



# Developing Intelligent Tutoring Systems Using Artificial Intelligence And Machine Learning: Design Frameworks, Pedagogical Effectiveness, And Implementation Challenges

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## **Abstract:**

Artificial Intelligence (AI) and Machine Learning (ML) are used in developing Intelligent Tutoring Systems (ITS), which can create personalized and adaptable learning environments. The purpose of this paper is to review the existing literature on AI-based ITS by conducting a systematic literature review of 78 peer-reviewed articles published between 2018 and 2025. The articles were collected from multiple databases including Scopus, ERIC, Web of Science, and IEEE Xplore. The results of this analysis show that most contemporary ITS utilize a combination of a domain model, dynamic learner profile, and pedagogical decision engine. Furthermore, there appears to be strong evidence from studies indicating a statistically reliable improvement in student learning and engagement as a result of using tool-based systems (i.e.,  $d = .35 - .62$ ) in K-12 and university environments. Despite making some progress, there remain several longstanding difficulties with regards to artificial intelligence in education, such as algorithmic bias and issues of data privacy (especially in developing countries), limited infrastructure in low-resourced environments and teacher resistance. The present study recommends the creation of a framework towards the context-sensitive development of Intelligent Tutoring Systems (ITS) and advocating for the incorporation of explainable AI, ethical governance and alignment with existing country-based educational policies like India's National Educational Policy (NEP) 2020. The findings also include recommendations for co-created teacher and AI partnerships as well as multilingual adaptations of Intelligent Tutoring Systems to improve equitable digital access to learning opportunities in developing nations.

**Keywords:** Intelligent Tutoring Systems, Artificial Intelligence in Education, Machine Learning, Adaptive Learning, Educational Equity, Learning Analytics, NEP 2020.

## Introduction:

Education's digital transformation is increasingly accelerated worldwide in response to individualised learning that is tailored to a variety of student needs [1]. The traditional model of a single teaching strategy for all students in a heterogeneous classroom presents challenges for educators, especially those working in regions with limited resources, such as in India where the average public-school student-to-teacher ratio is over 30:1 [2]. One approach to address these challenges is through the adoption of Intelligent Tutoring Systems (ITS). These systems use artificial intelligence (AI) and machine learning (ML) to provide real-time feedback, diagnose the learning needs of each student, create a customised learning path, and provide an interactive, social learning experience for the child [3]. The first ITS prototypes were created in the 1970s but the increase in the use of deep learning and natural language processing technology has revitalised the possibility for ITSs within the context of developing countries [4]. Although there have been advances in the use of ITS, further research is needed to better understand ITS's teaching effectiveness in Global South countries, as well as to explore the ethical consequences of algorithmic decision making and the implementation framework needed to support the scale-up of ITS activities in line with country-specific educational policies [5]. This article seeks to address the above gaps by providing a systematic review and conceptual synthesis of the data available on ITS, and will provide evidence-based recommendations for the development of equitable and effective ITS systems in alignment with India's National Education Policy 2020 (NEP 2020) vision for technology-integrated education [6].

## 2. Conceptual Background and Theoretical Framework

Intelligent Tutoring Systems (ITSs) are designed to deliver immediate, personalized instruction or feedback through an AI-based analysis of the cognitive and emotional (affective) state of the individual learners [7]. The primary components of an ITS consist of:

- The domain model, which describes the expert knowledge of the domain being studied.
- The learner model, which describes the learner's level of expertise and any misconceptions they may have.
- The pedagogical model, which selects the instructional strategies to be used by the ITS.
- An interface for facilitating interaction between the ITS and the learners.

One way to understand how these components fit together with one another is by examining the theories underpinning them.

Initially, Cognitive Tutoring Theory states that the best way to provide effective tutoring is to accurately identify a student's mental model, followed by providing them with the proper scaffolding to construct or modify that model [9]. Conversely, according to the Constructivist Theory of Learning, students have agency and, as such, should not be provided with instruction that is simply rote guidance [10]. Therefore, constructivists believe that ITS should provide opportunities for learners to engage in inquiry-based problem-solving and exploration, as opposed to providing learners with step-by-step instructions. Finally, Self-Regulated Learning (SRL) and metacognitive prompts (for example, asking learners to reflect on their attempts to solve a problem) are incorporated in the design of ITS to help build learner autonomy [11]. Combined, the aforementioned theoretical frameworks and the Learning Analytics approach provide an overarching view of how ITSs can leverage quantitative and qualitative data to develop actionable information through computational modelling [12]. Ultimately, this synergy suggests that ITSs are an adjunct to traditional teaching, as they operationalize evidence-based teaching practices on a large scale.

## 3. Review of Related Literature

### • Evolution and Technical Foundations

The evolution of ITS has evolved from rule-based systems (e.g., SCHOLAR, 1970s) to Data-Driven Architecture. While early ITS were based on static knowledge maps [13], today's ITS use machine learning for dynamic adaptation to learner behaviour. The first generation of ITS used Supervised Classification algorithms (e.g., Support Vector Machines, decision trees) which classified learner errors against a labelled Dataset [14]. Reinforcement Learning optimises pedagogical actions through the use of rewards (for

example, the more time a learner spends on a task, the more rewards they accumulate) [15]. Natural Language Processing (NLP) provides dialogue-based tutoring capabilities. For example, the SHERLOCK system utilizes Transformer models to evaluate learners' open-ended responses within the STEM Disciplines [16]. Knowledge Tracing (e.g., Deep Knowledge Tracing) predicts a learner's ability to acquire skills based on their latent state [17].

- **Empirical Evidence**

The studies that have been meta-analysed clearly support the efficacy of ITS. The study of 45 studies that used the term "ITS", revealed an average learning gain of  $0.48\sigma$  over traditional instruction for mathematics [18]. In the context of higher education in India, an ML-based ITS for programming, using personalized error feedback, has reduced the dropout rate of students by 22% [19]. Writing coherence scores of students in rural areas of Indiana have improved 31% from the use of NLP language tutors [20]. Nevertheless, the context is important, as under-resourced schools in India with unreliable electricity and no teacher support have shown no improvement from using ITS [21]. Further, equity gaps emerge when ITS are trained on non-representative datasets because a math tutor developed in the U.S. produced 18% poorer results for low-income learners compared to the original results produced while training on the same dataset [22].

#### 4. Methodology:

A combination of a systematic review of literature (SLR) and the presentation of a conceptual framework was used within this study. This SLR process adhered to PRISMA standards; specifically, the search was performed in Scopus, ERIC, Web of Science, and IEEE Xplore databases, for literature published between 2018 - 2025. Criteria for inclusion of literature included: (1) Peer-reviewed, empirical literature published about AI/ML Integrated Learning Systems as it relates to K-12 and/or higher education, (2) availability of quantitative or qualitative learning outcomes from these integrated learning systems, (3) inclusion of some explicit mention of ethical considerations or how the system is implemented. Exclusion criteria included: Literature written in languages other than English, Non-educational, or non-integrated learning systems (i.e., corporate training), and purely technical literature with no pedagogical basis. Of the initial 312 results found and screened, 98 study (full text), were reviewed; 78 studies fulfilled the inclusion criteria ( $\kappa = 0.89$  inter-rater reliability) Data synthesis based on thematic analysis was conducted to identify so-called "cross-cutting" areas in terms of architecture, effectiveness, and challenges to implementing this type of system. Finally, the conceptual framework presented in Section 7 is informed by the fact that there are currently few studies published to date regarding AI/ML Integrated Learning Systems in the Global South.

#### 5. Architecture of AI-Based Intelligent Tutoring Systems:

Modern Intelligent Tutoring Systems (ITSs) consist of four interdependent layers that leverage Artificial Intelligence (AI). The domain model is a way to organize knowledge through either an Ontology or a Bayesian Network, which are both improved through Machine Learning (ML) based Knowledge Discovery [24]. The learner model uses supervised ML classifiers to infer the learner's real-time proficiency from their interaction logs (e.g. what they answer, their pattern of answering, and how often they request hints) [25]. For example, Recurrent Neural Networks (RNNs) can track the decay of a skill to determine when to use Spaced Repetition in their instructions. The pedagogical model maps learner states to optimal actions using Reinforcement Learning (RL) [26]. The interface model has wide-ranging capabilities by using Multimodal Natural Language Processing (NLP) to develop chatbots for conversational Tutoring and transforming fluidity into blurring the lines between user interface and user experience (e.g., Chatbots using BERT) [27]. The linking of these layers occurs through Knowledge Tracing Algorithms (e.g., DKTM) that can infer future performance from a learner's historical performances [28]. Most modern ITSs will also have Explainability Modules (e.g., LIME) built into their architecture to provide educators with greater clarity on the how and why of the AI's decisions. This type of Explainability is critical for building trust with both educators and students in India where the level of scepticism about AI is high due to opaque algorithms [29].

## 6. Pedagogical Effectiveness of ITS

ITS has been shown to enhance student learning throughout all areas of the learning process. The results of meta-analysis revealed an overall effect size of  $d = 0.51$  for improving students' conceptual understanding of STEM subjects due to the use of adaptive scaffolding that decreases a student's cognitive load [30]. In India, a middle school algebra ITS did improve test scores by 27% in urban private schools compared to 9% in rural government schools; this example shows the variability in outcomes due to context [31]. In addition to improving student achievement, ITS supports the development of metacognition: there are systems that embed self-regulated learning (SRL) prompts, such as "Explain your reasoning." When using one of these systems, students increased the accuracy of their self-assessments by 35% [32]. Engagement metrics are also positively affected: dialogue-based tutor systems allow students to spend 40% more time on task than static content [33]. The effectiveness of a ITS diminishes without teacher oversight and support; in a Maharashtra study, students who used an ITS alone made no improvements in their learning outcomes because they had significant foundational literacy gaps, whereas students who used a hybrid ITS that included teacher support made a 22% improvement [34]. There are also additional access benefits for students with visual impairments through the use of speech-enabled ITS in Delhi; however, the potential exists for algorithmic bias to create greater inequity among learners without regional language support or culturally relevant material [35].

## 7. Challenges and Ethical Considerations

- **Technical and Infrastructural Barriers**

ITS solutions that depend on cloud operations cannot work properly in rural areas of India due to bandwidth limitations for internet access; currently only 28% of schools have a functioning internet connection [36]. Partially mitigating these issues, on-device machine learning models require the purchasing of additional hardware which many institutions cannot afford to upgrade [37]. There is a lack of data available to allow for customisation based on Indian languages; therefore, there is limited accuracy when serving people whose first language is not English [38].

- **Ethical Risks**

Serious risks to society are created by algorithmic bias. For example, one math tutor had been trained mostly on the data of urban students and, as a result, misidentified the problem solving strategies of tribal learners in Odisha. This reinforced stereotypes [39]. In addition, privacy issues arise as biometric tracking (such as eye gaze) by affective Intelligent Tutoring Systems (ITS) may violate the draft Digital Personal Data Protection Act (2023) without adequate consent mechanisms [40]. A significant amount of anxiety is being expressed by teachers that ITS will diminish their professional autonomy; 68% of Tamil Nadu teachers expressed this concern in response to a survey [41]. Transparency deficits increase distrust; only a small number of Indian ITS report how they generate their recommendations [42]. Importantly, the digital divide is widening because deployment of ITS is being heavily weighted to high fee private schools and does not provide equitable access to state institutions, contrary to the equity provisions of NEP 2020 [43].

## 8. Implications for Educational Practice and Policy

- **Teacher Development**

Teachers must be "orchestrators" of artificial intelligence (AI) tools through professional development. The nodal teacher-training institutes (NTTIs) established under the National Education Policy (NEP) 2020 should include instructional modules that provide insight into how best to interpret instructional technology system (ITS) analytics and help teachers understand how they can utilise AI-related feedback within their own contexts [44]. An example of this is the "AI Educators" programme in Kerala, which prepares teachers to collaborate with application developers to create tutor content, thus decreasing the likelihood of teacher resistance toward using the technology [45].

- **Curriculum and Assessment**

The NEP 2020 competency-based curriculum should be supported by an ITS (intelligent tutoring system) model, which uses modular components for integrated projects (i.e., simulations of climate change). The module can replace simple, memorised assessments with evaluations of more complex tasks, aided by artificial intelligence (AI) [46]. Nevertheless, AI does not have the capacity to evaluate either creativity or ethical considerations, both of which require human analysis [47].

- **Institutional and Policy Alignment**

It should be mandatory for India's National Digital Education Architecture (NDEAR) to establish open standards for ITS (Interoperability) as well as incorporating auditing frameworks for bias detection [48]. Public-Private Partnerships (PPP) can subsidise offline ITS (Information Technology Systems) in low-connectivity areas similar to Andhra Pradesh's (AP Cloud) initiative [49]. There should be policy coherence i.e. investment in ITS should complement as opposed to be a substitute for foundational literacy initiatives like NIPUN Bharat [50].

## 9. Future Research Directions

Five priorities emerge:

1. **Multimodal Learning Analytics:** Merging data from physiological devices, such as wearables that measure stress, with Academic Performance Data, to develop comprehensive Student Profiles, using Multimodal Learning Analytics for the Classroom Environment in India. [51].
2. **Emotion-Aware Systems:** Create culturally sensitive and context-specific Models of Emotion Recognition that can be used in India; Such as the difference between Frustration and Concentration in collectivist cultures. [52].
3. **Multilingual Adaptation:** Building Natural Language Processing models in 22 scheduled Indian Languages, using Transfer Learning Techniques to develop Low-Resource NLP models. [53].
4. **Longitudinal Studies:** Assessing the Impact of Intelligent Tutoring Systems (ITS) on students' Work Readiness over Time (5–10 years); focusing on vocational training areas identified by the NEP 2020. [54].
5. **Teacher-AI Collaboration:** Develop Prototypes of "Human-in-the-Loop" Systems, which allow Teachers to have the ability to Modify or Retrain Artificial Intelligence Algorithms, retaining and enhancing Teacher's Pedagogical Authority. [55].

## 10. Conclusion:

According to extensive empirical evidence, AI-based Intelligent Tutoring Systems (ITS) have enormous potential as tools for delivering personalized education to a large audience, and improving student learning outcomes, increasing student engagement, and developing metacognitive skills. Unfortunately, the potential of AI-based ITS for transforming education in a country such as India is not being realised at this time due to a variety of factors, including inadequate infrastructure, a lack of ethical safeguards, and a disconnect with the realities of the pedagogical environment. The authors of this review have concluded that no single technology solution will ever be as effective in addressing issues related to educational equity as the co-design of ITS with educational practitioners, the inclusion of features such as explainability and the mitigation of bias, and the establishment of deployment within formal policy frameworks such as the National Education Policy of 2020 (NEP 2020) and the Digital India initiative. Moving forward, the success of AI-based ITS will depend largely on the recognition of teachers as a primary stakeholder group and the prioritisation of context-driven adaptations to standard templates. As India continues its efforts to build a digital education ecosystem, it will be critical to develop balanced frameworks for leveraging the strengths of AI while continuing to promote the importance of human values as a foundation for the empowerment of learners.

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