

Beyond Answering: A Learner-Adaptive AI Tutoring Framework for Guided and Personalized Learning

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ABSTRACT

The increasing use of Artificial Intelligence (AI) in education has enabled learners to access immediate and flexible tutoring support. However, existing AI tutoring systems primarily operate based on user-provided prompts and may not continuously evaluate the learner's evolving knowledge, identify their learning needs, or adapt teaching methods accordingly. This may result in direct answer provision rather than supporting learners in developing independent thinking and problem-solving abilities. To address these limitations, this research proposes an Adaptive Teacher-like Learning Support AI Tutor System that continuously observes and evaluates the learner, understands their evolving knowledge state and learning preferences, selects appropriate teaching interventions, observes the learner's response, and continuously adapts the learning process. The framework personalizes learning pace, difficulty, teaching techniques, level of assistance, and learner support according to individual needs. Furthermore, the system gradually reduces assistance as learner competence increases to encourage independent reasoning and reduce dependency on AI. When persistent difficulties remain or AI-based support becomes insufficient, the framework enables escalation to a human teacher. Thus, the proposed framework aims to transform AI tutoring from an answer-providing mechanism into a support-oriented learning system that helps learners reach answers independently. The proposed work is currently conceptual, and future implementation and evaluation will investigate its effectiveness in improving learning efficiency, application ability, problem-solving, learner autonomy, and appropriate use of AI and human teaching support.

Keywords: Adaptive Learning, AI-Based Tutoring, Personalized Learning, Learner Modelling, Guided Learning, Learner Autonomy, Human–AI Collaboration

INTRODUCTION

The evolution of AI-based tutoring systems has transformed how learners access and engage with education. Traditional teacher–learner education offers valuable pedagogical support through motivation, encouragement, personalized guidance, identification of strengths and weaknesses, and continuous feedback. However, classroom learning is generally constrained by a common pace of instruction, which may not adequately address differences in learners' prior knowledge, understanding, abilities, and learning pace. Self-paced learning addresses this limitation by providing flexibility and learner autonomy, but the absence of continuous guidance may lead to misconceptions, reduced motivation, or superficial learning focused on completing tasks rather than understanding and applying knowledge.

Recent AI tutoring systems have explored conversational tutoring, adaptive scaffolding, learner modelling, Socratic questioning, self-regulated learning, and emotional support. However, these capabilities remain fragmented, and existing systems continue to face challenges in reliably modelling the learner's evolving state, maintaining pedagogical goals, supporting learner autonomy, and providing appropriate motivational and emotional guidance. Therefore, this study proposes a teacher-inspired, continuously adaptive AI tutoring approach that combines learner-state modelling, adaptive pedagogical support, guided rather than answer-oriented assistance, motivational support, and human intervention when automated

strategies are insufficient. The objective is not merely to help learners complete tasks or courses, but to foster genuine understanding, knowledge application, confidence, curiosity, and independent learning. In other words, AI should not merely help learners complete what they are required to do; it should help them become curious enough to want to learn what they need to know.

REVIEW OF LITERATURE

1. Sankalan Pal Chowdhury, Vilém Zouhar, and Mrinmaya Sachan (2024) proposed AutoTutor meets Large Language Models: A Language Model Tutor with Rich Pedagogy and Guardrails. This work builds on earlier intelligent tutoring systems like AutoTutor and integrates them with modern LLMs to combine conversational pedagogy with scalable AI. Their analysis emphasizes how combining rich pedagogical strategies (e.g., scaffolding, Socratic questioning, adaptive feedback) with guardrails for safety and trustworthiness can overcome challenges of hallucination, bias, and lack of instructional depth in LLM-based tutors by making educational interactions more effective, reliable, and aligned with human learning goals.
2. Clayton Cohn, Surya Rayala, Namrata Srivastava, Joyce Horn Fonteles, Shruti Jain, Xinying Luo, Divya Mereddy, Naveeduddin Mohammed, and Gautam Biswas (2025) proposed a theory of adaptive scaffolding for LLM-based pedagogical agents. This work builds on models of scaffolding in education, intelligent tutoring systems, and explainable AI approaches. Their analysis emphasizes how combining adaptive support strategies, learner modeling, and large language models (LLMs) can overcome challenges of personalization, engagement, and trust in educational environments by making instructional decisions transparent, flexible, and learner-centered.
3. Danial Hooshyar, Gustav Šír, Mutlu Cukurova, Yeongwook Yang, Tommi Kärkkäinen, Raija Hämäläinen, and Roger Azevedo (2025) proposed a critical framework analyzing why large language models (LLMs) alone are insufficient for responsible tutoring in K–12 education. This work builds on traditions of intelligent tutoring systems, learner modeling, and educational psychology. Their analysis emphasizes how combining structured pedagogical design, cognitive science principles, and trustworthy AI guardrails can overcome challenges of hallucination, lack of personalization, and weak theoretical grounding in LLM-only tutors by making educational interactions more reliable, interpretable, and aligned with human learning goals.
4. Kirk Vanacore, Avery H. Closser, Ryan S. Baker, and Jeremy Roschelle (2026) proposed The Path to Conversational AI Tutors: Integrating Tutoring Best Practices and Targeted Technologies to Produce Scalable AI Agents, a framework for **scalable conversational AI tutors** that integrates tutoring best practices with targeted technologies. This work builds on traditions of intelligent tutoring systems, learning sciences, and recent advances in large language models. Their analysis emphasizes how combining structured pedagogical strategies, evidence-based scaffolding, and AI-driven dialogue generation can overcome challenges of trust, scalability, and instructional depth in educational environments by making tutoring interactions both **pedagogically grounded** and **technologically adaptable**.
5. Rania Abdelghani, Peter Kaiser, and Kou Murayama (2024) proposed Regulating the AI Tutor: Intentions, Help-Seeking, and Self-Regulated Learning in Adolescent GenAI Use. This work investigates how adolescents interact with generative AI tutors, focusing on their intentions, help-seeking behaviors, and self-regulated learning strategies. Their analysis emphasizes that while GenAI tutors can support learning, unregulated use may hinder the development of critical self-regulation skills. By examining patterns of help-seeking and learner autonomy, the study highlights the need for pedagogical guardrails and intentional design to ensure AI tutors foster effective, trustworthy, and self-directed learning rather than dependency.
6. Arthur C. Graesser, Shulan Lu, George Tanner Jackson, Heather Hite Mitchell, Mathew Ventura, Andrew Olney, and Max M. Louwerse (2004) proposed **AutoTutor: A tutor with dialogue in natural language**. This work builds on earlier intelligent tutoring systems by introducing a conversational agent that engages learners in expectation-driven and misconception-tailored dialogue. Their analysis emphasizes how combining **constructivist learning theories**, **adaptive**

feedback, and Latent Semantic Analysis (LSA) enables AutoTutor to simulate human tutoring, foster deeper comprehension, and achieve significant learning gains. While effective in qualitative domains like physics and computer literacy, the system faces challenges in precise domains and fully interpreting arbitrary learner input, highlighting the need for future refinements in dialogue planning, emotional engagement, and broader domain coverage.

7. Hoda Fakour and Moslem Imani (2024) proposed *Socratic wisdom in the age of AI: a comparative study of ChatGPT and human tutors in enhancing critical thinking skills*. This work examines how AI tutors like ChatGPT compare with human tutors in fostering critical thinking, particularly through Socratic questioning and dialogic engagement. Their analysis emphasizes that while ChatGPT can provide scalable, accessible support for learners, human tutors remain stronger in adapting to nuanced contexts, emotional cues, and deeper pedagogical strategies. The study highlights the potential of combining AI-driven dialogue with human guidance to create more effective, balanced, and trustworthy educational experiences.
8. Rui Guan, Mladen Raković, Guanliang Chen, and Dragan Gašević (2024) proposed *How educational chatbots support self-regulated learning? A systematic review of the literature*. This work synthesizes prior studies on educational chatbots and examines their role in fostering self-regulated learning (SRL). By analyzing empirical evidence across diverse contexts, the authors highlight how chatbots can scaffold SRL processes such as goal setting, monitoring, reflection, and strategy use. Their analysis emphasizes that integrating conversational agents into learning environments can enhance learner autonomy and metacognitive engagement, while also pointing out challenges related to design quality, pedagogical alignment, and long-term effectiveness.
9. Greg Kestin, Kelly Miller, Anna Klales, Timothy Milbourne, and Gregorio Ponti (2025) proposed *AI tutoring outperforms in-class active learning: an RCT introducing a novel research-based design in an authentic educational setting*. This work builds on traditions of physics education research and integrates them with AI-driven tutoring systems to evaluate learning outcomes in real university classrooms. Their analysis emphasizes how combining structured pedagogical strategies (e.g., active learning, adaptive feedback, individualized support) with scalable AI tutoring can overcome challenges of limited instructor time, variability in student engagement, and instructional scalability by making educational interactions more effective, reliable, and aligned with authentic learning goals.

RESEARCH GAP:

Existing AI-tutoring research has developed several important capabilities independently, including pedagogical scaffolding, learner modelling, conversational tutoring, self-regulated learning support, emotional support, Socratic questioning, and self-paced instruction. However, the reviewed studies indicate a lack of an integrated, continuously adaptive tutoring framework that uses an evolving learner model to coordinate cognitive support, motivational or emotional support, learner autonomy, adaptive strategy switching, and escalation to human teachers within a self-paced learning environment.

PROPOSED ADAPTIVE TEACHER-LIKE LEARNING SUPPORT AI FRAMEWORK

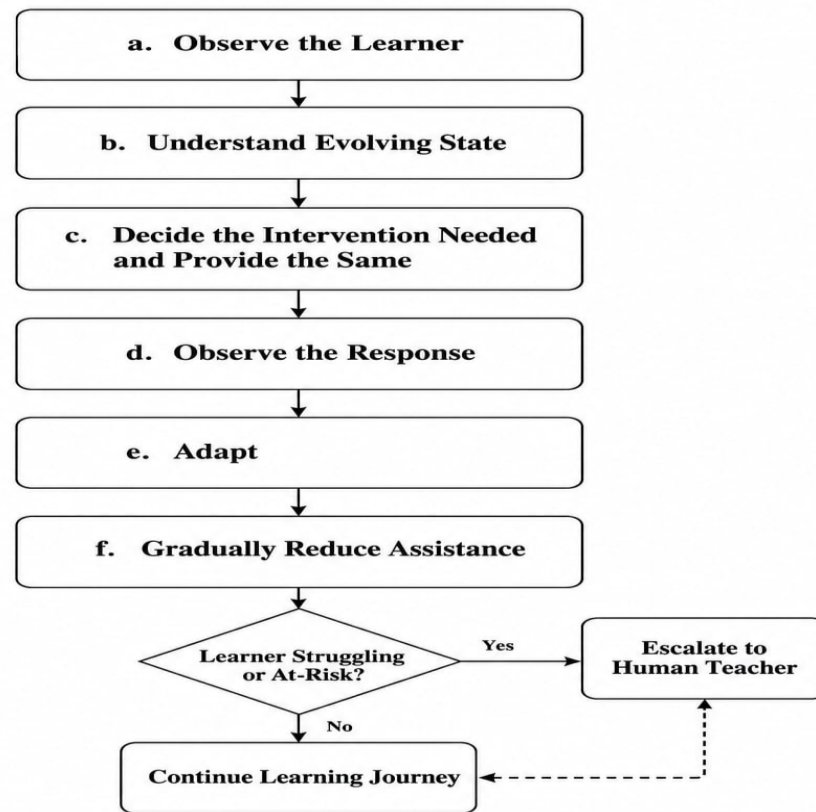


Fig: Proposed Adaptive Teacher-like Learning Support AI Tutor System

The proposed Adaptive Teacher-like Learning Support AI Tutor System follows a continuous, learner-centred framework designed to improve learning effectiveness through dynamic observation, personalized intervention, adaptation, and progressive development of learner autonomy. Rather than providing identical instructional support to every learner, the system continuously interprets the learner's evolving state and adjusts its teaching approach accordingly. The framework consists of the following stages:

a. Observe the Learner

The system first observes and evaluates the learner to develop an initial understanding of their learning characteristics. This stage considers the learner's strengths, weaknesses, preferences, prior experiences, engagement, performance, and other available learning-related evidence that may influence their ability to understand and acquire new concepts. Based on this information, the system identifies the probable instructional approaches that may be suitable for the particular learner. Thus, this stage establishes the foundation for personalized teaching and enables the system to move beyond a one-method-fits-all approach.

b. Understand the Evolving State

The system continuously determines the learner's evolving knowledge state, including the knowledge and skills acquired at a particular point in the learning process. Prior knowledge is particularly important because it influences how the learner should progress through a concept. If the learner already possesses sufficient prior knowledge, the system need not repeat foundational instruction; instead, it can briefly revise the relevant concepts and progress toward more advanced material. Conversely, when the learner has limited or no prior knowledge, the system can begin with foundational concepts and progressively transition toward the target concept.

Therefore, this stage enables the system to construct and continuously update an individualized learning pathway based on the learner's current state rather than following a fixed instructional sequence.

c. Decide the Intervention Needed and Provide It

In this framework, *intervention* refers to the instructional method selected to support the learner at a particular stage. This forms a central component of the proposed system because learners differ not only in their existing knowledge but also in the ways through which they understand concepts effectively. Similarly, different teachers employ different instructional strategies depending on the learner and learning situation.

The system therefore determines an appropriate teacher-like intervention based on the learner's observed state and learning history. Depending on the identified requirement, the intervention may involve explanation, questioning, hints, examples, analogies, application-based problems, guided practice, feedback, or other suitable instructional strategies. The objective is not merely to provide information but to select and deliver the form of instructional support most appropriate for the learner at that moment.

d. Observe the Response

Following the intervention, the system observes the learner's response to determine whether the provided support has resulted in meaningful understanding. An interactive question-and-answer or application-oriented assessment can be used to evaluate the learner's ability to apply the concept rather than merely recall a definition.

Application-oriented questions are particularly valuable because they can reveal whether the learner can transfer acquired knowledge to practical or unfamiliar situations. The learner's responses, errors, reasoning patterns, response time, and level of assistance required can provide evidence about areas that require further attention.

Where assessment integrity is required, this stage may be conducted within a controlled assessment environment, subject to appropriate learner consent, privacy requirements, and institutional policies. Such an environment may restrict external assistance or unauthorized resources to ensure that the resulting performance reflects the learner's own understanding.

e. Adapt

Based on the observed response, the system adapts the learner's instructional pathway. If the learner demonstrates persistent difficulty in a particular area, the system identifies the underlying learning gap and modifies the instructional strategy accordingly. Instead of repeatedly presenting the same explanation, it can employ an alternative method that may be more suitable for the learner.

Conversely, when the learner demonstrates sufficient understanding, the system can reduce unnecessary repetition, progress toward more advanced concepts, and update the learner model with the newly acquired evidence. These continuously updated learning preferences and learning-state information can subsequently influence future instructional decisions.

Thus, adaptation transforms the system from a static tutor into a continuously evolving personalized learning support system.

f. Gradually Reduce Assistance

An important objective of the proposed framework is to develop learner autonomy rather than long-term dependence on the AI tutor. If the system continuously provides direct answers, the learner may gradually become dependent on external assistance and lose opportunities to develop independent reasoning and problem-solving abilities.

Therefore, the system progressively reduces the level of direct assistance as the learner's competence increases, while continuing to provide appropriate support when required. Rather than immediately revealing an answer, the system may provide guiding questions, intermediate clues, hints, or partial reasoning steps that enable the learner to independently connect the relevant concepts and arrive at the solution.

In this manner, the system reduces assistance without reducing support, gradually shifting the learner from assisted problem-solving toward independent thinking and decision-making.

g. Escalate to a Human Teacher When Necessary

If the learner continues to experience difficulty despite repeated and appropriately adapted interventions, the system should recognize the limitation of continued automated assistance and escalate the learner to a human teacher when necessary.

Such escalation acknowledges that learning is not exclusively a computational process. Certain learning situations may require human interaction, contextual understanding, encouragement, trust, emotional awareness, or a different form of explanation that an AI tutor may not adequately provide. The human teacher can therefore intervene when persistent learning difficulties, lack of progress, or other circumstances indicate that human support would be more appropriate.

The human teacher and AI system should consequently be viewed as complementary rather than competing sources of learning support. The AI system can provide continuous personalized assistance while recognizing when human expertise and interaction are required.

Continuous adaptation enables the system to learn from the learner's evolving responses and continuously refine both the learner model and teaching strategy, resulting in progressively personalized learning.

DISCUSSION

Every learner possesses different strengths, weaknesses, prior knowledge, and abilities to understand and acquire new concepts. The proposed framework addresses these differences by continuously understanding the learner's evolving state and providing personalized guidance according to their specific learning needs.

Conventional AI-based systems generally respond according to the instructions provided by the user. When a learner asks for an answer, the system may directly provide the solution without considering whether the learner needs an explanation, a hint, guided questioning, or an alternative teaching approach. Such direct answer provision may reduce opportunities for learners to reason, attempt solutions, and develop independent problem-solving abilities. The proposed framework addresses this limitation by emphasizing guidance rather than immediate answer provision, helping learners progress toward the answer through appropriate support.

The personalization component further incorporates important aspects of traditional teaching into AI-based learning. Based on the learner's evolving state and responses, the system can modify its teaching approach, provide additional explanation where required, ask questions after conceptual instruction, and use application-oriented tasks to assess whether the learner has genuinely understood the concept. Thus, the framework attempts to combine the accessibility and flexibility of AI-based tutoring with the adaptive and learner-sensitive characteristics of traditional teaching.

Overall, the proposed framework aims not merely to help learners complete a learning task, but to help them understand, apply, and independently reason about what they learn. By continuously adapting to the learner while preserving the role of human teachers when necessary, the framework seeks to provide learning support according to the learner's needs and preferred ways of understanding, with the ultimate goal of enabling meaningful and effective learning rather than simply obtaining answers.

LIMITATIONS

- **Procrastination and Self-Regulation:**

The flexibility of self-paced learning may lead some learners to postpone learning activities or fail to maintain a consistent learning schedule. Unlike a traditional classroom, where fixed schedules and teacher supervision provide external motivation, the proposed system may require a greater degree of learner self-regulation.

- **Risk of Shallow Learning or Academic Dishonesty:**

Learners may attempt to bypass the learning process by using external resources, unauthorized assistance, or other means to complete assessments. Although controlled assessment mechanisms can reduce such behaviour, completely eliminating academic dishonesty in an AI-based learning environment remains challenging.

- **Internet and Financial Constraints:**

The effectiveness of the system depends on access to suitable technological resources, including reliable internet connectivity and compatible devices such as smartphones, tablets, or computers. Learners from economically or technologically disadvantaged backgrounds may therefore face difficulties in accessing the system consistently.

- **Dependence on Accurate Learner Modelling:**

- The quality of personalization depends on the system's ability to correctly understand the learner's evolving knowledge, behaviour, and learning needs. Incorrect interpretation of learner responses or behavioural evidence may result in inappropriate instructional decisions.

- **Risk of Over-Personalization:**

Excessive adaptation to a learner's existing preferences may unintentionally limit exposure to alternative learning strategies or challenging experiences. Therefore, personalization must be balanced with opportunities for exploration, diversity of instructional approaches, and intellectual growth.

- **Limitations of AI-Based Understanding:**

AI systems may not always accurately recognize complex learner difficulties, particularly those involving subtle emotional, contextual, or interpersonal factors. In such situations, automated intervention may be insufficient, reinforcing the need for human-teacher escalation.

- **Privacy and Data Security Concerns:**

Continuous observation and adaptation may require the collection of learner-related information, including performance, interaction patterns, response behaviour, and learning history. Managing such information securely while maintaining learner privacy and obtaining appropriate consent remains an important challenge.

- **Computational and Implementation Complexity:**

Maintaining a continuously evolving learner model, selecting appropriate interventions, evaluating responses, and adapting instructional strategies in real time may require considerable computational resources and sophisticated AI mechanisms.

ADVANTAGES

- **Self-Paced Learning:**

The learner can progress according to their individual learning speed. Concepts can be reviewed multiple times when necessary, while learners who demonstrate sufficient understanding can progress more rapidly through familiar topics.

- **Application-Oriented Knowledge:**

Since the system evaluates learners using application-oriented questions rather than relying exclusively on conceptual recall, it encourages learners to apply theoretical knowledge to practical and unfamiliar situations.

- **Flexibility of Time, Place, and Pace:**

The system provides flexibility in terms of when, where, and how quickly learning takes place. Learners can access learning support according to their availability and circumstances, overcoming some of the temporal and geographical constraints of traditional classroom environments.

- **Continuous Personalization:**
The system continuously observes learner responses and adapts the learner model and instructional strategy accordingly. This continuous adaptation progressively refines the learning experience and enables increasingly personalized learning support.
- **Learner Autonomy and Independent Thinking:**
By gradually reducing direct assistance while maintaining appropriate support, the system encourages learners to reason, analyze, and arrive at solutions independently rather than becoming dependent on immediate answers.
- **Adaptive Teaching Strategies:**
The system can employ different instructional approaches such as explanations, examples, analogies, hints, questioning, guided practice, and feedback according to the learner's evolving requirements. This provides a more flexible teaching experience than a fixed instructional method.
- **Early Identification of Learning Gaps:**
Continuous observation of learner responses can help identify misconceptions, knowledge gaps, and persistent difficulties at an earlier stage, allowing the system to provide targeted intervention before these gaps become more significant.
- **Reduced Dependency on a Single Teaching Method:**
Traditional learning environments may rely heavily on the teaching style of an individual instructor. The proposed system can dynamically change its instructional approach when the current strategy is not effective for a particular learner.
- **Human–AI Complementarity:**
The system does not attempt to completely replace the human teacher. Instead, it provides continuous personalized support while recognizing situations where human intervention is necessary. This creates a complementary relationship between AI-based tutoring and human teaching.
- **Continuous Learning Support:**
Unlike conventional classroom interactions that are often restricted by fixed class hours, the system can provide learning assistance whenever the learner requires it, enabling continuous access to personalized educational support.

FUTURE ENHANCEMENTS

- **Mitigating Learner Dishonesty:**
Develop appropriate mechanisms to detect and reduce learner dishonesty during assessments while maintaining learner privacy and ethical standards.
- **Implementation of the Proposed Framework:**
The proposed solution is currently conceptual. Future work will focus on implementing the framework as a functional AI-based tutoring system and evaluating its effectiveness with real learners.
- **Experimental Validation:**
Conduct experiments with learners to evaluate the effectiveness of continuous adaptation, personalized interventions, and gradual reduction of assistance using measurable learning outcomes.
- **Advanced Learner Modelling:**
Develop a more comprehensive learner model that continuously incorporates learning performance, responses, interaction patterns, and explicit learner feedback to represent the learner's evolving state.
- **Improved Intervention Selection:**
Explore advanced AI techniques for automatically selecting the most appropriate teaching intervention based on the learner's current knowledge, learning history, and response to previous interventions.

- **Human–AI Collaboration:**

Develop an effective mechanism for determining when AI-based support is insufficient and human-teacher intervention should be initiated.

CONCLUSION

The proposed Adaptive Teacher-like Learning Support AI Tutor System presents a learner-centred framework that aims to bridge the gap between AI-based tutoring and traditional human teaching. The framework continuously observes the learner, understands their evolving knowledge state, selects and provides appropriate interventions, observes their responses, and adapts the learning process accordingly. This continuous adaptation enables the system to progressively personalize both learning techniques and support according to the learner's changing needs.

Unlike systems that primarily provide answers, the proposed framework emphasizes supporting the learner to reach the answer. Through guided questions, hints, application-oriented tasks, and gradually reduced assistance, the system aims to strengthen independent thinking, problem-solving, and learner autonomy. At the same time, when automated support becomes insufficient, escalation to a human teacher ensures that AI and human teaching function as complementary rather than competing sources of learner support.

Although the proposed framework is currently conceptual and has limitations such as procrastination, academic dishonesty, technological constraints, and over-personalization, its implementation and experimental validation can determine its effectiveness. Future evaluation should examine learning outcomes, concept retention, application ability, reduced dependency on assistance, and learner autonomy. Ultimately, the proposed system is not intended to replace traditional teaching, but to provide an additional layer of continuous, adaptive, and personalized support, helping learners receive the attention they need while enabling human teachers to focus on aspects of learning where human interaction remains essential.

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