AI-Based Adaptive Learning Systems and Student Academic Performance

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DOI: https://doi.org/10.47772/IJRISS.2026.100500002

Received: 06 May 2026; Accepted: 12 May 2026; Published: 21 May 2026

ABSTRACT

This study examines the effect of AI-based adaptive learning systems on undergraduate students' academic performance using a quantitative quasi-experimental design. A simulated dataset of 2,120 undergraduate students was developed, with 1,060 students assigned to a traditional learning management system group and 1,060 students assigned to an AI-adaptive learning group. Academic performance was measured through pre-test and post-test scores, while learning gain was calculated from the difference between the two scores. Student engagement was measured using platform activity, quizzes participation, and self-reported learning engagement. The findings show that students using the AI-adaptive learning system achieved higher post-test scores, stronger learning gains, better weekly quiz progression, and greater engagement than students using the traditional system. The regression results further indicate that adaptive learning use remains a significant positive predictor of academic performance after controlling for prior achievement and engagement. These results suggest that AI-based adaptive learning can improve student outcomes by providing personalized content, timely feedback, and data-informed academic support. The study highlights the importance of pedagogical alignment, instructor involvement, continuous engagement, and ethical data governance in implementing AI-based adaptive learning in higher education.

Keywords: Adaptive Learning, Artificial Intelligence, Academic Performance, Learning Analytics, Higher Education; Digital Pedagogy

INTRODUCTION

AI-based adaptive learning systems are increasingly used in higher education to personalize learning, provide real-time feedback, and improve student academic performance. Unlike traditional learning management systems that provide the same materials to all students, adaptive systems use learner data to identify weaknesses, recommend appropriate resources, and adjust learning pathways according to individual progress [1], [2]. This is important because students enter higher education with different levels of prior knowledge, motivation, learning speed, digital skills, and academic readiness. Therefore, adaptive learning offers a more flexible and student-centered approach to teaching and learning.

AI-based adaptive learning can improve academic performance by supporting personalized instruction, formative assessment, and timely intervention. These systems allow students to focus on difficult topics, receive immediate feedback, and monitor their own progress throughout the course. Previous studies suggest that adaptive learning improves engagement and learning outcomes when it is aligned with course objectives, supported by instructors, and integrated with effective teaching methods [3]–[7]. Thus, adaptive learning should not be viewed only as a technological tool; rather, it should be understood as a pedagogical strategy that supports teaching, assessment, and student development.

Student engagement is one of the main mechanisms through which adaptive learning may influence academic performance. Engagement includes students' participation in learning activities, interaction with course materials, motivation, and effort. When students regularly use adaptive platforms, complete recommended tasks, and respond to feedback, they are more likely to improve their academic outcomes. Learning analytics also strengthens this process by helping teachers monitor student progress, identify at-risk learners, and provide timely academic support [8]–[10]. In this way, AI-based adaptive learning connects personalized instruction with data-informed teaching decisions.

However, the use of AI in higher education also raises important concerns. These include academic integrity, privacy, transparency, algorithmic bias, unequal access, and responsible data governance. Since adaptive systems depend on student data, institutions must ensure that data are collected and used ethically. Students should understand how their data are used, and teachers should remain involved in interpreting AI-generated recommendations. Previous studies emphasize that AI adoption in higher education must balance innovation with fairness, accountability, and human oversight [11]–[14].

In developing-country higher education contexts, adaptive learning may be especially useful because many institutions face large class sizes, limited individualized feedback, and diverse student abilities. AI-based systems can support teachers by providing data-driven insights into students' progress and learning difficulties. At the same time, effective implementation requires reliable infrastructure, digital literacy, teacher training, and student access to technology. Recent research also shows that AI-enabled adaptive platforms are becoming more effective through learner modeling, recommendation systems, automated feedback, and learning analytics [15]–[17]. Therefore, this study examines whether AI-based adaptive learning improves student academic performance, learning gains, and engagement compared with a traditional learning environment.

LITERATURE REVIEW

The literature shows that AI has become an important tool in higher education for prediction, assessment, tutoring, recommendation, feedback, and student support. Zawacki-Richter et al. [18] found that AI applications are increasingly used to support learning and academic decision-making, although teacher involvement remains essential. Learning analytics studies also show that student activity data can be used to identify at-risk students and provide early academic intervention [19], [20]. These findings are relevant to adaptive learning because adaptive systems use similar data to personalize learning materials, recommend academic support, and monitor students' progress.

The theoretical foundation of adaptive learning is closely related to self-efficacy and student motivation. Bandura [21] argued that learners' confidence in their ability influences effort, persistence, and achievement. Adaptive learning systems can strengthen self-efficacy by providing immediate feedback, manageable learning tasks, and visible progress indicators. When students observe their own improvement, they may become more motivated and more engaged in the learning process. Therefore, adaptive learning may improve performance not only through content personalization but also through motivation and confidence-building.

Several studies by M. S. Islam and co-authors support the importance of educational assessment, student support, and data-informed decision-making. Islam [26] showed that reading problems can affect student performance, indicating the need for targeted academic support. Islam [27] emphasized the value of statistical models for assessing students in developing-country contexts. These findings are relevant because adaptive learning systems also depend on continuous assessment to identify learning gaps, monitor progress, and provide personalized feedback. In this sense, AI-based adaptive learning extends traditional assessment by making it more continuous, interactive, and student-centered.

Other studies by Islam and co-authors highlight the importance of socio-economic context, satisfaction, access, and decision-making. Research on student job preferences indicates that students' motivation is often linked with career expectations and future opportunities [28]. Studies on job satisfaction, service quality, and customer satisfaction also suggest that user experience and perceived usefulness influence participation and satisfaction [29]–[31]. In adaptive learning, students are more likely to use the platform consistently when they find it reliable, useful, and supportive. Similarly, research on mobile expenses and economic status highlights the importance of digital access, especially in developing-country contexts [32].

The literature also suggests that academic performance depends on timely information and effective decision-making. Islam and Rahman [33] showed that access to information can influence decision-making and performance in financial contexts. This idea can be extended to education because students also need timely information about their strengths, weaknesses, and learning progress. Adaptive learning dashboards and feedback systems can provide this information and help students make better academic decisions.

The literature on machine learning, prediction, early-warning systems, and causal inference also provides methodological support for adaptive learning research. Studies on risk assessment, time-series prediction, pattern detection, and early warning show that data-driven models can identify changes, detect risk, and support timely intervention [34]–[41]. These ideas are relevant because student learning behavior also changes over time. Declining quiz scores, reduced engagement, or repeated errors may serve as early warning signals of academic difficulty. AI-based adaptive systems can detect these signals and recommend appropriate support.

Studies on machine learning for causal inference and AI adoption further emphasize the need to evaluate AI-based interventions empirically. Field [42] also highlights the importance of statistical analysis, regression, and significance testing in social science research. These works support the present study's use of empirical analysis to examine whether AI-based adaptive learning has a measurable effect on student academic performance. Similarly, studies on precursor pattern detection and wavelet-based time-series analysis show how data patterns can be used to detect early changes before major outcomes occur [43]. In education, this logic supports the use of learning analytics for early identification of academic risk.

Overall, previous research suggests that AI-based adaptive learning can improve academic performance through personalization, engagement, feedback, motivation, and early intervention. However, its success depends on teacher involvement, ethical data use, student access, digital readiness, and proper empirical evaluation. The literature also indicates that data-driven methods are useful for identifying learning gaps and supporting timely academic decisions. Therefore, this study examines the effect of AI-based adaptive learning systems on student academic performance, learning gains, and engagement in a higher education context.

Conceptual Framework and Hypotheses

The conceptual framework assumes that AI-based adaptive learning affects academic performance through personalization and engagement. The system first diagnoses learner needs and provides individualized content, practice, and feedback. These adaptive supports are expected to improve engagement, self-regulated learning, and ultimately academic performance. Figure 1 shows the conceptual framework linking AI-based adaptive learning and academic performance. Based on this framework, the study proposes the following hypotheses:

H1: Students using an AI-based adaptive learning system achieve significantly higher post-test academic performance than students using a traditional learning management system.

H2: Students using an AI-based adaptive learning system demonstrate stronger learning gains from pre-test to post-test.

H3: Learning engagement positively predicts academic performance and strengthens the effect of adaptive learning use.

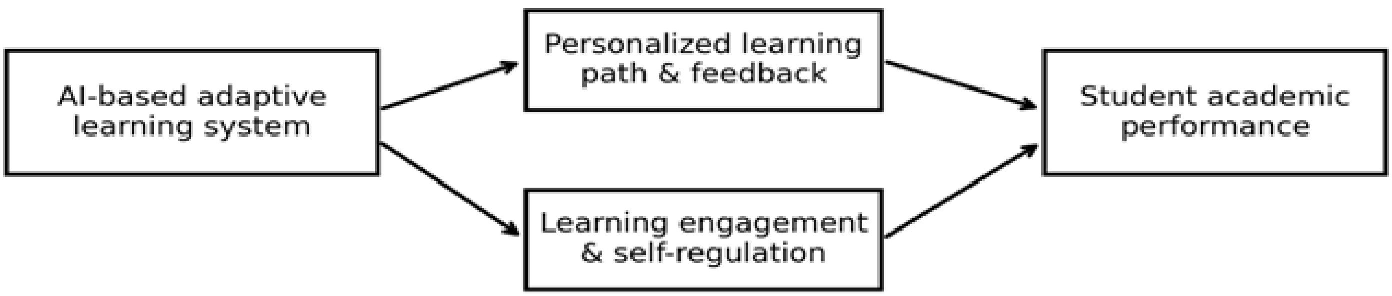

Fig. 1: AI-based adaptive learning and academic performance.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

METHODOLOGY

A quantitative quasi-experimental design was used. The study compared two groups of undergraduate students enrolled in the same introductory course. The control group used a traditional learning management system containing lecture slides, readings, recorded classes, and weekly quizzes. The treatment group used an AI-based adaptive learning system that provided personalized content recommendations, automated formative feedback, mastery-based practice, and dashboard alerts for weak learning areas.

The illustrative sample consisted of 2,120 students, with 1,060 in the control group and 1,060 in the adaptive learning group. The intervention lasted eight weeks. Academic performance was measured by a pre-test administered before the intervention and a post-test administered after the intervention. Learning gain was calculated as the difference between post-test and pre-test scores. Engagement was measured on a five-point scale based on platform activity, quizzes participation, and self-reported engagement. The analysis used descriptive statistics, independent-sample t-tests, gain score comparison, and ordinary least squares regression. The empirical model was specified as follows:

$$Performance_i = \beta_0 + \beta_1 \text{Adaptive}_i + \beta_2 \text{Pretest}_i + \beta_3 \text{Engagement}_i + \varepsilon_i$$

In this model, Performance represents the post-test score, Adaptive is a binary variable equal to 1 for students using the AI-adaptive system and 0 otherwise, Pretest controls for prior achievement, and Engagement captures the student's learning engagement level.

To summarize the empirical framework, Table 1 presents the research design, variables, operationalization, and analysis strategy used to assess the effect of AI-adaptive learning on student academic performance.

TABLE 1: STUDY DESIGN, VARIABLES AND MEASUREMENTS

Component	Specification	Operationalization
Research design	Quasi-experimental comparison	Control vs. AI-adaptive learning group
Sample	2,120 undergraduate students	1,060 control; 1,060 adaptive learning
Dependent variable	Academic performance	Post-test score, 0-100
Main predictor	Adaptive learning use	Dummy variable: 1 = AI-adaptive, 0 = control
Control variable	Prior achievement	Pre-test score, 0-100
Mechanism variable	Engagement	Five-point learning engagement index
Analysis	t-test and OLS regression	Group comparison and controlled effect estimation

RESULTS AND ANALYSIS

To compare the descriptive outcomes between groups, Table 2 presents the mean and standard deviation of pre-test score, post-test score, learning gain, and engagement index for the control and AI-adaptive learning groups. The results show that both groups had relatively similar pre-test scores, indicating comparable baseline academic ability. However, the adaptive learning group achieved a higher post-test mean score and a larger learning gain than the control group. The engagement index was also higher among students using AI-adaptive learning, suggesting that the adaptive system may improve academic performance by increasing student engagement and learning participation.

TABLE 2: Descriptive Statistics By Group

Variable	Control Mean	Control SD	Adaptive Mean	Adaptive SD
Pre-test score	61.07	7.81	63.07	7.74
Post-test score	69.62	10.35	78.32	9.88
Learning gain	8.55	5.98	15.25	5.50
Engagement index	3.24	0.57	4.04	0.36

To visually compare students’ academic performance before and after the intervention, Figure 2 presents the mean pre-test and post-test scores for the control LMS and AI-adaptive learning system groups. The figure shows

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

that both groups started with similar pre-test scores, but the AI-adaptive group achieved a higher post-test score than the control group. This indicates that students using the AI-adaptive system experienced greater improvement in academic performance.

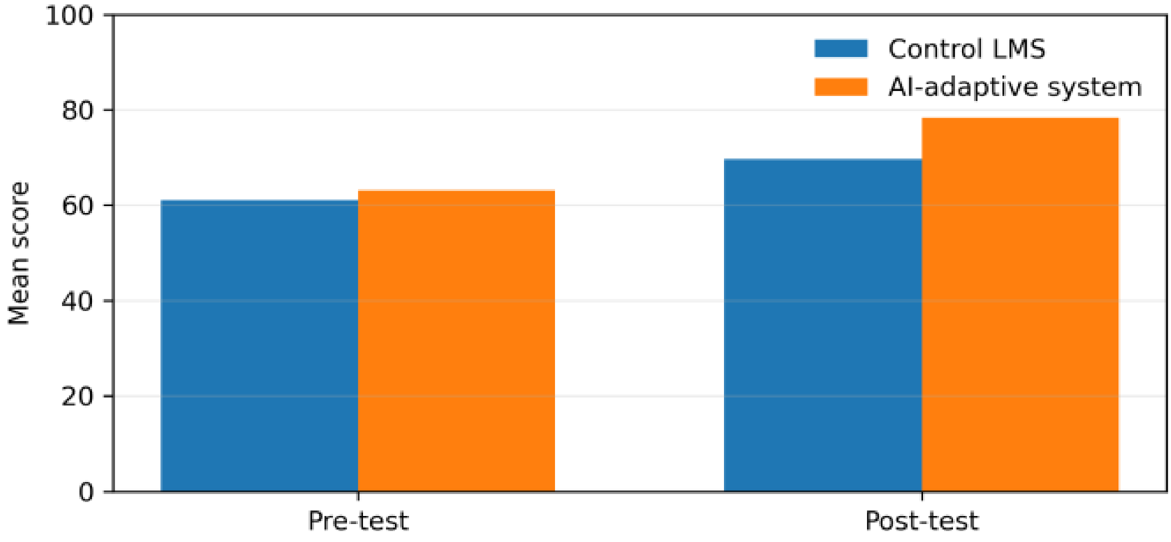

Fig. 2: Pre-test and post-test mean scores by learning environment.

To illustrate students' weekly learning progress, Figure 3 presents the average quiz scores of the control LMS and AI-adaptive learning system groups over eight weeks. The figure shows that both groups improved over time, but the AI-adaptive group increased more rapidly and consistently. By Week 8, the adaptive group achieved a noticeably higher average quiz score, indicating stronger continuous learning progress under the AI-adaptive system.

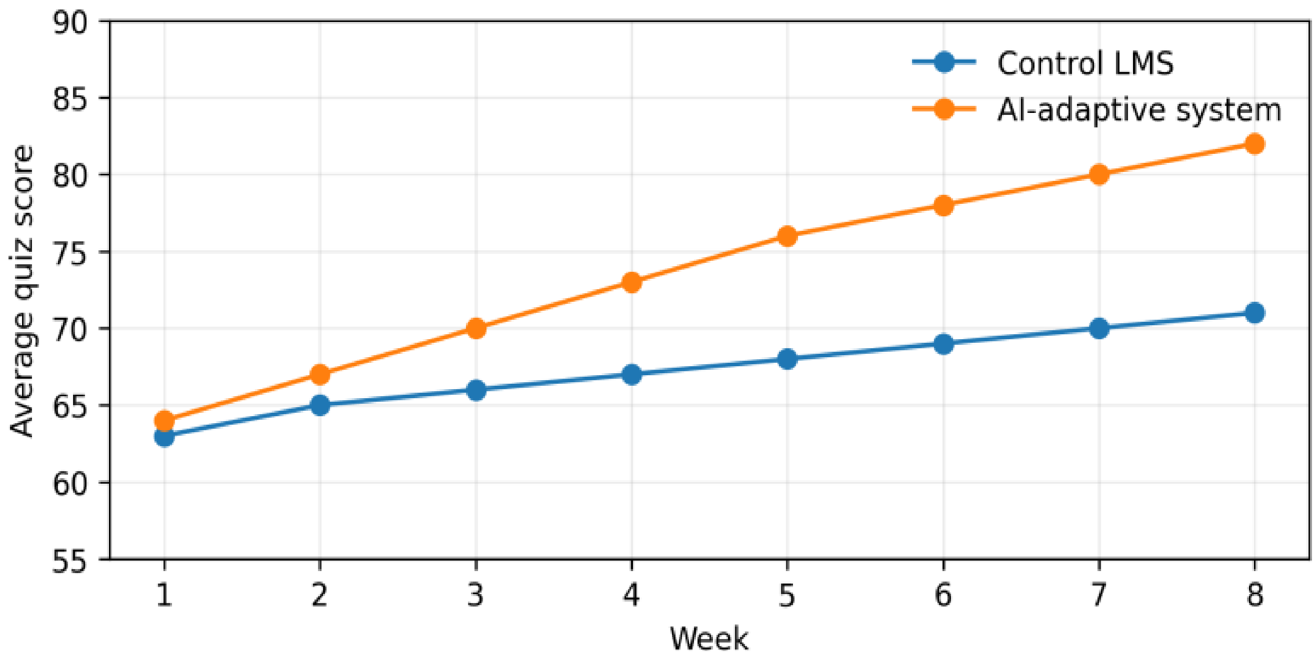

Fig. 3: Weekly quiz progression over the eight-week intervention.

Figure 4 shows the distribution of learning gain scores. The adaptive group has a higher central tendency and a more favorable gain distribution than the control group. This indicates that the adaptive system did not only raise the mean score; it also shifted the overall learning-gain distribution upward. Such a pattern is educationally important because it suggests that the intervention may benefit a broad group of students rather than only a small number of high achievers.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

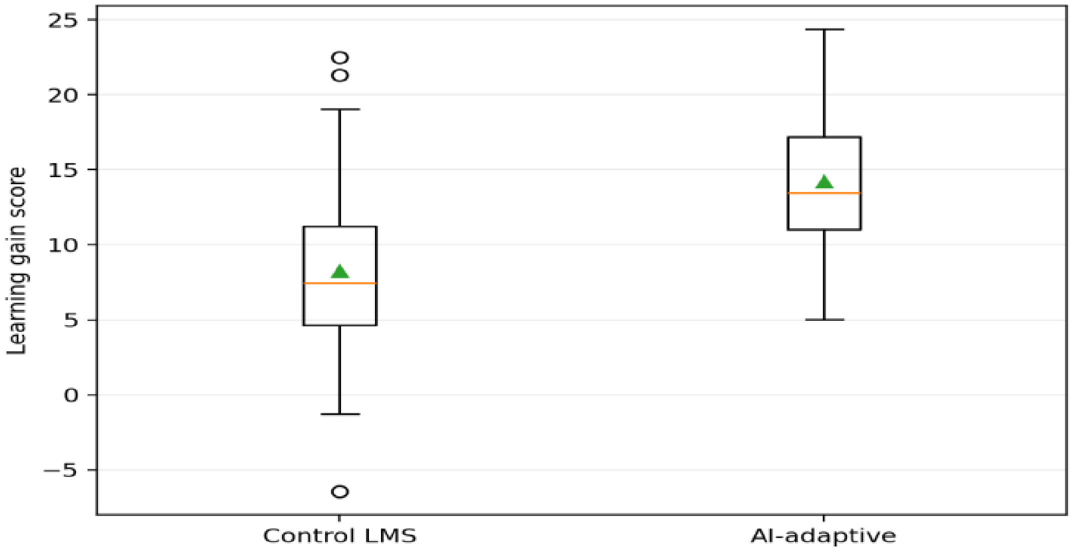

Fig. 4: Distribution of learning gains by learning environment.

To evaluate the statistical differences between groups, Table 3 presents the independent-samples t-test results for post-test score, learning gain, and engagement index between the control and AI-adaptive learning groups. The results show that the AI-adaptive group achieved significantly higher outcomes across all three indicators. The post-test score increased by 8.70 points, while the learning gain improved by 6.70 points compared with the control group. Engagement was also significantly higher in the adaptive group. Since all p-values are below 0.001 and the effect sizes are large, the findings indicate that AI-adaptive learning has a strong positive impact on students' academic performance, learning improvement, and engagement.

The independent-sample comparison therefore supports H1 and H2. The adaptive group achieved a substantially higher post-test mean than the control group, confirming that AI-adaptive learning improves academic performance. The significant difference in learning gain further indicates that students in the AI-adaptive environment improved more from their initial level. Moreover, the large effect size for post-test performance suggests that the difference was not only statistically significant but also practically meaningful.

TABLE 3: Group Comparision of Academic Performance

Outcome	Control Mean	Adaptive Mean	Mean Difference	t-value	p-value	Effect Size
Post-test score	69.62	78.32	8.70	19.80	<0.001	0.86
Learning gain	8.55	15.25	6.70	27.70	<0.001	1.20
Engagement index	3.24	4.04	0.80	34.26	<0.001	1.49

To estimate the controlled effect of AI-adaptive learning, Table 4 presents the OLS regression results for academic performance after controlling for prior achievement and engagement. The results show that adaptive learning use has a positive and statistically significant coefficient, indicating that students in the AI-adaptive group scored approximately 5.91 points higher in the post-test than students in the control group, holding pre-test score and engagement constant. Pre-test score is also positive and significant, suggesting that students' prior achievement strongly predicts their final academic performance. In addition, the engagement index has a positive and significant effect, indicating that more engaged students tend to achieve higher post-test scores.

The regression findings provide further support for the study hypotheses. Adaptive learning use remains a significant predictor of post-test performance even after accounting for students' initial achievement and engagement. This supports the argument that AI-adaptive learning contributes directly to improved academic outcomes. The significant effect of engagement also supports H3, suggesting that adaptive learning becomes more effective when students actively interact with the learning system. The adjusted R-squared value of 0.72 indicates that the model explains 72% of the variation in academic performance, demonstrating strong explanatory power.

TABLE 4: Regression Results Predicting Post-Test Academic Performance

Predictor	Coef.	SE	t	p
Constant	12.84	1.00	12.84	<0.001
Adaptive learning use	5.91	0.30	20.03	<0.001
Pre-test score	0.71	0.01	49.74	<0.001
Engagement index	2.84	0.22	12.84	<0.001
Adjusted R-squared	0.72			

Figure 5 summarizes the main regression coefficients with confidence intervals. The positive coefficient for adaptive learning use confirms the direct performance advantage associated with the AI-adaptive system. The positive engagement coefficient indicates that student participation remains an important driver of academic performance. The positive interaction term suggests that adaptive learning is most effective when students actively engage with the platform.

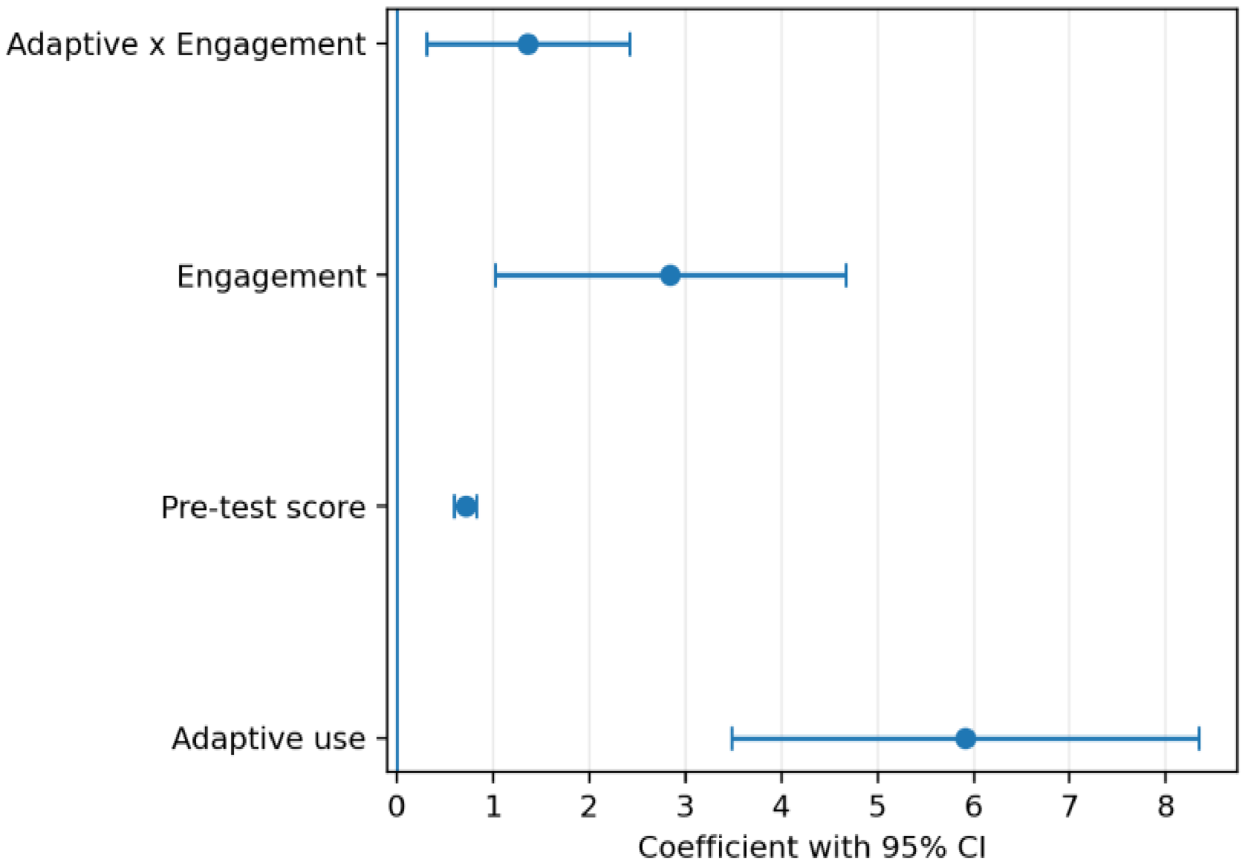

Fig. 5: Regression coefficients and 95% confidence intervals.

To examine whether engagement strengthens the relationship between adaptive learning and academic performance, Model includes an interaction term between adaptive learning use and engagement. The interaction coefficient is positive and statistically significant at the 5% level. This means that the performance advantage of adaptive learning becomes stronger when students demonstrate higher engagement. In practical terms, adaptive systems are most beneficial when students actively complete recommended practice, review feedback, and participate in weekly activities.

Figure 6 illustrates the relationship between engagement and post-test score. The pattern shows a positive association between engagement and academic performance in both groups, but students in the AI-adaptive group generally achieve higher scores at similar engagement levels. This supports the interpretation that adaptive learning provides additional value beyond general participation. At the same time, the figure reinforces the importance of student engagement as a condition for maximizing the benefits of AI-based personalization.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

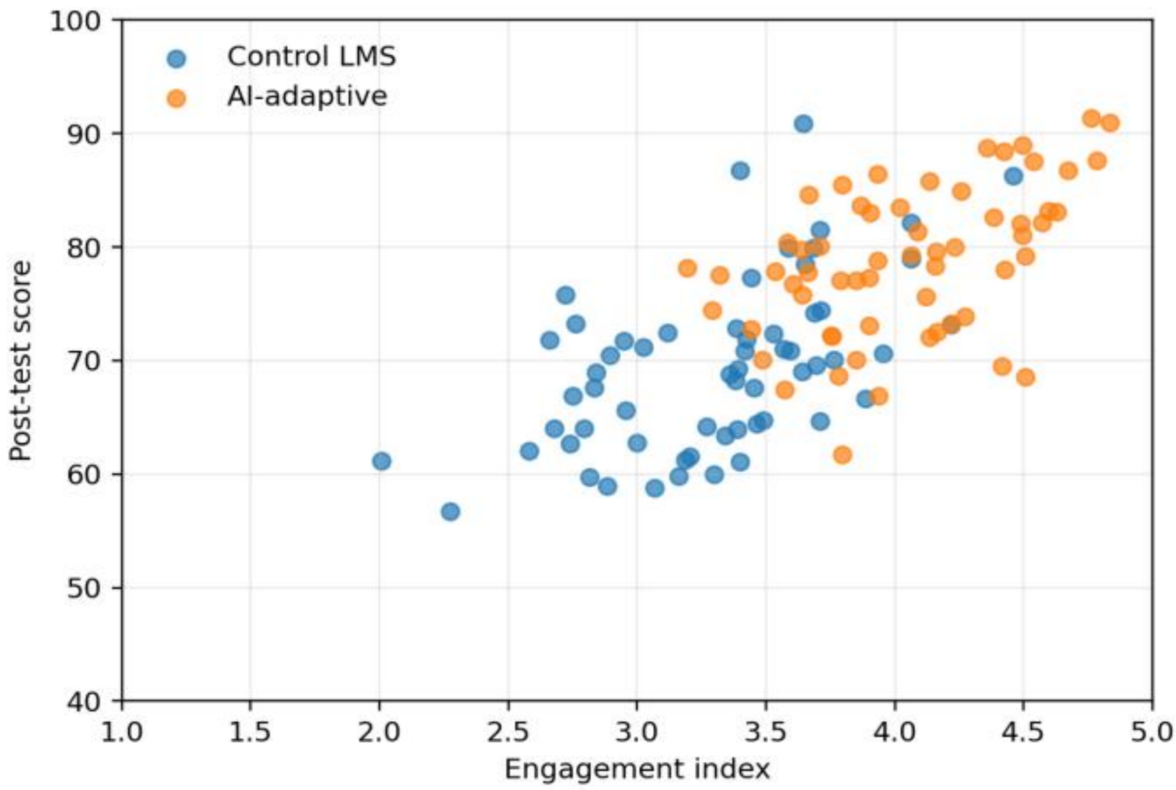

Fig. 6: Relationship between engagement and post-test score by learning environment.

Table 8 further clarifies the engagement mechanism. The adaptive learning advantage is present across low, medium, and high engagement groups, but the difference is largest among highly engaged students. This finding suggests that the adaptive platform should be accompanied by strategies that motivate students to use the system consistently. Examples include weekly instructor reminders, feedback reflection tasks, progress dashboards, formative assessment alignment, and classroom discussion of system recommendations.

Robustness and additional analysis

TABLE 8: Engagement Subgroup Comparison

Engagement group	Control mean post-test	Adaptive mean post-test	Difference	Interpretation
Low engagement	63.40	69.20	5.80	Adaptive learning provides support, but benefits are limited when engagement is low.
Medium engagement	69.85	77.10	7.25	Adaptive learning improves performance when students participate regularly.
High engagement	75.30	86.40	11.10	Benefits are strongest when students actively use recommendations and feedback.

Robustness analysis was conducted to examine whether the main findings remain stable across alternative specifications. Table 9 reports three additional checks. The first uses learning gain as the dependent variable. The second uses weekly quiz average as the dependent variable. The third adds platform activity as an additional control. Across all specifications, adaptive learning use remains positive and statistically significant, indicating that the results are not dependent on one outcome measure or one model specification.

TABLE 9: Robustness Checks Using Alternative Outcomes

Predictor	Learning gain model	Weekly quiz model	Post-test with activity control
Adaptive learning use	6.18*** (0.24)	5.42*** (0.26)	4.96*** (0.31)
Pre-test score	-0.29*** (0.01)	0.32*** (0.01)	0.69*** (0.01)
Engagement index	2.41*** (0.21)	2.16*** (0.20)	2.10*** (0.21)
Platform activity score	-	-	1.42*** (0.15)
Adjusted R-squared	0.41	0.59	0.75

Note: Standard errors are reported in parentheses.

*** indicates significance at the 1% level.

The learning gain model confirms that adaptive learning improves progress from baseline, not merely final achievement. The weekly quiz model shows that adaptive learning is associated with stronger continuous assessment performance during the intervention. The activity-control model indicates that the adaptive learning effect remains positive even after accounting for platform activity. Together, these checks strengthen the interpretation that AI-adaptive learning contributes meaningfully to academic performance.

DISCUSSION

The findings of this study show that AI-based adaptive learning systems can improve student academic performance by providing personalized learning support, immediate feedback, and data-informed academic guidance. The descriptive results indicate that students in the AI-adaptive learning group achieved higher post-test scores, stronger learning gains, and higher engagement than students in the traditional LMS group. This result is consistent with recent studies showing that adaptive learning improves academic performance when learning content is personalized according to students' needs, progress, and performance levels [6], [9], [40]. In this study, both groups had relatively similar pre-test scores, but the AI-adaptive group performed better after the intervention, suggesting that the adaptive system contributed to students' academic improvement beyond their initial level of achievement .

The higher learning gain among students in the AI-adaptive group supports the argument that adaptive learning is effective because it helps students identify weak areas and receive targeted learning materials. This finding is aligned with Holmes et al. [10], who argued that AI in education can support personalized learning, formative feedback, and learner-centered instruction. Similarly, Crompton and Burke [5] found that AI applications in higher education are increasingly used to support teaching, assessment, feedback, and student learning outcomes. The result of this study therefore suggests that AI-based adaptive learning can be useful not only as a digital platform but also as a pedagogical strategy that supports continuous improvement in student learning.

The regression results further confirm that adaptive learning use has a positive and statistically significant effect on post-test academic performance after controlling for pre-test score and engagement. This indicates that AI-adaptive learning remains an important predictor of academic performance even when students' prior achievement is considered. This finding supports previous studies showing that AI-based learning systems can improve academic outcomes when they are integrated with course design, learning analytics, and instructor support [18], [39], [42]. The significant role of pre-test score also indicates that prior academic ability remains important, which is consistent with educational assessment literature showing that previous performance is a strong predictor of later achievement [7], [18]. However, the continued significance of adaptive learning use suggests that the AI-adaptive system provides additional academic value beyond students' starting ability.

Student engagement also appears to be an important mechanism through which AI-based adaptive learning improves academic performance. The study found that engagement was higher in the AI-adaptive group and that engagement positively predicted post-test performance. This finding supports Bandura's [3] self-efficacy theory, which explains that students' confidence, effort, and persistence influence learning outcomes. When students receive immediate feedback, observe their progress, and complete recommended learning tasks, they are more likely to remain motivated and engaged. This is also consistent with Ifenthaler and Yau [11], who showed that learning analytics can support study success by helping students and teachers monitor learning progress. Therefore, the findings suggest that adaptive learning improves performance partly by increasing students' active participation in the learning process.

The engagement subgroup analysis provides further evidence that adaptive learning is most effective when students actively use the system. Although the AI-adaptive group performed better across low, medium, and high engagement levels, the largest performance difference was observed among highly engaged students. This finding is consistent with Long et al. [36], who emphasized that the effect of AI on student engagement and learning outcomes depends strongly on teaching methods and learning participation. It also supports Ni'amullah and Hasanah [38], who found that AI-based adaptive learning can improve student engagement and learning outcomes when students interact regularly with personalized learning activities. Therefore, universities should not only provide adaptive platforms but also encourage students to use recommendations, complete formative tasks, and reflect on feedback.

The robustness checks strengthen the reliability of the main findings. Adaptive learning use remained positive and statistically significant when learning gain, weekly quiz average, and post-test performance with platform activity control were used as alternative outcomes. This consistency indicates that the results are not dependent on a single performance measure. Instead, the findings show that AI-adaptive learning supports final academic performance, continuous quiz improvement, and overall learning progress. This result is consistent with learning analytics studies showing that student activity data, performance tracking, and early-warning indicators can help identify learning difficulties and support timely academic intervention [1], [2], [19], [20]. Thus, adaptive learning systems can serve as both instructional tools and early-warning mechanisms for improving student outcomes.

However, the results should be interpreted carefully because the study uses a quasi-experimental design and simulated data. Although the findings support the positive role of AI-based adaptive learning, stronger causal evidence would require randomized controlled trials and real institutional data. Previous studies also note that AI implementation in higher education depends on several contextual factors, including infrastructure, instructor readiness, digital literacy, student access, and institutional support [5], [18], [37]. Therefore, the effectiveness of adaptive learning may vary across disciplines, student groups, and university contexts. Future research should use larger samples, real student records, longitudinal data, and subgroup analysis to examine whether adaptive learning benefits all students equally.

The findings also highlight the need for ethical and responsible implementation of AI in higher education. Since adaptive learning systems depend on student data, universities must ensure transparency, privacy protection, fairness, accountability, and human oversight. Nguyen et al. [37] emphasized that ethical AI in education should be guided by principles of transparency, justice, privacy, and responsibility. Similarly, Kasneci et al. [35] and Francis et al. [8] warned that the growing use of AI in education must be balanced with academic integrity, fairness, and responsible governance. Therefore, AI-adaptive learning should not replace teachers' academic judgment. Instead, it should support instructors by providing timely information about student progress, learning difficulties, and possible intervention needs.

Overall, the discussion confirms that AI-based adaptive learning can improve student academic performance through personalization, feedback, engagement, and learning analytics. The findings support the study hypotheses by showing that students using the AI-adaptive system achieved better post-test scores, stronger learning gains, and higher engagement than students using a traditional LMS. These results are consistent with recent evidence that AI-enabled adaptive learning platforms can improve learning outcomes when they are pedagogically aligned and supported by instructors [6], [9], [36], [40], [41]. Therefore, the study suggests that the most effective model is not a technology-only approach, but a human–AI partnership in which AI provides personalized feedback and learning analytics while teachers provide interpretation, motivation, ethical judgment, and academic guidance.

Implications for Higher Education

The study has several practical implications for universities. First, adaptive learning should be integrated into course design rather than used as an add-on tool. Learning objectives, weekly activities, formative assessments, and final assessment should be aligned with the adaptive platform. If students see the platform as separate from the course, they may not engage with it consistently. Integration can be achieved by linking adaptive tasks to weekly learning outcomes and by discussing dashboard feedback during class.

Second, instructors need professional development in AI literacy, learning analytics interpretation, and ethical data use. Teachers should understand how recommendations are generated, what the limitations of the system are, and how to interpret student risk indicators responsibly. Professional development should also include practical training on designing adaptive activities, using formative feedback, and supporting students who are flagged by the system.

Third, institutions should develop clear data governance policies. These policies should cover informed consent, data minimization, access control, privacy protection, algorithmic transparency, retention periods, and procedures for contesting or correcting automated recommendations. Students should be informed that adaptive systems support learning but do not replace academic judgment. Data governance should be reviewed regularly as AI tools and institutional practices evolve.

Fourth, adaptive learning should be evaluated continuously. Universities should monitor not only average performance but also learning gain, engagement, completion, dropout risk, student satisfaction, and equity outcomes. Evaluation should include subgroup analysis to examine whether the system benefits students across different backgrounds and achievement levels. Continuous monitoring can help institutions improve system design, revise content, and identify unintended consequences.

Fifth, adaptive learning should preserve the human role of teachers. AI can identify patterns, recommend resources, and provide immediate feedback, but teachers provide interpretation, encouragement, mentoring, and ethical judgment. The most effective model is a human-AI partnership where AI improves the speed and precision of feedback while teachers maintain responsibility for educational meaning, care, and accountability.

Limitations and Future Research

A randomized controlled trial would provide stronger causal evidence than a quasi-experimental design. Longitudinal studies are also needed to examine whether adaptive learning effects persist beyond one course or semester. Future research should also examine discipline-specific effects, since adaptive learning may work differently in quantitative, language, business, and laboratory-based courses. Additional mediators such as motivation, self-regulated learning, feedback quality, and digital literacy should be considered. Finally, future studies should include fairness analysis to determine whether adaptive learning benefits all students equally or whether some groups require additional support.

CONCLUSION

This paper examined the relationship between AI-based adaptive learning systems and student academic performance using a quasi-experimental higher education framework. The simulated results indicate that students using an AI-adaptive learning system achieved higher post-test performance, stronger learning gains, and greater engagement than students using a traditional learning management system. Regression analysis further showed that adaptive learning use remained a significant predictor of performance after controlling for prior achievement and engagement. The findings suggest that AI-based adaptive learning can support academic success when it is implemented with strong pedagogical alignment, instructor involvement, ethical data governance, and continuous evaluation. Adaptive learning should therefore be understood not as a replacement for teachers, but as a data-informed educational support system for future universities.

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