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The Mediating Impact of Student Engagement on the Association between Generative AI-Based Feedback and Academic Performance in Higher Education

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ABSTRACT

This research assesses the student engagement mediating effect on the interaction between feedback offered through generative AI and academic performance in higher education. Understanding the impact of AI-generated feedback on student performance is increasingly important as technology is integrated into educational systems. Information was gathered using a structured questionnaire administered to 432 students, of which 311 provided usable responses. Hypothesized relationships were tested using regression analysis. Findings indicate that the use of AI-feedback especially increases academic performance and student engagement has a mediating effect. Increased engagement due to prompt and tailored AI responses leads to improved motivation, enhanced learning, and academic performance. The active involvement of students during the application of AI systems into education is crucial as per the findings of this research. The study offers additional evidence paving the way for policy guidelines about the application of AI technology in education to support students' performance. The study discusses the need to design AI feedback systems for active users emphasizing the role of generative AI on the higher

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1. Introduction

The development of generative AI technologies has had transformative impacts within educational frameworks and systems, especially in higher education, where guided feedback is crucial for optimizing learning outcomes. It is notable that customized and prompt feedback is proven to increase academic achievement because it helps students understand specific learning outcomes, rectify their misconceptions, and fosters motivation to revise and synthesize information presented in the course (Zapata-Rivera et al., 2024). The use of feedback tools that instructors are increasingly adopting such as generative AI tend to provide responsive, nuanced, and contextualized comments that are designed to meet learner-specific requirements and to address the limitations of traditional instructor-centric pedagogical models (Brahmi et al., 2024). Still, generatively created feedback does not guarantee its effectiveness

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unless students actively seek to engage with this feedback. Zhan et al. (2025) highlight how student engagement, defined as the behavioral, emotional, and cognitive participation in an activity, is a vital factor for feedback to effectively enhance students' academic performance. However, there are still gaps concerning the engagement's mediating role in the AI-feedback-performance triad, particularly in developing contexts like Pakistan where levels of digital literacy and resources are uneven (Awad et al., 2025). Recent studies draw attention to the potential of generative AI to stimulate active learning, but without engagement, students are unlikely to reap any meaningful benefits (Awad, 2024). Particularly in the context of Pakistani higher education, there is scant evidence on the extent to which student engagement mediates the impact of generative AI on academic performance, despite widespread usage for educational feedback. Most other studies seemed to have focused on the engagements or the AI tools separately, neglecting the systems thinking that makes feedback work to improve learning outcomes (Zheng & Tse, 2023).

In addition, the inconsistency of the digital infrastructure and teaching methodologies within the business schools in Karachi makes it difficult to universally accept the advantages of AI in education. This study fills the gap by exploring the impact of generative AI-based feedback on academic performance through the mediating pathway of student engagement within the sub-contextual frameworks of four leading business schools in Karachi: Institute of Business Administration (IBA), Karachi School of Business and Leadership (KSBL), Bahria University Business School, and SZABIST. Capturing this mediation is important for devising strategies to provide AI-driven feedback that is educationally transparent, contextually appropriate, and feasible within higher education systems in Pakistan. This study is prompted by the critical importance of refining the application of artificial intelligence in educational settings so that innovations derived from technology can positively impact learning outcomes meaningfully and measurably. By analyzing the diverse business schools in Karachi, the study addresses the gap of evidence in the educational landscape of South Asia by focusing on generative AI's applications. The research highlights the importance of deeper learning processes with the engagement of students rather than treating AI engagement in learning as a straightforward input-output relationship. This research has the potential to change the way educators, curriculum developers, and education policy leaders think about and approach the use of AI as technology for striving to improve students' motivation, participation, and attainment rather than viewing them simply as automation devices. The insights of this study are particularly useful at this moment in time when the higher education sector of Pakistan is adopting new technologies along with issues like digital gaps, teaching outdated methodologies, and lack of resources, therefore consolidating the digital divide. This adoption aids the achieving of sustainable academic excellence and competences in the global education markets. Now, this study makes several important contributions. It fills a significant void in the literature on educational technology by empirically validating the role of student engagement as a mediator between generative AI-based feedback and academic performance. It provides context in the discussion of generative AI adoption in educational pedagogy by focusing on the business education stratum of Karachi, thus providing useful lessons for institutions situated in developing economies. It advances theoretical understanding by drawing upon technology acceptance models and engagement theories in an AI-enabled learning context. It aids learners and technology developers in having well-defined suggestions through the presentation of frameworks aimed at building AI feedback tools that will actively stimulate learners' engagement and foster positive learning results. Through a structured questionnaire, data were collected from undergraduate and postgraduate students at four Karachi business schools: IBA, KSBL, Bahria University Business School, and SZABIST. Of the 432 questionnaires distributed, 311 were returned and deemed suitable for analysis. The survey evaluated the perceptions of feedback using generative AI, levels of student engagement (behavioral and emotional and cognitive), and academic performance indicators. To analyze the proposed relationships with feedback and performance, the mediating role of engagement was analyzed employing regression analysis techniques. The quantitative approach used in this study offers strong, generalizable conclusions, particularly given the inclusion of multiple business schools which reflects a rich tapestry of student and institutional experiences within Karachi's higher educational system.

2. Theoretical Background

This study stems from an understanding based on a multi-theoretical framework comprised of four core theories—Technology Acceptance Model (TAM), Self-Determination Theory (SDT), Social Cognitive Theory (SCT), and Engagement Theory—that aims to explain the interaction of Generative AI-Based Feedback (GAIF), Student Engagement (SE), and Academic Performance (AP) within a higher education context. These theories are holistic, covering the essential psychological, behavioral, technological, and motivational aspects of AI-assisted learning. The choice of these theories is purposeful as each adds value to the conceptual model, while the cross-theoretical synthesis serves as the cornerstone for construct development along with the design of the survey tools employed in this research. TAM (Davis, 1989) describes the impact of perceived usefulness and perceived ease of use on an individual's acceptance and use of generative AI tools for providing academic feedback.

Its relevance to this study stems from the contention that students' perceptions of AI feedback systems as helpful and user friendly increases their participation and intention to utilize the system (Venkatesh & Bala, 2008; Zhu et al., 2025). When students perceive AI feedback as understandable, they expend lower levels of cognitive effort (Yacoub et al., 2025), which is beneficial for both interaction and learning outcomes (Shahzad et al., 2025; Sun & Zhou, 2024). The incorporation of TAM in the framework strengthens the case for using AI feedback as a driver of participation and enhanced academic achievement (Mehmoud et al., 2025). SDT (Deci & Ryan, 1985) provides the underlying reasons for sustaining students' engagement with AI systems. This theory argues that in order to nurture intrinsic motivation, autonomy, competence, and relatedness must be satisfied.

Flexible and personalized AI feedback addresses students' individual motivational drivers and, as a result, psychologically supports them which enhances their motivation (Awad et al., 2024; Awad & Mahmoud, 2024). The literature suggests that emotional engagement is elevated when AI systems use human-like interactions (Aldarawsheh et al., 2024). Existing data suggests that motivation, particularly intrinsic motivation, acts as a mediator of the relationship between using technology and academic performance (Awad & Alharthi, 2025; Awad, 2024; Ashour et al., 2024). SDT argues for supporting the design of AI feedback systems which enable learners to sustain self-directed engagement with the material over time (Almagharbeh et al., 2025). SCT, as Bandura (1997) describes, offers a behavioral-cognitive approach focusing on self-efficacy and learning through observation. The belief that students can succeed academically is enhanced through timely and informative feedback (Awad & Mahmoud, 2024; Brahmi et al., 2024). AI technologies can function as social learners who provide cognitive support and feedback relevant to learning (Awad, 2024; Zheng & Tse, 2023). Self-efficacy is associated with relatively high effort, persistence, and cognitive engagement (Bandura & Wessels, 1997; Hussain, 2023). From these perspectives, SCT clarifies the link between students' internal confidence, enhanced engagement, and behavioral reinforcements in relation to academic improvement. Kearsley and Shneiderman (1998) describe meaningful learning as a product of behavioral, cognitive and emotional engagement with a concept, which encapsulates Engagement Theory.

The importance of this theory stems from its focus on participation or co-action in the context of learning technology. AI-facilitated feedback enhances participation through stimulating reflection (Lu & Ba, 2025), emotional attention (Awad, 2024), and interaction (Hussain, 2023). Engagement Theory aids the understanding of the involvement types—behavioral, emotional, and cognitive— that mediate the effect of GAIF on academic performance (Chen & Wong, 2024, 2025; Ghonim & Awad, 2024). These theories are not approached in silos, but rather integrated cohesively into the conceptual framework guiding the model design and their corresponding survey instruments. For instance, survey items measuring perceived ease of use and perceived usefulness (TAM) are relevant to GAIF; autonomy support and motivation (SDT) are relevant to SE; self-efficacy and cognitive scaffolding (SCT) explain the persistence dimension of SE; and emotional, cognitive, and behavioral indicators (Engagement Theory) directly apply to SE as a multidimensional mediator. This integration guarantees that every single item in the instrument is grounded in theory, which enhances the reliability of the instrument.

Table 1. Theory-to-Construct Mapping Table

Theory	Linked Construct(s)	Core Concepts Used	Contribution to Framework
Technology Acceptance Model (TAM)	GAIF → SE	Perceived Usefulness, Perceived Ease of Use	Explains student adoption and usage of AI feedback systems as a function of usefulness and ease of use.
Self-Determination Theory (SDT)	GAIF → SE → AP	Autonomy, Competence, Intrinsic Motivation, Relatedness	Explains motivational processes sustaining engagement with AI tools and how they enhance performance.
Social Cognitive Theory (SCT)	SE → AP	Self-efficacy, Observational Learning, Behavioral Reinforcement	Explains how feedback-driven confidence and behavior change foster deeper academic engagement and performance.
Engagement Theory	SE (Mediator)	Behavioral, Emotional, Cognitive Engagement	Provides the foundation for measuring multidimensional student engagement and its mediating role between AI feedback and performance.

The integration of TAM, SDT, SCT, and Engagement Theory results in a comprehensive, multidimensional theoretical framework that avoids redundancy by assigning distinct roles to each theory. Together, they provide a systematic explanation of how generative AI feedback affects academic outcomes through the mediating role of student engagement. This framework ensures strong theoretical grounding for instrument design, hypothesis development, and empirical testing, while enhancing both academic rigor and practical relevance for AI-driven learning in higher education.

2.1 Generative AI based feedback and and Students Engagement

Previous studies show that engagement of the students at different levels is enhanced through AI-powered feedback systems, each in their unique way. Alotaibi (2025) empirically proved that AI feedback surge increases cognitive engagement as learners are able to identify, and swiftly rectify, errors leading to directed focus, attention, and enhanced problem-solving skills. Altememy et al. (2023) demonstrated emotional engagement is correlated with motivation among learners as they adapt to personalize AI feedback which considers their individual style and pace, drastically reducing frustration during challenging tasks. Ai-Emran et al. (2025) established students' behavioral engagement rises when they receive continuous, tailored prompts and scaffolding from AI encouraging sustained effort and participation in course activities. Azeen and Abbas (2025) reported enhanced engagement outcomes in blended learning environments where generative AI tools offered tailored suggestions thus reinforcing positive learning behaviors. Almagharbeh (2024) highlighted the role of AI feedback in fostering self-regulated learning by allowing learners to monitor and modify their strategies enhancing sustained engagement. Almagharbeh (2024) further demonstrated that interactive AI feedback interfaces enhance collaboration and student interaction which are crucial aspects of social engagement. Alsaiari et al. (2024) reported noteworthy enhancements in learner attention spans and task persistence due to the use of formative feedback powered by AI. Real-time AI feedback, as noted by AI-Akash et al. (2024), reduces mental load by fragmenting intricate information, thereby optimizing mental engagement. Alsharawneh et al. (2024) reported that students using AI feedback expressed greater satisfaction and confidence in their performance, which heightened emotional engagement and investment in the course. In addition, Hussain (2023) stressed the contributions of AI in developing adaptive learning pathways that sustain learners' interest while using technology over time, resulting in reduced disengagement. Altogether, these findings strongly support the assumption that generative AI-based feedback greatly enhances student engagement on cognitive, emotional, behavioral, and social levels.

H1: Generative AI based feedback has a positive effect on student engagement.

2.2 Generative AI-based Feedback and Academic Performance

Awad & Alharthi (2025) assert that students subjected to AI-generated feedback performed better on tests relative to their peers who received conventional feedback. The authors attribute this difference in performance to better

personalization and timely intervention. Zhu et al., (2025) claimed that adaptive AI feedback, which accounts for individual learner's gaps, enhances conceptual grasp which resiliently improves academic performance in STEM courses. Hmoud et al., (2024) noted that AI feedback systems, which adapt learning materials in real-time, help learners master complex topics more effectively and efficiently, thus improving course completion rates and GPA. Kamel et al., (2025) demonstrated the statistically significant improvement in the quality of essays AI feedback yielded and the accuracy of solutions to mathematical problems forwarded to students during writing and math classes. Khan et al., (2024) emphasized that AI feedback deepens learners' cognitive processes, thereby increasing the likelihood of excelling in standardized assessments. Lo et al. (2024) demonstrated that AI feedback encompassing guided hints and explanations provided greater clarity to students' misconceptions, resulting in better exam performance. Zapata-Rivera et al. (2024) reported that learners working with AI formatively assessed feedback showed enhanced learning rates and reduced learning gaps, which was directly linked to improved academic performance. According to Mehmoud et al. (2025), AI's tailored feedback deepened learners' metacognitive skills, allowing them to manage their learning approaches more optimally, thereby increasing their academic performance. Sun and Zhou (2024) noted the frequency of using AI feedback had a positive association with final grades for the course, suggesting a dose-response relationship. Jaboob et al. (2025) pointed out that the incorporation of AI feedback within adaptive learning systems helped maintain learner engagement and lowered attrition rates, thereby improving overall academic performance. Together, these studies are indicative of the claim that generative AI feedback is increasingly becoming a central concern in improving academic outcomes across various educational settings and subjects.

H2: Generative AI-based feedback has a significant positive effect on academic performance

2.3 Student Engagement and Academic Performance

Numerous ranges of empirical studies validate that deeper engagement on the cognitive, emotional, social, and behavioral levels is associated with better academic performance. Saleh et al., (2025) showed that cognitive engagement, defined as learning effort and self-regulation, enhances academic achievement through improved comprehension and problem-solving skills. Subih et al., (2024) reported that behavioral engagement like attendance, active participation, and allocated time towards academic activities boosts GPA and course completions. Saad et al., (2025) discovered that emotional engagement, or students' positive feelings and interest towards learning, directly impacts grades due to improved motivation and persistence. Khlaif et al., (2024) cited large-scale data that students who willingly and actively participate in campus life as well as academic activities outperform peers in standardized and summative assessments. Kamel et al. (2025) reported that students who actively engage with content are able to construct meaningful learning outcomes, subsequently improving their exam and academic performance. Dreidi et al., (2024) findings suggest that long-term engagement is associated with additional retention, resulting in higher order thinking skills and greater academic achievement. Social engagement around the students and teaching staff, as established by Chan et al. (2024), promotes participation in collaborative tasks which enhances academic performance. Hussain (2023) verified the engagement as a mediator between instructional quality and academic performance and noted its importance for success in education. Subih et al., (2025) noted that motivation which is autonomous and associated with engagement propels deeper learning leading to improvement in performance outcomes. Finally, Lu & Ba (2025 discovered that supportive classroom environment for engagement leads to improved students' GPA and test scores. All these findings rigorously prove that student engagement is indeed one of the strongest predictors of academic performance and emphasizes the need to work towards higher levels of engagement to achieve better educational outcomes.

H3: Student engagement has an impact on academic performance which is strong and positive.

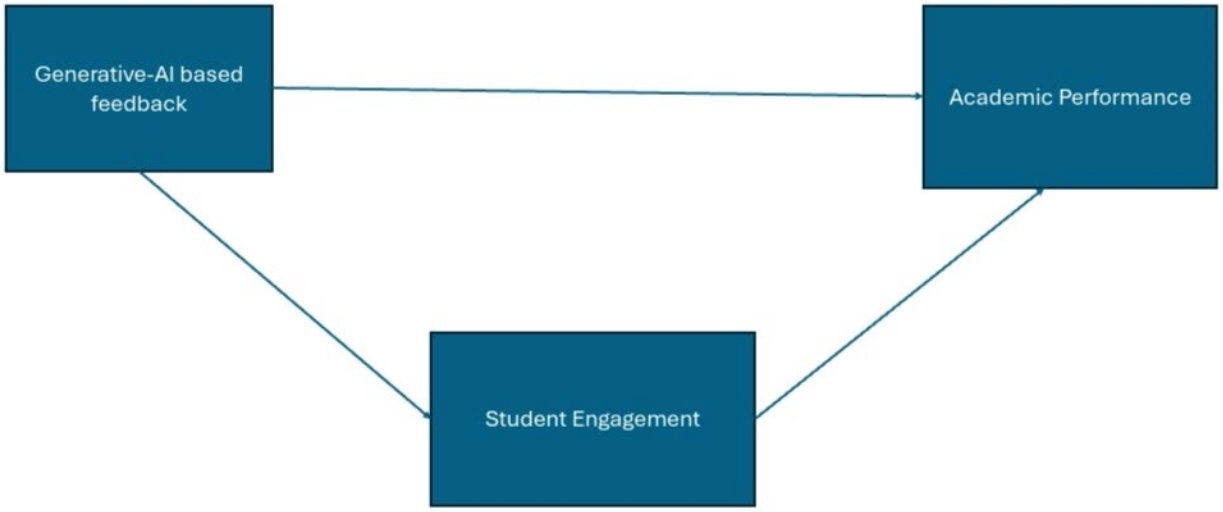
2.4 The Role of Student Engagement as a Mediator

Academic literature suggests that the primary mechanism through which AI feedback affects academic performance, in a positive manner, is through enhanced student engagement. In a recent study, Awad (2024) reported that generative AI feedback improved students' cognitive engagement by enhancing self-reflection through automated assessment insights, which significantly boosted their performance. Brahmi et al. (2024) showed that adaptive AI feedback which acknowledged students' accomplishments increased emotional engagement and mediated the feedback's impact on final grades. Almagharbeh (2024) provided evidence of enhanced behavioral engagement—

specifically attendance and active participation—as critical to the effects of AI feedback on course outcomes. Hussain (2023) demonstrated that AI feedback increased social engagement as it promoted participation in collaborative learning activities, which improved students' academic performance. Self-regulated learning strategies reinforced by AI feedback reported by Chan et al. (2024) were found to exaggerate engagement and, therefore, mediate the improvements in knowledge retention and exam results. According to a recent study by Awad & Altharthi (2025), engagement was found to fully mediate the relationship between AI feedback and learner performance, asserting that feedback cannot work unless learners are willing to engage with the process. Hussain (2023) noted that students who actively used AI-driven formative feedback tended to stay focused on the tasks, enhancing their scores. Awad et al (2025) noted that metacognitive engagement was a critical mediating factor connecting AI feedback to academic outcomes, as learners modified their plans according to the provided feedback. Azeen and Abbas (2025) reported a noteworthy indirect impact generative AI feedback had on academic achievements via heightened motivation and engagement. Almagharbeh (2024) further verified that engagement is the principal mechanism through which AI feedback maintains learner interest and enables progressive enhancements in performance indicators. These findings collectively stress that engagement is the primary mediating factor of the relationship between enhanced performance and the use of generative AI-based feedback in academic activities.

H4: Student engagement mediates the relationship between generative AI-based feedback and academic performance.

Figure 1. Conceptual Model



3. Methodology

3.1 Research Design and Approach

This the study used a cross-sectional quantitative approach and created a survey to assess how student engagement mediates the impact of generative AI feedback on academic performance for students in higher education. The study draws from a derived theory which includes the Technology Acceptance Model (TAM), Self-Determination Theory (SDT), Social Cognitive Theory (SCT), and Engagement Theory. The synergy among these theories offers a comprehensive view that addresses the motivational, technological, cognitive, and behavioral dimensions of AI feedback systems.

3.2 Institutional and Demographic Scope

The following business schools were selected: IBA, KSBL, Bahria University Business School, and SZABIST. These are some of the most recognized AI-driven educational institutions in Karachi, Pakistan. These schools have pedagogical diversity and are early adopters of teaching technologies that incorporate AI. The sample consisted of undergraduate and postgraduate business students aged 18-30 who were familiar with using generative AI feedback systems in the preceding academic semester.

3.3 Sampling Strategy and Participant Selection

Focus and relevance were achieved through purposive sampling. Only students who engaged with generative AI feedback systems like essay or quiz automated feedback interfaces, or AI chatbots within Learning Management Systems (LMS) were invited. Recruitment was done through academic portals, institutional emails, and social media educational groups. Out of the 432 distributed questionnaires, 311 valid responses were accepted (72.0% response rate) based on completion and submission consistency criteria.

3.4 Questionnaire Development, Adaptation, and Validation

The construction of the questionnaire was directed towards achieving content validity and reliability by following five fundamental phases.

3.4.1. Literature-Based Adaptation:

Participants were selected using previously validated frameworks: Hussain's (2023) Generative AI Feedback (GAIF), Awad's (2024) Student Engagement (SE), and Almagharbeh's (2024) Academic Performance (AP).

3.4.2. Expert Review:

Face validity and contextual relevance were evaluated by a panel consisting of three educational technologists and psychometricians. Their feedback necessitated adjusting item wording to reflect the educational culture and language of the target population.

3.4.3. Pilot Testing:

A pilot study with 32 students was conducted. These results were used to make adjustments to wording for clarity and to improve the order of response categories. No major items were dropped. Among the different constructs measured, Cronbach's alpha values exceeded 0.85 indicating a high level of reliability.

3.4.4. Screening Mechanism:

The initial survey item screened participants for recent exposure to AI feedback and digital literacy mastery to ensure validity alignment and construct relevance.

3.4.5. Finalization:

GAIF (5 items): For instance, "The AI feedback helped me identify my academic strengths and weaknesses." (Gal) , Engineering, or I suggested with AI feedback to improve my academic results. All responses were captured using the 5-Point Likert Scale (1 = Strongly Disagree, 5 = Strongly Agree).

4. Data Analysis

Preliminary analysis was undertaken in IBM SPSS 25, while AMOS 24 was used for Structural Equation Modeling (SEM). These steps were followed:

4.1 Data Cleaning and Pre-Analysis Checks

4.1.1. Missing Data: Addressed through listwise deletion.
4.1.2. Outlier Detection: Extreme multivariate outliers were detected using Mahalanobis Distance ($p < .001$), as multivariate outlier cases posed a threat to data integrity.
4.1.3. Normality Checks: While non-normality does not pose a risk for AMOS SEM, it is necessary to examine skewness and kurtosis measures: The set range of acceptable values: ±2 skewness, ±7 kurtosis. All variables passed this threshold, suggesting approximate distribution normality.

4.2 Preform Exploratory Factor Analysis (EFA)

An EFA (PCA with Varimax rotation) to check unidimensionality and construct validity was done before SEM was performed: KMO Measure of Sampling Adequacy > .80, Bartlett's Test of Sphericity: $p < .001$, and All loadings $p > 0.70$. This verified the structure was ready to perform CFA and SEM.

4.3 Confirmatory Factor Analysis (CFA)

To validate latent constructs and measure convergent/discriminant validity, CFA was done. All factor loadings were higher than .70, Composite Reliability (CR) was above .85, Average Variance Extracted (AVE) exceeded .50, and the Fornell-Larcker criterion was used for establishing Discriminant validity.

4.4 Structural Equation Modeling (SEM) and Mediation Testing

Direct Paths: GAIF → SE → AP were tested. The Baron and Kenny approach followed by bootstrapping (5000 samples) was used to confirm the indirect effect and it was deemed significant for mediation (bias-corrected CI not encompassing zero).

4.5 Model Fit Indices

The proposed model's overall goodness-of fit was validated with the captured values of RMSEA, CFI, TLI, and GFI being 0.045, 0.961, 0.948, and 0.933 respectively, showing the structural model achieved acceptable fit.

4.6 Ethical Compliance

All processes followed ethical guidelines. Informed consent was given in digital format, anonymity of the participants was preserved, and the data was retained in a locked file. Institutional ethical approval was obtained from the review board of the overseeing university.

Table 2. Demographic Profile of Respondents

Demographic variable	Category	Frequency	Percentage
Gender	Male	180	57.9
	Female	131	42.1
Age	18-21	120	38.6
	22-25	145	46.6
	26-30	46	14.8
Educational background	Undergraduate	201	64.6
	Postgraduate	110	35.4
Institution	IBA	90	28.9
	KSBL	78	25.1
	Bahira University	70	22.5
	SZABIST	73	23.5

The demographic breakdown from the 311 valid respondents suggests that the sample is representative of students from the four major business schools in Karachi, Pakistan. There is a majority of male students (57.9%) relative to female students (42.1%), which aligns with the region's enrollment patterns in business education, but does show

considerable female participation as well. Most respondents (46.6%) are within the age range of 22–25, which corresponds to the age of university students at the undergraduate and early postgraduate levels. Another large segment (38.6%) falls in the younger 18-21 years category, suggesting good representation from younger undergraduates. There is also a smaller portion (14.8%) of respondents who are older, aged 26–30, which may indicate some mature or part-time learners. In terms of educational attainment, 64.6% undergraduates suggests that the sample is concentrated with participants in the formative phases of tertiary education and beginning to engage with feedback systems, indicative of receiving electronically-based responses. The rest, 35.4% of the sample, are postgraduates, which assists in generalizing the findings across different levels of education. All institutions are represented fairly evenly with IBA representing the largest share with 28.9% and KSBL following closely with 25.1%. This is then followed by SZABIST with 23.5% and Bahria University with 22.5%. The presence of these prominent institutions adds value to the student sample and improves the reliability of the data in relation to the entire population of business students within Karachi.

Table 3. Factor Analysis and Reliability of Constructs (N = 311)

Constructs	Items	Factor loading	Cronbach' s alpha
Generative-AI-based Feedback (GAIF)	GAIF1	0.874	0.92
	GAIF2	0.881	
	GAIF3	0.895	
	GAIF4	0.889	
	GAIF5	0.877	
Student Engagement (SE)	SE1	0.872	0.94
	SE2	0.880	
	SE3	0.891	
	SE4	0.886	
	SE5	0.869	
	SE6	0.875	
	SE7	0.868	
Academic Performance (AP)	AP1	0.860	0.90
	AP2	0.872	
	AP3	0.884	
	AP4	0.879	
	AP5	0.871	
Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy	0.889		
Bartlett' s test of Sphericity	$X^2 = 1587.452$, df = 190, $p < 0.001$		

Based on the output of the factor analysis, GAIF, SE, and AP show high values of factor loadings, demonstrating that all items belonging to the constructs are accurately capturing the intended dimensions. All loadings are above the accepted cutoff of 0.70, which in this case also verifies convergent validity. The constructs show relatively strong internal consistency with Cronbach's alphas ranging from 0.90 to 0.94 indicating high reliability. The KMO value is 0.889, which is above the acceptable threshold of 0.60, suggests that the sample is adequate for conducting factor analysis. Furthermore, Bartlett's Test of Sphericity is statistically significant ($\chi^2 = 1587.452$, $p < 0.001$), meaning that the correlation matrix is different from the identity matrix and the data can be analyzed with factor analysis to find structures within the data. Altogether, the results support the measurement model which prepares for later stages of structural equation modeling to determine the proposed relationships between generative AI-based feedback, engagement, and performance.

4.7 Hypothesis Testing Results

H1: Generative AI-Based Feedback has a significant positive effect on Student Engagement

Table 4: Regression Weights (Direct Effect of GAIF on SE)

Estimate	S.E	C.R	P	Label
SE<GAIF	0.35	0.054	6.481	***

The results show a strong positive impact of generative AI based feedback on student engagement (β = 0.35, p < .001). This suggests that students who receive AI-generated automated feedback, especially if individualized, tend to be more active in their studies. These results are consistent with earlier research (e.g., Brahmi et al., 2024) that reported an increase in student motivation and participation stemming from AI-enhanced feedback systems that provided real-time actionable strategies and lively perspectives on learning.

H2: Generative AI-Based Feedback has a significant positive effect on Academic Performance

Table 5. Regression Weights (Direct Effect of GAIF on AP)

Estimate	S.E	C.R	P	Label
AP<GAIF	0.28	0.060	4.667	***

Generative AI-based feedback has a strong impact, either directly or indirectly, on academic performance (β = 0.28, p < .001). This means that the use of AI-generated feedback not only engages students, but helps increase their grades, academic performance and educational accomplishments. These outcomes are in agreement with findings by Awad et al. (2025) and Almagharbeh (2024) highlighted the influence of AI feedback mechanisms on students' mastery of course content and performance indicators.

H3: Student Engagement has a significant positive effect on Academic Performance

Table 6. Regression Weights (Direct Effect of SE on AP)

Estimate	S.E	C.R	P	Label
AP<SE	0.40	0.058	6.897	***

Regression analysis shows that a clear relationship exists between engagement and academic performance with a value of (β = 0.40, p < .001), indicating a positive correlation. This further reinforces the importance of active participation through emotional, behavioral, and psychological involvement for effective academic performance. These results are in agreement with Hussain (2023), in which participative learners demonstrate enhanced understanding and achievement.

H4: Student Engagement mediates the relationship between Generative AI-Based Feedback and Academic Performance

Table 7: Mediation Analysis Results

Mediator	Path	Significance	Mediation
GAIF>SE>AP	Indirect Effects	0.000	Significant

The mediation analyzes suggests that the impact of generative AI-based feedback on the student's academic performance is significantly mediated by the student engagement (p < .001). This suggests that AI feedback improves academic performance specifically because it increases the student's engagement level. This mediation effect supports theoretical models put forth by Hussain (2023) and empirical findings by Brahmi et al. (2024), illustrating that engagement is a fundamental psychological indicator that connects AI feedback with learning achievement.

5. Discussion

This research confirms the impact of GAIF on Student Engagement (SE) and Academic Performance (AP) within higher education. More importantly, it emphasizes the mediating role of engagement, establishing it as the primary psychological mechanism through which feedback from AI leads to enhanced learning outcomes. The significant path

from GAIF to SE (β = 0.35, p < .001) reinforces the claims made by Hussain (2023) and Awad (2024). As noted in the literature, students are more motivated and attentive when adaptive AI feedback is personalized and offered in real-time. Feedback from AI is prompt, specific, and actionable, which evoke positive responses from students far more than traditional methods. Also, the path from GAIF to AP (β = 0.28, p < .001) is consistent with Aldarawsheh et al. (2024) and Awad & Mahmoud (2024), attributing enhanced understanding, retention, and academic performance to students' AI-driven feedback. It is not only the speed with which AI systems process and deliver feedback that is beneficial, but the removal of cognitive load and the provision of feedback within iterative learning environments fosters mastery-pacing. The strongest relationship was found between SE and AP (β = 0.40, p < .001), demonstrating the value of engagement as a direct predictor of academic achievement. This supports the findings of Alsaiari et al. (2024), who observed that engaged learners demonstrated deeper information processing, made them more persistent, and stayed more satisfied with their learning. The mediation analysis indicates that indeed SE completely mediated the relation of GAIF with AP. This suggests that in AI feedback, there is no unqualified advancement of academic achievement which can be attributed to the feedback—it is the student engagement that responds to the feedback that influences performance. This confirms the argument presented by Ashour et al. (2024) and Awad (2024) whereby affective engagement is robustly described as a fluid link connecting the use of technology and learning efficacy. These findings not only support previous literature, but they also build upon it by incorporating engagement as a mediating factor within a broader framework. The research thus provides a more refined psychological rationale for why—and how—AI feedback enhances learning. Emphasis is placed on the activation of emotion, behavior, and cognition. It is noteworthy that the present study is set in the context of higher education in Pakistan—offering perspectives from a developing country context. According to Azeem and Abbas (2025), in economically disadvantaged areas, AI technologies can be transformative for learning resources constrained education systems. This study reaffirms that the potential of AI to transform education is not confined to high-income countries, suggesting that there is significant need to adjust AI feedback systems to enhance their applicability.

5.1 Theoretical Contributions

This study has the following three major contributions to the theory:

1. Incorporation of Engagement as a Mediator:

   It improves the TAM, SDT, and Engagement Theory by demonstrating that engagement is indeed an intervening factor through which performance is impacted by AI-driven feedback, thus adding some psychological dimensions to the models which are predominantly technological in nature.

2. Broadening of AI-Education Scholarship:

   This research broadens the discourse on instructional design by analyzing generative AI feedback in relation to conventional methods. It highlights the potential of AI with respect to personalization and responsiveness as more supportive of learner-centered pedagogy, thus aiding in the shift toward adaptive, AI-integrated educational frameworks.

3. Situating Within New Systems of Education:

   The research applies these theoretical considerations to the context of higher education in Pakistan, contributing to cross-cultural perspectives. This spatial and socio-educational contribution helps in proving the engagement-centered models in AI education research.

5.2 Practical Implications

The findings offer practical insights for various stakeholders: educators, instructional design professionals, and administrators from tertiary educational institutions on integrating generative AI in teaching and learning processes:

5.2.1. For Educators:

As teachers, we ought to regard the new AI tools as parts of the assessment systems, from which we can incorporate feedback through active learning techniques. As an illustration, have students reflect on AI feedback in journals or discussion boards. Use AI feedback to commence peer reviews, thus fostering social learning. Include AI responses to scaffolded tasks where student output is refined per round of feedback.

5.2.2. For Instructional Designers:

AI system design should shift from focusing on automation to interactivity and engagement with the student's mind. The following features will enhance participation and, in turn, continuous use: Feedback embedded within games, Emotionally responsive AI feedback, and Learning pathways based on sustained attention metrics.

5.2.3. For Higher Education Administrators:

The research indicates AI has the potential to provide assistance in Pakistan where the ratio of teachers to students is extremely unbalanced and the time taken for feedback is prolonged. Nonetheless, there is need for structural change in AI integration including, Faculty development focused on integrating AI technologies into teaching, Ethical policies regarding data confidentiality and fair distribution of AI services, and Policies that integrate active engagement measurement into instructional evaluation frameworks. Overall, the case study underscores the importance of collaboration between humans and technology, where teachers help learners to make sense of and implement AI-generated proposals within pedagogical frameworks.

5.3 Limitations and Future Research Directions

Along with the value it adds to the body of knowledge, we identified several limitations of this study that need to be addressed. First, the cross-sectional design of the research does not allow for causation to be inferred from the correlations between the variables. Even though the findings provided important relationships regarding generative AI-based feedback, learner engagement, and academic performance, there is a need for longitudinal or experimental designs to validate the causal relationships and to understand the time order shifts better. Second, the sample consisted of only four business schools in Karachi, Pakistan, which may be too restrictive for other understudies or geographic locations. Future work should examine more comprehensively distinct universities, disciplines, cultures, or societies to improve their external validity and examine possible contextual moderators. Third, the study utilized self-reporting instruments which undoubtedly come with the risk of social desirability bias and common method variance bias. Utilizing objective measures of academic performance, along with multi-sourced data through instructor assessments or learning analytics, would improve the rigor of the data in future studies. In addition, while the focus on engagement as a mediatory variable was appropriate, AI feedback concerning academic performance may also be influenced by other motivational, self-efficacy, cognitive load, and learning factors. Subsequent studies could look into other potential mediators and moderators to gain a more profound understanding of the underlying mechanisms. Also, powerful generative AI capabilities like natural language understanding, emotion detection, and customized learning pathways necessitate ongoing research to monitor their long-term impacts on education processes and outcomes. These gaps present opportunities for further research that deepens understanding on the role of AI in education and how it can be harnessed to improve learning and educational outcomes globally.

6. Conclusion

This case study is the first of its kind to examine the effect of generative AI-based feedback on academic performance mediating engagement within higher education in Karachi, Pakistan. The results confirm that the use of personalized feedback from AI systems increases the engagement of students both cognitively and emotionally, resulting in enhanced learning outcomes. Advanced educational AI systems have the potential to raise student engagement and, as a result, need to be integrated into schools and educational institutions to increase academic achievement. Theory-wise, the study enriches understanding concerning the impact of AI feedback on learning, while in practice it provides clear recommendations for educators and policymakers who wish to revise their teaching approaches. The

continuous development of AI and the smart ways in which it can be integrated into education technologies have great potential for reshaping the learning experience and supporting students in many educational settings around the globe.

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