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A STUDY ON THE IMPACT OF ARTIFICIAL INTELLIGENCE-BASED ADAPTIVE LEARNING SYSTEMS ON ACADEMIC PERFORMANCE IN HIGHER EDUCATION

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ABSTRACT Artificial Intelligence is reshaping higher education through adaptive learning systems that tailor content, pace and feedback to each learner in real time. This paper examines how AI-based Adaptive Learning Systems, referred to here as AI-ALS, influence student academic performance. Primary data were collected from 100 students through a 58-item, five-point Likert questionnaire covering eight constructs: awareness, perceived effectiveness, academic impact, engagement, institutional support, challenges, attitude and satisfaction. Analysis through IBM SPSS returned an overall reliability of 0.953, confirming strong internal consistency of the instrument. Results show moderate-to-high awareness, with a construct mean of 3.59, and high overall satisfaction, with a mean of 3.91. Student engagement and motivation emerged as the single strongest predictor of academic performance, with a standardised beta of 0.823, and the regression model jointly explained close to 80 percent of the variance in performance outcomes. Connectivity gaps, cost and data privacy concerns remain notable barriers, yet students display strong optimism about the future role of AI in their education. The study recommends faculty capacity-building and engagement-oriented design as priorities for institutions adopting AI-ALS.

KEYWORDS : Artificial Intelligence; Adaptive Learning Systems; Academic Performance; Higher Education; Student Engagement; SPSS Regression Analysis.

1. INTRODUCTION

Conventional classroom instruction has long followed a uniform model, offering the same content at the same pace through the same method to every learner, regardless of how widely students differ in ability and preparation. This rigidity tends to leave slower learners behind while leaving faster ones under-stimulated. AI-based Adaptive Learning Systems offer a credible alternative. By continuously analysing learner behaviour and performance through machine learning and learning analytics, such systems adjust content difficulty, sequencing and feedback to match individual needs. Global platforms including Knewton, Smart Sparrow, Carnegie Learning and BYJU'S illustrate how far this technology has already progressed in shaping learning outcomes.

For India, home to more than forty million higher education students, the case for personalised learning is especially strong. Large class sizes, faculty shortages, the rural-urban digital divide and uneven prior preparation make uniform instruction difficult to deliver effectively. The National Education Policy 2020 has accordingly pushed for deeper integration of technology and artificial intelligence into classroom practice. Yet much of the existing scholarship on AI-ALS originates from North American and European settings, leaving Indian higher education comparatively under-examined.

This paper addresses that gap using primary survey evidence gathered from 100 students enrolled across colleges in Karnataka. It examines five interconnected dimensions: awareness and usage of AI-ALS, their perceived effectiveness, measurable influence on academic performance, effect on student engagement and motivation, and the satisfaction and challenges students associate with these systems. The findings are intended to offer institutions, policymakers and EdTech developers evidence grounded in Indian classroom realities.

2. Literature Review

Adaptive learning research traces back to Brusilovsky's (1996) concept of student modelling, which proposed that systems should continuously update an individual learner profile to guide instructional sequencing. VanLehn's (2011) meta-analysis found that intelligent tutoring systems came close to matching the effectiveness of one-to-one human tutoring, lending early empirical weight to AI-driven personalisation. Zawacki-Richter, Marin, Bond and Gouverneur (2019), reviewing 146 studies, identified personalisation and assessment as the dominant applications of AI in higher education while noting a shortage of longitudinal performance research. Luckin, Holmes, Griffiths and Forcier (2016) argued that AI could reproduce, at scale, the long-recognised tutoring advantage of individualised instruction, while Holmes, Bialik and Fadel (2019) added an ethical dimension, stressing transparency, accountability and learner agency in system design.

Evidence from school settings, including the RAND Corporation's evaluation of personalised learning programmes across 62 schools (Pane, Steiner, Baird and Hamilton, 2015), pointed to measurable gains in mathematics and reading achievement. Closer to the Indian context, Kumar and Sharma (2020) and Nair and Rajan (2021) reported that while awareness of AI-based EdTech is rising among South Indian students, consistent usage remains constrained by connectivity, cost and limited faculty guidance, a pattern this study revisits using fresh, statistically validated evidence.

3. Objectives of the Study

1. To assess the level of awareness and usage of AI-based adaptive learning systems among higher education students.
2. To examine the perceived effectiveness of these systems in improving learning outcomes.
3. To analyse the influence of AI-ALS on students' academic performance.
4. To evaluate student engagement, motivation and attitude toward AI-based adaptive learning.
5. To identify the challenges associated with AI-ALS usage and measure overall student satisfaction.

4. Hypotheses

H_{01}: There is no significant relationship between the use of AI-based adaptive learning systems and students' academic performance.

H_{02}: Student engagement and motivation have no significant effect on academic performance in AI-ALS environments.

H_{03}: There is no significant relationship between faculty and institutional support and students' academic performance.

5. Research Methodology

The study adopted a descriptive-cum-analytical design, combining a profile of respondents with statistical tests of the relationships between constructs. A convenience sample of 100 students was drawn from undergraduate, postgraduate and doctoral programmes across Commerce, Engineering and Science streams, spanning autonomous, private and government colleges in Karnataka. Respondents completed a structured, 58-item, five-point Likert questionnaire built around eight constructs: awareness and usage, perceived effectiveness, impact on academic performance, engagement and motivation, faculty and institutional support, challenges and limitations, attitude and future scope, and overall satisfaction. The questionnaire was administered online over a three-week period and yielded 100 complete, usable responses.

Data were processed in IBM SPSS Statistics (Version 26) using frequency analysis, descriptive statistics, Cronbach's Alpha for reliability testing, Pearson's correlation for bivariate association, and multiple linear regression to identify the predictors of academic performance. Reliability testing returned construct-level alpha values between 0.890 and 0.953, with an overall instrument alpha of 0.953, well above the 0.70 threshold conventionally treated as acceptable, confirming that the instrument measured its intended constructs consistently.

6. RESULTS AND DISCUSSION

The sample was almost evenly split between female (54%) and male (46%) respondents, predominantly undergraduate (74%) and below the age of 22 (82% combined). Commerce students formed the largest disciplinary group (51%), and autonomous and private institutions together accounted for 94% of respondents, mirroring the generally stronger digital infrastructure available at such institutions. A majority of respondents (56%) had less than a year of experience with digital learning tools, suggesting that many were still relatively new to structured AI-mediated learning (Table 1).

Table 1: Demographic Profile of Respondents (N = 100)

Variable	Category	Percentage (%)
Gender	Female	54
	Male	46
Age	Below 22 years	82
	Above 22 years	18
Level of Study	Undergraduate	74
	Postgraduate / Doctoral	26
Discipline	Commerce	51
	Engineering	33
	Science / Others	16
Institution Type	Autonomous / Private	94
	Government	6

Source: Primary data.

Awareness of AI-ALS was moderate-to-high, with a construct mean of 3.59. Platform user-friendliness (3.73) and general awareness (3.71) scored highest, while formal institutional training scored lowest (3.24); only 48% of respondents reported receiving any structured training, pointing to a gap between organic, consumer-driven exposure to AI tools and deliberate institutional capacity-building.

Perceived effectiveness averaged 3.63, led by personalised content delivery (3.72) and the ability of systems to flag learning gaps (3.69), with 61% of respondents rating AI-ALS as more effective than conventional instruction. The impact-on-performance construct averaged 3.67, with the strongest endorsement for assignment-completion support (3.82; 76% agreement), suggesting that AI-ALS delivers its most immediate benefit by easing task-level academic pressure rather than necessarily reshaping long-term study habits.

Engagement and motivation emerged as the highest-rated construct overall (mean 3.75) and, more significantly, as the dominant statistical driver of performance. Reliability across all eight constructs ranged from 0.890 to 0.953 (Table 2), confirming a psychometrically sound instrument.

Table 2: Reliability Statistics – Cronbach's Alpha by Construct

Construct	Cronbach's Alpha
Awareness and Usage	0.890
Perceived Effectiveness	0.943
Impact on Academic Performance	0.953
Engagement and Motivation	0.943
Faculty and Institutional Support	0.925
Challenges and Limitations	0.898
Attitude and Future Scope	0.933
Overall Satisfaction	0.914
Overall Instrument (58 items)	0.953

Source: Primary data, SPSS output.

Pearson correlation analysis showed engagement correlating most strongly with academic performance ($r = 0.884$, $p < 0.01$), the single strongest relationship in the matrix, followed by perceived effectiveness and performance ($r = 0.698$). Multiple regression, with academic performance as the dependent variable, produced an R-squared of 0.799 ($F = 72.38$, $p < 0.001$), meaning the model explains close to 80% of the variation in performance outcomes. Engagement was by far the strongest predictor ($\beta = 0.823$, $t = 10.28$, $p < 0.001$), with awareness contributing a smaller but still significant effect ($\beta = 0.182$, $p = 0.021$); effectiveness, attitude and satisfaction lost statistical significance once engagement was controlled for, suggesting their influence on performance operates mainly through engagement rather than independently (Table 3). On this basis, H_{01} and H_{02} are rejected, while H_{03} is also rejected given the significant positive correlation between faculty and institutional support and academic performance ($r = 0.602$, $p < 0.01$).

Table 3: Significant Predictors of Academic Performance – Regression Coefficients

Predictor Variable	Beta	t-value	Sig.
Awareness and Usage	0.182	2.348	0.021
Engagement and Motivation	0.823	10.281	0.000

Source: Primary data, SPSS output. Model Summary: $R^2 = 0.799$, Adjusted $R^2 = 0.788$, $F = 72.38$, $p < 0.001$. Perceived Effectiveness, Attitude and Overall Satisfaction were not significant predictors and are omitted above.

Faculty and institutional support recorded the second-lowest construct mean (3.56), with faculty integration of AI tools into classroom teaching (3.47) and faculty training (3.49) as the weakest items, even though technical support availability (3.74) was rated comparatively well. This points to infrastructure that has outpaced pedagogical readiness. Among challenges, concern that over-dependence on AI may weaken critical thinking (3.73) and unreliable internet connectivity (3.72) ranked highest, while cost concerns were comparatively muted (3.48), likely reflecting the availability of free-tier AI tools. Attitude toward AI's future role in education was strongly positive (mean 3.85, with zero “strongly disagree” responses), and overall satisfaction was the highest-scoring construct in the entire study (mean 3.91), with 73% of respondents willing to continue using AI-ALS.

7. Suggestions

1. Strengthen faculty training so instructors can integrate AI tools meaningfully into classroom teaching rather than leaving adoption entirely student-driven.
2. Design AI-ALS features around engagement, such as gamification, real-time feedback and peer-learning challenges, since engagement is the strongest lever for academic gains.
3. Expand reliable internet access, particularly in rural and government institutions, and encourage offline-capable, mobile-first AI tools as an interim measure.
4. Embed AI-ALS formally into course curricula rather than treating it as an optional, self-initiated supplement.
5. Build transparent, clearly communicated data-privacy practices into AI platforms to address student concerns.
6. Promote free, open-access and vernacular-language AI learning resources to widen equitable access across institution types.
7. Pair AI usage with explicit critical-thinking exercises so that reliance on AI strengthens rather than substitutes independent reasoning.

8. CONCLUSION

This study confirms that AI-based Adaptive Learning Systems exert a significant, positive influence on academic performance in Indian higher education, operating chiefly through their capacity to engage students rather than through the sophistication of content alone. With engagement and awareness together explaining close to 80% of the variance in performance outcomes, institutions seeking to maximise the academic value of AI-ALS should direct resources toward engagement-oriented design and faculty readiness, not infrastructure alone. The persistent gap between strong student satisfaction and comparatively weak institutional support, particularly in faculty training, stands out as the most actionable finding for college administrators and policymakers. With students expressing near-unanimous confidence in AI's expanding role in education, the responsibility now rests with institutions to ensure that adoption is structured, equitable and pedagogically sound rather than incidental.

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