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The Impact of Ai-Based E-Learning Tools on Students' Learning Outcomes

[1]Shaily Nileshbhai Maniyar (Research Scholar), [2]Dr. Alpa Joshi (Research Supervisor)

[1,2]Atmiya University (Department of commerce)

Abstract

Artificial intelligence is spreading quickly through digital education, reshaping how students find, process, and engage with learning material. This study looks at how AI-based e-learning tools—among them adaptive learning platforms, AI tutoring assistants, automated feedback systems, and intelligent content recommendation engines—affect the academic learning outcomes of undergraduate students. Working from a primary, survey-based quantitative design, data were gathered from 186 undergraduate students across three disciplines (Commerce, Science, and Computer Applications) at a private university, along with their self-reported semester assessment scores. Learning outcomes were tracked across four dimensions—knowledge retention, conceptual understanding, academic performance, and learning motivation—and linked to how often and how deeply students used AI tools. The data were examined using descriptive statistics, correlation analysis, an independent-samples t-test, and simple linear regression. The results point to a statistically significant positive relationship between frequency of AI-based e-learning tool usage and self-reported learning outcomes ($r = 0.52$, $p < 0.01$); students in the high-usage group reported markedly higher performance scores than those in the low-usage group ($t(184) = 4.71$, $p < 0.001$). Regression analysis shows that usage frequency alone accounts for roughly 27 percent of the variance in learning outcome scores. That said, the study also turns up early signs of over-reliance and weaker independent problem-solving among some heavy users, echoing concerns already raised in the literature. It closes with practical recommendations for weaving AI tools into higher education in a balanced, pedagogically guided way, and points to directions for future longitudinal research.

Keywords: Artificial Intelligence, E-Learning, Adaptive Learning, Student Engagement, Learning Outcomes, Higher Education

1. Introduction

Education systems around the world are being reshaped by digital technology, and artificial intelligence has become one of the strongest forces changing how students learn. AI-based e-learning tools now cover a wide range of applications: adaptive learning management systems, intelligent tutoring systems, AI-driven chatbots and virtual assistants, automated assessment and feedback engines, and generative AI applications that can produce explanations, summaries, and practice material tailored to individual learners. Traditional e-learning platforms tend to deliver the same static content to everyone; AI-enabled systems, by contrast, continuously read learner behaviour and performance data to adjust the pace, sequence, and difficulty of the material in real time.

The COVID-19 pandemic pushed digital learning platforms into widespread use almost overnight, and in the years since, generative AI tools—large language model-based assistants in particular—have worked their way into everyday student life. Students now turn to them for revision, clearing doubts, drafting essays, coding help, and exam preparation. This has fuelled real optimism about AI's ability to personalise instruction, close learning gaps, and boost engagement. But it has also worried educators, who point to over-dependence on AI-generated content, weakened critical thinking, and learning that stays surface-level instead of going deep.

Even though the theoretical and review-based literature on AI in education keeps growing, there is still comparatively little primary, field-level evidence—especially evidence that links student self-reports to actual academic performance—on how the frequency and manner of AI-tool use translates into measurable learning outcomes. This study tries to close that gap by collecting and analysing primary survey data from undergraduate students, assessing how far AI-based e-learning tools shape knowledge retention, conceptual understanding, academic performance, and learning motivation.

2. Problem Statement

AI-based e-learning tools are being taken up quickly across higher education, yet what they actually do to student learning outcomes is still debated. Several studies argue that adaptive AI systems and AI-driven feedback improve engagement, comprehension, and academic achievement by tailoring content to individual learners. Other evidence points the other way, flagging risks such as cognitive offloading, over-reliance on AI-generated answers, and a possible drop in independent critical thinking when AI tools are used without proper pedagogical guidance.

Institutions, instructors, and policymakers still lack detailed, locally grounded evidence on how to build AI tools into curricula in a way that maximises the learning benefits without also feeding over-dependence. Much of what is currently written is theoretical, built on secondary or review data, or drawn from narrow contexts—language learning, a single AI platform, a one-institution experiment—that may not carry over across disciplines. What is missing is primary, cross-disciplinary survey data that ties the frequency and type of AI-tool use directly to multiple dimensions of learning outcomes, while also checking for possible downsides such as reduced self-reliance.

This study centres on one core research problem: to what extent, and through what mechanisms, do AI-based e-learning tools shape the learning outcomes of undergraduate students—and how does the intensity of AI-tool usage relate to both the benefits and the risks that come with it?

3. Literature Review

3.1 AI-Based Adaptive Learning and Personalisation

A sizeable body of research connects AI-based adaptive learning systems to better learning outcomes through personalised instructional content. Studies on adaptive platforms describe systems that adjust content, pacing, and assessment to individual learners by drawing on real-time performance data, letting a diverse group of students move at their own optimal pace rather than being held to one uniform curriculum. Research on AI-driven feedback tells a similar story: timely, individualised feedback tends to deepen comprehension and strengthen knowledge retention, which in turn shows up as better assessment performance.

Cognitive load theory offers one way to explain this: AI tools that break down complex tasks, offer step-by-step guidance, and take over routine administrative or cognitive work may reduce the extraneous load placed on learners, leaving more mental capacity for engaging with the core material. In other words, the value of AI tools does not come simply from giving students access to information—it comes from how well those tools manage the learner's cognitive resources along the way.

3.2 Engagement, Motivation, and Academic Achievement

A number of empirical studies find a strong positive link between AI-powered educational tools—intelligent tutoring systems and adaptive platforms among them—and student motivation, classroom participation, and overall academic achievement. Wider reviews of tools such as generative AI chat assistants suggest that AI-supported education can meaningfully lift learning outcomes, mainly by improving the learning process itself, delivering more adaptive content, and increasing engagement. These reviews also note that AI can support instructors directly, automating grading, content creation, and individualised feedback, and freeing up instructional time for higher-order teaching.

Other research, drawing on extensions of the Technology Acceptance Model, has examined what predicts students' intention to use AI tools for academic work, identifying perceived usefulness, career relevance, and how easily the tools fit into existing study routines as significant predictors of adoption. Taken together, this work suggests that the learning benefits of AI tools depend partly on students' attitudes toward and comfort with the technology, rather than following automatically from mere access.

3.3 Risks of Over-Reliance and Reduced Critical Thinking

A growing body of counter-literature warns against adopting AI tools in education uncritically. Large-scale survey and interview research has found a significant negative association between frequent AI-tool use and critical thinking ability, pointing to cognitive offloading as a key mechanism: students who routinely hand off effortful cognitive tasks to AI systems appear to exercise less independent judgement over time. Experimental work comparing AI-assisted, search-engine-assisted, and unaided writing tasks has likewise found differences in neural engagement and recall depending on how much assistance was used, suggesting that heavier reliance on generative tools can come at the cost of deeper cognitive processing during learning.

Systematic reviews of AI's negative effects in education raise similar concerns: less human interaction, algorithmic bias in adaptive recommendations, and fewer opportunities to build independent problem-solving skills. Survey evidence from university students backs this up—while students clearly value the convenience of AI tools, a meaningful share of them also report growing dependence and less confidence doing academic work unaided.

3.4 Discipline- and Context-Specific Findings

Studies that zoom in on specific domains—personalised AI tutors in language learning, for example—report that AI systems tuned to individual learner needs boost both engagement and measurable performance in the target skill area. Most of this literature, however, is either discipline-specific or leans on secondary or review-based evidence rather than fresh primary data gathered across several academic disciplines. That is the gap this study tries to fill, by collecting original survey data from students across Commerce, Science, and Computer Applications, so as to build a broader and more generalisable picture of how AI-tool usage relates to learning outcomes.

3.5 Research Gap

Pulling this together, the literature points to three broad conclusions. First, AI-based e-learning tools are consistently linked to gains in engagement, personalisation, and, in many settings, academic performance. Second, these gains are not unconditional — they depend on how the tools are used and woven into instruction. Third, evidence on the potential downside of over-reliance, especially around critical thinking and independent learning, is emerging but still limited. Very few studies measure positive learning outcomes and over-reliance risk together using primary, cross-disciplinary data, and that is precisely the gap this study is designed to fill.

4. Research Objectives

This study's specific objectives are as follows:

- To look at how widely, and in what patterns, undergraduate students use AI-based e-learning tools.
- To assess how the frequency of AI-tool usage relates to self-reported learning outcomes across knowledge retention, conceptual understanding, academic performance, and learning motivation.
- To compare the learning outcome scores of high-usage and low-usage AI-tool users through statistical hypothesis testing.
- To gauge how far AI-tool usage frequency statistically predicts learning outcome scores, using regression analysis.
- To identify potential risks tied to AI-tool usage, particularly over-reliance and weakened independent problem-solving.
- To recommend strategies for integrating AI-based e-learning tools into higher education in a balanced, pedagogically sound way.

In line with these objectives, the study tests the following hypotheses:

- H1: The frequency of AI-based e-learning tool usage is significantly and positively related to student learning outcomes.
- H2: Students who use AI tools more frequently report significantly higher learning outcome scores than those who use them less frequently.
- H3: The frequency of AI-tool usage is a significant predictor of learning outcome scores.

5. Research Methodology

5.1 Research Design

This study uses a descriptive and correlational quantitative design, built on primary data gathered through a structured questionnaire. This design was chosen because it allows systematic measurement of both the independent variable (frequency and depth of AI-tool usage) and the dependent variable (learning outcomes) across a reasonably large sample, and because it supports the inferential statistics needed to test the stated hypotheses.

5.2 Population and Sampling

The population for this study is undergraduate students enrolled in Commerce, Science, and Computer Applications programmes at a private university. A stratified random sampling technique ensured proportional representation across the three disciplines and across the three years of study (first, second, and final year). The structured questionnaire was administered both online and in person over a four-week window. Of the 210 questionnaires distributed, 186 valid, fully completed responses were retained for analysis once incomplete submissions were removed, giving a response rate of roughly 88.6 percent.

5.3 Data Collection Instrument

Primary data were collected through a structured, self-administered questionnaire made up of four sections: (a) demographic information (gender, discipline, year of study); (b) frequency and type of AI-based e-learning tool usage (adaptive learning platforms, AI tutoring/chat assistants, automated feedback and grading tools, AI-based content recommendation and summarisation tools); (c) a 5-point Likert-scale battery of 12 items covering four learning outcome dimensions—knowledge retention, conceptual understanding, academic performance, and learning motivation (1 = Strongly Disagree, 5 = Strongly Agree); and (d) three items capturing perceived over-reliance and reduced independent problem-solving. Self-reported semester assessment percentage scores were also collected to cross-check the performance dimension. The instrument was piloted with 20 students before full administration, and minor wording changes were made afterward to improve clarity. The learning outcome scale's internal consistency, checked with Cronbach's alpha, came out at 0.84, indicating good reliability.

5.4 Variables

The independent variable, AI-tool usage frequency, was measured on a composite scale from 1 (rarely/never) to 5 (multiple times daily), based on students' self-reported use of AI-based e-learning tools for academic purposes. The dependent variable, learning outcome score, was calculated as the mean of the 12 Likert-scale items covering knowledge retention, conceptual understanding, academic performance, and learning motivation, giving a composite score from 1 to 5. Respondents were then split into a 'high-usage' group (usage frequency 4 or 5) and a 'low-usage' group (usage frequency 1 or 2) for comparison; the moderate-usage group (3) was kept in the correlation and regression analyses but left out of the two-group comparison, to sharpen the contrast between the groups.

5.5 Data Analysis Techniques

Data were coded and analysed using descriptive statistics (frequencies, percentages, means, and standard deviations), Pearson's correlation coefficient to test H1, an independent-samples t-test to test H2, and simple linear regression to test H3. A significance threshold of $p < 0.05$ was applied throughout, and all analyses were run on the cleaned primary dataset of 186 responses.

5.6 Ethical Considerations

Participation in the survey was voluntary and anonymous. Respondents were told the purpose of the study and gave informed consent before completing the questionnaire. No personally identifiable information was collected, and the data were used solely for this academic study.

6. Results And Data Analysis

6.1 Demographic Profile of Respondents

Table 1 sets out the demographic distribution of the 186 respondents included in the final analysis.

Category	Group	Frequency (n)	Percentage (%)
Gender	Male	98	52.7
	Female	88	47.3
Discipline	Commerce	64	34.4
	Science	61	32.8
	Computer Applications	61	32.8
Year of Study	First Year	62	33.3
	Second Year	64	34.4
	Final Year	60	32.3

Table 1: Demographic Profile of Respondents (N = 186)

6.2 Patterns of AI-Based E-Learning Tool Usage

Table 2 summarises how often students reported using AI-based e-learning tools for academic purposes. Most respondents said they used such tools at least weekly, with AI tutoring/chat assistants the most common category, followed by AI-based content summarisation and recommendation tools.

Usage Frequency	Frequency (n)	Percentage (%)
Rarely / Never (1)	14	7.5
A few times a month (2)	27	14.5
A few times a week (3)	58	31.2
Daily (4)	61	32.8
Multiple times a day (5)	26	14.0

Table 2: Frequency of AI-Based E-Learning Tool Usage (N = 186)

AI Tool Type	Users Reporting Regular Use (n)	Percentage (%)
AI tutoring / chat assistants	152	81.7

AI Tool Type	Users Reporting Regular Use (n)	Percentage (%)
AI content summarisation / recommendation tools	121	65.1
Adaptive learning platforms (LMS-based)	96	51.6
Automated feedback / auto-graded quizzes	88	47.3

Table 3: Type of AI-Based E-Learning Tools Used Regularly (multiple responses permitted)

6.3 Descriptive Statistics for Learning Outcome Dimensions

Table 4 lists the mean and standard deviation for each of the four learning outcome dimensions on the 5-point Likert scale, alongside the composite learning outcome score and the over-reliance sub-scale.

Learning Outcome Dimension	Mean	Std. Deviation
Knowledge Retention	3.74	0.68
Conceptual Understanding	3.81	0.71
Academic Performance	3.66	0.74
Learning Motivation	3.92	0.65
Composite Learning Outcome Score	3.78	0.58
Perceived Over-Reliance on AI (sub-scale)	3.35	0.81

Table 4: Descriptive Statistics for Learning Outcome Dimensions (5-point scale, N = 186)

A composite learning outcome mean of 3.78 (SD = 0.58) points to a generally favourable view of AI-based e-learning tools among respondents, with learning motivation scoring highest (3.92) and academic performance lowest (3.66). The over-reliance sub-scale also came out relatively high (3.35), suggesting that a meaningful share of students already sense some degree of dependence on AI tools.

6.4 Correlation Analysis (Testing H1)

A Pearson correlation analysis examined the relationship between AI-tool usage frequency and the composite learning outcome score; the results appear in Table 5.

Variable Pair	Pearson r	p-value	N
AI-Tool Usage Frequency × Learning Outcome Score	0.52	< 0.01	186
AI-Tool Usage Frequency × Academic Performance	0.46	< 0.01	186

Variable Pair	Pearson r	p-value	N
AI-Tool Usage Frequency × Perceived Over-Reliance	0.44	< 0.01	186

Table 5: Pearson Correlation Coefficients

The correlation between AI-tool usage frequency and the composite learning outcome score was positive, moderate, and statistically significant ($r = 0.52$, $p < 0.01$), which supports H1. Usage frequency was also significantly and positively correlated with perceived over-reliance ($r = 0.44$, $p < 0.01$) — the students reporting the greatest learning benefit also tend to be the ones reporting the greatest dependence on AI tools.

6.5 Independent-Samples t-Test (Testing H2)

To test H2, respondents were split into a high-usage group (usage frequency 4–5, n = 87) and a low-usage group (usage frequency 1–2, n = 41), and an independent-samples t-test compared the composite learning outcome scores of the two groups.

Group	n	Mean Learning Outcome Score	Std. Deviation	t-value	df	p-value
High-Usage Group	87	3.98	0.51	4.71	126	< 0.001
Low-Usage Group	41	3.49	0.63			

Table 6: Independent-Samples t-Test Comparing High- and Low-Usage Groups

The high-usage group reported a significantly higher mean learning outcome score ($M = 3.98$, $SD = 0.51$) than the low-usage group ($M = 3.49$, $SD = 0.63$), $t(126) = 4.71$, $p < 0.001$. This supports H2 and suggests that more frequent use of AI-based e-learning tools goes along with meaningfully better self-reported learning outcomes.

6.6 Regression Analysis (Testing H3)

A simple linear regression treated AI-tool usage frequency as the predictor and the composite learning outcome score as the outcome variable.

Model Statistic	Value
R	0.52
R^2	0.27
Adjusted R^2	0.27
F-statistic (1, 184)	68.94
Significance (p)	< 0.001
Unstandardised Coefficient (B)	0.29

Model Statistic	Value
Standard Error	0.035
Standardised Coefficient (Beta)	0.52
t-value	8.30

Table 7: Regression Model Summary — Predicting Learning Outcome Score from AI-Tool Usage Frequency

The regression model was statistically significant, $F(1, 184) = 68.94$, $p < 0.001$, with AI-tool usage frequency alone explaining roughly 27 percent of the variance in composite learning outcome scores ($R^2 = 0.27$). The unstandardised coefficient ($B = 0.29$) means that, on average, each one-unit rise in usage frequency (on the 5-point scale) goes with a 0.29-point increase in the composite learning outcome score, holding other factors constant. This supports H3, confirming usage frequency as a significant, if partial, predictor of learning outcomes — about 73 percent of the variance is left to other factors not captured here, such as instructional quality, student motivation, and prior academic ability.

6.7 Discipline-Wise Comparison

An exploratory one-way ANOVA checked whether learning outcome scores differed significantly across the three academic disciplines.

Discipline	n	Mean Learning Outcome Score	Std. Deviation
Commerce	64	3.71	0.60
Science	61	3.77	0.55
Computer Applications	61	3.88	0.57

Table 8: Learning Outcome Scores by Discipline

The one-way ANOVA found no statistically significant difference in composite learning outcome scores across disciplines, $F(2, 183) = 1.92$, $p = 0.15$, though Computer Applications students reported a marginally higher mean score, which may reflect their greater familiarity and comfort with digital and AI-based tools.

6.8 Evidence of Over-Reliance

Beyond the main hypotheses, the survey also asked students about their sense of over-reliance on AI tools. About 41.4 percent agreed or strongly agreed with the statement 'I sometimes accept AI-generated answers without verifying them myself,' and 36.6 percent agreed or strongly agreed that 'I feel less confident solving problems without AI assistance than I did before using these tools.' Both figures were notably higher in the high-usage group (54.0 percent and 47.1 percent) than in the low-usage group (14.6 percent and 12.2 percent), which reinforces the correlational finding in Section 6.4: the benefits of AI-tool usage may come with a parallel rise in dependence.

7. Discussion

These findings broadly line up with the literature reviewed in Section 3. The significant positive correlation between AI-tool usage frequency and learning outcomes (Section 6.4), together with the t-test and regression results (Sections 6.5 and 6.6), backs up earlier research suggesting that AI-based adaptive and tutoring tools can meaningfully improve engagement, comprehension, and academic performance by personalising the learning experience and cutting extraneous cognitive load.

At the same time, this study offers primary, locally grounded evidence for the concerns raised in the over-reliance literature. The positive correlation between usage frequency and perceived over-reliance ($r = 0.44$), together with the markedly higher share of high-usage students reporting weaker independent problem-solving confidence, suggests the relationship between AI-tool usage and learning outcomes is not straightforwardly beneficial. Heavier AI usage appears to bring short-term gains in perceived comprehension, motivation, and performance, while also raising the risk of cognitive dependence — a pattern that fits the cognitive-offloading mechanism identified in recent large-sample studies.

The relatively modest R^2 value (0.27) in the regression model tells its own story: while AI-tool usage frequency is a statistically significant predictor, most of the variance in learning outcomes comes from other factors. This fits a more nuanced reading of the literature, which stresses that AI's benefits in education hinge on pedagogical design, instructor guidance, and how thoughtfully students weave AI tools into their study habits — not simply on how often the tools are used.

The lack of a statistically significant discipline effect (Section 6.7) suggests that the benefits and risks of AI-tool usage are fairly consistent across academic fields at the undergraduate level, at least within this sample, though the marginally higher scores among Computer Applications students hint that digital literacy and technical comfort may shape how effectively students draw learning value from AI tools.

8. Conclusion And Recommendations

8.1 Conclusion

This study set out to examine how AI-based e-learning tools affect undergraduate students' learning outcomes, using primary survey data. The results show a statistically significant, moderate positive relationship between how often students use AI tools and their self-reported learning outcomes across knowledge retention, conceptual understanding, academic performance, and learning motivation. Students who used AI-based e-learning tools more frequently reported significantly higher learning outcome scores than infrequent users, and usage frequency turned out to be a significant predictor of learning outcomes in the regression analysis. At the same time, the study finds credible primary evidence that heavier AI-tool usage goes hand in hand with higher perceived over-reliance and less confidence in independent problem-solving, particularly among high-usage students. Together, these findings point to a balanced conclusion: AI-based e-learning tools bring genuine, measurable benefits to student learning, but those benefits carry a parallel risk of over-dependence that needs to be actively managed rather than assumed away.

8.2 Recommendations

- Higher education institutions should build AI-based e-learning tools into a structured pedagogical framework, rather than leaving adoption entirely up to unguided student discretion.
- Instructors should design assessments and in-class activities that periodically require students to work without AI assistance, to protect independent problem-solving and critical thinking skills.
- Digital literacy and 'responsible AI use' training should be built into orientation or foundation courses, helping students tell the difference between using AI as a learning aid and using it as a substitute for learning.
- Institutions should track over-reliance indicators (of the kind used in this study) alongside performance metrics, to catch early signs of cognitive dependence among high-usage student groups.
- Future curriculum design should lean on AI tools mainly for formative purposes — personalised practice, feedback, and revision support — while keeping high-stakes assessment formats that require students to demonstrate competence unaided.

8.3 Limitations and Directions for Future Research

This study rests on cross-sectional, self-reported data from a single private university, which limits how far causal claims and generalisations can be pushed. Learning outcomes were measured mainly through self-perception rather than objective, standardised test scores, which could introduce social desirability or common-method bias.

Future research would do well to adopt a longitudinal design that tracks objective academic performance (examination scores, for instance) before and after structured AI-tool integration, add qualitative interviews to better understand what drives over-reliance, and widen the sample across multiple institutions and educational levels to strengthen external validity.

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