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Impact of AI-Supported Formative Assessment on Academic Engagement And Achievement of B.Ed. Students

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Abstract: *The present study examined the effect of AI-supported formative assessment on the academic engagement and achievement of Bachelor of Education (B.Ed.) students. A quasi-experimental pre-test-post-test control group design was used. The sample consisted of 100 B.Ed. students, with 50 students in the experimental group and 50 students in the control group. The experimental group received AI-supported formative assessment through instant quizzes, automated feedback, adaptive practice questions, and progress dashboards for eight weeks, while the control group received conventional classroom assessment. Academic engagement was measured through a researcher-prepared Academic Engagement Scale, and achievement was measured through a 50-mark achievement test. The findings showed that the experimental group obtained significantly higher post-test scores in both academic engagement and achievement than the control group. The effect size was large for both outcomes. The study concluded that carefully guided AI-supported formative assessment can improve student participation, regularity of learning, feedback use, and academic performance in teacher education. The numerical dataset used in this paper is illustrative and is included to demonstrate a complete research-paper format; it should be replaced with field data before formal publication.*

Keywords: *Artificial Intelligence, Formative Assessment, Academic Engagement, Academic Achievement, B.Ed. Students, Teacher Education.*

1. Introduction: Assessment is an essential part of teaching and learning because it helps teachers understand what students know, where they face difficulty, and what kind of support they require. Traditional assessment often provides feedback after a considerable delay. In contrast, formative assessment gives continuous information during the learning process and allows both teachers and students to make timely improvements. In teacher education, where future teachers learn how to plan lessons, assess learners, and improve classroom practice, formative assessment has special importance.

Artificial intelligence (AI) has introduced new possibilities for formative assessment. AI-enabled systems can generate practice questions, provide immediate feedback, identify frequently repeated errors, recommend additional learning tasks, and display individual progress. These features may make assessment more regular, responsive, and learner-centred. However, technology alone does not guarantee better learning. Its value depends on the quality of questions, teacher supervision, ethical use, and the way students act upon the feedback.

Academic engagement refers to the extent to which students participate actively, invest effort, remain attentive, complete learning tasks, and show emotional and cognitive involvement in academic activities.

When feedback is timely and specific, students may be more willing to correct mistakes and continue learning. Therefore, AI-supported formative assessment may influence both engagement and achievement. The present study was designed to examine this relationship among B.Ed. students.

2. Review of Related Literature: Black and Wiliam (1998) established that classroom assessment can improve learning when evidence of student understanding is used to modify teaching. Hattie and Timperley (2007) explained that effective feedback helps learners understand their present performance, expected goals, and the next steps needed for improvement. Shute (2008) similarly emphasized that formative feedback should be timely, specific, and supportive rather than merely judgmental.

Research on student engagement has shown that behavioural, emotional, and cognitive engagement are closely connected with persistence and academic success (Fredricks et al., 2004). In technology-supported environments, students benefit when digital tools encourage active response, self-monitoring, and repeated practice. More recent discussions of AI in education highlight the potential of adaptive systems, automated feedback, and learning analytics, while also warning about bias, privacy, overdependence, and the need for human oversight (Holmes et al., 2019; UNESCO, 2023).

The available literature suggests that AI can support formative assessment, but there remains a need for classroom-level studies in teacher education. B.Ed. students are future teachers; therefore, their experience with responsible AI-supported assessment may also influence their later professional practice. This study addressed that need by comparing an AI-supported group with a conventional-assessment group.

3. Research Gap: Most studies on technology-enhanced assessment have focused on school students, large online courses, or general higher education. Comparatively fewer classroom studies have examined both academic engagement and achievement among B.Ed. students through a controlled pre-test-post-test design. Moreover, many studies discuss the potential of AI without presenting a clear intervention process. The present study attempted to fill this gap by using an eight-week structured intervention and analysing two learning outcomes.

4. Objectives of the Study

1. To compare the pre-test academic engagement scores of the experimental and control groups.
2. To compare the post-test academic engagement scores of the experimental and control groups.
3. To compare the pre-test academic achievement scores of the experimental and control groups.
4. To compare the post-test academic achievement scores of the experimental and control groups.
5. To determine the effect size of AI-supported formative assessment on academic engagement and achievement.

5. Hypotheses

H01: There is no significant difference between the mean pre-test academic engagement scores of the experimental and control groups.

H02: There is no significant difference between the mean post-test academic engagement scores of the experimental and control groups.

H03: There is no significant difference between the mean pre-test academic achievement scores of the experimental and control groups.

H04: There is no significant difference between the mean post-test academic achievement scores of the experimental and control groups.

6. Methodology

6.1 Research Design: The study used a quasi-experimental pre-test-post-test control group design. Two intact groups of B.Ed. students were selected. Both groups completed pre-tests before the intervention and post-tests after eight weeks.

6.2 Sample: The sample consisted of 100 B.Ed. students. The experimental group included 50 students and the control group included 50 students. The groups were comparable in terms of course level and instructional duration.

6.3 Tools: Two tools were used: (a) a researcher-prepared Academic Engagement Scale containing 30 items across behavioural, emotional, and cognitive engagement, with a maximum score of 150; and (b) a 50-item achievement test in Educational Technology, carrying one mark per item. Content validity was established through expert review. For the illustrative dataset, the engagement scale reliability was taken as Cronbach's alpha = .88 and the achievement test reliability as KR-20 = .82.

6.4 Intervention: For eight weeks, the experimental group participated in weekly AI-supported formative assessment activities. These included short diagnostic quizzes, immediate explanatory feedback, adaptive practice questions based on errors, self-progress dashboards, and teacher-reviewed remediation tasks. The teacher checked the accuracy and suitability of AI-generated material before use. The control group studied the same units for the same duration but received conventional oral questioning, written class tests, and delayed teacher feedback.

6.5 Statistical Techniques: Mean, standard deviation, independent-samples t-test, gain scores, and Cohen's d were used for analysis. The level of significance was fixed at .05.

7. Data Analysis and Interpretation: The following numerical values are an illustrative dataset prepared to demonstrate the analysis and presentation of a complete research paper. They should not be represented as actual field findings without primary data collection.

Table 1: Comparison of Pre-test Academic Engagement Scores

Group	N	Mean	SD	Mean Difference	t	p
Experimental	50	92.40	10.20	0.70	0.34	.736
Control	50	91.70	10.40			

Interpretation: The pre-test difference in academic engagement was not statistically significant, $t(98) = 0.34$, $p = .736$. Therefore, H01 was not rejected, and the two groups were considered comparable before the intervention.

Table 2: Comparison of Post-test Academic Engagement Scores

Group	N	Mean	SD	Mean Difference	t	p	Cohen's d
Experimental	50	119.60	11.10	17.50	8.02	< .001	1.60
Control	50	102.10	10.70				

Interpretation: The experimental group obtained a significantly higher mean academic engagement score than the control group, t(98) = 8.02, p < .001. H02 was rejected. Cohen's d = 1.60 indicated a large practical effect.

Table 3: Comparison of Pre-test Academic Achievement Scores

Group	N	Mean	SD	Mean Difference	t	p
Experimental	50	24.80	5.10	0.40	0.39	.699
Control	50	24.40	5.20			

Interpretation: The pre-test difference in academic achievement was not statistically significant, t(98) = 0.39, p = .699. H03 was not rejected, showing that both groups began at a similar achievement level.

Table 4: Comparison of Post-test Academic Achievement Scores

Group	N	Mean	SD	Mean Difference	t	p	Cohen's d
Experimental	50	39.20	4.80	7.60	7.78	< .001	1.56
Control	50	31.60	4.95				

Interpretation: The experimental group achieved a significantly higher post-test mean than the control group, t(98) = 7.78, p < .001. H04 was rejected. Cohen's d = 1.56 showed a large effect of the intervention on achievement.

Table 5: Mean Gain Scores of the Experimental and Control Groups

Outcome	Experimental Gain	Control Gain	Difference in Gain	Result
Academic Engagement	27.20	10.40	16.80	Higher gain in experimental group
Academic Achievement	14.40	7.20	7.20	Higher gain in experimental group

Interpretation: The gain in academic engagement was 27.20 points in the experimental group compared with 10.40 points in the control group. The achievement gain was 14.40 marks in the experimental group compared with 7.20 marks in the control group. These results support the positive contribution of AI-supported formative assessment.

8. Major Findings

1. The experimental and control groups did not differ significantly in pre-test academic engagement.
2. The experimental group showed significantly higher post-test academic engagement than the control group.
3. The experimental and control groups did not differ significantly in pre-test academic achievement.

4. The experimental group showed significantly higher post-test academic achievement than the control group.

5. Large effect sizes were obtained for both engagement and achievement, indicating educational as well as statistical importance.

9. Discussion: The findings indicate that AI-supported formative assessment may improve learning when it is integrated with teacher guidance. Immediate feedback likely helped students identify errors before misconceptions became fixed. Adaptive questions provided repeated practice at an appropriate level, while progress dashboards encouraged self-monitoring and regular participation. These features may explain the higher engagement score of the experimental group.

The improvement in achievement is consistent with the general principle that assessment supports learning when evidence is used to guide the next instructional step. The large effect sizes should be interpreted cautiously because the dataset is illustrative and the sample is limited to one educational context. Nevertheless, the pattern demonstrates how a structured intervention can be evaluated through a controlled design.

The study also suggests that AI should not replace teacher judgment. The teacher remained responsible for checking content accuracy, protecting student information, interpreting learner difficulties, and deciding suitable remedial action. Thus, the most productive model is not AI alone, but teacher-guided AI use.

10. Educational Implications

1. Teacher education institutions may use AI-supported low-stakes quizzes for continuous diagnosis of learning difficulties.

2. B.Ed. students should be trained to evaluate AI-generated questions and feedback before using them in classrooms.

3. Faculty members may combine automated feedback with personal guidance, especially for complex or sensitive learning needs.

4. Institutions should develop clear rules regarding privacy, academic honesty, transparency, and responsible AI use.

5. AI dashboards may be used to identify students who need timely academic support, but final decisions should remain with teachers.

11. Limitations: The study was limited to a small sample of B.Ed. students and an eight-week intervention. The tools focused on engagement and achievement only. Variables such as digital confidence, socioeconomic background, prior AI experience, and long-term retention were not included. Most importantly, the numerical data in this paper are illustrative rather than collected from participants; therefore, the paper serves as a model draft and must be supported by real field data before journal submission.

12. Conclusion: AI-supported formative assessment, when used under responsible teacher supervision, has the potential to strengthen academic engagement and achievement in teacher education. The illustrative results showed that students receiving immediate feedback, adaptive practice, and progress information performed better than those receiving conventional assessment alone. The study supports a balanced approach in which AI improves the speed and personalization of feedback while teachers provide academic judgment, ethical oversight, and human support.

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