

Can Artificial Intelligence Personalize Learning? An Analysis of AI-Based Adaptive Learning Systems for Senior School Students

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Abstract: *Most classrooms still move at one speed. A teacher with thirty or forty students has to choose a pace that suits the middle of the class, which leaves weaker students behind and keeps stronger students waiting. AI-based adaptive learning systems promise to change this by watching how each student answers, estimating what that student already knows, and choosing the next task to match. This paper examines how far that promise holds for senior school students. It explains how adaptive systems work in simple terms, reviews findings from major meta-analyses and field experiments, including a randomised study of the Mindspark program in Delhi, and compares adaptive learning with the traditional one-size-fits-all approach. The evidence suggests that well-designed adaptive systems produce real and sometimes large learning gains, with reported effect sizes between about 0.2 and 0.8 standard deviations, and that students who are furthest behind often gain the most. However, the gains depend heavily on how the system is designed and how it is used. Systems that simply give answers can weaken learning, and results shrink when teachers are not involved. The paper concludes that AI can personalise practice, feedback and pacing to a significant extent, but it cannot replace the motivational, social and judgement-based work of a teacher. A blended model, in which AI handles adaptive practice and teachers use the data to guide instruction, is proposed for Indian senior schools.*

Keywords: adaptive learning, artificial intelligence in education, personalised learning, intelligent tutoring systems, knowledge tracing, senior school

1. Introduction

Every teacher knows the problem. In a single Grade 11 mathematics class, one student may still be unsure about fractions while another is ready for calculus. The syllabus, the timetable and the board examination all push the teacher to cover the same chapter with everyone in the same week. Some students are lost and some are bored, and both groups learn less than they could.

Education researchers have known for a long time that personal attention works. In 1984, Benjamin Bloom reported that students taught one-to-one by a tutor performed about two standard deviations better than students in a normal classroom. In simple words, the average tutored student did better than roughly 98 percent of the students taught in a regular class. Bloom called this the "2 sigma problem" because the real challenge was to find a method that gives similar results without the impossible cost of a personal tutor for every child (Bloom, 1984).

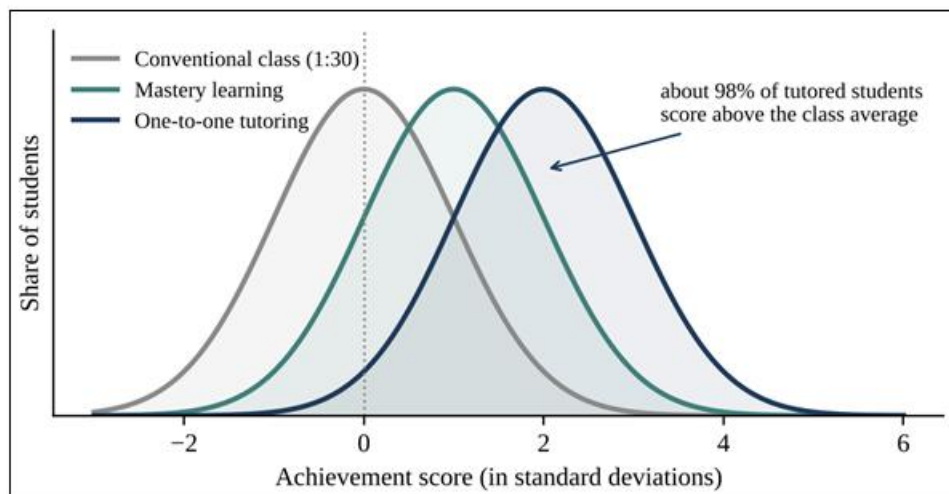


Figure 1: The 2 sigma problem: achievement distributions under conventional teaching, mastery learning and one-to-one tutoring (redrawn from the pattern reported by Bloom, 1984).

Artificial intelligence (AI) is now offered as a possible answer to Bloom's problem. Adaptive learning platforms, intelligent tutoring systems and, more recently, chatbots based on large language models all claim to give each

learner a personal path. India's National Education Policy 2020 also encourages the use of technology to support personalised and adaptive learning (Ministry of Education,

2020). With so much interest, it is important to ask a careful question rather than simply accepting the claims.

2. Research Question and Objectives

Research Question

To what extent can AI-based adaptive learning systems improve personalised learning outcomes compared with traditional one-size-fits-all approaches?

To answer this question, the paper sets out four objectives:

- To explain, in plain language, how AI-based adaptive learning systems decide what a student should do next;
- To review the strongest available evidence on how much these systems improve learning;
- To compare adaptive learning with traditional classroom teaching across important dimensions; and
- To identify the risks and limits of these systems and suggest a sensible way for senior schools to use them.

3. Background: What Does "Personalised Learning" Mean?

The phrase "personalised learning" is used loosely, so it helps to be precise. In this paper it means adjusting at least one of the following to the individual learner: the pace of learning, the difficulty and order of content, the type and timing of feedback, and the amount of support given. It does not mean that every student studies a completely different syllabus.

Two ideas from learning science explain why personalisation should help. The first is Vygotsky's zone of proximal development: students learn best when a task is slightly beyond what they can do alone but within reach with some help (Vygotsky, 1978). A task that is too easy teaches little, and a task that is too hard causes frustration. The second is mastery learning, the idea that a student should show a solid understanding of one step before moving to the next. In a fixed-pace class, both ideas are difficult to apply because the teacher cannot track the exact level of every student at every moment.

It is also worth noting what personalisation is not. A popular belief holds that students learn better when teaching matches their "learning style", for example visual or auditory. A major review found almost no reliable evidence for this idea (Pashler et al., 2008). Good adaptive systems therefore personalise according to what a student knows and can do, not according to a supposed style.

4. How AI-Based Adaptive Learning Systems Work

Although commercial products differ, most adaptive systems are built from three connected parts. The **learner model** keeps an estimate of what the student knows. The **content model** stores questions, explanations and videos, each tagged with the skills it practises and its difficulty. The **decision engine** uses the learner model to choose the next item from the content model. Figure 2 shows how these parts form a continuous loop.

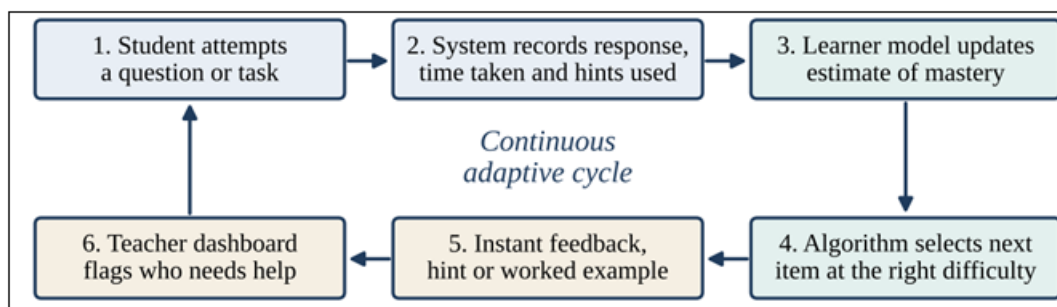


Figure 2: The adaptive learning cycle. Each response updates the learner model, which in turn decides the next task and the type of feedback

A widely used technique for the learner model is knowledge tracing. In its classic form, Bayesian Knowledge Tracing treats each skill as either learnt or not yet learnt, and updates the probability after every answer, while allowing for lucky guesses and careless slips (Corbett & Anderson, 1994). Newer versions, such as Deep Knowledge Tracing, use

neural networks to find patterns across many skills at once (Piech et al., 2015). The student never sees these calculations. What the student sees is that after two correct answers on a topic the questions become harder, and after a few mistakes the system offers a hint or an easier example.

Table 1: Main components of an AI-based adaptive learning system

Component	What it does	Simple example
Learner model	Estimates the current knowledge of each student for each skill	Records that Riya has mastered linear equations but not quadratics
Content model	Organises items by skill, difficulty and prerequisites	Tags a question as 'quadratics, level 3, needs factorisation'
Decision engine	Chooses the next item and the type of support	Gives Riya a level-2 quadratic question with a hint
Feedback module	Explains errors and shows worked examples	Points out the sign error in her second step
Teacher dashboard	Summarises progress so the teacher can act	Shows that eight students are stuck on factorisation

Large language models such as chatbots have added a new layer. They can answer questions in natural language and

explain a concept in several ways. However, a chatbot on its own is not automatically adaptive in the sense described

above. Unless it is connected to a learner model and given clear teaching rules, it may simply give the answer, which can reduce real learning. This difference becomes important in Section 6.4.

5. Methodology

This study uses a structured secondary analysis. Instead of collecting new classroom data, it brings together the results of published meta-analyses and large field experiments, because these give the most reliable picture of what adaptive systems achieve in practice. Sources were chosen using three rules:

- The study had to compare an adaptive or intelligent tutoring system with regular teaching or a non-adaptive alternative;
- It had to report learning outcomes in a comparable form, usually as an effect size; and
- Preference was given to meta-analyses, randomised experiments and studies with school-age students, including at least one study from India.

Results are reported as effect sizes, measured in standard deviations (SD). An effect size of 0.4 means that the average student in the adaptive group scored higher than about 66 percent of students in the comparison group. As a rough guide, effects around 0.2 are small but useful, 0.4 is generally treated as meaningful, and 0.8 or more is large. The analysis is descriptive and does not combine the studies

statistically, as the studies use different subjects, ages and tests. Figure 4 is a simple illustration built by the author to explain a pattern found in the literature; it is not measured data and is labelled as such.

6. Findings

6.1 What the large reviews show

Figure 3 brings together the main effect sizes. The most important finding comes from VanLehn (2011), who compared human tutoring with computer tutoring systems. Step-based tutoring systems, which give feedback on each step of a problem rather than only the final answer, achieved an effect of about 0.76, almost the same as human tutors at 0.79. This is far below Bloom's 2 sigma, but it is close to what real human tutors achieve in modern controlled studies.

Kulik and Fletcher (2016) reviewed 50 controlled evaluations and found a median effect of 0.66, while Ma et al. (2014) found a smaller overall effect of about 0.41 across 107 comparisons. The differences between reviews are themselves informative. Effects tend to be larger when the test closely matches what the system taught, and smaller when broad standardised tests are used. Effects are also smaller when the comparison group already receives good teaching. Even the lower estimates, however, are positive and meaningful.

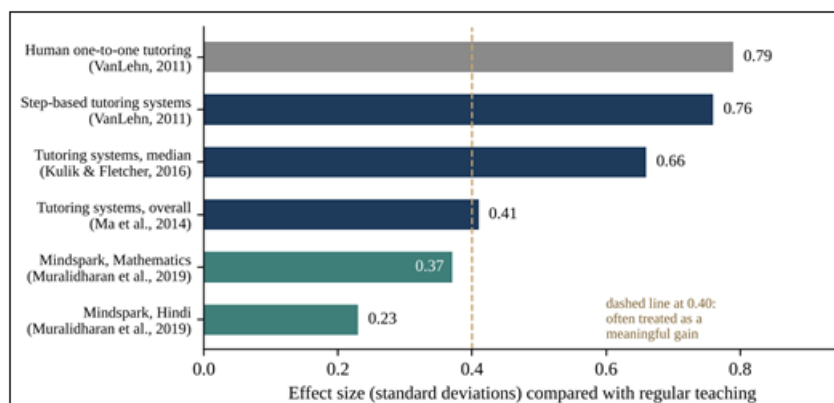


Figure 3: Reported effect sizes of tutoring and adaptive systems compared with regular teaching. Blue bars are computer tutoring systems; teal bars are the Mindspark field experiment in India

Table 2: Summary of key studies reviewed

Study	Type and scope	Main finding
Bloom (1984)	Classroom experiments	One-to-one tutoring about 2 SD above conventional class
VanLehn (2011)	Review of tutoring studies	Step-based systems 0.76; human tutors 0.79
Ma et al. (2014)	Meta-analysis, 107 effects	Overall advantage of about 0.41 for tutoring systems
Kulik & Fletcher (2016)	Meta-analysis, 50 studies	Median effect 0.66; larger on locally made tests
Pane et al. (2014)	Large US trial, Algebra I	No gain in year one; about 0.2 in year two in high schools
Muralidharan et al. (2019)	Randomised trial, Delhi	0.37 in mathematics and 0.23 in Hindi in about 4.5 months
Bastani et al. (2025)	Field experiment, high school maths	Unguided chatbot helped practice but lowered exam scores

6.2 Evidence from India: the Mindspark study

For Indian schools, the most relevant evidence comes from a randomised experiment on Mindspark, an adaptive learning program developed in India. Students in after-school centres in Delhi used the software along with group instruction for about four and a half months. Compared with a control

group, they gained about 0.37 SD in mathematics and 0.23 SD in Hindi (Muralidharan et al., 2019). The researchers also found that many students in middle school were working several grade levels below their enrolled grade. Because the software diagnosed each student's actual level instead of following the textbook for their grade, it could teach them what they were ready to learn. This is a clear

example of personalisation solving a problem that fixed-pace teaching could not.

Why this matters for senior schools

Gaps that are not fixed in middle school travel with students into Grades 11 and 12. A student who struggles with algebra will struggle in physics, chemistry and economics too. Adaptive diagnosis can find and repair these older gaps without slowing down the rest of the class.

6.3 Who benefits most?

Several studies report that students who start furthest behind gain the most from adaptive practice, because traditional teaching gives them the least suitable material. Figure 4 illustrates this pattern using simple curves. In a fixed-pace class, the gap between a student needing support and an advanced student stays wide. In an adaptive system, all three students improve, but the student needing support improves fastest because every task is pitched at the right level.

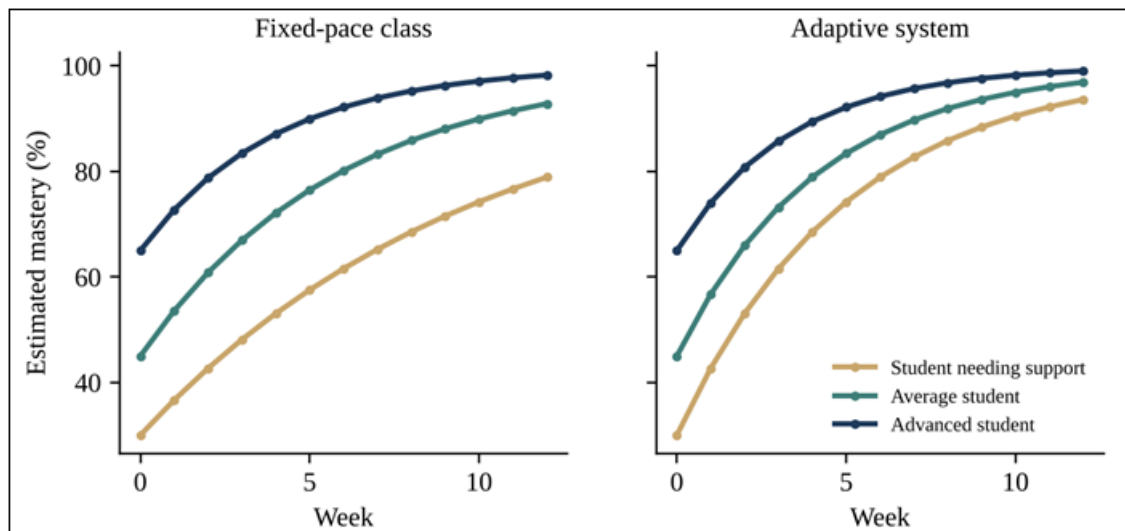


Figure 4: Illustrative mastery growth of three types of learners in a fixed-pace class and in an adaptive system. Author's illustration of the pattern described in the literature; not measured data.

6.4 Where the gains shrink or disappear

The evidence also contains warnings. In a large trial of Cognitive Tutor Algebra I across many American schools, there was almost no benefit in the first year. A gain of about 0.2 SD appeared in the second year in high schools, once teachers had learned how to use the program well (Pane et al., 2014). Technology alone, in other words, does not produce results; the way schools put it into practice matters.

A newer concern comes from generative AI. In a field experiment with high school mathematics students, those given an unrestricted chatbot did much better on practice problems, but when the chatbot was removed they performed worse on the exam than students who never had it. A version of the chatbot designed to give hints instead of answers removed most of this harm (Bastani et al., 2025). The lesson is simple: an AI system that thinks for the student does not personalise learning; it replaces it.

7. Adaptive Learning versus One-Size-Fits-All Teaching

Figure 5 compares three options, traditional teaching, an AI system used alone and a blended model, on a five-point scale, and Table 3 sets out the main differences in words. These ratings are the author's judgement based on the reviewed studies and are meant to show trade-offs rather than precise measurements.

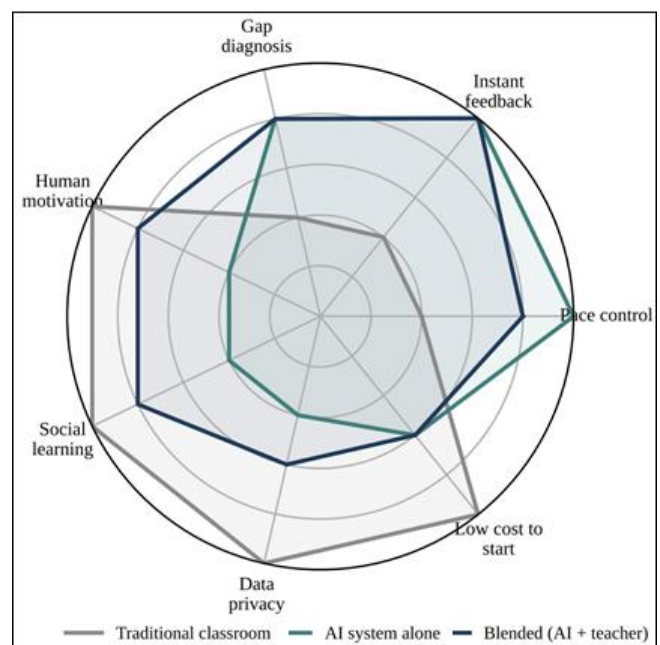


Figure 5: Author's comparative rating (1 = weak, 5 = strong) of traditional teaching, an AI system used alone and a blended model

The comparison shows that neither approach wins everywhere. Adaptive systems are clearly stronger at pace, diagnosis and feedback, which are exactly the areas where traditional teaching struggles. Traditional teaching is stronger at motivation, discussion and human care, which matter greatly for teenagers preparing for board examinations and career choices. The blended model scores

reasonably well on all dimensions, which explains why most successful studies, including Mindspark, combined software

with human instruction.

Table 3: Comparison of traditional and AI-based adaptive approaches

Feature	Traditional one-size-fits-all	AI-based adaptive system
Pace	Same for the whole class	Adjusted for each student
Diagnosis of gaps	Mainly through periodic tests	Continuous, after every response
Feedback	Delayed, often days later	Immediate and specific
Practice difficulty	Same worksheet for everyone	Matched to current level
Motivation and care	Strong human relationship	Limited; relies on points and badges
Discussion and teamwork	Natural part of class	Weak unless designed in
Data and privacy risk	Low	Higher; needs safeguards
Cost to start	Low	Devices, internet and licences needed

8. Challenges and Ethical Concerns

Even when adaptive systems work, schools must deal with several serious issues before using them widely.

- **Data privacy.** Adaptive systems collect detailed records of every answer and mistake. In India, the Digital Personal Data Protection Act, 2023 sets rules for processing children's data, including verifiable parental consent. Schools must check where student data is stored and who can see it.
- **Algorithmic bias.** If a system is trained mostly on data from one type of student, its predictions may be less accurate for others, for example students from a different language background (Baker & Hawn, 2022).
- **Over-reliance and shallow learning.** As Section 6.4 showed, systems that give answers too easily can weaken independent thinking.
- **The digital divide.** Students without reliable devices or internet at home may fall further behind if adaptive work is set as homework.

- **Narrow measures of success.** Systems are best at skills that can be checked automatically, such as solving equations. Writing, creativity and ethical reasoning are much harder to personalise well.

UNESCO's guidance on generative AI in education recommends a human-centred approach, age-appropriate use and clear rules on data protection (UNESCO, 2023). These principles fit the findings of this paper closely.

9. A Practical Framework for Senior Schools

Based on the evidence, the paper proposes a gradual four-stage approach for Indian senior schools, shown in Figure 6. The central idea is that the teacher remains in charge. The AI system handles adaptive practice and diagnosis, while the teacher uses its dashboard to form groups, reteach difficult ideas, and support students emotionally.

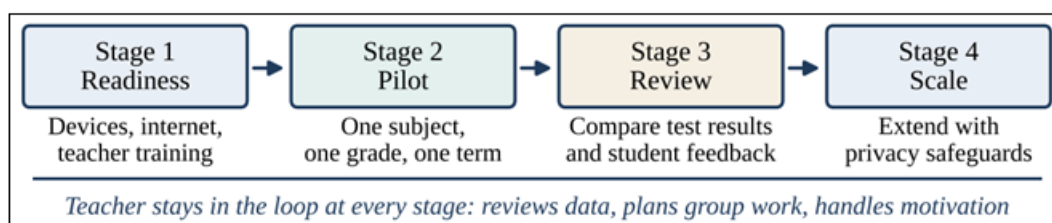


Figure 6: A four-stage framework for introducing adaptive learning in senior schools, with the teacher in the loop throughout

In practice, this could mean using an adaptive platform for two or three periods a week in mathematics or science practice, with the remaining periods used for discussion, experiments and project work. The school should compare test results and student feedback after one term before deciding to expand.

10. Conclusion

The research question asked to what extent AI-based adaptive learning systems can improve personalised learning outcomes compared with traditional approaches. The answer from the evidence is: to a significant but limited extent. Well-designed systems, especially those that give step-by-step feedback, can raise achievement by about 0.4 to 0.8 standard deviations in controlled studies and by about 0.2 to 0.4 in large real-world settings. They are especially helpful for students who have fallen behind, because they diagnose the true level of each learner and teach from there. This is a

real step towards solving Bloom's 2 sigma problem, even if it does not fully solve it.

At the same time, AI personalises only part of learning. It personalises practice, pace and feedback very well, but it does not personalise motivation, belonging or wise guidance. The results also depend on design choices: a system that hands out answers can do harm. The strongest conclusion, therefore, is that AI works best not as a replacement for the teacher but as a powerful assistant. For senior school students in India, a blended model, guided by clear rules on privacy and fair access, offers the most realistic path to genuinely personalised learning.

11. Limitations and Future Research

This paper relies on published studies rather than new data, so its conclusions are only as strong as those studies. Most large studies come from mathematics and from countries

outside India, and very few focus specifically on Grades 11 and 12. Newer chatbot-based tutors are developing quickly, and their long-term effects are not yet well understood. Future research could run a one-term pilot in an Indian senior school, comparing an adaptive platform with regular practice in one subject and measuring both test scores and student attitudes.

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Appendix: Glossary of Key Terms

Table 4: Key terms used in this paper

Term	Meaning in simple words
Adaptive learning	Teaching that changes the next task according to how the student is doing
Intelligent tutoring system	Software that guides a student step by step and gives feedback like a tutor
Learner model	The system's running estimate of what a student knows
Knowledge tracing	A method that updates the chance a student has learnt a skill after each answer
Effect size	The size of a difference between two groups, measured in standard deviations
Meta-analysis	A study that combines the results of many earlier studies on the same question
Randomised trial	An experiment in which students are placed in groups by chance, making the comparison fair
Mastery learning	Moving to a new topic only after the current one is properly understood
Zone of proximal development	The level of difficulty a student can manage with some help, but not yet alone