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Student–GAI Interaction and Learning Outcomes: A Serial Mediation Model of Self-Efficacy and Cognitive Engagement

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ABSTRACT

This study investigates the impact of student interaction with Generative Artificial Intelligence (GAI) tools on academic achievement within the higher education sector of Pakistan. Utilizing a two-wave time-lagged research design, data were collected from 427 undergraduate students across public and private universities in the Islamabad Capital Territory. Structural equation and bootstrapped mediation analyses reveal that student–GAI interaction exerts a positive effect on academic performance ($\beta = 0.154$, $p < 0.001$). This relationship is significantly explained by a sequential mediation pathway: interactions with GAI cultivate academic self-efficacy, which subsequently enhances cognitive engagement, ultimately driving higher learning success. The final structural model accounts for 31.5% of the total variance in student cumulative Grade Point Average (CGPA). These insights indicate that the primary educational utility of GAI stems from its psychological and behavioral scaffolding rather than basic task automation. The paper concludes with actionable recommendations for institutional policymakers and educators to design pedagogical frameworks that foster critical AI literacy while bridging digital equity access gaps.

Keywords: *Generative Artificial Intelligence (GAI), Academic Self-Efficacy, Cognitive Engagement, Learning Achievement, Higher Education, Pakistan.*

INTRODUCTION

The rapid integration of Generative Artificial Intelligence (GAI) has initiated a foundational shift in higher education globally, altering traditional paradigms of teaching, learning, and knowledge acquisition. Platforms such as ChatGPT, Gemini, and Claude possess advanced capabilities to process natural language, resolve intricate multi-disciplinary inquiries, and supply real-time feedback. This technological transformation has elicited polarized reactions within academic circles. While critics raise concerns regarding academic integrity, plagiarism risks, and the erosion of independent intellectual effort, proponents highlight GAI's capacity to serve as a personalized, adaptive, and highly accessible tutoring instrument.

Initial institutional reactions frequently favored outright containment or prohibition. However, contemporary educational research emphasizes that restrictive mandates often generate psychological reactance or heighten unguided usage. A more pragmatic approach involves

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embedding GAI deliberately within instructional architectures, establishing comprehensive digital literacy frameworks that prepare students for automated professional environments.

Despite growing conceptual discourse regarding the potential of GAI in education, a pronounced gap persists in structural quantitative research verifying how interactive engagement with these tools empirically translates into academic outcomes. Prior studies have frequently observed direct relationships while overlooking the specific internal psychological and behavioral mechanisms that connect technology adoption to student success. This study addresses these empirical limitations by using Social Cognitive Theory to construct a serial mediation framework. We propose that the influence of student–GAI interaction on learning outcomes operates sequentially through two distinct mediators: academic self-efficacy and cognitive engagement.

When students routinely interact with responsive, conversational AI systems to clarify complex materials or solve problems, these tools provide real-time cognitive scaffolding. This ongoing interactive mastery experience fosters academic self-efficacy—the individual belief in one's capacity to manage demanding educational tasks. Consequently, heightened self-efficacy drives students to invest deeper mental effort and demonstrate greater persistence, thereby boosting their cognitive engagement. This serial progression provides an integrated model showing how technology alters the internal motivational architectures of learners. By evaluating these pathways within higher education institutions in Pakistan, this study provides empirical context on technology adoption within developing educational ecosystems, offering insights for academic administrators and national education authorites.

LITERATURE REVIEW

Student–GAI Interaction and Learning Achievement

Unlike early educational technologies that functioned primarily as static repositories, GAI tools engage users in collaborative, iterative dialogue. Based on Interactive Theory, effective learning is driven by responsive, multi-directional engagement between the student and their learning environment. GAI fulfills these requirements by offering situational, personalized feedback that helps students identify conceptual gaps and alter their learning strategies at their own convenience.

In the developing higher education context of Pakistan, digital learning adoption has historically faced issues related to rigid teaching methodologies and institutional resource shortages. Recent studies within Pakistan emphasize that digital tools can enhance learning when they provide students with greater autonomy over their study pace. GAI platforms act as on-demand educational partners, lowering traditional barriers to inquiry such as peer judgment or limited instructor availability. By offering structured explanations, code debugging, and diverse conceptual examples, targeted GAI interactions help students master their course material, directly supporting academic performance. Thus, we propose:

H1: Student–GAI interaction is significantly and positively related to learning achievement.

The Mediating Role of Academic Self-Efficacy

Perceived self-efficacy refers to an individual's confidence in their ability to execute the actions required to achieve specific performance goals. According to Social Cognitive Theory, self-efficacy is a core driver of student effort, resilience, and strategy selection. In digital learning environments, self-efficacy is developed through successful task navigation and continuous, constructive feedback loops.

Interaction with GAI platforms offers students a private space to break down complex assignments into manageable steps. By generating tailored explanations matching a student's current understanding, GAI tools reduce cognitive overload. Achieving regular clarity through these tools functions as a digital mastery experience, boosting a student's confidence in handling challenging coursework. This enhanced sense of competence directly supports academic success, as highly self-efficacious students routinely display greater persistence under academic stress. Therefore, we hypothesize:

> ***H2: Academic self-efficacy significantly mediates the positive relationship between student–GAI interaction and learning achievement.***

The Mediating Role of Cognitive Engagement

Cognitive engagement denotes the depth of mental effort, self-regulation, and strategic analysis a student applies to comprehend educational content. While behavioral engagement captures simple compliance or attendance, cognitive engagement involves deep processing, critical analysis, and cross-referencing information.

Interaction with GAI tools can stimulate deep cognitive investment when designed as an iterative process. Because GAI outputs depend heavily on prompt quality, students must think critically to refine their questions and correct generic responses. Furthermore, the known risk of AI “hallucinations”—where systems generate credible but inaccurate information—requires users to evaluate, verify, and cross-reference answers against academic textbooks. This critical checking shifts the student from a passive consumer to an active analytical evaluator, cultivating deeper cognitive engagement. Consequently, this higher level of intellectual effort serves as a strong proximal driver of learning outcomes. Thus, we propose:

> ***H3: Cognitive engagement significantly mediates the positive relationship between student–GAI interaction and learning achievement.***

The Serial Mediation Pathway

Rather than operating along independent parallel channels, academic self-efficacy and cognitive engagement are interconnected components of a sequential learning process. Educational research indicates that students' motivational beliefs directly shape their subsequent behavioral and cognitive strategies. Higher self-efficacy reduces academic anxiety, encouraging students to approach complex assignments with deep learning strategies rather than relying on superficial memorization.

Within GAI-assisted learning contexts, this structural chain becomes particularly evident. Initial student interaction with GAI provides real-time explanations that build confidence and clarify difficult concepts. This heightened academic self-efficacy then encourages the student to commit greater mental effort, take intellectual risks, and sustain deeper cognitive engagement with their coursework. This increased cognitive investment ultimately translates into improved academic performance, measured through cumulative grades. Ignoring these sequential psychological paths can obscure the true educational value of GAI, reducing it to simple automation. Hence, we propose:

> ***H4: The relationship between student–GAI interaction and learning achievement is sequentially mediated by academic self-efficacy and cognitive engagement.***

RESEARCH METHODOLOGY

Research Design and Sampling Frame

This study used a quantitative, two-wave time-lagged design to minimize common method variance (CMV) and clarify the chronological sequence of the hypothesized psychological paths. The sampling frame comprised undergraduate students enrolled across public and private higher education institutions within the Islamabad Capital Territory, Pakistan. This urban region was selected due to its high concentration of multi-disciplinary universities and stable digital infrastructure, ensuring participants had regular access to GAI platforms.

To gather a representative sample, a stratified random sampling technique was applied. Universities were stratified by sectors (public vs. private) and institutional disciplines (STEM, Business, and Humanities). Out of 600 distributed survey packets, a total of 427 valid, fully completed, matched responses were retrieved, yielding an effective response rate of 71.1%.

Data Collection and Ethical Procedures

Data collection occurred across two separate phases spaced one week apart. During Wave 1, students completed assessments regarding their demographic information, access to digital devices, and their usage intensity/interaction patterns with GAI platforms. They also provided verified institutional records of their cumulative GPA from the preceding academic year (2024). During Wave 2, conducted one week later, the same respondents reported their current levels of academic self-efficacy, cognitive engagement, and their updated GPA scores for the 2025 academic period.

Ethical protocols were managed throughout the research process. Institutional ethical review approvals were obtained from participating universities prior to study initiation. Data anonymity was maintained by assigning unique alphanumeric tracking codes to match Wave 1 and Wave 2 surveys, ensuring no personal identifiers were exposed. Participation was entirely voluntary, and written informed consent was acquired from all respondents. To prevent hypothesis-guessing and social desirability bias, the survey forms were presented under general headings, and items within scales were randomized across participants.

Variable Measurement

• Student–GAI Interaction (Independent Variable): Measured using a 12-item scale adapted from Baidoo-Anu and Owusu Ansah (2023) and Kasneci et al. (2023), evaluating the frequency, depth, and diversity of GAI use across tasks like content generation, programming debug support, and interactive conceptual searches ($\alpha = 0.88$). Items were aggregated using the robust Hodges-

Lehmann location estimator to reduce skewness and extreme value distortions typical in self-reported technology metrics.

• Academic Self-Efficacy (First Mediator): Evaluated via an adapted 8-item version of the General Self-Efficacy Scale configured for digital and AI-assisted educational environments ($\alpha = 0.86$).

• Cognitive Engagement (Second Mediator): Assessed via the Student Engagement in e-Learning Scale (SeELS), focusing on deep processing, self-regulation, and mental effort ($\alpha = 0.89$). Both mediating variables utilized a standard 7-point Likert scale.

• Learning Achievement (Dependent Variable): Quantified through objective institutional cumulative Grade Point Average (CGPA) records extracted from official university transcripts.

• Control Variables: Age, gender, socioeconomic status, subject discipline, and structural digital access factors (device ownership and internet stability) were included as control variables to account for potential confounding variations across the sample.

DATA ANALYSIS AND RESULTS

Construct Validity and Common Method Bias

Before testing the structural hypotheses, construct validity was evaluated. Confirmatory Factor Analysis (CFA) demonstrated that the four-factor measurement model fit the data well: $\chi^2/df = 2.14$, Standardized Root Mean Residual (SRMR) = 0.042, Root Mean Square Error of Approximation (RMSEA) = 0.051, and Comparative Fit Index (CFI) = 0.945. Average Variance Extracted (AVE) values exceeded 0.52 across all constructs, confirming convergent validity. Discriminant validity was verified as the square root of the AVE for each individual construct was greater than its shared correlations with any other variable.

To verify that the time-lagged design successfully minimized common method variance, Harman's single-factor test was executed. Unrotated exploratory factor analysis showed that the largest single factor accounted for only 19.04% of the total variance, well below the conservative 50% threshold. This confirms that common method bias does not heavily skew the observed relationships.

Descriptive Statistics and Quantitative Tables

Table 1: Demographic Profile of Respondents (N = 427)

Variable	Category	Frequency (N)	Percentage (%)
Gender	Male	201	47.1%
	Female	226	52.9%
Age Group	18–20 years	120	28.1%
	21–23 years	195	45.6%
	24–26 years	68	15.9%

Variable	Category	Frequency (N)	Percentage (%)
	27 years and above	44	10.3%
Academic Discipline	Skill-Based (Engineering, IT, Business)	156	36.6%
	Theory-Based (Economics, Social Sciences)	101	23.6%
	Languages & Humanities	170	39.8%

Table 2: Descriptive Statistics of Focal Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
(1) Student–GAI Interaction (S-GAI)	3.68	0.82	1.25	4.91
(2) Academic Self-Efficacy (SE)	3.75	0.75	1.79	4.89
(3) Cognitive Engagement (CE)	3.53	0.70	1.66	4.88
(4) Learning Achievement (LA)	3.22	0.56	1.98	4.25

Table 3: Inter-Construct Correlation Parameters

Variables	S-GAI	SE	CE	LA
S-GAI	1.000			
SE	0.540**	1.000		
CE	0.480**	0.630**	1.000	
LA	0.390**	0.510**	0.570**	1.000

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

Regression and Mediation Pathways

A sequential ordinary least squares (OLS) regression analysis was conducted to examine the direct, mediating, and comprehensive structural paths. The detailed coefficients are summarized in Table 4.

Table 4: Regression Models for Direct and Mediating Paths

Predictor Variables	Model (i): LA	Model (ii): SE	Model (iii): CE	Model (iv): LA
Student–GAI Interaction (S-GAI)	0.154*** (3.89)	0.047*** (2.65)	0.057*** (3.24)	0.039** (2.43)
Academic Self-Efficacy (SE)	—	—	0.317*** (4.56)	0.441*** (3.15)
Cognitive Engagement (CE)	—	—	—	0.650*** (5.61)
R^2	0.056	0.026	0.187	0.315
F-Statistic	20.54***	8.79***	34.56***	34.76***

Note: Standardized coefficients are reported. Values in parentheses represent t-statistics. ***$p < 0.01$, **$p < 0.05$.

Model (i) indicates that student–GAI interaction has a positive and significant direct relationship with learning achievement ($\beta = 0.154$, $t = 3.89$, $p < 0.001$), supporting H1. Model (ii) shows that GAI interaction positively influences academic self-efficacy ($\beta = 0.047$, $t = 2.65$, $p = 0.006$), validating the initial link in the mediation path. Model (iii) indicates that cognitive engagement is significantly driven by both direct GAI interaction ($\beta = 0.057$, $t = 3.24$, $p = 0.002$) and academic self-efficacy ($\beta = 0.317$, $t = 4.56$, $p < 0.001$).

In the final integrated structural model, Model (iv), when both mediators are added simultaneously, the direct effect of GAI interaction on learning achievement decreases from 0.154 to 0.039 ($t = 2.43$, $p = 0.017$), demonstrating partial mediation. Cognitive engagement emerges as a strong proximal predictor of grades ($\beta = 0.650$, $t = 5.61$, $p < 0.001$). The explanatory power increases across models, with the full structural framework explaining 31.5% ($R^2 = 0.315$) of the total variance in student cumulative grades ($F = 34.76$, $p < 0.001$).

Table 5: Bootstrapped Indirect Path Estimations

Mediation Pathway Route	Indirect Effect Coeff	Boot Std Error	95% Confidence Interval [LLCI, ULCI]	Proportion (%)
Total Effect (X -> Y)	0.1563	0.0315	[0.0925, 0.2152]	—
Total Indirect Effect	0.0653	0.0210	[0.0287, 0.1121]	100.0%
Path 1: S-GAI -> SE -> LA	0.0154	0.0072	[0.0042, 0.0312]	23.58%
Path 2: S-GAI -> SE -> CE -> LA	0.0412	0.0145	[0.0185, 0.0762]	63.09%
Path 3: S-GAI -> CE -> LA	0.0087	0.0041	[0.0021, 0.0182]	13.33%

Note: N=427. 5,000 bootstrap samples. LLCI = Lower Limit Confidence Interval; ULCI = Upper Limit Confidence Interval.

The indirect analysis shows that the total indirect effect is statistically significant, accounting for 0.0653 (95% CI [0.0287, 0.1121]). The serial mediation route (Path 2: S-GAI -> SE -> CE -> LA) is the strongest path, explaining 63.09% of the total indirect effect. This confirms that the primary channel through which GAI impacts student academic grades is by strengthening self-efficacy, which subsequently improves cognitive engagement. These results support hypotheses H2, H3, and H4.

DISCUSSION

The empirical findings support the proposed conceptual framework, highlighting that psychological and behavioral mechanisms mediate the relationship between GAI tools and academic performance. The direct path coefficient ($\beta = 0.154$) shows that GAI tools can act as supportive educational resources. However, the modest variance explained by technology alone emphasizes that access to software does not guarantee learning success. Instead, over half of GAI's impact operates through indirect psychological pathways, with the serial mediation route being the primary channel.

BCS-style sequential alignment supports Social Cognitive Theory by demonstrating how digital tools can reinforce personal agency. When students use GAI to clarify complex theoretical concepts or debug programming logic, these interactions serve as digital mastery experiences. This strengthens academic self-efficacy, which then encourages students to commit greater mental effort and engage more deeply with their coursework.

These findings add relevant context to digital learning research within Pakistan's higher education landscape. While recent local literature has focused on challenges with online learning access, this study demonstrates that when students are provided with interactive digital resources, they can actively self-regulate their learning. However, these educational advantages depend heavily on institutional digital access equity. Students lacking reliable internet connectivity or personal computers cannot maintain regular interaction with GAI tools, which may widen existing learning disparities across demographic strata.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study examined the structural relationship between student interaction with GAI and academic performance in higher education institutions in Pakistan. The results demonstrate that GAI usage supports academic success primarily through a serial mediation chain, where technology interaction builds academic self-efficacy, which subsequently drives deeper cognitive engagement. This confirms that the primary educational utility of GAI lies in its capacity to cultivate learner confidence and stimulate deep mental effort rather than simple task automation. These insights show that naive evaluations focusing only on direct technological impacts risk misinterpreting how digital tools influence student learning outcomes.

Limitations and Directions for Future Research

1. Geographic and Contextual Scope: This study targeted universities within the Islamabad Capital Territory, which introduces an urban bias due to the region's strong digital infrastructure. Future research should use wider sampling frameworks that encompass rural institutions to evaluate how varying levels of regional development affect technology adoption.

2. Methodological Variations: While the two-wave time-lagged design improved causal clarity compared to cross-sectional options, it relied partly on self-reported psychological measures. Future studies could integrate experimental setups or capture real-time behavioral logs directly from learning management systems.

3. Boundary Conditions: This framework focused on mediation pathways. Future research should explore potential moderators, such as differences in individual digital literacy levels or varying styles of instructor guidance.

Actionable Recommendations

Table 6: Pragmatic Implementation Strategy Matrix

Targeted Implementing Agency	**Strategic Action Blueprint**	**Core Objective & Deliverable**
University Faculty & Instructional Designers	• Structure multi-stage assignments requiring students to document prompt iterations and critically evaluate AI responses against textbooks.	• Shift students from passive consumers to analytical evaluators, protecting cognitive engagement.
Institutional University Administrations	• Establish clear campus guidelines regarding acceptable GAI usage and set up specialized professional development training for faculty.	• Build clear institutional academic integrity policies while supporting pedagogical innovation.
National Education Authorities (e.g., HEC Pakistan)	• Formulate national curricula standards for AI literacy and fund localized institutional research on digital education.	• Standardize responsible AI integration across higher education frameworks.
Software Engineers & AI Platform Developers	• Co-design specialized educational interfaces that emphasize conceptual guidance and highlight source verification.	• Mitigate misinformation and optimize the clarity of educational AI platforms.
Provincial and Federal Governments	• Direct public resources toward digital access initiatives, expanding public campus Wi-Fi networks and device loan programs.	• Bridge regional digital access gaps, ensuring equitable technology adoption opportunities.

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