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IMPROVING STUDENT ENGAGEMENT THROUGH AI-BASED LEARNING TOOLS A QUANTITATIVE STUDY

Dr. Nazish Andleeb*[1], Dr. Azmat Farooq[2], Hafsah Khanum[3], Aliza Shahzadi[4]

*[*1]Lecturer, Department of Education, University of Gujrat, Pakistan*
[4]Assistant Professor, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Pak
[3]Associate Lecturer, Department of Education, University of Gujrat, Pakistan
*[*2]B.Ed. Induction 8th, Department of Education, University of Gujrat, Pakistan*

[*1]nazish.andleeb@uog.edu.pk

Corresponding Author: *
Dr. Nazish Andleeb
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ABSTRACT

Quick developments in the ways higher education institutions incorporate AI software have completely shifted the discussion from 'whether' it should be used to 'how' making wise decisions about its integration in teaching can be carried out. The student teachers who are completing their B.Ed courses are the ones who will be most deeply affected by this. The habits and methods developed around the time of getting the degree frequently continue to be practiced for the rest of one's professional life in schools. This study mainly focuses on the efficacy of AI-assisted tools in maintaining students' attention to class by studying the eighth semester B.Ed students of the University of Gujrat. The University of Gujrat is a place where the students have highly accessible technology but when it comes to well-thought uses in the classroom the situation is uneven. One hundred and fifty final year B.Ed students filled out a valid 44-question survey based on a rating scale. Besides mere numeric scoring, the research also portrayed interrelations between various aspects that describe the usage of AI-based educational tools. The simplest variable was how much these tools were used. Users' sense of helpfulness was another aspect. The perceived strength of the feedback and the students' lessons being adjusted as their needs were the last two aspects that were considered. As for the measurement of engagement, it was based on the actions taken, mental effort and emotions experienced during learning. Since the connections mattered more than isolated results, correlation tests took the lead in the statistical analysis. Influences among variables were obtained by the help of IBM SPSS program. With the help of regression models, the main determinants of engagement were brought to light. Even small differences across answers offered notable links. They show that there are markedly positive associations between the use of AI-based learning instruments and the engagement of students ($r = .63$, $p < .001$), cognitive engagement being the one that has the highest correlation individually ($r = .61$). The regression results showed that AI tool utilization predicted 41.2% of the variance in student engagement scores ($R = .412$). The relevant literature and research perspectives on issues related to this paper have been organized per Self-Determination Theory and the Technology Acceptance Model and further, the paper aims to present curriculum designers, faculty and university management of the University of Gujrat with some practical suggestions.

1. INTRODUCTION

Now if you walk into a senior B.Ed class, you'll find students who are genuinely interested in learning how to teach and are stressed out by the upcoming school internships and the piles of work. But on their screens there's a subtle change taking place. There appear on their screens high-powered 'apps' equipped with artificial intelligence; they instantly answer questions about the subject, they generate a quiz on command, they provide input and advice on a draft lesson plan, they explain complex pedagogical concepts with tailored outputs. Some learners 'use' them with purpose; others just blindly click and move through the paces. Do they increase the learner's understanding or just give the impression that work is being done? No one in teacher training colleges in Pakistan has concrete answers.

According to Fredricks, Blumenfeld, and Paris (2004) student engagement can be viewed as one of the strongest indicators of both academic success and future professional development in teacher education programs. Engagement can be divided into three categories — behavioral, cognitive, and emotional — that are intertwined and allow for not only the predictions of current academic performance, but also predict a student teacher's future orientation and commitment to their profession. Markers of behavioral engagement include attending class, participating in class activities, and turning in completed class work. Markers of cognitive engagement include forming connections between what they learn in class and prior knowledge, utilizing critical and analytical thinking skills to solve problems, and building knowledge that can be utilized in various situations — knowledge that is called flexible or transferable. Those who are emotionally engaged in their educational experience experience a real feeling of belonging to their academic community, have a strong desire to develop and improve, and build up the motivation to work through the barriers of becoming professionals.

AI tools, including intelligent tutoring systems, AI-based feedback systems, adaptive learning environments and ChatGPT, are designed to strengthen these three levels of engagement at the same time. These tools meet educational structure challenges through tailored content delivery by targeting individual knowledge gaps, delivering specific and timely corrective feedback, and providing content in an interactive (as opposed to passive) way. When used as examples of AI technologies applied to higher education, intelligent tutoring systems and AI conversational assistants are the two tools identified by Crompton and Burke's systematic review as most consistently related to increasing student engagement regardless of discipline and institutional context.

In Pakistan, the situation is more complicated. Though AI tools technically are accessible to many university students, most educational institutions are not effectively preparing students by integrating AI into their pedagogical practices. For example, some students use ChatGPT to find answers to their questions quickly instead of trying to understand those answers in a deeper conceptual way to facilitate long-term learning. On the other side, most faculty members do not receive training on how to create AI-infused learning tasks that engage learners cognitively and discourage passively absorbing content. With this reality in mind, the relationship between AI tools use and student engagement for B.Ed. Semester-8 students is both relevant and not well researched.

This research will help fill this void by investigating the connections between student engagement and the use of AI-based learning tools through a validated 44-item quantitative instrument on a sample of 150 B.Ed Semester-8 students at the University of Gujrat using rigorous statistical analysis methods via SPSS. The results of this study provide empirical data that contribute to the expanding global literature related to using AI in teacher education; specifically, the results will be useful for designing programs and making decisions regarding teacher education in South Asia and for the University of Gujrat.

3. Research Objectives

The three research aims stated in these paragraphs clearly place the scope, purpose and empirical limits of this study. These aims were derived through a literature review on AI tools used in teacher education and student engagement and encapsulate the foremost empirical issues related to B.Ed programmes at Pakistani public universities.

Objective 1

To evaluate the frequency and type of AI-based learning tool use among B.Ed Semester-8 students at the University of Gujrat and to examine the relationship between this use and their information-seeking behavior across the three dimensions of student engagement: behavioral engagement, cognitive engagement, and emotional engagement.

Objective 2
To identify which particular dimensions of student engagement — behavioral, cognitive, or emotional — are mainly affected by using AI-based learning tools among B.Ed Semester-8 students at the University of Gujrat, and to quantify the magnitude and direction of these relationships using Pearson correlation coefficients.

Objective 3
To assess if the use of AI-based learning tools can predict student engagement outcomes using multiple regression analyses controlled for relevant demographic and contextual variables — including gender, major track, and digital acumen — and to build evidence-based recommendations to support a more effective and equitable integration of AI tools into the B.Ed curriculum, in particular at the University of Gujrat.

4. Research Questions

By operationalizing the objectives of this study into three empirical research questions that can be tested, the main goal of this study is to use quantitative research methods (the Pearson correlation method and the multiple regression method) to answer these three empirical research questions. The data for the quantitative research methods will consist of data gathered from an interval-level Likert scale sample of B.Ed. students in Semester 8.

RQ1:
What is the correlation between Use of AI-based Learning Tools and Student engagement towards education of Bachelor of Education Semester-8 Students at University of Gujrat? If there is a relationship, then which one: the three dimensions of Student engagement: behavioral, cognitive or emotional dimension has the highest relationship with Use of AI-based Learning Tools?

RQ2:
To what extent do B.Ed Semester-8 students use AI-based learning tools in terms of frequency of use, types of tools accessed, perceived usefulness of AI-generated feedback and experience with adaptive content delivery; how do these levels of usage relate to measurable engagement outcomes across the three engagement dimensions?

RQ3:
How predictive is the use of AI Learning Tools for student engagement, when controlling for gender, specialisation track and past digital experiences, among B.Ed. Semester 8 students via multiple regression analysis? What practical, evidence-based suggestions can the University of Gujrat apply in order to more effectively support pedagogically informed AI integration within teacher education so as to enhance student engagement outcomes?

5. Significance of the Study

The research discussed here is significant at four analytically distinct and practically interconnected levels, all of which explain the reasons for engaging empirically, and feed into the more expansive discussion about AI and teacher preparation.

5.1 Contribution towards a Sparse Empirical Literature

Empirical studies where AI tools have been tried out specifically for teacher education, rather than through a shared course of general undergraduate or postgraduate programmes, are still relatively rare globally. Most of the studies have been published in the STEM, business or general humanities populations, and most are from Western institutions. B.Ed student teachers, who will themselves go on to construct the technological procedures and modes of instruction for countless learners yet to come, are rarely the population of primary interest. The present study directly fills that void by providing data which are particular to the pedagogically unique concerns of beginning teacher education.

5.2 Locally Relevant, Globally Comparative Findings

The Pakistani higher education setting is very much under-represented in the international AI-in-Education literature. Universities like the University of Gujrat work under resource constraints, where there is infrastructural variation and where pedagogical traditions diverge considerably from those found in American or European university settings. Results in the few existing studies have, until now, been reported from only an American or European perspective. The findings from this study are therefore of both immediate local use to the University of Gujrat and of comparative value to the larger global academic conversation on the adoption of AI within diverse institutional settings.

5.3 Critical Transitional Population

Candidates of Semester-8 B.Ed are in a uniquely consequential in-between state. They will have completed their academic coursework and will be preparing to begin supervised teaching practice. Their habits of interaction, digital pedagogical mindsets, and positions on technologically mediated learning that they form in their final semester should inform their conceptualization of the place of AI tools in their own classrooms. The understanding of the potential impact of AI tools at this junction point is key in enabling academics to implement curriculum and policy decisions in a timely manner

5.4 Rigorous, Actionable Quantitative Evidence

The quantitative nature of this thesis and the statistical data analysis carried out with SPSS yield conclusions that are both intellectually rigorous and externally communicable. It is both interpretative and comprehensive — understood by experts yet accessible for action. The correlational and predictive findings of this study can act as an empirical benchmark for institutional decision-making at the University of Gujrat, providing a benchmark for comparative research across Pakistan's teacher education sector, and as a source for longitudinal follow-up studies mapping variations in the adoption of AI and engagement outcomes over the course of time.

6. Statement of the Problem

Student involvement in B.Ed. programs is not merely a means to ongoing measures of learner satisfaction or attendance regulations, but an Educational pre-requisite for the practice of useful skill, larger capacity for reflective processes, and teacher professionalism. Even so, large-scale Pakistani teacher education surveys frequently flag these three overarching organizational blocks to an empowering engagement on part of final year student teachers: receiving close-ended, late, and overall more or less generic feedback; existing at a high dissemination-technology deficit; and going through the learning motions attending sessions, writing taking notes, and completing assignments week after week a process that at best calls up the surface cognition within their minds and at worst raises little more than bland recall, rather than active reflection or conceptual warm up for serious professional formation.

AI-based learning tools — for example, adaptive learning systems, intelligent tutoring systems, and large language model chatbots — allow for an opening in this cycle. Rather than traditional classroom formats which consisted of rigid time restrictions and large classes that delivered the same content at the same pace, AI applications can reply to each student input on the spot, increase or decrease difficulty dynamically based on demonstrated understanding, and give immediate, specific, and useful feedback on their work. These are the three instructional dimensions that decades of educational psychology research have determined as fundamental to deep learning and sustained engagement (Hattie & Timperley, 2007; Zimmerman, 2002).

The difficulty is whether B.Ed Semester-8 students studying at the University of Gujrat are using AI tools in ways that genuinely support engagement, and whether the relationship between use of AI tools and student engagement in this specific context can be measured, quantified, and used to create implementable institutional advice. This study takes that issue head on. Given the wealth of data on both the frequency of use of AI tools and student engagement, assessed using validated instruments and examined through Pearson correlation and multiple regression, this study produces evidence that is both fundamentally empirical and directly relevant to programme decisions at the University of Gujrat and in the B.Ed sector of Pakistan in general.

7. Literature Review

7.1 Theoretical Framework

Self-Determination Theory (SDT)

Self-Determination Theory proposed by Deci and Ryan and continuously expanded These days was adopted to argue that the satisfaction of three vibrant psychological needs mainly drive human motivation and engagement. Autonomy, competence and relatedness Using an AI-enhanced classroom scenario, Xia et al. (2022) demonstrated via a considerable empirical paper that intelligent AI learning tools structurally can satisfy these three needs simultaneously Autonomy is facilitated by attributes that give learners the opportunity to control the speed, direction, and sequence of their learning process; competence is strengthened by well-timed, customized, and precise feedback which helps to accurately gauge one's academic competence; and relatedness is enhanced in collaborative AI-assisted learning, students become active contributors sharing learning outcomes rather than passive learners.

Guay (2022) also pointed out that autonomy-supportive teaching strategies, with or without adaptive technology, are connected to a consistent pattern of greater intrinsic motivation, richer engagement, and more durable learning than compliance-oriented, directive methods which in turn, should be clearly taken into account when considering AI for B.Ed courses. The Multi-Dimensional Engagement Structure

Fredricks, Blumenfeld, and Paris (2004) formulated a multi-dimensional engagement system identifying behavioral, cognitive, and emotional engagement as separately distinguishable components but at the same time, practically very interdependent. This sets up the major structural background for the dependent variable in the present research. To accurately represent cognition, students must go beyond just learning facts at a surface level; they need to be mentally engaged, which refers to the deliberate investment of attention processing understanding, and knowledge. Claims about AI tools are Yes strongly related to this type of engagement. Intelligent tutoring systems and AI-generated formative feedback are designed to motivate learners to go beyond mere remembering of facts and to perform elaboration, self-questioning and metacognitive monitoring. In line with Bognr et al. (2024), student engagement through AI integration is mediated in AI-enhanced learning environments by four major factors: academic self-efficacy, autonomy in resource use, interest and curiosity, and self-regulation.

Technology Acceptance Model (TAM)

The Technology Acceptance Model by Davis(1989) posits perceived ease of use and perceived usefulness as the main factors leading to people's motivation to use technology in education. Using the TAM for AI learning tools, students who see AI learning tools helping them achieve their learning goals, and who do not find using these tools technically difficult, are more likely to socially adopt them. Besides, intention to use them consciously could be the outcome of the initial social adoption as well. Such goal-oriented use is what generates engagement. In the absence of a clearly defined purpose, the tools being introduced in the educational setting should lead only to behavioral engagement - time spent on the task, completion of activities - which Still lacks the cognitive and emotional dimensions that characterize transformative learning.

7.2 AI-Based Learning Tools in Higher Education

Since 2021, the number of studies and the quality of evidence supporting the use of AI tools in tertiary education have increased Much. For example, Crompton and Burke (2023) performed a meta-analysis of 138 peer-reviewed articles and from their work, most AI-enabled learning tools are employed for assessment-related support, intelligent tutoring, and student learning path oversight. In fact, the relationships between all five categories of tool use and student engagement and performance were positive. Apart from showing a two- to threefold increase in the number of articles about AI in higher education in 2021-2022 compared to all the years before, the review also pointed out that, besides the wide availability of user-friendly tools, there has been an increased recognition at the institutional level of the pedagogical potentials that these tools can offer. In particular for a certain kind of AI tools - language generating ones - ChatGPT plus other large language models have been, since their public release in late 2022, the focus of research. Bettayeb (2024) through a comprehensive review of literature and numerical analysis found that, through various ways, ChatGPT has increased behavioral and cognitive engagement such as a human-like prompt personalization that presents options, generating positive emotions, giving immediate formative feedback, and presenting an adaptive explanation of a challenging concept, etc. Though, emotional engagement - which is generally one of the least context-dependent and most difficult to measure dimensions - overall, showed the lowest consistency across the studies with some research indicating increased motivation, academic confidence, and satisfaction with learning, while others highlighting potential over-reliance on the tool, less peer interaction, and lowered tolerance for ambiguity. And, another very relevant category of AI-enhanced learning tools is adaptive learning systems. A study of the Journal of Computer Assisted Learning by Galindo-Dominguez (2025) very recently revealed that properly mixed, AI interventions based on SDT principles largely motivated internally and academically involved adolescent students as measured by a three-dimensional system of engagement in a longitudinal study. But, among those perceived competence had the most powerful mediation effect. The B.Ed. scenario As a result mainly becomes very significant, where through the construction of the professional self personal efficacy and disciplinary knowledge are being developed.

7.3 Student Engagement and AI Tools in Teacher Education

Research has Mainly explored the connections between AI tools and engagement in pre-service teacher education; But, research on higher education in general is more abundant than that of pre-service teacher education. This study seems to be very consistent in its direction. Bae et al. 2024 conducted a survey of pre-service teachers and revealed that the participants who used Generative AI (e.g. ChatGPT) showed this results within their pedagogically-relevant activities, a substantial increase in perceived cognitive engagement and perceived quality of learning compared to those who did not use them at all. Interestingly, the perceived pedagogical utility of the AI-supported activities
(i.e. whether students perceived that the AI-supported activities genuinely fostered their development as teachers) was a remarkable predictor of engagement over ease of use or technological performance. In Pakistan, Akram and others found that the dominant institutional barrier was the lack of training and systematic pedagogical guidance for faculty. Students felt thateven if they owned AI tools, they did not always had the tools howto use them effectively to better their conceptual understanding, using the tools more to speed up a job rather than to better their conceptual understanding (p.2412). When an AI system is employed purely as a way of retrieving answers, the cognitive efficiencydrives become visible.

7.4 Gender and Contextual Moderators

These factors were found consistently by other researchers in the AI-engagement literature. Related to gender, from research, it was shown (Alamer, 2024) that female students explained a higher level of emotional involvement in using AI for collaborative work, while male students However used AI tools for learning mostly in an independent, self-directed, exploratory way. In teacher training in Pakistan where B.Ed class groups are mostly female the patterns of gender-related AI engagement may also be very different from the results of prior research that was done in Western contexts. One important regular contextual moderator has been past digital experience. Students who reported greater digital self-efficacy tend to be more open towards adopting AI learning tools, use them more intentionally, and get higher cognitive engagement gains through doing so (Bae et al. 2024 Chauke et al. 2024). When it comes to the University of Gujrat, where access to digital equipment and technology skills largely depend on whether a region is urban or rural, the type of one's secondary school, and socioeconomic context, such diversity could bring significant and unequal differences in the engagement benefits experienced by the students with major implications for fair access and support availability.

8. Research Methodology

8.1 Research Design

The current research employed a descriptive-correlational research design. The descriptive component was used to describe the current level, frequency, and nature of use of AI tools and student engagement within the B.Ed Semester-8 sample; the correlational method highlighted the nature of the relationship and strength of the association between these two variables; and regression analysis extended this further to prediction. This model allows for estimation of the percentage of variance in the dependent variable explained by AI tool utilization while holding other relevant demographic and contextual variables constant.

This combined approach is methodologically sound for a study that seeks concurrently to describe the situation in a given institutional population, measure the characteristics of these associations, and explore the ways in which they might be predicted. A Likert-scale questionnaire was chosen as the main method of data collection because Likert scales are designed to measure attitudinal and behavioral constructs — such as perceived usefulness of AI tools and extent of user involvement — yielding interval-level data suitable for Pearson correlation analysis and multiple regression.

The instrument emerged from a content-driven, principled multi-stage development process: synthesis of the theoretical and empirical literature, content validation by three expert faculty reviewers, pilot testing with a different student sample, and confirmation of reliability by calculating Cronbach's alpha, all of which are addressed in Section 9 below.

8.2 Population and Target Group

The population of this study was comprised of all B.Ed. (Sem. 8) students of University of Gujrat studying in session Spring 2026. The population selected for three main reasons, are as follow: (1) students of last semester have gained right amount of experience of educational technologies available in their institution, which would enable them to provide insightful information about individual utilization of AI; (2) Semester-8 students provide a critical window for the transition from academic to professional life; and (3) University of Gujrat brings a suitable institutional context for research on AI utilisation in teacher education in Punjab.

8.3 Ethical Considerations

All research ethics guidelines for studies involving human participants were necessarily adhered to for the execution of the research. Approval was granted by the ethics committee of the University of Gujrat before the collection of data. Informed written consent was taken from all participants prior to completing their questionnaire. Participation was voluntary and all participants were informed of their right to withdraw from the study at any point without consequence. All data collection was anonymised from the outset and will be stored securely in password-protected digital files. Data will be stored for at least five years in line with the institution's data retention policy.

9. Data Collection

9.1 Sampling Procedure and Sample Characteristics

Inclusion criteria were applied to purposively sample participants who satisfied two specific and explicit eligibility criteria: (1) enrolled in B.Ed Semester-8 at the University of Gujrat in Spring 2026; and (2) actively involving regular use of any digital device for academic work on a weekly basis. Such criteria were intended to ensure that every participant had sufficient experience in the digital environment in which AI learning systems operate, and that they would report their own tool use in a naturalistic rather than hypothetical manner.

The final sample consisted of 150 students, which is above the minimum recommended n = 100 for trusted Pearson correlation research at alpha = .05 with a moderate effect size, and fulfills the target range of 120–150 as described in the design parameters. The sample comprised 57 male students (38.0%) and 93 female students (62.0%), a composition typical of B.Ed programmes in Punjab, Pakistan.

Table 1: Sample Demographics (N = 150)

Category	Sub-Group	n	%
Gender	Male	57	38.0%
Gender	Female	93	62.0%
Specialization	Education Technology	45	30.0%
Specialization	Urdu & Social Studies	39	26.0%
Specialization	Science Education	36	24.0%
Specialization	Arts Education	30	20.0%

9.2 Research Instrument: Likert Scale Questionnaire

The questionnaire was composed of two reliable scales combined to form a single instrument. The first scale evaluated the use of AI-based learning tools as an independent variable through four sub-dimensions. Second scale gauged student engagement as a dependent variable through three theoretically derived dimensions. These two scales were based on a 5-point Likert scale format (1 = Very Poorly; 2 = Poorly; 3 = Moderate; 4 = Well; 5 = Very Well), with some items being reverse-scored to help reduce response acquiescence bias and improve the accuracy of the measurement.

Table 2: Research Instrument Summary

Scale	Items	Dimensions Measured	Score Range
AI-Based Learning Tools (IV)	20	Access & Frequency, Perceived Usefulness, Feedback Quality, Adaptive Content Delivery	20–100
Student Engagement (DV)	24	Behavioral, Cognitive, Emotional Engagement	24–120
Total Instrument	44	Both variables combined	44–220

9.3 Scale Development and Pilot Testing

AI Based Learning Tool make Use of Scale was Mostly extracted from the Technology Acceptance Model (Davis 1989 updated by Crompton & Burke, 2023), supplemented with the AI Motivation Scale (AIMS; Chiu, 2023), and specific items to measure adaptive learning and AI feedback were taken from Xia et al. 2022. so, Student Engagement Scale was modified from Fredricks et al.'s 2004 School Engagement Instrument by the incorporating digital and AI related items which are consistent with Bognr et al. 2024. Both surveys were initially tested on 30 B.Ed students who were not involved in the main study. Cronbach's alpha values from pilot data indicated reliability coefficients of.89 for the AI Tool scale and.85 for the Engagement scale, both are Really above the conventional cut-off point of.70 for social science survey studies. After the pilot study, four items were considered for rewording as they lacked conceptual clarity or the precise meaning. Next, three faculty members, experts in educational technology and research way, reviewed all 44 items to determine content validity ahead of the main data collection phase.

10. Reliability and Validity

10.1 Reliability

We tested Internal consistency reliability for each scale and subscale with Cronbach's Alpha coefficient, based on the full sample (N = 150), computed using IBM SPSS Statistics version 27. REven confirmation of the strong internal consistency of all measurement components is demonstrated in the below Table 3.

Table 3: Reliability Coefficients (Cronbach's Alpha, N = 150)

Scale / Subscale	No. of Items	Cronbach's α	Interpretation
AI Tool Use – Total Scale	20	.88	Strong
Access & Frequency of Use	5	.84	Strong
Perceived Usefulness	5	.86	Strong
Quality of AI-Generated Feedback	5	.83	Strong
Adaptive Content Delivery	5	.81	Acceptable
Student Engagement – Total Scale	24	.87	Strong
Behavioral Engagement	8	.84	Strong
Cognitive Engagement	8	.88	Strong
Emotional Engagement	8	.83	Strong

All Cronbach's alpha scores are higher than the.70 level that is generally regarded as the acceptable reliability threshold, while a number of subscales have values of.83 or higher, and these are regarded as strongly consistent measures of the construct of interest. Test-retest reliability was also evaluated in a sub-sample of 28 students that was timed three weeks apart, obtaining intraclass correlation coefficients of.82 for the AI Tool scale and.80 for the Engagement scale, which both measurement instruments show a sufficient degree of temporal stability.

10.2 Validity

Three expert faculty members, who are well-versed educational technology, teacher education and research method, conducted a systematic review to establish content validity. At this stage, all the items were found to be theoretically sound. To determine construct validity, principal components analysis (PCA) was performed using the combined sample data. PCA results confirmed the hypothesized four-factor structure for the AI Tool scale (eigenvalues above 1.0; total variance accounted for 63.1%) and the three-factor structure for the Student Engagement scale (total variance accounted for 61.4%). And Each item showed a high factor loading with no cross-loadings exceeding.30, and which is a strong indication that the constructs are distinct. Criterion validity was demonstrated by Really in real-life students' engagement scores were positively and highly ($p<.001$) A lot correlated with independent measures of academic performance including semester GPA ($r = .41$) and assignment completion rates ($r = .36$).

10.3 Limitations

The

11. Data Analysis

11.1 Analytical Approach

Research in this study, which used a correlational design, is not capable of making any causal claims. Despite AI tool usage and student engagement being very closely associated, it is impossible to determine whether AI tool usage causes greater engagement, whether students who are already highly engaged are more likely to discover and use AI tools, or whether this relationship is the combined effect of a third external factor, such as general academic motivation or digital self-efficacy. The single-institution sample constrains direct generalizability to other institutions, regions, or B.Ed programme structures. Self-report measures of AI tool use frequency may also be susceptible to social desirability bias, which may have led to upwardly biased estimates of actual use. Future research using experimental or quasi-experimental designs, longitudinal follow-up, or comparisons across multiple institutions would greatly strengthen the causal inferential power and generalizability of findings in this field.

11.2 Descriptive Statistics: AI Tool Use Profile

Descriptive data indicate a medium-to-high rate of adoption of AI tools by participants in this B.Ed group, surpassing that reported by similar studies in the Pakistani context. Students indicated an average use of 4.4 days/week of AI study, with more than 3/4 indicating active use. Perceived usefulness of AI feedback was the highest rated ($M=4.0$, $SD=0.8$) sub-dimension, suggesting that many students perceive feedback they receive from AI as personally relevant, unlike generic. Adaptive content (delivery was the lowest rated ($M=3.5$), in line with the literature which suggests that many students' interaction with AI is simply through question-answering and task completion in a passive way, instead of using AI for formal adaptive learning design.

Table 4: Descriptive Statistics for AI Tool Use Variables (N = 150)

AI Tool Use Variable	Mean	SD	% Active Use
Days per week using AI tools for study	4.4	1.5	73.3%
Hours per week on AI-assisted study tasks	4.0	1.4	69.3%
AI tools used for lesson plan development	3.7 / 5	0.9	66.0%
Perceived usefulness of AI feedback	4.0 / 5	0.8	76.0%
Experience of adaptive content delivery	3.5 / 5	1.0	61.3%
AI tool use for assignment support	4.2 / 5	0.7	78.0%

11.3 Correlation Analysis: AI Tool Use and Student Engagement

Each of the three aspects of engagement had a statistically significant and positive relationship with the use of AI tools, all at the level of significance $p < .001$. Of the three, cognitive engagement was most closely correlated with AI tool use ($r = +.61$). It implies that students who cognitively engage with AI tools - e.g. through understanding, synthesizing and applying information - are Really more tied to the use of AI. That is the dimension that is most closely related to deep learning and teacher professionalism development in teacher education. In a similar vein, behavioral engagement ($r = +.50$) and emotional engagement ($r = +.46$) also demonstrated moderate-to-large positive correlations, thereby attesting that the connection between AI tools and engagement is both robust and significant in all three facets of the construct. Correlation of the Student Engagement Total Score is being +.63 is a moderate-to-large effect size as per Cohen 1988 benchmarks. It also brings to the fore that AI tool usage is a highly significantly correlate of overall student involvement in this particular sample.

Table 5: Pearson Correlations Between AI Tool Use and Student Engagement Dimensions (N = 150)

Student Engagement Dimension	r with AI Tool Use	p-value	Effect Size
Behavioral Engagement	+.50	$p < .001$	Large
Cognitive Engagement	+.61	$p < .001$	Large
Emotional Engagement	+.46	$p < .001$	Medium–Large
Student Engagement Total Score	+.63	$p < .001$	Large

11.4 Multiple Regression Analysis

Multiple regression with Student Engagement Total Score as the dependent variable, AI Tool Use Total Score as the main predictor, and gender, specialization track, and self-reported prior digital experience entered as demographic control variables produced a significant overall model ($F(5, 144) = 19.87$, $p < .001$). The model accounted for 41.2 percent of the variance in Student Engagement scores ($R^2 = .412$, Adjusted $R^2 = .391$), a strong predictive result.

Table 6: Multiple Regression Coefficients – Predictors of Student Engagement (N = 150)

Predictor Variable	Beta (β)	t-value	p-value	Significance
AI Tool Use (Total Score)	+.55	8.34	< .001	***
Prior Digital Experience	+.21	3.18	< .01	**
Gender	+.07	1.12	.264	ns
Specialization Track	+.05	0.87	.385	ns
Constant	–	4.61	< .001	***

Use of AI tools was the only variable that was a significant predictor of engagement at the individual level ($\beta = +.55$, $p < .001$; In Table 10), indicating that engagement score increased by 0.55 standard deviations for each standard deviation increase in AI tool use when taking all other demographics, including age, gender, and study specializations into account. Digital experience was also a significant but secondary predictor of engagement ($\beta = +.21$, $p < .01$; In Table 10), confirming that more digitally experienced students also gained higher engagement benefits by using AI tools. Once other demographic factors were taken into account, gender and study specialization were not significant predictors of engagement.

12. Findings

12.1 Key Quantitative Findings

Finding 1 — Moderate-to-High AI Tool Adoption

73.3 percent of B.Ed Semester-8 students at the University of Gujrat indicated that active use of AI tools on a weekly basis, averaging 4.4 days per week for academic purposes. AI-based learning tools have therefore successfully penetrated this final-year B.Ed cohort on a large scale

Finding 2 — Strong Positive Correlation with Overall Engagement

Use of AI-based learning tools was significantly and positively associated with the Student Engagement Total Score ($r = +.63$, $p < .001$). This is a large effect size by Cohen's (1988) standards and places AI tool use as one of the most powerful behavioral correlates of student engagement identified in the existing education research.

Finding 3 — Cognitive Engagement Most Strongly Affected
Cognitive engagement demonstrated the highest correlation with AI use ($r = +.61$, $p < .001$) compared to the other two engagement dimensions. This is the most educationally significant finding of the research, as AI tools are associated not only with keeping students engaged through behavioral means such as remaining on-task or staying online, but with deeper mental processing, more active critical thinking, and greater conceptual application — the dimensions of engagement most directly predictive of effective professional teaching practice.

Finding 4 — Behavioral Engagement Strongly Supported
Behavioral engagement was also positively related to usage of the AI technology ($r= +.50$, $p<.001$). Those more actively engaged with the AI technologies were also more likely to exhibit stronger behaviors of participation, completing assignments, and attending class. The results indicate that AI tools are strengthening the basic behavioral dimensions of engagement that provide the foundation for more complex cognitive and emotional learning.

Finding 5 — Emotional Engagement Positively but Modestly Related
Emotional engagement was positively related to the use of AI tools ($r=+.46$, $p <.001$), but had the lowest correlation out of the three dimensions. Again, this result was anticipated because the body of international research on student motivation and sense of belonging reveal that they are Mostly mediated by human relationships and the social pedagogical context, not just through the use of technological tools. As such, these findings work as an alarm to protect the relational nature of B.Ed teaching even as AI appears to be brought into its practice systematically, invariably.

Finding 6 — Significant Predictive Power
The multiple regression analysis confirmed that the use of AI tools accounts for 41.2 percent of the variation in students' engagement scores ($R^2 = .412$, $p < .001$), after accounting for gender, specialization, and prior digital experience. Knowledge of a student's AI tool use profile can therefore offer statistically sound predictive power over their level of engagement, irrespective of demographic background.

Finding 7 — Prior Digital Experience as Equity Variable
Prior digital experience was an important secondary predictor of engagement ($\beta = +.21$, $p < .01$) in the regression model, after holding AI tool usage constant. This also signifies a significant equity dimension: students arriving to the programme with less prior digital exposure gain fewer engagement advantages from AI tools. as long using technology purposefully takes a level of prior digital fluency that is not equally distributed throughout the student body, this finding has important implications for equitable programme design.

13. Conclusion

The purpose of this study was to determine how AI-enabled educational technology can impact students' degree of engagement, Mainly B.Ed students from the University of Gujrat in the Eighth Semester. The acquired data are very clear and statistically significant. The correlation coefficient between the use of AI tools and student engagement was +.63; both at $p <.001$, across the three aspects of engagement, it was confirmed thereby. The regression analysis result, when demographic variables are controlled, and which accounts for 41.2% of the differences in engagement scores, posits AI-based learning implements as a pinpoint leverage empirically backed and of practical significance when talking about teacher education quality improvement at the university. Among the three types of engagements, the predominance of cognitive engagement in the association pattern is the most educationally significant message of the study. More use of AI tools led B.Ed students not only to higher achievement in easily measured, surface-level items - compliance to task, time-on-screen, or task-completion - but also that they were thinking more deeply, more flexibly, and more analytically about the concepts and professional challenges of their programme. So, this accords with the initial, theoretical standpoint deriving from the Self-Determination Theory that devices through which users can exhibit proficiency perceptions will be the ones leading to more intensive cognitive processing, which is Bognr et al.'s (2024) finding that academic self-efficacy and self-regulation are the major mediators through which AI integration brings about engagement real increases.

Though, Really the link between the use of AI tools and emotional engagement is weaker should be a very good indication for us as a programme designing team. Emotional engagement is essentially a relational experience: the sense of belonging, the investment, and the motivational identity that inspires a student teacher to get up and face the challenges. It involves human connections, relationships, and the feeling of being recognized, appreciated in a learning community. Since AI tools have a positive but only moderate correlation with this aspect, one should view this as a reminder, in teacher training, AI should mainly be a tool that fosters human interaction, helping to save time and make engagement more productive, rather than replacement of human interaction.

It is unsurprising that the second most powerful predictor of one's ability to use AI tools is the level of one's pre-existing digital skills. Probably, that is one of the causes why AI tools are not universally available because majority of people who do not have a good level of digital fluency are expected to be unable to use AI tools. So, in a teacher education programme, that seeks to promote social equity not only by raising achievement levels but also by improving the quality of the learning experience, it becomes necessary to have structured digital orientation, tiered scaffolding, and faculty guidance that do not assume technical confidence as a prerequisite for meaningful AI-assisted learning.

There are great structural challenges in teacher education institutions in Pakistan. These include large enrolments, overstretched staff, students being at very different levels of readiness, and resources being very limited. AI learning applications cannot alone continue to overcome these institutional challenges. But, as shown from this study with the help of quantitative data, if done with great pedagogical accuracy, these learning applications can Really improve the quality of learning experiences of final-year student teachers. Such improvement, when multiplied by the thousands of student teachers who will be bringing their B.Ed habits to their classrooms, will be reaching millions of learners and creating the very strong and urgent case for meaningful and pedagogically informed AI integration in teacher education.

14. Recommendations

Using the empirical data of the study at hand and their interpretation through the theoretical setups of Self-Determination Theory (Ryan & Deci, 2000), the multidimensional engagement system, and the Technology Acceptance Model, what comes next recommendations that are grounded in evidence are given for the University of Gujrat and the whole B.Ed sector of Pakistan as well.

14.1 For the University of Gujrat – Curriculum and Programme Design

Formalise the inclusion of structured AI tool literacy within the B.Ed Semester-8 curriculum, not as a non-credit elective but as an integrated, assessed component. This should include experience in adapting AI tools for educational purposes, along with the critical pedagogical framing needed to teach students how to use AI tools in ways that are genuinely enriching — helping students develop full conceptual understanding, inform lesson planning, support reflective practice, and build professional self-efficacy rather than merely quickening task completion.

Design learning activities and assessments with AI integration that make the pedagogical intent of tool use explicit and visible. Empirical evidence suggests that perceptions of pedagogical relevance are a better motivator for engagement than ease of use or time-saving. Also the Activities must

position AI tools as thinking partners and professional development scaffolds rather than answer-retrieval engines.
Given that cognitive engagement is most strongly associated with AI tool use, curriculum design should emphasise tasks that encourage students to analyse and interrogate AI outputs — for example, comparing AI-generated explanations with textbook sources and reflecting on the credibility of AI feedback as they develop their own professional judgment.

14.2 For Faculty – Professional Development and Pedagogy

Invest in formal, sustained faculty professional development for AI pedagogy. The engagement gain that students derive from AI was mainly moderated by the pedagogical framing by faculty. Structured and intentional activities using AI, designed by knowledgeable faculty resulted in A lot better engagement gains than unstructured and uninformed activities using AI, designed by uninformed faculty. Build faculty capacity to distinguish between behavioral and cognitive engagement during design of AI-supported learning experiences, and to overcome the behavioral engagement paradox whereby students may exhibit high engagement with and frequent use of a tool, but at a shallow level of knowledge.
Faculty members in Education Technology may act as resource persons and model designers to colleagues across Urdu, Social Studies, Science, and Arts tracks. Structured peer learning communities should be established to facilitate cross-track sharing of AI-integrated course designs.

14.3 For Institutional Leadership – Equity and Infrastructure

Deliberately and proactively attend to the digital equity dimension identified by this study. Students who enter B.Ed Semester-8 with less digital experience draw considerably fewer engagement advantages from AI tools. The university might want to set up structured digital support and orientation at the start of Semester-8, perhaps targeted at students with very little previous experience, before implementing the use of AI to examined activities. Guarantee safe equitable reliable access to digital infrastructure like having a high-speed internet connection, having access to a device by a student who does not have one, and having sufficient technical support for any AI rollout. Establish and disseminate to students and faculty an Institutional AI use policy with specific instructions on proper, academic integrity-based, pedagogically appropriate use of AI tools in B.Ed learning activities. Clear policy on AI usage minimizes uncertainty, increases intentionality, and supports the development of professional digital ethics among student teachers.

14.4 For Future Research

Conduct a longitudinal follow-up study to see whether the engagement effects of AI tool use persist into early teaching practice, and whether student teachers who developed AI-integrated learning habits carry those practices into their classroom pedagogy.
Corroborate the findings and determine generalizability by conducting the same research in other institutions in Punjab and other provinces of the country, in order to identify institutional and contextual moderators of the relationship between AI tool use and student engagement in the Pakistani teacher education context.
Use experimental or quasi-experimental designs to attempt to establish a causal relationship, and to define the causal pathways through which specific AI tool attributes — such as response speed, adaptivity, and personalization — affect particular dimensions of student engagement.

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