

Effect of Artificial Intelligence-Based Adaptive Learning on the Academic Achievement and Self-Regulated Learning of Secondary School Students: A Quasi-Experimental Study

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ABSTRACT

The promise of artificial intelligence (AI) in education is that software which adapts to each learner might deliver, at scale, some of the benefit of one-to-one tutoring. This study tested that promise in an Indian secondary classroom. Using a quasi-experimental pre-test–post-test non-equivalent control group design, it examined the effect of an AI-based adaptive learning programme on the academic achievement in Science and the self-regulated learning of Class IX students, and asked whether boys and girls benefited equally. Eighty students of a CBSE-affiliated school in Meerut formed the sample, split into an experimental group ($n = 40$) that learned a Science unit through an adaptive platform and a control group ($n = 40$) taught the same content conventionally, over six weeks. A researcher-made Science Achievement Test ($KR-20 = 0.84$) and an adapted Self-Regulated Learning Scale ($\alpha = 0.88$) were administered before and after the intervention, and the data were analysed using the t -test and analysis of covariance. The experimental group significantly outperformed the control group on post-test achievement ($t = 7.34$, $p < .01$; $d = 1.66$), an advantage that survived adjustment for pre-test scores by ANCOVA ($F = 48.60$, $p < .01$), and reported significantly higher self-regulated learning ($t = 5.62$, $p < .01$; $d = 1.27$). Achievement gains did not differ significantly between boys and girls ($t = 0.62$, $p > .05$). The findings indicate that AI-based adaptive learning, used to support rather than replace the teacher, can improve both what students learn and how they manage their learning, with implications for the technology agenda of the National Education Policy 2020.

Keywords- artificial intelligence; adaptive learning; academic achievement; self-regulated learning; secondary education; NEP 2020.

I. INTRODUCTION

Every teacher who has stood before a crowded class knows the same frustration: the lesson can move at only one pace, and that pace is right for almost nobody. Some children are left behind and quietly give up; others, already ahead, lose interest. Bloom (1984) gave this difficulty a memorable name when he reported that a student tutored one-to-one performed about two standard deviations better than a student in a conventional class the “two sigma problem” and observed that no school system could afford a private tutor for every child. The challenge he handed to later researchers was to find some scalable method that could reproduce that advantage.

For decades the answer was disappointing. Teaching machines, programmed instruction and early computer-assisted learning each promised to individualise teaching and each fell short, largely because they could not really tell what a particular learner understood at a given moment. What has changed is the maturing of artificial intelligence. Adaptive learning systems now model a learner’s knowledge continuously from their responses and decide what to present next — an easier item, a hint, a harder problem, or a fresh explanation behaving, at their best, like an attentive tutor who notices struggle and adjusts (Luckin et al., 2016; VanLehn, 2011).

India is encountering these possibilities directly. The National Education Policy 2020 explicitly endorses the integration of artificial intelligence and adaptive assessment into schooling, while insisting that technology serve pedagogy rather than dictate it (Ministry of Education, 2020). Affordable smartphones and data have spread widely, so the hardware for adaptive learning is already in many students' hands. Whether this access deepens learning, however, is an empirical question rather than a settled one, and the Indian classroom evidence remains thin.

A second concern runs alongside achievement. A good tutor teaches not only content but the craft of learning itself setting goals, monitoring whether a strategy works, managing effort. Psychologists call this self-regulated learning, and it predicts success across subjects and stages (Zimmerman, 2002). A reasonable worry about any tool that supplies the next step on demand is that it may erode these habits, raising marks while leaving learners more dependent. It is therefore worth asking not merely whether AI-based adaptive learning lifts achievement, but what it does to students' capacity to direct their own learning. The present study takes up both questions in an ordinary secondary school, with Class IX students learning Science.

II. REVIEW OF RELATED LITERATURE

The strongest early evidence for computer tutoring comes from VanLehn (2011), whose review found that the better intelligent tutoring systems produced learning gains approaching those of human tutors and well above conventional instruction. Kulik and Fletcher (2016), meta-analysing fifty such studies, reported a consistent advantage for tutoring systems, larger when they supplemented a teacher than when they replaced one. On personalised learning more broadly, Pane et al. (2015) found modest but positive achievement effects that grew with longer implementation, while cautioning that the technology's contribution is hard to separate from the teaching changes that accompany it.

Reviews of the wider field are more guarded. Zawacki-Richter et al. (2019) noted that much published work concentrates on the technology rather than on its effect on learning, and that careful classroom studies of outcomes are comparatively rare. Holmes et al. (2019) and Chen et al. (2020) reached similar conclusions, arguing that the promise of educational AI must be tested against sound pedagogy rather than assumed from novelty. On self-regulated learning the literature is genuinely divided: some studies report that feedback-rich, progress-visible environments scaffold monitoring and reflection, while others warn that systems which always supply the next step reduce the need for learners to plan and monitor for themselves. The balance appears to turn on design. In the Indian context, research has expanded rapidly since the pandemic but remains largely descriptive or attitudinal; rigorous studies measuring both achievement and self-regulated learning together at the secondary stage are scarce. This study addresses that gap.

III. OBJECTIVES AND HYPOTHESES

The study pursued four objectives: to examine the effect of AI-based adaptive learning on (i) academic achievement in Science and (ii) self-regulated learning; (iii) to compare the adjusted post-test achievement of the two groups after controlling for pre-test scores; and (iv) to examine whether the achievement gains of boys and girls in the experimental group differ. The following null hypotheses were tested at the .05 level:

1. H01: There is no significant difference between the post-test achievement mean scores of the experimental and control groups.
2. H02: There is no significant difference between the post-test self-regulated learning mean scores of the two groups.
3. H03: There is no significant difference between the adjusted post-test achievement means of the two groups when pre-test scores are controlled.
4. H04: There is no significant difference between the achievement gain scores of male and female students in the experimental group.

IV. METHOD

4.1 Research design

A quasi-experimental, pre-test–post-test non-equivalent control group design was adopted. True randomisation was not feasible because the school required intact sections to be kept together, so two intact Class IX sections were used, one as the experimental group and one as the control group. Because the groups were not randomly formed, pre-test scores were collected and later used as a covariate in analysis of covariance, the standard remedy for non-equivalence in this design. The overall design is summarised in Figure 1.

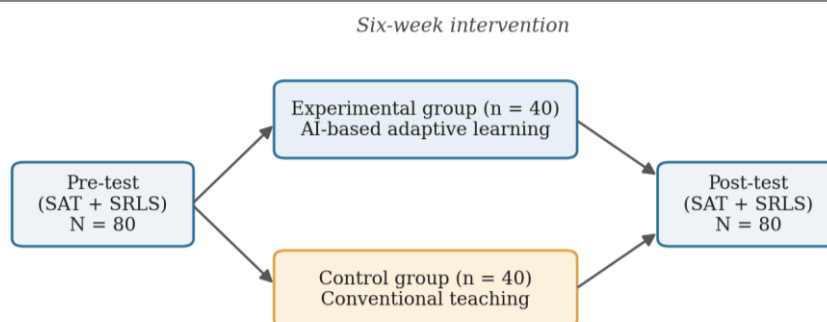


Figure 1. Schematic of the quasi-experimental research design.

4.2 Participants

The population comprised Class IX students of CBSE-affiliated schools in Meerut district. One school was selected by convenience on the basis of willingness to participate and the availability of a functioning computer laboratory with internet access. Two intact sections were assigned to the two conditions, giving a sample of eighty students, forty per group. Table 1 shows the composition.

Table 1. Composition of the sample

Group	Boys	Girls	Total
Experimental (adaptive learning)	21	19	40
Control (conventional)	22	18	40
Total	43	37	80

Note. Groups were intact class sections; assignment to condition was at the section level.

4.3 Instruments

Two instruments were used. The Science Achievement Test (SAT) was a researcher-made test of fifty multiple-choice items on the selected Class IX unit, built from a content-by-objective blueprint and reviewed by two Science teachers and a teacher educator for content validity. After a try-out on thirty comparable students, weak items were revised in the light of difficulty and discrimination indices; the final reliability, by the Kuder-Richardson Formula 20, was 0.84. The Self-Regulated Learning Scale (SRLS) was adapted from the motivated-strategies framework of Pintrich (2004), comprising forty statements on a five-point scale across goal-setting, strategy use, self-monitoring and reflection; its internal consistency (Cronbach's α) was 0.88. Both instruments served as pre-test and post-test.

4.4 Procedure

After obtaining the school's permission and explaining the purpose to teacher and students, both groups were pre-tested under uniform conditions. Over the following six weeks both groups studied the same unit for the same number of periods with the same teacher. The experimental group worked through the unit on an AI-based adaptive platform in the computer laboratory: correct responses advanced students to harder material, while errors triggered additional examples, hints and explanations before they moved on. The teacher introduced each topic, circulated to help, and consolidated the learning — the platform supplemented her rather than replacing her. The control group covered the same content through conventional explanation, textbook reading, note-making and routine practice. In the week after the intervention, the same instruments were re-administered as the post-test, and scripts were scored against a fixed key.

4.5 Data analysis

Means and standard deviations described group performance. Independent-samples t-tests compared the post-test means on achievement and self-regulated learning (H01, H02); analysis of covariance compared adjusted post-test achievement with the pre-test as covariate (H03); and an independent-samples t-test compared the achievement gains of boys and girls in the experimental group (H04). Effect sizes were estimated with Cohen's d . All tests used the .05 level of significance.

V. RESULTS

Table 2 reports the descriptive statistics. The two groups began almost level on both measures, with pre-test differences of 0.50 marks on achievement and 0.70 points on self-regulated learning, neither significant. After the intervention the groups diverged sharply.

Table 2. Descriptive statistics for the two groups (N = 80)

Measure	Group	Pre M	Pre SD	Post M	Post SD
Achievement (max 50)	Experimental	22.40	5.10	38.60	4.80
Achievement (max 50)	Control	21.90	4.90	30.20	5.30
Self-reg. learning (max 200)	Experimental	138.20	14.60	162.40	12.10
Self-reg. learning (max 200)	Control	137.50	15.20	145.80	13.90

Note. *M* = mean; *SD* = standard deviation.

5.1 Effect on academic achievement (H01)

On the post-test, the experimental group ($M = 38.60$) scored well above the control group ($M = 30.20$). The difference was significant, $t(78) = 7.34$, $p < .01$, with a large effect size, $d = 1.66$. The null hypothesis H01 was rejected. Figure 2 displays the pre- and post-test means with their standard deviations.

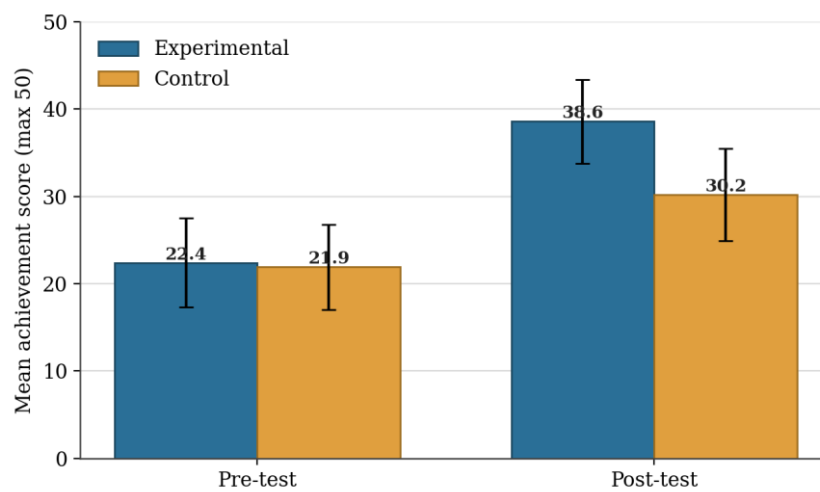


Figure 2. Mean Science achievement of the two groups before and after the intervention (error bars show ± 1 SD).

5.2 Effect on self-regulated learning (H02)

The experimental group also reported markedly higher self-regulated learning after the intervention ($M = 162.40$) than the control group ($M = 145.80$), $t(78) = 5.62$, $p < .01$, $d = 1.27$. H02 was rejected. The pattern, shown in Figure 3, suggests that the adaptive programme — with its immediate feedback and visible progress, and with the teacher prompting review and reflection — supported rather than weakened students' self-regulation.

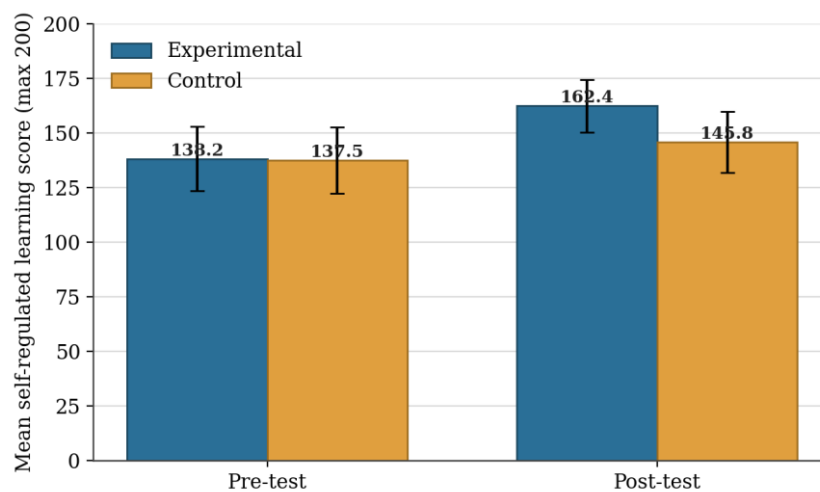


Figure 3. Mean self-regulated learning of the two groups before and after the intervention (error bars show ± 1 SD).

5.3 Adjusted achievement: analysis of covariance (H03)

Because the groups were not randomly formed, achievement was re-examined by ANCOVA with the pre-test as covariate. The group effect remained large and significant, $F(1, 77) = 48.60$, $p < .01$, and the adjusted means (experimental 38.40, control 30.40) barely differed from the observed means, confirming that the advantage was not an artefact of initial differences. H03 was rejected. Table 3 summarises the ANCOVA and Figure 4 shows the adjusted means.

Table 3. Summary of ANCOVA for post-test achievement (pre-test as covariate)

Source	SS	df	MS	F
Pre-test (covariate)	612.30	1	612.30	29.10*
Group	1022.60	1	1022.60	48.60*
Error	1620.40	77	21.04	—

Note. * $p < .01$. Adjusted means: experimental = 38.40; control = 30.40.

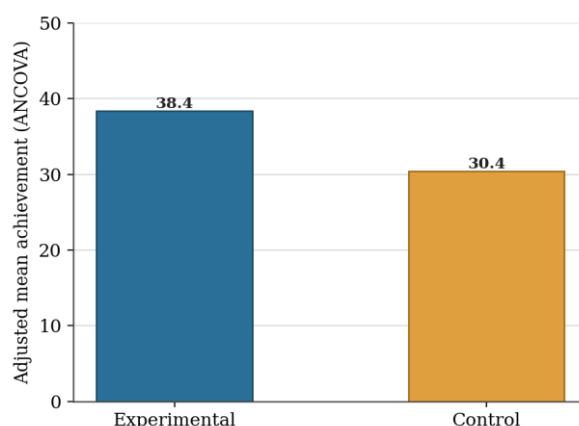


Figure 4. Adjusted post-test achievement means of the two groups (ANCOVA).

5.4 Gender and achievement gain (H04)

Within the experimental group, gain scores (post minus pre) were compared across gender. Both boys ($M = 15.80$) and girls ($M = 16.60$) gained substantially, and the difference was not significant, $t(38) = 0.62$, $p > .05$. H04 was retained: the programme benefited boys and girls to a comparable degree. Table 4 reports the comparison and Figure 5 illustrates it.

Table 4. Achievement gain by gender in the experimental group

Gender	N	Mean gain	SD	df	t
Boys	21	15.80	4.20	38	0.62
Girls	19	16.60	3.90	—	(ns)

Note. ns = not significant at the .05 level (critical t at $df = 38 \approx 2.02$).

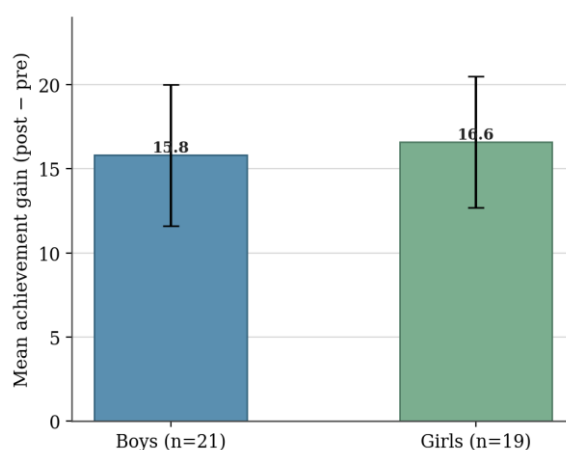


Figure 5. Mean achievement gain of boys and girls in the experimental group (error bars show ± 1 SD).

VI. DISCUSSION

The achievement result aligns with the international evidence. VanLehn (2011) and Kulik and Fletcher (2016) both found that well-designed tutoring systems lift achievement above conventional teaching, and the same held here in an Indian secondary classroom. The effect was large, consistent with the observation in those reviews that the advantage is greatest when the system supplements a teacher — precisely how the platform was used. In Bloom's terms, by matching difficulty and feedback to each learner the programme appears to have recovered some of the individual attention that one teacher in a full class cannot provide.

The self-regulated learning result is the more striking, because the literature was divided on what to expect. The improvement in the experimental group supports the more optimistic reading: when a system makes progress visible and supplies timely, specific feedback, it can scaffold rather than supplant students' own monitoring and reflection. The teacher's continuous presence, consolidating learning and prompting students to review their errors, very likely contributed; the safer interpretation is that the combination of an adaptive tool and an attentive teacher, not the software alone, supported self-regulation.

The absence of a gender difference is reassuring. A recurring fear about educational technology is that it may widen existing gaps, including in subjects such as Science. No such widening appeared here; boys and girls gained alike. A single study cannot settle the matter, but the result is at least evidence against the claim that adaptive learning inherently favours one gender over the other in this setting.

VII. CONCLUSION, IMPLICATIONS AND LIMITATIONS

Within its limits, the study's conclusion is straightforward: an AI-based adaptive learning programme, used to supplement conventional teaching, was associated with significantly better Science achievement and stronger self-regulated learning among Class IX students, and its benefit was shared by boys and girls. The qualification matters as much as the finding — the gains were obtained with a teacher firmly in the room. The study does not show that software can teach by itself, but that a good adaptive tool in the hands of a good teacher can help students learn more and learn better.

Three implications follow. For teachers, adaptive tools are worth integrating, but as an aid rather than a substitute, since the teacher's role in introducing, helping and consolidating remained central to the benefit. For schools and policymakers implementing the technology provisions of NEP 2020, the findings suggest that investment pays off when it is matched by teacher preparation and equitable access, not when hardware is supplied alone. For teacher education, there is an implied need to prepare teachers to work alongside such systems and keep pedagogy in charge of the technology.

Several limitations temper these conclusions. The study used a single school and a small sample of eighty students, so the findings cannot be generalised to schools with very different resources. The groups were intact sections rather than randomly assigned; although ANCOVA addresses this, the design is weaker than a true experiment. The intervention lasted only six weeks and covered one unit of one subject, and retention over time was not measured. Finally, some of the experimental group's gain may reflect the novelty of a new tool rather than the adaptive mechanism itself. Future research should replicate the study on larger and more varied samples, including rural and government schools, extend the intervention across subjects and a full year, and add qualitative observation to explain the mechanisms behind the numbers.

DECLARATIONS

Funding: This study received no external funding. **Conflict of interest:** The authors declare no conflict of interest. **Ethics:** Permission was obtained from the school, participation was voluntary, and data were anonymised and used solely for research.

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