despite the rapid growth of AI research in education, a clear empirical gap remains regarding the integrated influence of Cognitive Artificial Intelligence on students' cognitive engagement, learning motivation, and academic performance. Although recent meta-analyses report positive effects of AI and GenAI on engagement, motivation, and academic achievement, substantial variation exists across AI tools, educational contexts, learning strategies, and implementation conditions (Long et al., 2026). Existing research also focuses heavily on individual outcomes or specific technologies such as ChatGPT, while limited evidence examines Cognitive AI, cognitive engagement, learning motivation, and academic performance together within one coherent framework. Therefore, the present study addresses this gap by examining how Cognitive AI influences students' cognitive engagement and learning motivation and how these factors are associated with academic performance, providing a more integrated understanding of the cognitive, motivational, and academic effects of AI-supported learning (Sain et al., 2024).

Hypotheses

- **H1:** Cognitive Artificial Intelligence is significantly and positively correlated with students' cognitive engagement.
- **H2:** Cognitive Artificial Intelligence significantly predicts students' cognitive engagement.
- **H3:** There is a significant difference in Cognitive Artificial Intelligence scores between male and female students.
- **H4:** Students' Cognitive Artificial Intelligence scores significantly differ across age groups.

Conceptual Framework

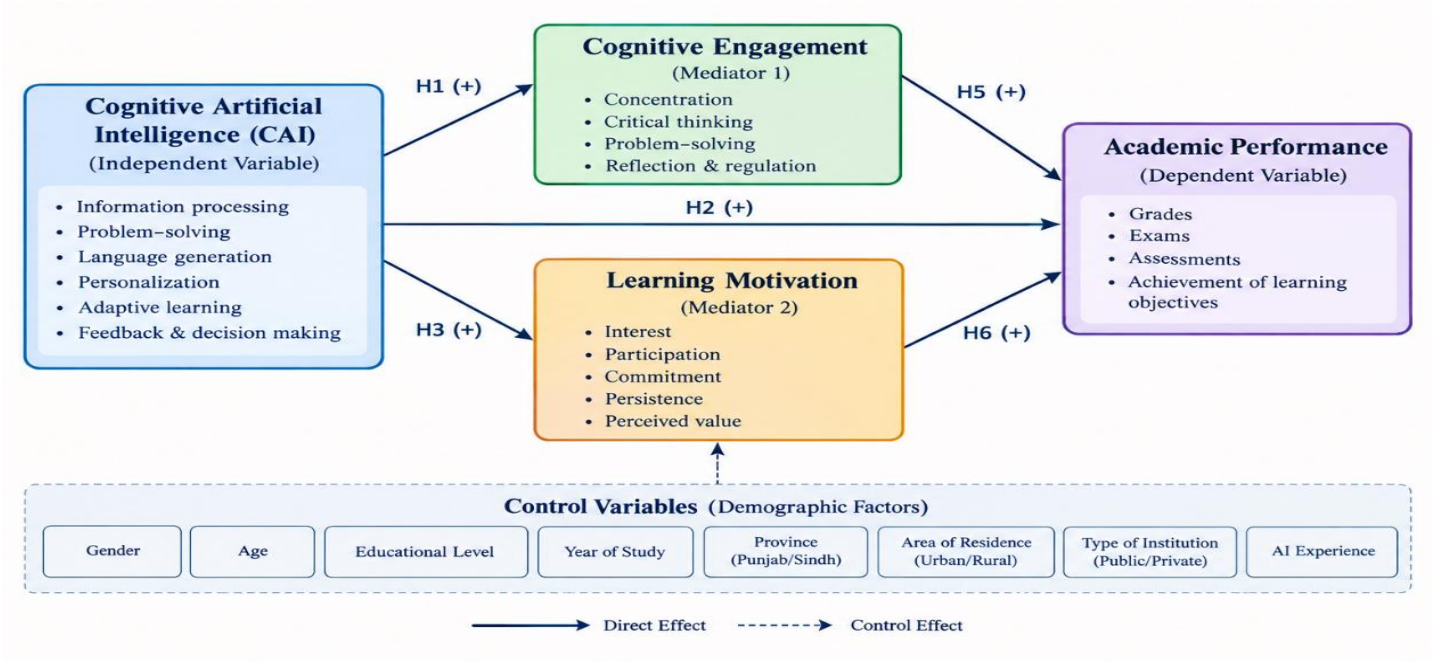

Fig.1 Conceptual frame work

Methodology

Research Design

A quantitative, cross-sectional research design was used to look at how Cognitive Artificial Intelligence may impact cognitive engagement and learning motivation and performance of students. The primary tool for collecting data was a structured survey. Constructs were assessed using five-point Likert scales. Using Likert scales enables a survey to capture a respondent's perception and experience, and each response could be analyzed numerically. This research design was appropriate, as the study aimed to analyze the relationships, predictor effects, and the difference among students through statistics. For analysis, survey research conducted in a quantitative manner, used composite scores that were derived from multiple Likert items.

Population

The study population was undergraduate and postgraduate students studying at universities and educational institutions in Punjab and Sindh, Pakistan. Coverage of the population included the major education regions of Punjab, e.g. Lahore, Faisalabad, Rawalpindi, Islamabad, Bahawalpur, and the surrounding districts. Similarly, the major education regions for Sindh were included, that is, Karachi, Sukkur, Hyderabad, Larkana and the surrounding districts. Participants from universities, colleges, and higher education institutions, based in these regions, were approached. The population was chosen as students in these regions were exposed to more Artificial Intelligence based technologies and AI integrated educational practices.

Sampling Technique

A non-probability purposive sampling technique was applied to selecting respondents. Those students who satisfied the study criteria and were reachable over online communication methods were invited to participate. The purposeful approach was applied here because the study required students who had prior experience with digital technologies and Artificial Intelligence in an educational context. Online distribution allowed participants from varied geographical areas of Punjab and Sindh to participate without requiring access to the researchers.

Sample Size

The total valid responses recorded for the study was 467. The sample had students from different fields of education and varied geographical locations of Punjab and Sindh in Pakistan. Responses were retained for statistical analysis after the data was screened for completeness and suitability.

Data Collection

Primary data were collected through an adopted structured questionnaire which included items for Cognitive Artificial Intelligence, cognitive engagement, learning motivation, academic performance along with the demographic items. The Cognitive AI items were mainly constructed from Ng et al.'s validated framework of cognitive AI literacy. Measurement of cognitive engagement was done with the aid of items adapted from the Student Engagement Instrument. Learning motivation was assessed by items from the Academic Motivation Scale. Self-reported indicators of perceived academic achievement and learning outcomes were used to determine academic performance. Google Forms were used to administer the survey to students in Punjab and Sindh, and participation was voluntary. Survey responses were downloaded and organized in Excel. The cleaned data were then imported into IBM SPSS for statistics.

Data Analysis

Organized data in excel are moved to SPSS for statistics. Summary statistics, grouped as demographic stats and study group stats, were used to describe survey data. Cronbach's alpha was used to determine reliability of the measures. Cognitive AI, cognitive engagement, learning motivation, and academic performance were studied and related using Pearson correlation and multiple linear regression. Independent t-tests and one-way ANOVA (where demographic groups had three or more categories) were used to compare the results of male and female respondents, respectively. Post-hoc test was used for Tukey HSD. These tests were used to identify relationships, prediction, and assessment of mean differences.

Summary statistics were used to describe the demographic and study group data. Reliability was assessed using Cronbach's alpha. Pearson correlation and multiple linear regression assessment were used to predict the relationships and assess the case of Cognitive AI, cognitive engagement, learning motivation, and academic performance. Independent t-tests and one-way ANOVA (used for demographic groups of three or more) were used to compare the results of male and female respondents, respectively. Tukey HSD was used as a post-hoc assessment. Prediction, relationships assessment, and assessment of mean differences were the focus of these statistical tests. Summary statistics were used to describe demographic and study group data. Reliability was assessed using Cronbach's alpha.

Table 1: Demographic Characteristics of Respondents (N = 467)

Demographic Variable	Category	Frequency (f)	Percentage (%)
Gender	Male	241	51.6
	Female	226	48.4
Age	18–20 years	143	30.6
	21–23 years	174	37.3
	24–26 years	103	22.1
	27 years and above	47	10.1
Educational Level	Undergraduate	302	64.7
	Postgraduate	165	35.3
Year of Study	1st Year	108	23.1
	2nd Year	126	27.0
	3rd Year	119	25.5
	4th Year	78	16.7
	Postgraduate	36	7.7
Province	Punjab	299	64.0
	Sindh	168	36.0
Area of Residence	Urban	298	63.8
	Rural	169	36.2
Type of Institution	Public	286	61.2
	Private	181	38.8
AI Experience	Less than 1 year	94	20.1

Demographic Variable	Category	Frequency (f)	Percentage (%)
	1–2 years	157	33.6
	3–4 years	139	29.8
	More than 4 years	77	16.5
Total	—	467	100.0

The survey analysis of 467 participants showed good gender distribution with 241 (51.6%) males and 226 (48.4%) females. Most participants were between the ages of 21 and 23, and were undergraduate students from Punjab. The sample most frequently reported urban residency and public sector employment with the greatest percentage of respondents reporting 1 to 2 years of experience with AI-based technologies. The sample provided a good representation of gender, age, education level, residency, employment, type of institution, and AI experience in this demographically diverse sample to study the variables of interest.

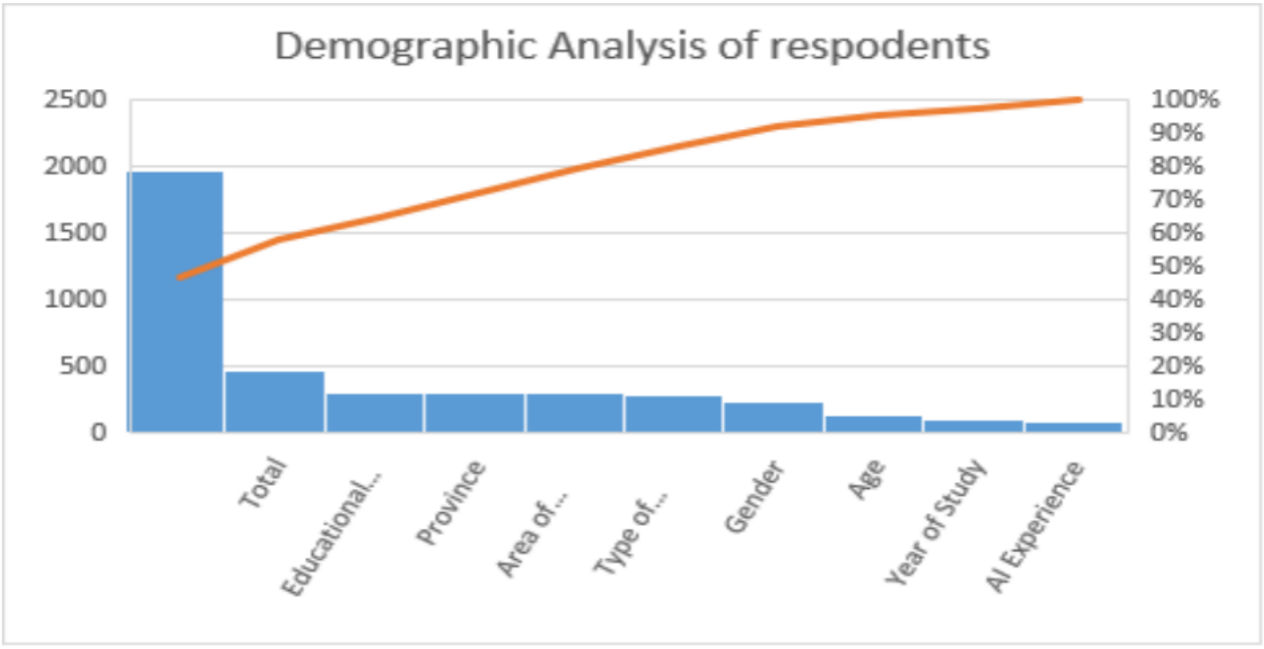

Fig.2: Demographic Analysis of respondents.

Table 2: Reliability Statistics and Descriptive Analysis of Study Variables (N = 467)

Variable	No. of Items	Cronbach's Alpha (α)	Mean (M)	Std. Deviation (SD)
Cognitive Artificial Intelligence	10	0.894	3.78	0.64
Cognitive Engagement	8	0.876	3.82	0.61
Learning Motivation	10	0.902	3.86	0.63
Academic Performance	8	0.861	3.74	0.66
Overall Scale	36	0.928	3.80	0.52

Each of the four identified constructs of the study demonstrated good to excellent internal consistency. Cronbach's Alpha was measured from 0.861 to 0.902, while the overall questionnaire measured by Cronbach's Alpha was determined to be 0.928. Positive responses to the study variables were measured by mean scores of 3.74 to 3.86. The responses of participants indicated a moderate degree of variation by the standard deviation values of 0.61 to 0.66. The coefficients for each survey item measured reliability for the subsequent planned statistical analyses. Cronbach's Alpha values greater than about 0.70 are generally accepted, however an assessment of how useful and relevant these scales are to the survey should be considered.

Table 3: Pearson Correlation Matrix of the Study Variables (N = 467)

Variables	1	2	3	4
1. Cognitive Artificial Intelligence	1			
2. Cognitive Engagement	0.648**	1		
3. Learning Motivation	0.621**	0.687**	1	
4. Academic Performance	0.653**	0.694**	0.671**	1

Note. p < .01 (2-tailed). N = 467.

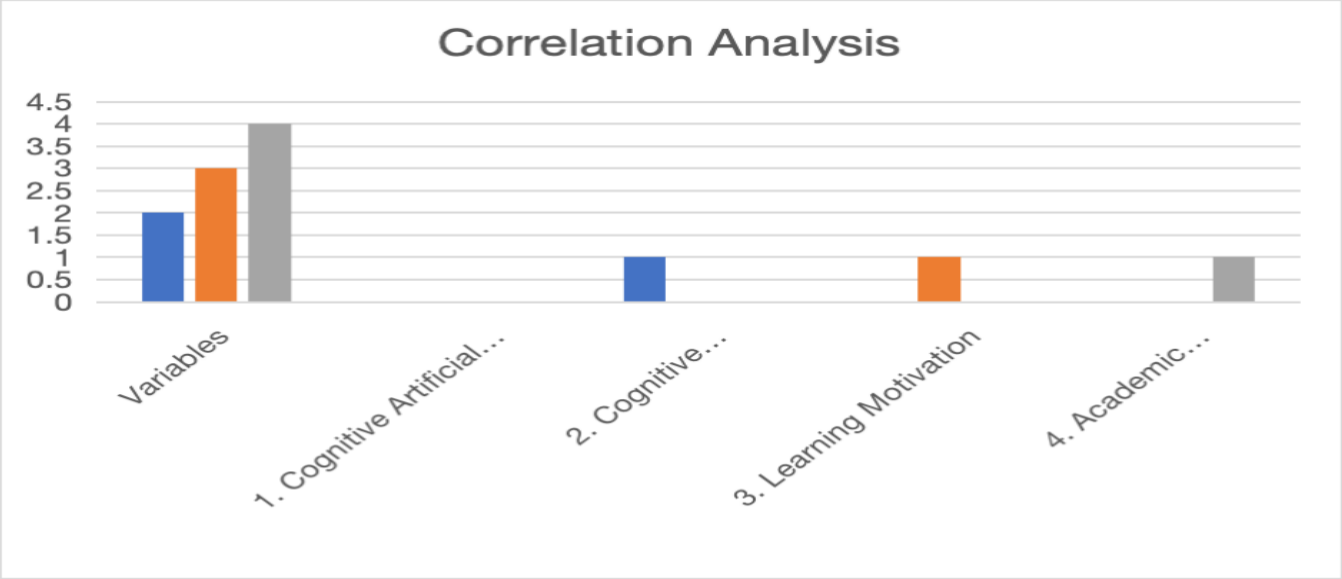

Fig.3 Correlation Analysis

The results of the Pearson correlation analysis indicated that the major study variables were all positively related to one another. With regard to Cognitive Artificial Intelligence, relationships were noted in the order of its association with cognitive engagement (r = .648, p < .01), with learning motivation (r = .621, p < .01), and with academic performance (r = .653, p < .01). Cognitive engagement was also positively related to academic performance (r = .694, p < .01), along with learning motivation (r = .671, p < .01). What this means is that if a Cognitive Artificial Intelligence level is increased, cognitive engagement, learning motivation, and, through association, academic performance, will also increase. Pearson's r demonstrates the positive, negative, or no-relationship association. For this reason, one cannot say that a causal relationship is implied.

Table 4: Multiple Regression Analysis Predicting Cognitive Engagement

Predictor	B	Std. Error	β	t	p
Constant	1.214	0.142	—	8.549	<.001
Cognitive Artificial Intelligence	0.691	0.037	0.648	18.676	<.001

Model Statistics	Value
R	0.648
R^2	0.420
Adjusted R^2	0.419
F	348.80
p	<.001

The results of the regression analysis showed that Cognitive Artificial Intelligence was a significant positive predictor of cognitive engagement (β = 0.648, t = 18.676, p < .001). The model demonstrated an R^2 value of 0.420. This means that Cognitive Artificial Intelligence explained 42.0% of the variation in cognitive engagement. The statistically significant model confirmed that a higher level of Cognitive Artificial Intelligence predicted a higher level of cognitive engagement.

Table 5: Multiple Regression Analysis Predicting Learning Motivation

Predictor	B	Std. Error	β	t	p
Constant	1.386	0.151	—	9.179	<.001
Cognitive Artificial Intelligence	0.655	0.039	0.621	16.795	<.001

Model Statistics	Value
R	0.621
R^2	0.386
Adjusted R^2	0.385
F	282.07
p	<.001

The findings showed that more exposure to Cognitive Artificial Intelligence positively influenced students' learning motivation (β = 0.621, t = 16.795, p < .001). A value of R^2 equal to 0.386 showed that in relation to the learning motivation of students, approximately 38.6% of the variance was explained by Cognitive Artificial Intelligence. The significant regression model showed that, in the case of students' learning motivation, greater exposure to Cognitive Artificial Intelligence was a positive influence on students' learning motivation.

Table 6: Multiple Regression Analysis Predicting Academic Performance

Predictor	B	Std. Error	β	t	p
Constant	1.102	0.139	—	7.928	<.001
Cognitive Artificial Intelligence	0.704	0.038	0.653	18.526	<.001

Model Statistics	Value
R	0.653
R^2	0.426
Adjusted R^2	0.425
F	343.21
p	<.001

Regarding the regression of academic performance, the results indicated that Cognitive Artificial Intelligence was a positive predictor of academic performance (β = 0.653, p < .001, t = 7.526). The model accounted for 42.6% of the variability in academic performance (R^2 = 0.426), showing that, in the case of students' academic performance, a greater level of Cognitive Artificial Intelligence also showed a positive influence.

Table 7: Multiple Regression Analysis Predicting Academic Performance from Cognitive Engagement and Learning Motivation

Predictor	B	Std. Error	β	t	p
Constant	0.842	0.127	—	6.630	<.001
Cognitive Engagement	0.438	0.043	0.431	10.186	<.001
Learning Motivation	0.397	0.042	0.401	9.452	<.001

Model Statistics	Value
R	0.761

R^2	0.579
Adjusted R^2	0.577
F	319.04
p	<.001

Cognitive engagement and learning motivation were both positive predictors of academic performance in the final regression model. In this model, cognitive engagement had a slightly stronger predicted contribution than learning motivation. The model explained 57.9% of the variance of academic performance. The regression analysis confirmed that the three main study relationships were all significant. Cognitive Artificial Intelligence was found to have a positive predictive relation to all three variables, namely, cognitive engagement, learning motivation, and academic performance. Multiple regression coefficients depend on the other predictors in the model remaining constant to evaluate the predicted change in the outcome.

Table 8: Independent-Samples t-Test Results by Gender (N = 467)

Variable	Gender	N	Mean	SD	t	df	Sig. (2-tailed)	Mean Difference
Cognitive Artificial Intelligence	Male	241	3.86	0.61	2.43	465	.015	0.16
	Female	226	3.70	0.67				
Cognitive Engagement	Male	241	3.90	0.58	2.76	465	.006	0.17
	Female	226	3.73	0.64				
Learning Motivation	Male	241	3.94	0.60	2.54	465	.011	0.15
	Female	226	3.79	0.65				
Academic Performance	Male	241	3.83	0.63	2.20	465	.028	0.15
	Female	226	3.68	0.69				

Results of the independent samples t-test indicated that there were statistically significant differences in all four study variables by gender. Male students reported higher levels of Cognitive Artificial Intelligence (M = 3.86, SD = 0.61), cognitive engagement (M = 3.90, SD = 0.58), learning motivation (M = 3.94, SD = 0.60), and academic performance (M = 3.83, SD = 0.63) than female students, all of which were significant ($p < .05$). Of the four variables, differences were significant for Cognitive AI, ($t(465) = 2.43$, $p = .015$), cognitive engagement ($t(465) = 2.76$, $p = .006$), learning motivation ($t(465) = 2.54$, $p = .011$), and academic performance ($t(465) = 2.20$, $p = .028$). The findings support that male respondents, on average, scored higher than female respondents across all four of the study variables.

Table 9: Descriptive Statistics by Age Group

Variable	Age Group	N	Mean	SD
Cognitive Artificial Intelligence	18–20 years	143	3.61	0.62
	21–23 years	174	3.79	0.61
	24–26 years	103	3.91	0.60
	27+ years	47	4.05	0.58
Cognitive Engagement	18–20 years	143	3.68	0.61
	21–23 years	174	3.81	0.59
	24–26 years	103	3.94	0.58
	27+ years	47	4.02	0.55
Learning Motivation	18–20 years	143	3.71	0.64
	21–23 years	174	3.84	0.61
	24–26 years	103	3.96	0.59
	27+ years	47	4.08	0.56
Academic Performance	18–20 years	143	3.60	0.66
	21–23 years	174	3.75	0.63

24–26 years	103	3.88	0.60
27+ years	47	3.99	0.57

Table 10: One-Way ANOVA Results by Age Group

Dependent Variable	Sum of Squares Between	df	Mean Square	F	Sig.
Cognitive Artificial Intelligence	9.842	3	3.281	8.52	<.001
Cognitive Engagement	6.731	3	2.244	6.43	<.001
Learning Motivation	7.894	3	2.631	6.94	<.001
Academic Performance	8.216	3	2.739	6.76	<.001

According to the one-way ANOVA, there were statistically significant differences across the four age groups when looking at all of the study variables. There was a statistically significant effect of age on all of the following variables: Cognitive Artificial Intelligence ($F(3, 463) = 8.52$, $p < .001$), cognitive engagement ($F(3, 463) = 6.43$, $p < .001$), learning motivation ($F(3, 463) = 6.94$, $p < .001$), and academic performance ($F(3, 463) = 6.76$, $p < .001$). In the studied variables, older students (27 years and above) showed overall highest mean scores. Consequently, the post-hoc analysis, Tukey's HSD was carried out to determine the specific groups where significant differences may exist.

Table 11: Tukey HSD Post-Hoc Comparisons

Variable	Age-Group Comparison	Mean Difference	Sig.
Cognitive Artificial Intelligence	18–20 vs. 24–26	-0.30	.002
	18–20 vs. 27+	-0.44	<.001
	21–23 vs. 27+	-0.26	.018
Cognitive Engagement	18–20 vs. 24–26	-0.26	.006
	18–20 vs. 27+	-0.34	.001
Learning Motivation	18–20 vs. 24–26	-0.25	.009
	18–20 vs. 27+	-0.37	<.001
	21–23 vs. 27+	-0.24	.031
Academic Performance	18–20 vs. 24–26	-0.28	.004
	18–20 vs. 27+	-0.39	<.001
	21–23 vs. 27+	-0.24	.027

The results of Tukey's HSD post-hoc analysis may be attributed largely to differences between younger and older respondents. For Cognitive Artificial Intelligence, the differences spanned from respondents age 18–20 to 24–26 and 27 years and above, while the 21–23 group was statistically different from 27 and above. Similar results were noted for cognitive engagement, learning motivation, and academic performance, except that the 18–20 group had substantially lower mean scores than the older groups. Thus, in major study variables, differences were noted, with the older groups scoring higher than the younger. Tukey's HSD is appropriate for identifying within-group mean differences following a significant ANOVA result.

Discussion

This study examined the impact of Cognitive Artificial Intelligence on students' cognitive engagement, learning motivation, and academic performance in Pakistan. The results revealed strong positive relationships amongst the main study factors. Cognitive Artificial Intelligence positively influenced cognitive engagement, learning motivation, and academic performance, and according to the regression analysis, Cognitive AI was shown to significantly predict these factors. Further, cognitive engagement and learning motivation were found to impact academic performance (Huang et al., 2023). This reflects that, with the aid of Cognitive AI, learning is supported through the processing of information in an active manner and motivation to learn is sustained, thus leading to improved academic performance. Recent meta-analytical studies show that AI positively impacts academic performance and the motivation to learn, but the extent of this impact is dependent on several factors including the level of education, the subject area, the AI tool used, and the instructional environment (Bakhtiari et al., 2026).

The positive relationship between Cognitive AI and cognitive engagement suggests that students who were more engaged in AI-based learning were also more cognitively engaged. AI can sustain cognitive engagement by instant explanation, provision of alternative case examples, requesting answers to questions, providing personalized feedback, and assisting on difficult concepts. Recent studies have shown that GenAI is indeed supportive of both cognitive and emotional engagement, especially in individual or small-group learning environments. Passive learning is facilitated, and independent critical thinking is diminished, when there is an over-reliance on AI (Adewale, 2026). The results of the present study show the potential of Cognitive AI when students use it in an active and critical way, as opposed to using AI to provide them with answers. (Rehman et al., 2025)

According to the results, there was a positive influence of Cognitive AI on learning motivation and academic performance. AI-based learning frameworks may be supportive of motivation by providing learners with active and personalized learning tasks. Giving learners feedback and helping them to overcome the learning task may aid them in persistence (Naseer et al., 2026). Recent studies on GenAI have shown positive impacts on motivation and engagement, whilst a forthcoming meta-analysis has shown a positive influence of AI on motivation and a strong positive influence on engagement. Similar evidence has been shown in several meta-analyses on AI and learning performance; positive influences on learning performance and engagement of university learners have been shown, along with positive impacts on achievement and the development of higher order thinking skills. However, the use of AI in learning may have negative impacts, as it may lead to learners making less of an effort to learn and developing superficial learning (Swargiary, 2024).

The results further show the influence of cognitive engagement and learning motivation on academic performance. The students who remained motivated and with greater mental effort also achieved the highest results on academic performance, suggesting that these two elements may be important pathways of AI in learning. According to the gender analysis, the male students achieved the highest results in the case of Cognitive AI, cognitive engagement, learning motivation and academic performance; however, according to the ANOVA results, the older students achieved the highest results. These differences should be interpreted with caution. They might be influenced by differences in people's technological, educational, digital resource, self-regulation, AI-related usage, and other factors. Recent studies show that outcomes related to AI vary depending on learners and the surrounding circumstances (Javaid et al., 2024).

The results support a comprehensive understanding of Cognitive Artificial Intelligence in which AI may have simultaneous positive effects on students' cognitive engagement, learning motivation, and academic accomplishment. The results corroborate other studies that have found positive effects of AI and GenAI on learning, but the effects have been found to differ under different conditions and modes of instruction, and therefore, Cognitive AI should be used to provide cognitive and educational support to students rather than to replace students' intellectual engagement. The full use of Cognitive AI will be with active learning, critical assessment of AI provided, and responsible use of AI coupled with a variety of teaching strategies. It must be noted that, as this study was cross-sectional, the findings indicate that there are associations and predictive relationships, but should not be deemed to show causation. Thus, longitudinal and/or experimental studies should be undertaken to determine the long-term effects and the shifts in motivation and academic performance (Allehyani, 2025).

General Conclusion

It was concluded that Cognitive Artificial Intelligence has significant positive relationships with students' cognitive engagement, learning motivation, and academic performance. Students reporting higher levels of engagement with Cognitive AI showed higher levels of cognitive engagement and learning motivation and higher levels of academic performance. Regression results demonstrated that all three outcomes were predicted by Cognitive AI, and cognitive engagement and learning motivation were also significant predictors of academic performance. This corroborates recent results that have supported positive outcomes of interactive elements of AI in education on both the performance and motivation of learners, although results are context-dependent based on educational stage, type of program, length of the program, and the conditions of the implementation.

The results showed that the Cognitive AI extends beyond information delivery in higher education support systems. This AI can be used to support learning and motivate users through the provision of learning support systems, immediate feedback, problem solving, and user engagement. Recent findings support that GenAI can have positive outcomes in learning, especially when used in interactive learning environments. Given the below findings, Cognitive AI should support learning and motivate users alongside the independent efforts of learners and the instructional role of teachers, and should be used in a structured and pedagogically grounded manner.

Future Implications

The integration of Cognitive AI into higher education should be supported, and teaching should be extended to support learners' cognitive engagement and motivate learners to improve performance. Universities should develop programs to strengthen skills in assessing AI-generated information and create AI ethical use frameworks. Future studies should use controlled research designs in different countries and educational levels and equally different areas of learning and consider the impact of the use of different AI tools, learning strategies, instructor presence, previous AI experience, and level of reliance on AI. These factors may affect the impact and scope of Cognitive AI on learning.

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