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Ai-Powered Intelligent Tutoring Systems: A Review Of Learner Modelling, Adaptive Instruction And Conversational Tutors

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Abstract—Intelligent Tutoring Systems (ITS) aim to give every student the benefits of one-to-one tutoring by using Artificial Intelligence to understand individual needs, abilities and progress. This paper reviews AI-powered ITS. It explains the classic architecture of domain, learner, pedagogical and interface models, and surveys learner modelling through knowledge tracing with Bayesian and deep recurrent approaches, adaptive selection of content and practice, automated feedback and hints, and conversational tutors from early dialogue systems to tutors built on large language models. Evidence on effectiveness is examined, including meta-analyses comparing ITS with human tutoring and classroom instruction, and recent studies of language-model-generated hints. A five-layer AI tutoring architecture is proposed, comprising a content and domain layer, a learner model, an adaptive engine, an AI chatbot tutor and a teacher and parent dashboard with progress reports, quizzes and practice tests. Research gaps, objectives, a comparison of tutoring approaches and challenges including accuracy of generated explanations, over-reliance, privacy, equity of access and multilingual support are discussed. The review concludes that AI tutors can deliver personalized, interactive and effective learning when designed with sound pedagogy and teacher involvement.

Index Terms—Intelligent tutoring system, personalized learning, knowledge tracing, adaptive learning, educational chatbot, large language models, learning analytics

I. INTRODUCTION

Bloom [1] reported that students tutored one-to-one performed about two standard deviations better than students in conventional classrooms, a result known as the "2 sigma problem" because individual tutoring for every student is unaffordable. Intelligent tutoring systems try to approximate the benefits of a personal tutor with software that adapts to each learner.

ITS research began decades ago with cognitive tutors for mathematics [2] and conversational tutors such as AutoTutor [3]. Today, machine learning and large language models allow tutors that track knowledge in detail and converse naturally. In Indian classrooms with large student–teacher ratios, such systems could provide personalized practice and explanation at scale.

This paper reviews AI-powered ITS and proposes an architecture that combines adaptive learning with a conversational tutor.

II. THEORETICAL BACKGROUND

2.1 Classic Its Architecture

Fig. 1 shows the four components of a traditional ITS: the domain model (what to learn), the learner model (what the student knows), the pedagogical model (how to teach) and the interface (how to interact).

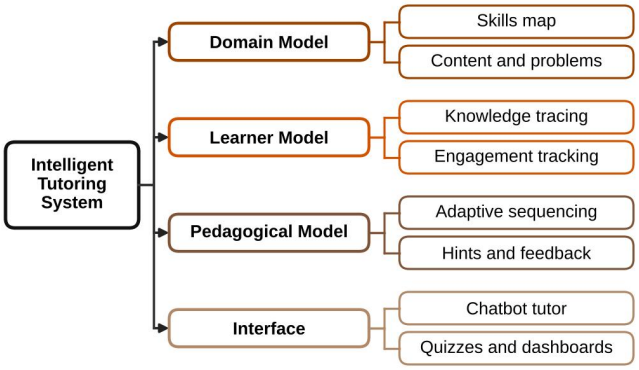


Fig. 1. Components of an intelligent tutoring system.

2.2 Knowledge Tracing

Bayesian knowledge tracing [4] estimates the probability that a student has mastered each skill from their answers, and deep knowledge tracing [5] uses recurrent networks to model learning across many skills.

III. SURVEY OF EXISTING APPROACHES

Anderson *et al.* [2] summarized lessons from cognitive tutors that model expert problem solving and give step-by-

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step feedback, which improved mathematics achievement in schools. Graesser *et al.* [3] developed AutoTutor, which holds natural-language dialogues with students and responds to their explanations.

VanLehn [6] reviewed comparisons of human tutoring, step-based ITS and answer-based systems and found that step-based ITS were nearly as effective as human tutors. Kulik and Fletcher [7] conducted a meta-analysis of ITS evaluations and found that students taught with ITS outperformed those in conventional classes in most studies.

With large language models, Kasneci *et al.* [8] discussed opportunities for personalized explanations and the risks of inaccuracy and over-reliance. Pardos and Bhandari [9] compared hints generated by a language model with human-tutor hints in algebra and found learning gains from both, though human hints produced larger gains in their study. Holmes *et al.* [10] discussed the promises and pedagogical implications of AI in education. Table I summarizes these works.

Ref.	Authors	Year	Technique Used	Merits	Demerits
[1]	Bloom	1984	2 sigma problem	One-to-one tutoring highly effective	Expensive at scale
[4]	Corbett and Anderson	1994	Bayesian knowledge tracing	Skill mastery estimation	Simplified assumptions
[2]	Anderson et al.	1995	Cognitive tutors	Step-level feedback improves maths	Labour-intensive authoring
[3]	Graesser et al.	1999	AutoTutor dialogue	Natural-language tutoring	Limited language understanding
[6]	VanLehn	2011	Review of tutoring effectiveness	Step-based ITS near human tutors	Mostly STEM studies
[7]	Kulik and Fletcher	2016	Meta-analysis of ITS	ITS outperform conventional classes	Varied study quality
[9]	Pardos and Bhandari	2023	LLM vs. human hints	LLM hints produce learning gains	Smaller gains than humans
[8]	Kasneci et al.	2023	LLMs for education	Opportunities and risks	Position paper

TABLE I Summary of Literature Survey

IV. COMPARATIVE STUDY

Table II compares tutoring approaches. Rule-based cognitive tutors give precise step feedback, data-driven adaptive systems scale across subjects and LLM tutors provide flexible natural dialogue but need grounding and pedagogical control.

Approach	Personalization	Flexibility	Accuracy Control
Cognitive (rule-based) tutor	High	Low	High
Adaptive learning (ML)	High	Medium	High
LLM chatbot tutor	Medium	Very high	Low–Medium
Hybrid (proposed)	High	High	High

TABLE II Comparison of Tutoring Approaches

V. RESEARCH GAPS

1. 1) Many ITS cover narrow subjects such as algebra; broad curricula are less supported.

2. 2) LLM-based tutors can give incorrect or overly direct answers that bypass learning.

3. 3) Evidence from Indian classrooms and regional languages is limited.

4. 4) Teachers are often not integrated into ITS decisions.

5. 5) Privacy of children's learning data needs strong protection.

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VI. AIMS AND OBJECTIVES

1. 1) To review the architecture and components of intelligent tutoring systems.

2. 2) To examine learner modelling and adaptive instruction methods.

3. 3) To study conversational tutors and the role of large language models.

4. 4) To propose an AI-powered tutoring architecture with teacher involvement.

5. 5) To identify challenges and future directions.

VII. PROPOSED ARCHITECTURE

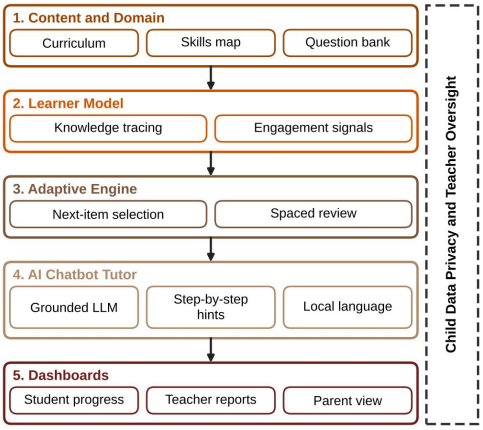


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed AI-powered intelligent tutoring architecture.

7.1 Content And Domain Layer

Curriculum content, skills maps, practice questions and worked examples are organized by topic and difficulty.

7.2 Learner Model Layer

Knowledge tracing estimates mastery of each skill from quiz answers and interaction patterns; engagement signals are tracked.

7.3 Adaptive Engine Layer

The engine selects the next lesson, practice item or review based on mastery, spacing and learning goals.

7.4 Ai Chatbot Tutor Layer

A language-model tutor grounded in curriculum content answers questions, gives step-by-step hints rather than final answers, and explains in the student's language.

7.5 Dashboard Layer

Students see progress; teachers and parents see reports, quiz results and alerts about students who need help.

VIII. PROCESS FLOW AND EVALUATION

Fig. 3 outlines the tutoring cycle. In Bayesian knowledge tracing, after a correct answer the probability of mastery is updated as

$$P(L|c) = P(L)(1-S) / [P(L)(1-S) + (1-P(L))G] \quad (1)$$

where S is the probability of a slip and G the probability of a guess; a learning transition then increases mastery. Items are chosen when predicted probability of a correct response lies in a productive range, neither too easy nor too hard.

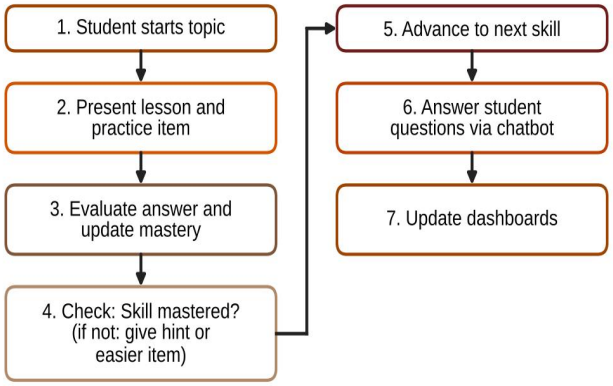


Fig. 3. Intelligent tutoring cycle.

Effectiveness is evaluated with pre- and post-test learning gains, time to mastery and engagement measures.

IX. LIMITATIONS AND FUTURE SCOPE

Table III summarizes challenges. Future directions include hybrid tutors combining knowledge tracing with LLM dialogue, multilingual voice tutors for Indian students, emotion-aware engagement support and classroom trials measuring learning outcomes.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Incorrect explanations	Curriculum grounding; teacher review
Over-reliance	Hints instead of answers
Privacy	Consent; minimal data; secure storage
Access gaps	Low-bandwidth and offline modes
Language diversity	Multilingual voice tutoring

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X. CONCLUSION

AI-powered intelligent tutoring systems can bring personalized learning to every student. The reviewed literature shows that well-designed ITS approach the effectiveness of human tutors, that knowledge tracing supports precise adaptation and that language models make tutoring conversational. Combining these strengths with sound pedagogy, safeguards against incorrect answers and active teacher involvement can make AI tutors an effective complement to classroom teaching.

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