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# Effectiveness of Artificial Intelligent Tutoring Systems for Learners with Limited Academic Proficiency: An Analytical Review in STEM Higher Education

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## ABSTRACT

This analytical review explores the effectiveness of Artificial Intelligent Tutoring Systems (ITS) for academically underprepared learners in STEM higher education. The study synthesises recent advancements in generative AI and ITS, examining their potential to deliver personalised instruction, adaptive feedback, and scalable learning environments. It highlights the architectural components and operational mechanisms of ITS, evaluating their strengths in fostering academic improvement. The paper identifies key limitations including challenges in real-time adaptability, equitable access, and ethical data management, as well as concerns regarding the reliability of online assessments and the ability of ITS to replicate nuanced human guidance. The review calls for future research on emotion-aware computing, collaborative learning, explainable AI, emphasising the necessity for ethical, transparent, and accessible ITS solutions. Ultimately, the article argues that while ITS platforms hold significant promise for transforming STEM education and supporting underprepared learners, their success depend on continual innovation, robust evaluation, and a commitment to educational equity and excellence.

**Keywords:** Intelligent Tutoring System, STEM Education, Higher Education

## INTRODUCTION

In recent years, generative artificial intelligence (AI) has grown quickly and shows great promise for many practical uses.[1,2] While AI was earlier mainly used for language processing, it is now making its way into education,[3,4] turning AI in education into an important research topic. Researchers are looking at how AI tools such as chatbots, AI-powered learning platforms, systems that support data-driven decisions, and tools for analysing students' learning behaviours can improve teaching and learning.[5,6] The idea that AI may transform education is being explored widely, but there are also concerns, like AI might reduce the importance of teachers, lower the quality of education, or negatively affect students' cognitive development.[7,8] Despite these worries, education experts continue to study how AI tools can benefit teaching. With the fast progress of generative AI, especially systems based on large language models like ChatGPT, education is seeing new and exciting opportunities. These AI technologies can not only produce text and images, but also handle tasks like coding and creative writing.[9,10] AI based Intelligent Tutoring Systems (ITS) are also being created, which aim to boost student performance significantly.[11,12] These computer-based tutors offer guidance and feedback tailored to each student, adapting to individual learning needs. This makes them useful in both traditional classrooms and online learning environments. These systems are designed to provide individual instruction and feedback to help each student learn better.[13] Therefore, ITS are being explored and continuous development in the field is being witnessed. However, a major concern regarding the ITS in higher education is their effectiveness in developing countries, where education is given paramount importance and students face intense pressure to pursue joboriented and STEM degree programmes. This pressure often creates a gap between what students are being taught, what they truly understand, and what they can reproduce in assessments. In such contexts, the reliability of online teaching and evaluations becomes questionable, especially when students can always rely on AI assistance during tests, raising concerns about whether these systems can accurately measure student calibre. Moreover, many students struggle to choose appropriate subjects and to clearly articulate their questions, either in writing or verbally. Human teachers can interpret students' gestures and expressions to identify their difficulties, assess their strengths and weaknesses, and guide them toward suitable courses or fields. These human

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touch facilities are not available with ITS. This highlights a critical question: can ITS provide comparable support to students with lower learning efficiency? Addressing this gap represents an important and promising direction for future research. Therefore, The current article aims to review existing Intelligent Tutoring Systems (ITS) and analyse their usefulness for learners with limited academic proficiency—particularly students who struggle to identify and manage their own strengths and weaknesses.

**Intelligent Tutoring Systems (ITS)**

An Intelligent Tutoring System (ITS) is a computer-based platform designed to simulate the role of a human tutor by delivering immediate, tailored instruction and feedback to learners, typically operating independently of direct teacher involvement. The central objective of an ITS is to foster effective and meaningful learning by leveraging advanced computing technologies. These systems strive to mirror the benefits of personalised, oneon-one tutoring—especially in situations where students would otherwise engage in group instruction or selfdirected online tasks without teacher support. ITSs have been implemented in both educational institutions and workplace training environments, where they have showcased both strengths and limitations. While the architectural designs of ITSs vary, they generally comprise four fundamental elements: the domain model (which encapsulates subject matter expertise), the student model (which tracks the learner's understanding), the tutor model (which determines instructional strategies), and the user interface (which manages communication with the learner). Through the interplay of these components, ITSs are able to customise instruction, monitor student progress, and adjust teaching methods accordingly.

**Structural Components and Operation of ITS**

Domain Model: This component houses subject matter expertise, including core facts, principles, and problem-solving strategies relevant to the field. It is responsible for generating accurate solutions, evaluating student responses, and supporting diverse solution approaches. Knowledge within the domain model is commonly represented through rules, Bayesian networks, or hybrid methodologies. The three primary traditional approaches are as follows:

1. Cognitive Model: Outlines step-by-step solutions and commonly occurring student errors, thereby facilitating instant feedback and enabling the tracking of skills acquired by the learner.
2. Constraint-Based Model (CBM): Emphasises key principles that any correct solution must adhere to, allowing for creative responses as long as they do not breach defined constraints.
3. Expert Systems: Utilises advanced AI techniques—such as rule-based frameworks or neural networks—to assess and compare student solutions. While powerful, this approach may require significant computational resources.

Student Model: This model continuously monitors the learner's current knowledge, skills, misconceptions, and preferences. It enables the ITS to adapt learning materials, feedback, and interventions to individual needs. Noteworthy student modelling strategies include:

1. Overlay Model: Assumes the learner's knowledge is a subset of the expert's understanding, seeking to identify and address knowledge gaps.
2. Stereotype Model: Categorises students based on shared characteristics, facilitating efficient initialisation and personalisation of instruction.
3. (iii)Perturbation Model: Builds upon the overlay model by explicitly capturing misconceptions, allowing for targeted corrective measures.
4. Constraint-Based Model: Detects errors by comparing learner actions against established domain constraints.
5. Cognitive Theories and Bayesian Networks: Employs cognitive science principles and probabilistic models to manage uncertainty and predict learning trajectories.

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6. Fuzzy Logic: Handles uncertainty and imprecision in evaluating student knowledge and behaviour.

Tutor Model: Functions as the pedagogical core of the ITS, determining the content and instructional approach for each learner. It customises feedback and selects appropriate teaching strategies based on insights from the domain and student models. Methods include various feedback mechanisms (such as hints, error messages, and stepwise guidance), dialogue-based and spoken interactions to enhance engagement and support natural communication, exemplified by platforms like AutoTutor.

User Interface: Serves as the medium through which information is delivered and interactions with the learner occur. Interfaces may range from conventional graphical displays to sophisticated spoken dialogue systems, aiming to create an intuitive and engaging user experience.

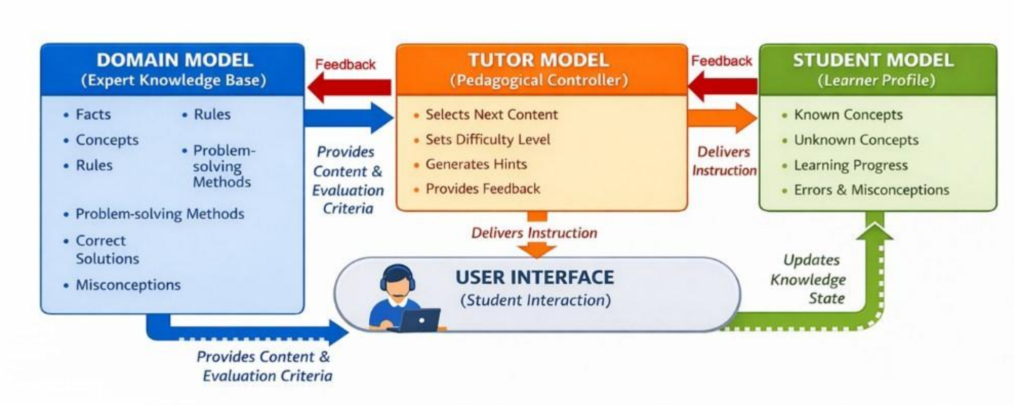


**Figure 1: Operation of Intelligent Tutoring System**

The coordinated interaction of four main components: the Domain Model, Tutor Model, Student Model, and User Interface has been represented in Figure 1. It can be clearly seen that the tutor model acts as the pedagogical controller, using information from both the Domain Model and the Student Model to select the next content, adjust the difficulty level, generate hints, and deliver feedback. The Student Model continuously updates the learner's knowledge state based on interactions. Through the User Interface, the system delivers instruction to the student and collects responses, enabling an adaptive feedback loop in which instruction is personalized according to the learner's evolving understanding.

**Recent ITS: Effectiveness and Limitations**

ITS have been found to be highly effective in subjects such as mathematics and programming, particularly because these disciplines often involve concepts that build upon each other in an organised sequence. Studies by Kolekar et al., indicated that learners using rule-based ITS can achieve academic improvements that surpass those attained through traditional teaching approaches by approximately one standard deviation. Nevertheless, these systems typically face constraints in their ability to adapt dynamically during real-time learning. Recent advances in ITS technology, particularly those utilising neural networks and deep learning techniques, have addressed these limitations and made significant strides in adaptive learning.[14]

Contemporary ITS solutions have increasingly focused on delivering personalised learning experiences. For example, Nimy et al. developed a probabilistic framework that estimated a student's understanding based on their interactions, enabling tailored support in algebraic topics. While effective in certain areas, the static nature of probabilistic models can hinder their performance in environments requiring flexible, dynamic problemsolving, such as programming, where multiple solution paths may exist.[15] To address this, recent research by Tian et al. employed transformer-based models, leveraging pre-trained language models to provide adaptive feedback for coding assignments, thereby accelerating student learning.[16]

Despite the progress made by earlier research in the field, there are still notable challenges that call for further exploration. Initial rule-based systems, as detailed by Kolekar, improved learning outcomes but lacked the agility needed for real-time, dynamic adaptation. Probabilistic systems, like those described by Nimy et al., attempt to handle uncertainty and personalise instruction, but often remain static and struggle with highly interactive tasks, especially in programming. Recent innovations, such as advanced language models[16] and improved feedback mechanisms[17,18], tend to focus on specific subjects or platforms like MOOCs, and there is limited evidence of their integration into versatile, modular ITS frameworks that are applicable across various STEM disciplines.

Additionally, most of the current ITS implementations treated semantic feedback, adaptive content delivery, and real-time analytics as distinct components, seldom combining them into unified systems. While research has established a link between learner engagement duration and academic achievement in platforms such as Google Classroom,[19] this understanding is rarely embedded in ITS designs that can actively adjust instruction and feedback in response to student participation. Moreover, ethical concerns about privacy are also starting to be acknowledged,[20] but practical ITS solutions that robustly safeguard user data remain scarce. Naya-Forcano et al. has introduced a comprehensive ITS framework that integrates adaptive feedback, natural language processing, personalised content recommendations, and real-time assessment, applicable to a broad spectrum of STEM subjects.[21] The effectiveness of this system is evaluated in varied educational contexts using both quantitative and qualitative metrics, with strong ethical measures in place to protect privacy. On the other hand, the architecture of the ITS designed by Ouyang et al. for STEM education emphasises an adaptive and personalised learning experience, utilising a modular structure to facilitate seamless interaction among various AI-powered components.[22] Each component is responsible for a distinct function, including customising educational materials, interpreting student queries, recommending relevant resources, and monitoring learner progress in real time. This modularity not only promotes scalability but also enables the ITS to support a wide range of STEM subjects and accommodate learners at different proficiency levels.[23] By incorporating deep learning algorithms, natural language processing techniques, and adaptive feedback mechanisms, the system has achieved marked improvements in accuracy, learning advancement, and student attitudes, with significant effects observed in mathematics, physics, and programming. The ability to personalise content and provide immediate feedback proved particularly valuable in areas where traditional teaching approaches have been insufficient. As reported by Hurley M et al., in an experimental study an average mastery rate of 85% on evaluated topics of programming has been achieved. This indicated that adaptive, structured instruction is highly effective for subjects with sequential learning paths. In mathematics and physics, mastery rates of 78% and 70% were recorded respectively, highlighting the inherent complexity and abstract nature of these disciplines. Despite initial challenges, students who engaged more frequently with the ITS demonstrated steady improvement and overcame learning barriers over time.[23] The study also noted certain limitations like the controlled study environment may not fully reflect the complexities of real-world scenarios, where infrastructure and cultural factors can influence outcomes. Some students with limited technological background initially encountered adaptation difficulties.

Naya-Forcano A et al. introduced an AI-powered intelligent tutoring system designed with mechanisms to regulate the scope of its responses. The initial development stage involved a diagnostic process to identify and select the foundational materials for use by the neural network or classification algorithm, thereby ensuring that educators retain authority over the system's answers by limiting accessible information sources. Both these carefully chosen documents and students' questions are processed through a large language model (LLM) comparable to ChatGPT, utilising exclusively open-access resources and tools. This represented the first step in a larger initiative focused on predictive analysis of individual student learning trajectories.[24]

It is apparent that contemporary students access information differently as compared to their predecessor, often favouring online sources such as YouTube and AI applications like ChatGPT over traditional courserecommended bibliographies, owing to their familiarity with digital platforms. Consequently, integrating AI effectively into educational environments is now a vital aspect of teaching, encompassing the assessment of sources and references used by students to strengthen the reliability and quality of their work. Leveraging AI's strengths to personalise and enrich learning experiences according to individual requirements is, therefore, crucial.

Technically, there is scope to enhance the ITS by incorporating advanced data analytics such as reinforcement learning, which could improve adaptive feedback and real-time recommendations. Integrating collaborative tools for virtual learning may further extend the system's impact. Future research should explore the incorporation of emotion-aware and affective computing capabilities to better personalise instruction according to learners' emotional and motivational states. Validating the system in heterogeneous academic contexts lays the groundwork for wider adoption in higher education and supports informed policy decisions and investments in

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AI-enabled learning. Various recent key researches in the field along with their key contributions and limitations have been presented in Table 1.

**Table 1: Recent Intelligent Tutoring Systems**

| Author | Theme | Key Contribution / Importance | Main Limitations | Reference |
|---|---|---|---|---|
| **Kolekar et al. (2019)** | Rule-based ITS | Showed that rule-based ITS can achieve learning gains up to one standard deviation above traditional teaching, particularly in structured domains like mathematics and programming. | Limited real-time adaptability; rigid rules struggle with dynamic or open-ended tasks. | 14 |
| **Nimy et al. (2023)** | Probabilistic / Student Modelling ITS | Developed a probabilistic framework that estimates learner understanding from interactions to personalise algebra instruction. | Models remain largely static; less effective in highly interactive domains like programming. | 15 |
| **Tian et al. (2023)** | LLM / Transformerbased ITS | Used transformer-based and pre-trained language models to provide adaptive feedback for coding assignments, accelerating learning and supporting multiple solution paths. | Mainly focused on programming; limited evidence of crossdomain integration. | 16 |
| **Descalço et al. (2018)** | Feedback Mechanisms | Demonstrated that well-designed, timely feedback improves learner engagement and performance in digital environments. | Often studied in isolation from broader ITS architectures. | 17 |
| **Turan & Yilmaz (2024)** | Advanced Feedback Strategies | Provided recent evidence that sophisticated feedback strategies improve achievement and learner satisfaction in AI-supported learning. | subject-specific. | 18 |
| **Septian et al. (2021)** | Learning Analytics / Engagement | Established relationship between engagement duration and academic achievement (e.g., in Google Classroom). | Insights rarely embedded directly into adaptive ITS designs. | 19 |
| **Dari et al. (2024)** | Ethics & Privacy in ITS | Highlighted emerging privacy and ethical risks in AI-driven education systems. | Few practical ITS solutions fully implement robust safeguards. | 20 |
| Naya-Forcano **et al. (2025)** | Integrated & Modular ITS | Proposed a comprehensive ITS combining adaptive feedback, NLP, personalised recommendations, and real-time assessment across STEM. | Still under evaluation; long-term scalability and adoption need further validation. | 21 |
| **Ouyang & Xu (2024)** | Modular ITS Architecture | Designed a modular ITS architecture enabling scalable, interoperable components for STEM subjects. | Validated mainly in university contexts. | 22 |
| **Author** | **Theme** | **Key Contribution / Importance** | **Main Limitations** | **Reference** |
| **Hurley et al. (2024)** | Scalable & Flexible ITS | Supported modular AI-driven ITS designs for diverse learners and proficiency levels. | Needs broader testing across educational levels. | 23 |

**Current Challenges in ITS**

Administering a large cohort of students in online or blended educational environments poses distinct difficulties, especially when learners are dispersed across remote locations or during extraordinary circumstances such as the COVID-19 pandemic. In these contexts, educators increasingly depend on intelligent tutoring systems to support digital instruction and maintain continuity. Inequities in global connectivity, coupled with inadequate access to devices and unstable internet services, create formidable barriers. Learners residing in isolated areas often face challenges in participating in live sessions due to limited bandwidth or unreliable connections, which can adversely affect their educational outcomes. The capability of teachers to effectively utilise Information and Communication Technology (ICT)—comprising telecommunication networks, computer hardware and software, data storage, and audiovisual tools—is of paramount importance. To facilitate the seamless adoption of emerging technologies, educators require ongoing professional development and encouragement to build confidence in these new systems. Virtual platforms commonly lack the avenues for direct physical and emotional engagement, which many educators deem vital for fostering meaningful student involvement. This limitation is particularly pronounced in remote learning, where opportunities for spontaneous interaction are diminished. Collaborative learning experiences are often constrained in digital settings, as the absence of in-person contact and group activities can hinder teamwork and peer-to-peer exchanges. Maintaining high levels of student engagement and retention within virtual classrooms is another significant challenge. There is an elevated risk of disengagement and dropout when students lose focus and there is limited scope for timely teacher intervention. Safeguarding students' privacy and security becomes critically important in online education, especially when participation necessitates sharing personal or biometric information. Addressing fairness and mitigating bias in AI-powered systems is inherently complex. It is essential for these technologies to deliver equitable learning opportunities and outcomes for all participants. Furthermore, educators require well-articulated and transparent explanations from AI systems to foster trust in automated decisions and recommendations. Ensuring clarity and interpretability remains a central challenge in the effective integration of such technologies into educational practice.

## CONCLUSION

The study reveals that ITS platforms offer significant benefits by delivering personalised instruction, adaptive feedback, and scalable learning environments. They also present challenges concerning real-time adaptability, equitable access, and ethical data management. The integration of modular architectures, deep learning algorithms, and natural language processing has enabled systems to provide tailored support, fostering greater engagement and achievement. The studies reviewed here indicated that AI-powered ITS can substantially improve academic outcomes for learners, especially those with limited academic proficiency or difficulties in self-assessment; provided certain challenges are overcome. The applicability of ITS in rural areas, online assessment reliability, student privacy, and the ability of ITS to replicate the nuanced guidance of human tutors should be addressed to ensure fair and meaningful learning experiences. Additionally, the need for transparent and explainable AI solutions is paramount to building trust among educators and students.

There are tremendous future scope on expanding ITS capabilities to incorporate emotion-aware computing, collaborative learning tools, and advanced analytics for real-time adaptation.

In summary, ITSs hold immense promise for transforming STEM education and supporting academically underprepared learners but their success hinges on continual innovation, rigorous evaluation, and a commitment to address the unique challenges of diverse educational landscapes. By prioritising personalisation, transparency, and ethical practice, AI-driven educational tools can contribute significantly to closing achievement gaps and empowering learners to realise their full potential.

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