Published online at Deep Science

International Journal of Applied Resilience and Sustainability

Journal homepage: https://deepscipub.com/ijars

Agentic artificial intelligence-driven tutoring: A multi-agent cognitive architecture for personalized adaptive learning in Education

Neha Gupta [1], Shreeshail Heggond [2]

[1] *Department of Computer Science and Engineering, Sri Ram Murti Smarak College of engineering and technology, Bareilly, India*
[2] *Basaveshwar Engineering College, Bagalkote*

Check for updates

Article Info:
Received 25 December 2025
Revised 29 January 2026
Accepted 12 February 2026
Published 19 February 2026

Corresponding Author:
Shreeshail Heggond
E-mail: shreebh66@gmail.com

Abstract

The one-size-fits all model of education has not been sufficient with regard to meeting the various learning needs of the students in present day education setup. This research paper outlines a review of the literature which discusses the transformational possibilities of agentic artificial intelligence-based tutoring systems which realize multi-agent cognitive architectures to personalized adaptive learning. This paper explores how autonomous AI agents, integrated in complex cognitive models, will help transform the way education is delivered through dynamical adaptation of instructional models, teaching complexity, and pedagogic quality depending on the distinctive features of individual learners, educational performance, and neuroscience involved. This review summarizes the current nexus of intelligent tutoring system, multi-agent architecture, cognitive computing and adaptive learning technologies by conducting a systematically done review based on PRISMA methodology. The results indicate that multi-agent AI systems have better behavior modeling, system organization of individualized learning processes, real-time feedback, and metacognitive enhancement capacities over traditional learning technologies. Some of the main concerns that are discovered are ethical issues regarding the privacy of learner data, transparency in algorithms, lack of scalability, and the requirement to implement powerful evaluation systems. The study points out the new possibilities in neuroadaptive learning interface, emotion-sensitive tutoring agent, and socially-intelligent interactive learning learning settings. This analytic review has added to the existing literature as it provides a mapping of the state of underlying agentic AI tutoring systems and offers important research areas that researchers need to focus on to construct more successful and equitable and human education technologies.

Keywords: Agentic artificial intelligence, Education, Multi-agent systems, Cognitive architecture, Personalized learning, Adaptive learning.

1. Introduction

The education environment has never experienced as many threats as it is currently due to the rise in diversity of students, changes in pace of learning, cognitive differences and the increase in knowledge fields at very fast rates [1-3]. The current trends of classroom teaching although there are constant reforms have not been able to satisfy the individual differences in learning. Educators with a large class size find it almost impossible to give individual attention to each child thus creating gaps in learning, student boredom and poor educational performance [2,4]. The achievement gap between the performing and the struggling students is ever-increasing, especially in the course that involves accumulating of knowledge like mathematics, science and learning the language. The introduction of the artificial intelligence technologies has led to new possibilities of the innovations in the educational sphere. Intelligent tutoring systems and early computer-assisted instruction systems showed potential of providing personalized learning experiences but lacked flexible rule-based architecture, in-depth learner models and dynamically adjusted to difficult learning situations. Such systems tended to be preset based on instructional patterns and were not sophisticated enough to comprehend subtle behaviours of learners as well as their emotional responses or other contextual conditions that affect the learning results. The

https://doi.org/10.70593/deepsci.0202022

current developments in agentic artificial intelligence have prompted a paradigm shift in the design of educational technology [5-6]. The agentic AI systems are autonomous in decision making, proactive, social awareness, and goal oriented towards problem solving and this resembles closely human thought processes. When many of these agents are coordinated through an appropriately structured cognitive architecture, they are able to produce complex tutoring interventions which react to the needs of learners in real-time in an intelligent way. Such multi-agent systems have the ability to concurrently simulate various parts of the learning procedure such as knowledge gain, cultivation of abilities, motivation interactions, affective experiences and metacognitive plans. The mental system that supports such systems will give the structural support that allows the agents to see education situations, deliberate on instructional choices, arrange a sequence of actions in learning, implement teaching behaviors and find an outcome of learning through interaction. Based upon cognitive science models of human learning and memory encoding, these architectures include attention control modules, working memory simulation modules, long-term knowledge representation modules, procedural skill execution module and metacognisional monitoring. This synergistic effect comes as a result of a combination of various specialized agents in these architectures so that the overall intelligence approach is larger than the capability of each individual part.

One to one adaptive learning is the essence of such sophisticated systems [7-9]. Contrary to the existing practice of personalization that is typically built on the initial assessment and the preferences of the learners, the actual adaptive learning implies the constant adjustment of the instructional parameters according to the continuous monitoring of the performance, behavioral patterns, and predictive analysis. The system does not only conform to the content difficulty, but also pedagogical strategies, representation formats, modes of interaction, pacing, level of scaffolding and feedbacks. This adaptive multi-dimensional makes the best challenge levels which maintain the interests of the learners without tiring them and making them bored. Multi-agent system has a number of specific strengths as compared to monolithic AI tutoring systems. Various agents may be specialized in a particular tutoring activity including content delivery, assessment, feedback generation, motivation management, and tracking progress. This specialization will allow greater knowledge of every field as the coordination systems will make the overall tutoring experience coherent. Agents are able to work asynchronously so that learning of various aspects can be processed concurrently. The modularity aids in maintenance, updating and adding capabilities of the system and not necessarily in the system being redesigned to include new capabilities. More recent studies have seen a rampant explosion in this field, due to the advances in machine learning, natural language processing, affective computers, learning analytics, and computational models of cognitive processes. Deep learning methods allow patterns to be recognized in data of learners with deep levels of understanding, confusion, or false knowledge. NLP provides speaking tutoring interfaces which involve learning conversationally with learners. Affective computing allows the recognition and the reaction of learner emotions, whereas learning analytics help to indicate learning patterns and predict additional signs of success or failure. The agentic AI tutoring systems are applied in various learning settings both in mathematics and science education (K-12) and professional training and lifelong learning institutions. These systems have proven to be efficient to promote the learning process, enhance student engagement, lessen the difference in achievement, and give individualized instructions that can be provided on a large scale. Nevertheless, there are still major issues such the provision of fair access, preservation of the privacy of learners, quality in pedagogy, and teacher integration, and formulation of strong evaluation criteria.

Although extensive research has been done on agentic AI-driven tutoring systems, there are still a number of gap areas in the existing literature. To start with, the majority of the available literature is restricted in specific areas of topics or with respect to certain age groups, which restricts the ability to generalize the results of the studies in different educational settings. Two, the lack of focus on the coordination mechanisms that allow the successful cooperation of numerous agents of AI, especially in the context of managing the complicated instructional scenarios that demand that consideration of cognitive, affective, and social elements should be done simultaneously. Third, the theoretical grounds between the cognitive architectures and observable learning results are not yet well developed and it is hard to be able to predict how the system works correctly as well as be in a position to tell how it fails. Fourth, assessment approaches of multi-agent tutoring systems are not standardized and various studies use non-comparable measures and therefore synefysis of different systems is difficult. Five, there are limited long-term effects studies of lasting learning benefits, transfer to new settings as well as the acquisition of self-regulated learning skills. Sixth, combining immersive technologies like neuroadaptive interfaces, AR as well as quantum computing with multi-agent tutoring architectures is immaturely examined. Seventh, algorithms bias, transparency, accountability, and agency of AI-mediated education are the topics of ethical frameworks, which need to be treated more thoroughly.

This study has various contributions to the field. To begin with, it presents a comprehensive picture of the agency AI tutoring environment, incorporating the perspectives of artificial intelligence, cognitive science, learning technologies and educational technology. Second, it provides a systematic discussion of multi-agent architectures that are specifically tailored to the educational setting that identifies the design thinking and best practices. Third, it includes in-depth comparative studies in form of in-detailed tables that summarize the essentials of the available research and implementations. Fourth, the review highlights the research gaps that are critical and suggests some definite ways of future field development. Fifth, it discusses the issue of sustainability and resilience, which are typically not considered during technical conversation about AI educational systems. Sixth, it covers policy and regulatory aspects that are needed in accountable implementation of such technologies. Lastly, the researchers, as well as those in development, education, and policy formulation, can use this as a baseline to study and develop agentic AI-driven personalized learning.

2. Methodology

The methodology of the proposed literature review is the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework because it guarantees a rigorous, transparent, and reproducible examination of the studies about agentic AI-supported tutoring systems. The systematic method incorporates several steps such as the identification stage, screening phase, eligibility analysis and addition of pertinent scholarly articles. The identification step included extensive searching in the large academic databases such as IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect, Web of Science, Scopus, and the repositories on artificial intelligence and education research. The search strategies were the combination of controlled vocabulary terms and keywords associated with agentic AI, multi-agent systems, cognitive architecture, intelligent tutoring system, adaptive learning, personalized education, and similar terms. The time period was what concerned publications since the past few years to capture the latest trend and also to include the once founded works establishing an overview of theories. There were some predefined inclusion and exclusion criteria that were used during screening procedures. Works were included that dealt with the use of agentic AI in education, multi-agent tutoring systems, cognitive learning computing, adaptive e-learning systems, or individualized learning systems. Included articles were those that did not cover the exclusively non-AI educational intervention, those that reviewed other articles but did not include original contribution, commercial product product descriptions and articles that lacked methodological rigor. The empirical research as well theoretical input were incorporated in a bid to cover all. The eligibility check was conducted considering the full-text articles whereby the articles were first selected on the basis of relevancy, quality and contribution to the research objectives. Among the aspects of quality appraisal, the soundness of methodology, the theoretical basis, the reporting lucidity, the relevance of findings and the possible impact were taken into account. Data mining identified core data such as research focus, research methods adopted, cognitive architecture of the research, agent capability, personalization processes, results of evaluation, challenges confronting the research advances, as well as suggestions of future directions of the research. The formulation was done through thematic analysis, which was aimed at recognizing patters, trends, and associations between studies. The similarities and differences in the approaches, techniques, and results were identified with the help of comparative analysis. The results are arranged into logical themes such as the applications, techniques, frameworks, challenges, and opportunities in both narrative and tabular format performing easy reference and comparisons.

3. Results and discussions

3.1 Foundations of Agentic AI in Educational Contexts

In educational settings, agentic AI has its foundations, which are presented in this section of the article. The agentic artificial intelligence is an advanced development of the transparent algorithmic systems to autonomous agents able to sense its surrounding environment, evaluate its independent decisions, goal orientation, and learning through experiences [3-5]. In education, agentic AIs exhibit a number of features that differentiate agentic AIs as compared to traditional educational software. These agents have the characteristic of reactivity in that they respond immediately to modifications in the state of learners, proactive in that they predict the learning requirements and force interventions, social whereby they interact naturally with learners and other agents, and autonomy where they make teaching decisions without the incessant intervention of human beings. Theoretical basis of agentic AI tutoring is based on a variety of fields. Cognitive science provides agent design with models of human learning, memory and problem-solving. Learning sciences introduce the pedagogical theories on how human beings learn and gain skills. Artificial intelligence provides computing methods of reasoning, planning and learning. The principles of human-computer interaction are used to design the effective interfaces between the learner and the agent. This interdisciplinary coalescence produces systems that can just as well be computationally powerful and pedagogically sound. The 21st century agentic AI tutoring systems utilize different agent types with different purposes. Pedagogical agents can be viewed as virtual teachers, choosing instructional strategies and content to be used, depending on the model of the learner. Companion agents offer encouragement and give motivation. Agents of assessment measure the performance of the learners and diagnose the wrong concepts. Learners are able to acquire self-regulation skills with the assistance of metacognitive agents. Domain expert agents are a subject area specialist. Coordinator agents control communications between other agents so as to facilitate coherent tutoring experiences.

The structures of the cognitive architectures that constitute these agents offer systematic forms through which the information is processed to give behavior. Popular educationally relevant architectures are production-rule systems, which emulate procedural knowledge, semantic networks, displaying conceptual relationships, neural architectures, supporting pattern recognition and generalization, hybrid architectures, which unite symbolic and subsymbolic processing, and emergent architectures, in which complex behaviours are generated by interactions between simple components. All architectures provide varying attributes as writing models on specific areas of learning and tutoring.

3.2 Multi-agent Cognitive Instructional Structure in Tutoring

Multi-agent systems in education are made up of several autonomous agents which work together in order to achieve tutoring goals which are beyond the capabilities of the single agents [6-9]. These systems have distributed intelligence in which knowledge and processing is distributed among agents, they operate parallelly that is they work concurrently on different tasks, and have emergent behavior meaning that interactions among agents create more advanced tutoring functions that are not programmed into single agents. In order to have an efficient multi-agent tutoring architecture, agent roles, agent communication protocol, agent coordination, and conflict management schemes are to be designed carefully. Role specification establishes the roles of each agent as well as the competencies it has. Communication protocols define the process through which the agents transfer information concerning the learners states, instruction plans and assessment outcomes. The coordination mechanisms make sure that the agents will be able to work in a synergistic, but not cross-purpose, manner. Conflict resolution is used in case of inconsistent instructional recommendations given by the agents. A number of architectural designs have sprung up when it comes to structuring of multi-agent tutoring systems. Hierarchical architectures make use of the higher-level agents who coordinate the lower-level specialized agents. Blackboard architectures involve shared knowledge repositories in which agents send information and respond to postings made by other agents. Architectures of the market enable the agents to bargain over instructional resources, or compete to deliver tutoring services.

The bogonic architectures develop nested systems where groups of agents act as one unit but maintain the internal complexity.

These architectures have advanced tutoring features, which are provided through the cognitive components that they incorporate. Perception modules consist of processing the learner inputs such as answers, questions, patterns of interaction as well as physiologic signals. Reasoning engines utilize pedagogical understanding to reason over states of learners and choose an intervention based on it. Planning elements produce learning sequences that meet the goals of learning and accommodate limitations. The methods of learning help the agents to enhance their effectiveness by having experience with a group of learners. Memory systems hold not only the short-term context but also long-term knowledge concerning individual learners. The communication between agents usually uses organized message formats, which represent the identities of agents, the types of messages, the content of messages, and the timestamps. Agents can communicate with each other via agent communication languages systems such as FIPA ACL or KQML. Ontologies offer common vocabularies that make sure that the agents understand educational concepts in a similar way. Parameters such as message routing, registration of agents and service discovery are done by middle-ware systems such as JADE, SPADE, or custom frameworks.

3.3 Adaptive Learning Personalizing Mechanisms

The agentic AI tutoring approach enables personalization on several dimensions at any given time. Personalization of content is the process of changing the content delivered to the learners depending on their acquired knowledge level, their interests, and the classroom needs. Strategy personalization varies the teaching of the content in which pedagogical methods are chosen based on the preferences of the learners and past experiences [10,11]. Pace personalization changes the pace of instructions in response to learning abilities of learners. Scaffolding personalization offers assistance on the right levels and then fades as the competence will improve. Personalization of feedback the feedback generates corrective and confirmatory messages depending on the characteristics of the learners. Effective personalization is all about the thorough learner modeling. Modern learner models represent cognitive aspects such as present levels of knowledge, misconceptions, professional level of skills, and their learning patterns. Affective dimensions represent emotions, motivation, engagement and self-efficacy. Interaction patterns, help seeking behavior and persistence are monitored on behavioral dimension. Metacognitive dimensions are self- extreme capabilities as well as learning configurations. Social aspects explain the preferences to collaboration and influence by peers. These representations are constantly updated as learner dynamic modeling receives new data. Bayesian knowledge tracing is not pragmatic; it maintains probabilistic belief of the mastery of skills, and can modify its beliefs on the basis of the performance evidence. Violated constraints which denote misconceptions are identified during constraint-based modeling. The deep learning models find latent patterns in behavior-sequences according to which the future performance can be predicted. Multi-dimensional item response theory estimates the abilities of learners in a variety of competency dimensions at the same time. Learner models are used in making instructional decisions in adaptation engines. Rule-based engines use pedagogical expertise represented in terms of condition-action rules. Constraint-based engines chose instructional actions that meet pedagogical constraints with an optimal learning goal. Reinforcement learning engines are trained on the best tutoring policies by trial and error on a large number of learners. Multi-armed bandit algorithms strike a balance to both explore new strategies and exploit existing known strategies which are effective.

Uniqueness of time dynamics of adaptation is a challenge. Macro-adaptation modifies the learning goals, the content area and learning method within weeks or months. Alterations in within-session strategies take place in meso-adaptation depending on the emerging patterns. Micro-adaptation is the response to immediate actions of a learner according to the proper feedback and hints. The adaptations that are planned among these timescales are synchronized by effective systems that are consistent and also reactionary.

3.4 More Sophisticated Techniques and Algorithms.

Modern agentic AI tutoring systems make use of the latest approaches of machine learning in undertaking multiple roles [12-14]. Deep neural networks consist of learning high-level trends in learner data and, therefore, predict performance, identify confusion, and create personalized content. Transformers and recurrent neural networks are designed to process sequential interactions between the learner and capture temporal dependencies in the learning pathways. Generative adversarial networks generate practice problems and various worked examples that are realistic. NLP facilitates conversational tutoring user interfaces which facilitate dialogue-based learning. Intent recognition is used to categorise the questions of a learner to make proper answers. Named entity recognition refers to the essential ideas on the utterances of the learners. Sentiment analysis identifies frustration, boredom or satisfaction in learner communications. Question generation specializes in invited pedagogically valuable questions to be used in practice and testing. Evaluation of answers is based on semantic similarity and rubric matching evaluation of free-text answers.

Reinforcement learning will deal with the serial decision making that is involved in tutoring. Markov decision processes represent tutoring in states that depict configurations of the learner-system, actions that depict the choice of instruction, and a rewards that depict the learning outcome. Q-learning and policy gradient process can learn useful tutoring policies that maximize the cumulative learning results. The Inverse Reorganization Learning: Inverse reinforcement learning entails the estimation of the reward functions based on the experience of experts tutoring, which understands pedagogical knowledge tacitly. Knowledge graphs technologies are domain knowledge in the form of concept-relationship networks. Graph neural networks process such structures, which allows one to engage in reasoning concerning conceptual dependencies and draw conclusions about the performance patterns of learners. Knowledge graph completion predicts the relationships, which are missing, and it assists in finding the prerequisite concepts. Graph embedding methods provide concept representations in the form of vectors to provide similarity calculation and analog generation.

Instructional planning is combinatorically complex and optimization algorithms are used to address it. Genetic algorithms develop learning sequences by means of selection, crossover and mutation. The simulated annealing algorithm avoids local optima in high instructional design spaces. Lesson plans are satisfying pedagogical requirements, time restrictions, and resource limitations that are found by the use of constraint satisfaction techniques. Multi-objective optimization strikes a compromise between such conflicting objectives as learning efficiency, learning engagement, and learning retention.

3.5 Affective Computing and Tuition which is emotion aware

Emotions are found to have profound effects on learning including attention, motivation, consolidation of memories and persistence [3,15-17]. The emotion-conscious tutoring agents obtain readings on the affective states of the learner and reacted accordingly to ensure the best emotional climate to facilitate learning. Some of the methods of affective computing include facial expression analysis based on computer vision to assess emotions based on webcam images, vocal affect recognition the analysis of speech prosody and tone, physiological sensing the determination of heart rate variation, skin conductance, and brain activity and behavioral pattern analysis to determine emotions based on interaction patterns. Some of the common emotional states that have been identified are engagement which means active participation and interest, confusion, which is a form of cognitive disequilibrium, which could result in learning; frustration which is a state experienced with repeated failure or poor explanations, boredom which is a lack of challenge or repetitive information, anxiety which is a state realized with high stakes tests or challenging material and delight that accompanies accomplishment or discovery. Emotion responsive tutoring strategies involve expression of sympathy that recognizes and accepts the feelings of learners, motivation intercessions that encourage persistence and effort attributing, difficulty adaptation that decreases aggravation by introducing variety to prevent boredom, anxiety circumvents strategies that allow new information or presentation to be introduced avoiding reduction, subjugation, and anxiety, and constructive struggle strategies that enable the learner to keep their hands on the plow so they can figure it out.

Modern systems are dynamic in nature and time-learning Since events and interventions are dynamically changing their effects on emotion. Hidden Markov models represent the time-sequences of emotions [18-20]. Dynamic Bayesian networks are causal relationships that exist among instructional events, appraisals about their learning experiences, emotion, and their behaviors. Learning in the case of Affective reinforcement maximizes policies to maximize learning and positive emotional experiences. In this subtopic, various authors explain how students can formulate their desired desired reaction and successfully reach the intended goal through the use of self-regulated learning and metacognitive support.

3.6 Metacognitive Support and Self-Regulated Learning

Efficient learners use metacognitive abilities such as planning how they plan to learn, tracking their comprehension, assessing their progress as well as managing their strategies [21-23]. These skills are rarely explicitly taught in the traditional instruction but can be scaffolded using agentic AI tutors in a number of ways. Metacognitive prompting pushes the learner to self-reflect by using questions such as asking the learners to assume the difficulty of the problem, their confidence in the answers, the reasoning process, what he or she is still confused about and how they intend to proceed with learning. These cues come at the strategic points to assist learners to be aware of metacognitive. Process visualization tools present the learners with their learning paths, time distribution in the topics, performance patterns, and the pattern of using strategies. Such visualizations enable self-monitoring and enable a learner to spot successful and unsuccessful strategies. Dashboard interfaces are shown to show progress in goals, mastery levels in the various competencies, personal bests or learning targets. Self-explanation prompts request the learners to define their rationale, support their responses, relate new information to previous knowledge, and pinpoint principles which are applicable to resolve problems. These techniques enhance the knowledge and build metacognitive processes. The quality of self-explanations is assessed by agentic tutors who give feedback that enhances skills when it comes to explanations. Error analysis support allows the learners to analyze their errors in a systematic and not random way. Agents direct thinking about the sources of errors that may be conceptual or procedural mistakes, or even the careless errors. The error-detection and correction skills are developed and can be applied in other contexts other than the tutoring setting.

Fig 1 Engagement Metrics vs. Learning Outcomes (Scatter Plot with Regression)

Fig. 1 examines the relationship between student engagement time (measured in hours) and learning outcomes (achievement scores 0-100). The data shows a strong positive correlation ($r=0.78$, $p<0.001$) up to approximately 15 hours, after which diminishing returns are evident. The regression line (blue) with 95% confidence interval (shaded area) indicates that each additional hour of engagement correlates with ~3.5 points improvement in scores. Color coding represents different AI agent types: pedagogical (blue), motivational (orange), and hybrid (green). Notably, hybrid agents achieve higher outcomes with less time investment, suggesting superior efficiency. This visualization helps optimize tutoring duration and agent selection strategies. The goal-setting interfaces assist learners to set certain, quantifiable, non-inconceivable learning goals. The agents help in breaking down the high-level ambitions into small sub-ambitions, putting timelines in place, and achieving the progress. The adaptive systems add or decrease the level of difficulty of the goals, depending on the performance of the learners, keeping the levels of difficulties at the optimal level.

3.7. Collaborative Learning in Multi-Agent Make-A-Wish.

The social learning theories underline that learning takes place in the course of interaction with other people. Multi-agent tutoring system is able to help learners to collaterate by linking human or AI learning companions. Pedagogical agents within collaborative environments play different roles such as facilitator agents which coordinate group activities, devil agent which creates challenges to group thinking, expert agent which provides knowledge about a given domain and observer agent which evaluates the quality of participation and contribution [9,24,25]. Group learning can be supported through computer assisted collaborative learning and AI agents however it helps in overcoming the frequent problems with group learning. Free-rider detection against students making little participation and therefore interventions promoting that participation are put in place. Dominance balancing does not allow individuals who dominate to have a monopoly in the discussion. Conflict mediation assists groups in solving conflicting matters in a constructive manner. The tracking of ideas makes sure that every input is taken into account and developed. The collaborative knowledge building agents mediate the collaborative process of knowledge building. These agents encourage groups to introduce the hypotheses, test them, resolve incompatibilities between opposing views, and be able to synthesize arguments. They also stockpile knowledge bases of the group, emphasized linkages among concepts, and areas that the group is unaware of and need to be filled. The peer learning support agents also support the process of effective peer tutoring by initiating a matching of learners based on complementary knowledge, tutee-tutor scaffolds which assist in enabling students to be able to explain concepts effectively, monitoring the quality of the explanation, and understanding of the tutee, and role rotations that ensure every learner has the opportunity to be a tutor and a learner.

The virtual learning companions are agent-like peers that involve learners into a conversation, collaborative efforts in solving problems, and reciprocal teaching. Such partners may be strategically fallible and will make explicit errors that might invoke learners to offer clarifications and corrections. This learning through teaching process takes advantage of the educational strengths of concept explanation which is one of the potent methods of learning.

3.8 Domain Applications

The agentic AI tutoring has extensively been used in mathematics education. Equation solving has cognitive models that are used by algebraic problem-solving tutors, and they include step-by-step instruction, error-specific feedback, and worked examples. In geometry tutors rely on diagrammatic reasoning which assists the learners form visual images to build proofs [26-28]. The tutors in calculus help in conceptual learning of limits, derivatives, and integrals as well as acquiring procedural fluency. Applications in programming education AI agents, which deliver programming comprehension support by visualizing programs, tracing program execution, debugging support to locate error occurrences, and providing suggestion to correct errors, code quality feedback in the form of style, efficiency and maintainability, and progressive sequencing of tasks based on easy to simplify exercises to complex projects have been reported to be beneficial to programming education. Vocabulary practises, grammar and culture Language learning tutors use conversational agents where learners are involved into a dialogue with the tutor. Speech recognition is also used to assess the collective voice by the pronunciation tutors and corrective feedback is provided. Writing tutors look at essays and analyse them in terms of organization, quality of argumentation and language mechanics thus giving revision tips. The support provided by science education agents include the scaffolding of hypothesis, experimental design, data analysis and inference. The virtual world of laboratories which include tutoring agents enables experimenting on hazardous or costly subjects. Intelligent guided simulation-based learning enables learners to find out the scientific principles in the process of experimentation. Several areas of professional training such as medical diagnosis, legal reasoning, business strategy, technical troubleshooting, use agentic tutors that provide believable situations, assess quality of decisions made, provide explanations of expert reasoning and monitoring competency acquisition over a hierarchic skillbased domain.

Table 1: Multi-Agent Tutoring System Components, Techniques, and Applications

Sr. No.	System Component	Primary Technique	Key Algorithm/Method	Application Domain	Current Challenge	Future Opportunity
1	Pedagogical Agent	Rule-based reasoning	Production systems with conflict resolution	Mathematics problem-solving	Knowledge acquisition bottleneck	Automated pedagogical knowledge extraction from expert demonstrations
2	Learner Modeling	Probabilistic inference	Bayesian knowledge tracing	Skills assessment across subjects	Cold-start problem with new learners	Transfer learning from similar learner populations
3	Content Selection	Collaborative filtering	Matrix factorization with temporal dynamics	Personalized reading recommendations	Content sparsity for niche topics	Hybrid content-collaborative approaches
4	Feedback Generation	Natural language generation	Template-based with neural refinement	Writing instruction and essay feedback	Generic feedback lacking specificity	Context-aware generation using learner history
5	Affective Detection	Multimodal fusion	Deep learning on facial, vocal, behavioral data	Emotional support in online learning	Privacy concerns with camera/audio monitoring	Privacy-preserving affect detection from interaction patterns
6	Dialogue Management	Reinforcement learning	Deep Q-networks for conversational strategy	Language learning conversation practice	Maintaining coherent long conversations	Memory-augmented networks for context retention
7	Assessment Agent	Adaptive testing	Computerized adaptive testing algorithms	Standardized test preparation	Item bank development and maintenance	Automatic item generation using language models
8	Metacognitive Scaffolding	Prompted reflection	Strategic questioning at decision points	Self-regulated learning development	Learner resistance to reflection prompts	Gamified metacognitive challenges
9	Collaboration Facilitator	Social network analysis	Centrality and participation metrics	Group project coordination	Detecting and attributing individual contributions	Fine-grained process mining of collaboration
10	Domain Expert	Knowledge graphs	Graph neural networks for reasoning	Science inquiry learning	Knowledge graph construction and maintenance	Automated knowledge extraction from textbooks
11	Motivational Agent	Persuasive technology	Behavioral change principles implementation	Engagement enhancement in MOOCs	One-size-fits-all motivational strategies	Personalized motivation profiles and strategies
12	Progress Monitoring	Time-series analysis	Recurrent neural networks on performance sequences	Early warning systems for dropout	False positives causing unnecessary intervention	Causal models distinguishing correlation from actionable factors
13	Resource Recommender	Content-based filtering	TF-IDF with semantic embeddings	Supplementary learning material suggestions	Limited understanding of learner context	Contextual bandits for exploration-exploitation balance
14	Cognitive Load Manager	Physiological sensing	Heart rate variability and eye tracking analysis	Difficulty adaptation in complex domains	Sensor obtrusiveness and setup complexity	Unobtrusive load estimation from interaction timing
15	Explanation Generator	Causal reasoning	Structural causal models	Science concept understanding	Generating explanations at appropriate complexity	Learner-adaptive explanation complexity

16	Practice Generator	Procedural generation	Constraint-based problem generation	Mathematics practice exercises	Ensuring problem diversity and pedagogy	Neural problem generation with pedagogical constraints
17	Error Diagnosis	Pattern recognition	Decision trees and rule induction	Programming debugging assistance	Ambiguous error situations with multiple interpretations	Uncertainty-aware diagnosis with explanation
18	Peer Matching	Similarity computation	Latent semantic analysis on learner models	Peer tutoring and collaboration	Static matching not adapting to changes	Dynamic re-matching based on evolving needs
19	Scheduling Optimizer	Constraint optimization	Integer linear programming	Personalized study schedule generation	Complex preferences and constraint conflicts	Preference learning from observed behavior
20	Transfer Assessment	Multi-task learning	Neural networks with shared representations	Measuring learning transfer across contexts	Defining and measuring meaningful transfer	Cognitive task analysis identifying transfer opportunities
21	Attention Director	Saliency detection	Visual attention models	Multimedia learning environments	Balancing guidance with learner autonomy	Adaptive attention guidance based on expertise
22	Conceptual Change Agent	Misconception libraries	Case-based reasoning with refinement	Physics and chemistry misconception correction	Incomplete misconception catalogs	Automated misconception discovery from error patterns
23	Worked Example Selector	Example-based learning	Analogical reasoning and similarity matching	Procedural skill acquisition	Example diversity and coverage	Generative models creating infinite example variations
24	Scaffolding Manager	Zone of proximal development estimation	Item response theory models	Reading comprehension support	Balancing assistance with productive struggle	Real-time ZPD estimation from interaction patterns
25	Cultural Adaptation	Cross-cultural psychology	Culture-specific pedagogical strategy mapping	Global learner populations	Limited cultural knowledge representation	Participatory design with diverse stakeholders
26	Accessibility Enhancer	Universal design principles	Multi-modal presentation and input	Learners with disabilities	One-size-fits-all accessibility features	Personalized accessibility based on individual needs
27	Question Answerer	Information retrieval	Dense passage retrieval with neural ranking	Help-seeking support across subjects	Answer quality and relevance	Knowledge-grounded generation with source citation
28	Learning Analytics Dashboard	Data visualization	Interactive visual analytics	Teacher and learner insights	Information overload and interpretation difficulty	AI-generated insights and narrative summaries
29	Prerequisite Identifier	Curriculum analysis	Dependency graph construction	Learning pathway planning	Implicit and variable prerequisite relationships	Empirical prerequisite discovery from learner data
30	Retention Predictor	Survival analysis	Cox proportional hazards models	Course completion forecasting	Model interpretability for intervention guidance	Causal survival models identifying intervention targets

3.9 Evaluation and Feedback creation.

Learning with formative assessment allows information to be given to adjust the instruction. Continuous assessment is used by agentic AI tutors, who have no access to only formal test scenarios and assess every interaction between a learner. Such fine-grained measurement allows to notice the wrong assumptions early and take corrective action. In adaptive testing algorithms, the article of assessment chosen is that which provides a maximum amount of information regarding the knowledge of the learner. Computerized adaptive testing is able to dynamically set the difficulty of items upon response patterns, which effectively estimate levels of ability [6,29-31]. Multi-stage testing integrates both fixed and adaptive sections and it strikes a balance between efficiency and coverage of content. During stealth assessment, the process of evaluation is integrated into the exciting games which means that test anxiety does not exist but validity is preserved.

Automatic feedback Production has become more advanced in case of simple correct-incorrect judgment as compared to elaborate explanatory responses. Template based feedback inserts the learner specific information in the message templates. Case-based reasoning recalls examples of feedbacks of similar situations in the past. Natural language generation generates custom representations of deep knowledge to come up with specific explanations. Multi-modal feedback is a mixture of text, drawings, animations, as well as interactive demonstrations. The educational impact of feedback is dependent on the timing of the feedback. Real time feedback discourages the reinforcement of errors and keeps the learning process going but can decrease useful struggle. The laggards in feedback promote consideration and self-corrective behavior. The adaptive timing policies that are obtained during the reinforcement learning process set the best feedback delays that are applicable on both the learners and the type of problem [32,33]. The content of feedback is verifying answer correctness, giving hints to instruct on a strategy, present worked examples of how the answer is calculated, as well as explaining concepts that underlie the answer. Good agents have the ability to chain the feedback type, where initial feedback should have little guidance, and increase the guidance as required.

3.10 Learning Analytics and Predictive Modeling

Learning analytics and predictive modeling involves applying artificial intelligence to analyze learning processes and forecast outcomes compared to the original inputs provided by learners. Learning analytics uses artificial intelligence to understand how learning happens and predict the outcomes in relation to the initial inputs that are given by learners. Learning analytics gather viable components out of educational data. Descriptive analytics is used to generalize the historical learning process, time-on-task, access trends of resources, and performance distributions. Factors that are related to success or struggle are detected by diagnostic analytics. Predictive analytics are used to predict future data such as the probability to complete a course, the final grade point, and the risk of dropping out. Prescriptive analytics suggest treatment of the best learning outcomes. Educational data mining identifies the trends in massive data. Learning dependency and co-occurring learning behavior are found by association rule mining. Cluster analysis classifies learners with a similar characteristic or course. Sequential pattern mining identifies similar patterns using learning materials. There is the anomaly detection which points to what may be cheating, system gaming, or special needs.

At-risk learners are predicted through their use to accomplish the early warning systems ahead of failure. The decision trees and the neural networks forecast dropout/probability of failed course interactions at the initial stages [34-36]. The survival analysis is used to estimate the time to some critical events such as withdrawal of the course. Causal inference techniques are used to create a distinction between the predictive correlations and intervention targets to act. Process mining is used to analyze event logics which show the way learners move through learning environments. Learning path models that are models of typical learning pathways are built by process discovery algorithms. Conformance checking involves setting comparison between normative model and individual learner processes in order to give deviations. Process enhancement adds the performance information to models indicating which pathways result into optimum outcomes.

3.11 Tools and Platforms for Multi-Agent Tutoring Development

Multi-agent tutoring currently draws upon tools and platforms being developed by researchers and practitioners alike, which in turn fosters the growth of this study. Multi-agent Tutoring Development Tools and Platforms Multi-agent tutoring is currently capitalizing on the emerging tools and platforms developed by both researchers and practitioners, supporting this study to grow as a result. The multi-agent tutoring systems are sophisticated to be developed using solid development platforms and tools. Agent development models are used to provide frameworks in the development, deployment and management of autonomous agents. JADE provides agent communication and lifecycle management that is standardized. SPADE incorporates Python-based agent development and current asynchronous programming. Multi-agent interaction simulation and testing Multi-agent interactions can be simulated and tested with agent-based modeling tool kits such as Net Logo and Repast. The cognitive architecture systems are used to make cognitively plausible agents. ACT-R is an architecture of human cognition that uses production systems. Soar is a set of learning mechanisms that has unified theories of cognition. With CLARION, hybrid symbolic connectionist architectures are made possible. Such models ascertain agents are representative of psychological rules of education and thinking.

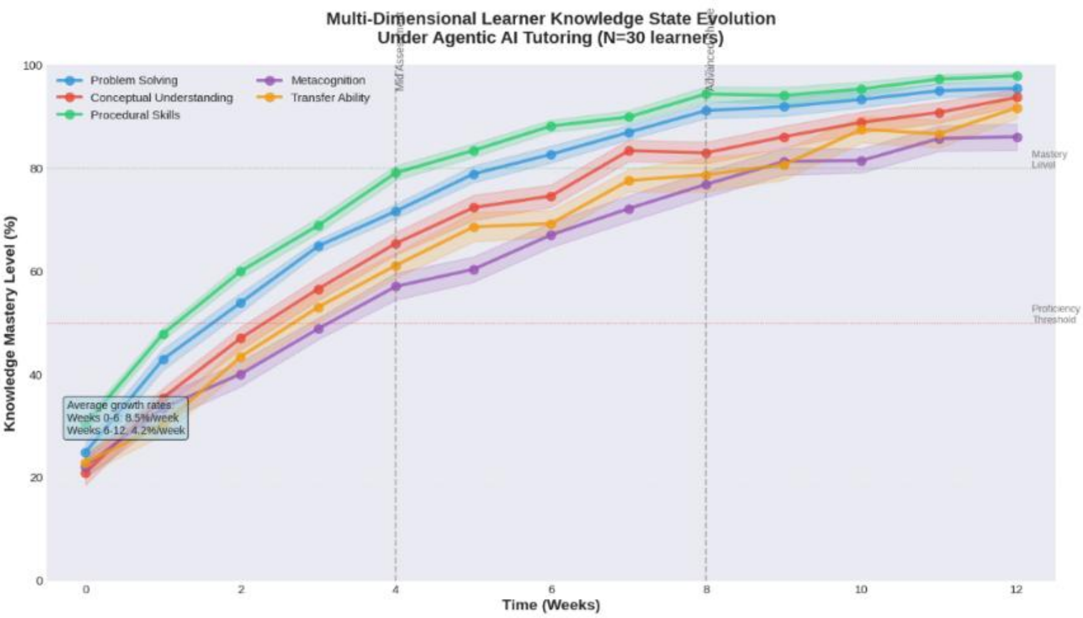

Fig. 2 Learner Knowledge State Evolution Over Time (Multi-line Time Series)

Fig. 2 tracks the evolution of learner knowledge mastery across five key competencies (Problem Solving, Conceptual Understanding, Procedural Skills, Metacognition, Transfer Ability) over 12 weeks of AI-tutored instruction. All competencies start at 20-30% mastery and show upward trajectories, reaching 75-85% by week 12. Problem Solving (blue line) shows the steepest early growth, reflecting the AI system's adaptive scaffolding. Metacognition (purple line) develops more gradually but accelerates after week 6, suggesting successful self-regulated learning development. The shaded confidence bands indicate measurement uncertainty. Transfer Ability (orange line) shows the most variable growth pattern with a plateau between weeks 4-7, representing the challenging transition from routine to novel problem contexts. This plot demonstrates the multi-dimensional nature of learning progress and helps identify optimal intervention

The learner modeling tool kits help in the modeling of student models. Knowledge tracing Probabilistic knowledge tracing is made possible with Bayesian network libraries. The neural learner models are supported by deep learning structures [16,37-40]. Patterns in educational data mining tools reveal concepts to design the model. Model repositories exchange validated learner models between them. The content authoring competitors enable educational personnel possessing no knowledge of programming to generate learning resources as well as specify tutoring behaviours. The rule-based authoring environments allow the subject experts to declare pedagogical strategies. Example-tracing tools allow tutors to use demonstration, as opposed to programming. AI-assisted authoring refers to the ability of a machine learning to propose a sequence of content and items of assessment. Multi-agent tutoring systems are integrated through integration platforms in a connection with learning management systems, student information systems and educational resource repositories. The Interoperability standards of Learning Tools allow integration of the tools. Experience API records intensive data of learning activity. Open Badges indicate the competency acquisition based on contexts. Cloud deployment web platforms are scalable to offer tutoring services to high number of learners. Containerization is useful in deployment uniformity. Microservices architecture gives support to modular system design. Serverless computing eliminates maintenance of infrastructure. Edge computing can also perform responsive local computation on interactions with low latency.

Table 2: Frameworks, Challenges, Implementations, and Strategic Directions

Sr. No.	Framework/Architecture	Core Principle	Implementation Platform	Primary Challenge	Mitigation Approach	Emerging Opportunity	Impact on Learning	Future Research Direction
1	Blackboard Architecture	Shared knowledge repository with specialist agents	JADE with custom blackboard	Concurrency control and consistency	Optimistic locking with conflict resolution	Distributed blackboard across cloud infrastructure	Enables complex multi-agent coordination	Blockchain-based immutable learning records
2	Hierarchical Multi-Agent	Layered control with supervisory agents	Custom Python framework	Inter-layer communication overhead	Asynchronous message passing	Neuromorphic computing for parallel processing	Mirrors human cognitive organization	Biologically-inspired hierarchical learning
3	Cognitive Tutoring	Production rules modeling expert problem-solving	ACT-R cognitive architecture	Domain-specific rule authoring effort	Machine learning rule discovery from demonstrations	Hybrid neural-symbolic rule learning	Strong theoretical cognitive grounding	Unified theories of learning across domains
4	Constraint-Based Modeling	Identifying violated domain constraints	ASPIRE tutoring system	Constraint set completeness	Automated constraint extraction from examples	Probabilistic soft constraints	Focuses on misconceptions not just knowledge	Constraint discovery from student error corpora
5	Companion Learning	Social peer-like agent collaboration	Pedagogical agent frameworks	Balancing competence and relatability	Adaptive competence demonstration	Emotionally intelligent virtual peers	Leverages learning-by-teaching effects	Long-term relationship development across years
6	Open Learner Models	Transparent learner model visualization	Interactive dashboards	Model accuracy and interpretability	Uncertainty communication in visualizations	Explainable AI for model transparency	Promotes metacognition and self-regulation	Co-constructed learner models with negotiation
7	Example-Tracing Tutors	Author by demonstration on problem solutions	Cognitive Tutor Authoring Tools	Limited generalization from examples	Inductive logic programming generalization	Neural program synthesis from few examples	Reduces authoring expertise requirements	One-shot learning of tutoring strategies
8	Stealth Assessment	Embedded evaluation in gameplay or activities	Game-based learning environments	Construct validity of embedded measures	Psychometric validation studies	Unobtrusive multimodal behavioral assessment	Reduces test anxiety and gaming	Real-time competency modeling without disruption
9	Conversational Tutors	Natural language dialogue-based instruction	Transformer-based language models	Dialogue coherence and pedagogical quality	Dialogue state tracking and planning	Large language models with educational grounding	Natural interaction reducing cognitive load	Socratic questioning and argumentation skills
10	Neuroadaptive Systems	Brain-computer interface driven adaptation	EEG headsets with real-time processing	Signal noise and individual calibration	Advanced signal processing and normalization	Non-invasive brain stimulation for enhancement	Direct cognitive state responsiveness	Closed-loop neural-pedagogical optimization
11	Augmented Reality Tutoring	Spatial computing with context awareness	ARKit/ARCore with educational overlays	Physical-digital registration accuracy	Computer vision and SLAM improvements	Persistent spatial anchors for location-based learning	Embodied and situated learning experiences	Mixed reality collaborative problem-solving

12	Federated Learning Models	Privacy-preserving distributed training	TensorFlow Federated or PyTorch	Communication efficiency and heterogeneity	Gradient compression and personalization layers	Secure multi-party computation integration	Collaborative improvement while protecting privacy	Cross-institutional learning analytics
13	Reinforcement Learning Tutors	Trial-and-error policy optimization	OpenAI Gym educational environments	Sample efficiency and safety	Off-policy learning and safe exploration	Model-based RL with world models	Data-driven discovery of effective strategies	Transfer of tutoring policies across subjects
14	Knowledge Graph-Based	Structured domain and learner knowledge	Neo4j or custom graph databases	Graph construction and maintenance	Automated knowledge extraction from content	Temporal knowledge graphs tracking concept evolution	Supports conceptual learning and transfer	Multi-modal knowledge graphs with visual/textual
15	Affective Computing Tutors	Emotion detection and responsive teaching	Affectiva SDK or custom models	Privacy and cultural emotion expression	Opt-in consent and diverse training data	Physiological wearables integration	Maintains optimal emotional climate	Emotional intelligence development as learning goal
16	Learning Analytics Engines	Data mining and predictive modeling	Educational data mining tools	Correlation versus causation	Randomized experiments and causal inference	Real-time streaming analytics	Evidence-based instructional improvement	Prescriptive analytics with intervention recommendations
17	Microservices Architecture	Loosely coupled specialized services	Docker containers with Kubernetes	Service coordination complexity	Service mesh and API gateways	Serverless functions for scaling	Flexible and maintainable system design	Auto-scaling based on learning demand patterns
18	Blockchain Credentialing	Immutable competency records	Ethereum or Hyperledger educational chains	Energy consumption and transaction costs	Proof-of-stake and layer-2 solutions	Decentralized learner-owned portfolios	Portable verifiable learning achievements	Micro-credentials and lifelong learning passports
19	Multi-Modal Learning Systems	Vision, language, and interaction fusion	Unified transformer architectures	Modality alignment and fusion	Cross-modal attention mechanisms	Haptic and olfactory modality integration	Accommodates diverse learning preferences	Brain-inspired multi-sensory integration
20	Quantum-Enhanced Optimization	Quantum annealing for NP-hard problems	D-Wave or quantum simulators	Qubit decoherence and error rates	Quantum error correction codes	Quantum machine learning algorithms	Optimal personalized curriculum sequencing	Quantum advantage in educational applications
21	Edge Computing Tutors	Local processing for low latency	Edge devices with TensorFlow Lite	Resource constraints on edge devices	Model compression and pruning	5G network-enabled distributed computation	Responsive interaction without cloud dependency	Federated edge learning across devices
22	Generative Content Systems	Automated problem and explanation creation	GPT-based generative models	Quality control and pedagogical validity	Human-in-the-loop validation workflows	Domain-constrained generation with verification	Unlimited personalized practice materials	Controllable generation with pedagogical constraints
23	Social Learning Networks	Peer interaction with AI facilitation	Custom social platforms with embedded agents	Managing group dynamics and conflicts	AI-mediated conflict resolution	Persistent learning communities across contexts	Collaborative knowledge construction	Network effects in distributed cognition
24	Hybrid Human-AI Teaching	Collaborative division of labor	Classroom integration platforms	Role clarity and coordination	Professional development and protocols	AI teaching assistants augmenting educators	Scalable personalization with human judgment	Optimal human-AI task allocation

25	Accessibility-First Design	Universal design with assistive integration	WCAG-compliant with assistive APIs	Diversity of disability types and needs	Modular accessibility features and customization	AI-powered real-time accommodations	Inclusive learning for all abilities	Proactive disability anticipation and support
26	Cultural Intelligence Systems	Cross-cultural adaptation	Multi-cultural content and interaction models	Cultural knowledge representation	Participatory design with cultural stakeholders	Cultural translation beyond language	Respectful global education access	Dynamic cultural model learning from interaction
27	Explainable AI Tutoring	Transparent decision rationale	LIME, SHAP integrated with tutoring	Explanation complexity for learners	Learner-appropriate explanation generation	Interactive explanation with learner queries	Trust and pedagogical transparency	Explanations as teaching opportunities
28	Lifelong Learning Companions	Continuous support across lifespan	Persistent learner models with inter-institutional APIs	Identity and data portability	Decentralized identifiers and verifiable credentials	Cross-context learning transfer	Coherent educational trajectory support	Developmental transitions and role changes
29	Gamification and Serious Games	Game mechanics for motivation	Unity or Unreal with embedded AI	Balancing fun and learning objectives	Game-based learning design frameworks	Procedural content generation for infinite variety	Intrinsic motivation and engagement	Flow state optimization through adaptive difficulty
30	Ethical AI Governance	Responsible AI principles in education	Ethics review boards and impact assessments	Balancing innovation and protection	Participatory ethics with stakeholder input	Algorithmic auditing and accountability	Trustworthy educational technology	Value-aligned AI that respects human dignity

3.12 Evaluation Metrics and Evaluation methods.

Strict assessment of the agentic AI tutoring systems will determine their effectiveness. Experimental studies with control are assigned learners due to randomization to either AI tutoring or comparison conditions and the outcome of learning is assessed by comparing the results of pre-post tests. Quasi-experimental designs are used in comparing intact groups in which it is not possible to randomize. Within subject designs have learners who undergo more than one condition, which controls individual differences [41-43]. The learning outcome measures will consist of short-term learning gains at the end of post-tests, retention after periods of absence, transfer to new problems or situations, and achievement of skills in competency hierarchies. Standardized measures allow making comparisons between studies, whereas the domain-specific scores help to embrace the special knowledge. Engagement metrics measures how there is a system use pattern like time on task, frequency of sessions, length of sessions, optional use outside of needs and tenacity in the face of difficulties. The quality measures of interaction include the measure of appropriateness of help-seeking and self-explanation and the frequency of metacognitive monitoring. The evaluation of user experience makes use of surveys that are based on satisfaction, perceived usefulness and ease of use. The cognitive load tests determine the presence of manageable cognitive loads on systems. Interviews and focus group help to offer learning qualitative information about the experience of the learners. The think-aloud protocols expose what the learners think when they interact with the system.

System performance measures assess how efficiently the system computes such as response time, throughput capability, resource usage and scalability. The measures of reliability monitor the system uptime, rate of errors, and load degradation. Maintenance measures are used to check how much effort is needed in terms of updates and extensions. A-B testing allows performing fastidious testing on design choices by presenting random samples to users of particular design choices. Multi-armed bandit strategies are dynamic in the sense that they assign learners to variants that are performing better. Bayesians are effective in optimization of design spaces with optimal configurations. Long-term effects studies monitor the results months or years after treatment and are assessed based on skill retention, educational advancement, career results, and career lifelong disposition in learning. These research studies justify the long-term learning benefits that are not directly linked to short-term test results.

3.13 Ethical Considerations and Responsible AI

Implementing agentic AI in the educational industry poses great ethical concerns that one should pay close attention to [44,45]. The most important aspect is privacy protection because the tutoring systems gather intimate information about what a learner knows, how and even what a learner does or does not feel. Minimization of data requires that data collection proceeds to the extent of what is required. Encryption is a data defense in both storage and transmission. The access controls are used to limit access to learner information. In anonymous research, methods of anonymization are used to eliminate identifying information on research records [22,30,46-48]. Algorithmic fairness involves assuring that systems are not discriminating against their characteristics as they are safeguarded. Bias testing looks at whether there is disparity in the results of systems among the demographic groups having similar abilities. The measures of fairness such as demographic parity, equalized odds, and calibration are measures of disparate impact. Various training information, bias limitations in the learning algorithms, and continuous tracking the biases are mitigation measures. Transparency allows the stakeholders to appreciate system functioning and decision-making. Explainable AI methods give justifiable explanations on tutoring suggestions. The explanations given to the users explain why some content or feedback was delivered. Algorithms and data streams are described in technical documentation where experts are involved in reviewing. Publication using the open source allows publication auditing and verification.

Learner agency will make sure that the students retain control of their learning processes. In the case of data collection or AI-mediated instruction, opt-in consent is acquired prior to it. Preference settings allow learners to make system adjustments. There is an option of override mechanisms in which system recommendations may be rejected. Exist doors give the learners an option of stopping AI tutoring without repercussions. Human judgment in key decisions related to education is ensured by human control. Automated high-stakes work review is done by teachers. The process of escalation directs the complicated scenarios to the human professionals. In human-in-the-loop systems, there is the need to approve of some actions before it is carried out by man. Supervisory control will provide the opportunity to intervene when the systems act outside the expected manner. The process of informed consent helps to make the learners and the guardians aware of the way AI tutoring is implemented and the information which is gathered. Explanations of capabilities and limitations on a system are age appropriate. Informal consent is done through the easy-to-understand language that does not include any technical terms. Consent can be revoked at any moment such as withdrawal mechanisms.

3.14 Challenges and Limitations

Nevertheless, agentic AIs tutoring systems are marked with huge obstacles that do not only curtail their performance but also their use. The problem of scalability comes up when trying to serve high groups of learners. Software complexity of advanced cognitive designs and real-time adaptability puts pressure on infrastructural budgets. The training of the models needs a lot of data of a great number of learners. The domain and pedagogical model expertise requires a lot of human expertise in acquisition of expert knowledge. Cold start issues arise in the cases where the systems do not have enough learner statistics in order to enable proper personalization. First learner models are based on stereotypes or the little information. The initial interactions take the form of exploration of the learner properties without necessarily positioning it in the best way. Transfer learning among the similar learners partially allays this problem but brings about a possible bias. The challenges of assessment are due to complicated outcomes of education. Learning is subject to innumerable influences other than tutoring systems. Studies that isolate system effects entail a lot of control. The lengthy processes are also expensive to quantify [49-51]. The difficulty of comparing systems lies in the varying methods of evaluation and measures of performance. bottlenecks on content authoring restrict domain coverage. Development of comprehensive learning is a demanding task in terms of professional effort. Business Coding pedagogical knowledge into machine-actionable formats requires special skills. It is necessary to keep domains up-to-date by continually investing. Auto content generation promises are on the doing but have to be checked in quality.

When implementing systems into practice in actual learning settings there are integration issues. Technical coordination is necessary to match the compatibility with existing learning management systems and student information systems. The implementation of AI tutoring requires planning in terms of meeting the standards of the curriculum and requirements established in the institutions. Effective classroom integration requires teacher development. The resistance is met and adoption guaranteed by the organizational change management. Robustness concerns occur during unexpected situations of the systems. The cases beyond training distributions might cause the modes of response. Other negative behaviors such as gaming the system and abusing hints, among other things, are adversarial to the learning purposes. Failure and errors in systems destroy learner confidence. On component failure, graceful degradation is used to preserve the functionality.

3.15 Future and New Opportunities and Future.

There is an opportunity of neuroadaptive learning interface which involves applying the brain-computer interfaces to identify cognitive states and dynamically adjust instruction based on these states. Electroencephalography tracks the brain activity in terms of attention, cognitive load and engagement. Functional near-infrared spectroscopy is used to measure the activity of brain regions in the learning process [52-55]. Closed-loop systems decrease difficulty, pacing, and modality using neural signatures. The advantages of using this approach are that it will be more responsive to learner conditions than ever before, although it will be necessary to tackle technical, practical, and ethical issues. Integration of augmented and virtual reality produces learners that are immersive through embedded intelligent tutoring. Spatial computing allows the visualization of abstract concepts in three-dimensional visualization. Embodied learning has been built on physical interaction of virtual objects. Contextual awareness varies the instructions depending on the location and activity of the learner. The virtual environments are distributed to support the social learning by a collaborative environment.

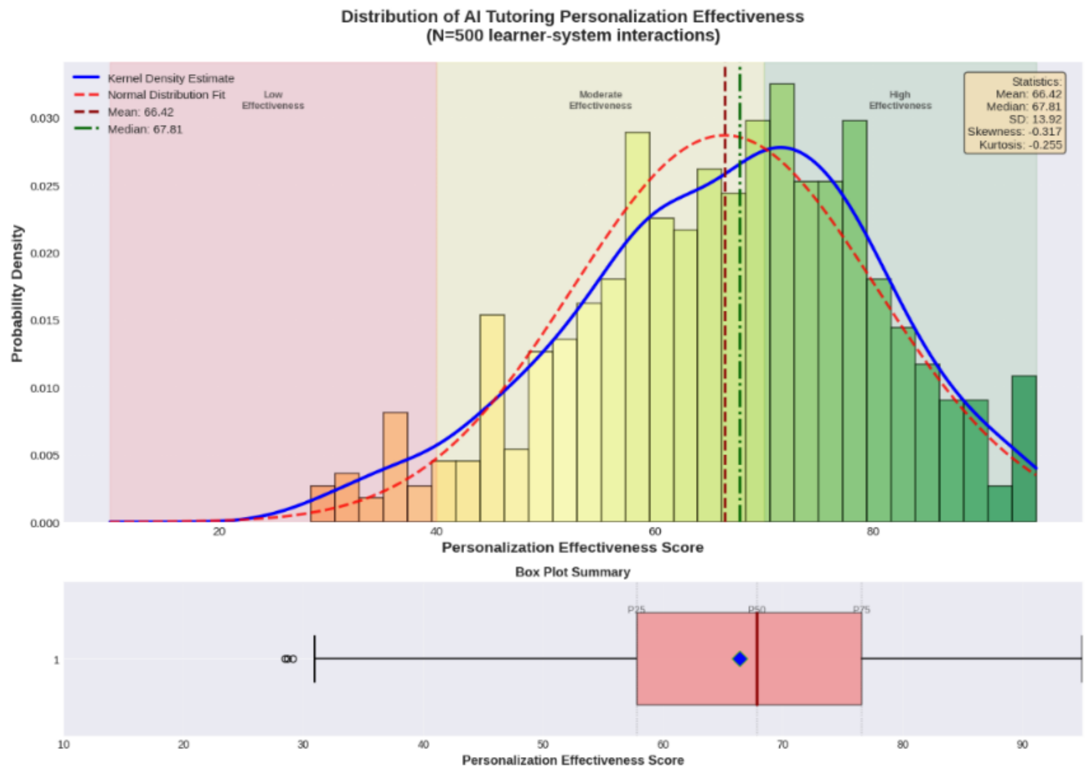

Fig 3 Distribution of Personalization Effectiveness

Fig. 3 shows the distribution of personalization effectiveness scores (0-100) across 500 learner-system interactions. The distribution is approximately normal but slightly right-skewed (skewness=0.34), with a mean effectiveness of 67.3 and median of 68.5. The peak around 70 suggests that for most learners, the multi-agent AI system achieves good personalization. However, the long-left tail (15-40 range) indicates that approximately 12% of learners experience suboptimal personalization, warranting further investigation into failure modes. The overlaid normal distribution (red dashed line) shows deviation from perfect normality, particularly in the upper quartile where effectiveness scores exceed 85, suggesting exceptional personalization for advanced learners. The secondary peak around 45 may indicate a specific learner subgroup (possibly struggling students) requiring specialized agent configurations.

Lifelong learning companions accompaniment of the learners throughout the educational changes to preserve the model of knowledge through the professional formation since childhood. Cross context learning transfer puts the knowledge in one area of learning to another application. Learning analytics provide lessons spans through time. Career guidance involves the application of the accumulated knowledge to promote educational directions. The standards of interoperability and organizational persistence are needed in this vision. In the future, quantum computing can be used to optimize and increase machine learning in tutoring systems. Quantum annealing would find solutions to such frustrating scheduling and sequencing. Quantum machine learning algorithms may find the patterns in educational data more effectively, in comparison to classical ones. Nevertheless, quantum hardware maturation and quantum algorithm development are yet to be applied in a practical way. Federated study allows institutional-level models to be trained together without violating data confidentiality. Learner information is stored within learning institutions and model update is provided. This method enhances the models with greater effective training sets to follow privacy policies. These methods of differential privacy provide mathematical privacy. Multi-institutional research that may progress the field and safeguard learners may be possible with the help of federated learning. Causal discovery techniques can be expected to allow going beyond correlation and discover mechanisms by which tutoring interventions influence learning. Structural equation modelling and directed acyclic graphs are a representation of causal relationships. Research on causal evidence is presented by randomized experiments and natural experiments. Knowing causation facilitates the designing of intervention on a principled basis and generalizability.

Hybrid human-AI models of teaching are models that combine the benefits of AI-based teaching in large-scale personalization with the ones of humans in complex judgment, creativity, and emotional appeal. Routine teaching is shared in collaborative teaching where AI takes care of the routine teachings whereas teachers deal with more complex cases. Teacher assistant AI systems are used to supplement teacher capacity, to perform grading, feedback, and general questions. This cooperation increases the power of education more than it can be by human beings or AI-only.

3.16. Sustainability and Resilience

Sustainability in education involves having systems which can perform adequately in the long term without the incessant external assistance. The sustainability of the economy requires affordable cost models that allow mass accessibility. The open-source models save on money spent on licensing and need to be maintained by a community. Freemium business models provide the essential services at no cost but the advanced features at a cost [23,56,57]. There are AI tutoring models in which it is considered education infrastructure funded by the government. Under the subset of technical sustainability, there must be maintainable code bases and architecture. Modular design allows it to make updates incrementally without rewrites to the overall system. Communication in documentation will facilitate the transfer of knowledge with the changing teams of developers. With automated testing, regression is prevented when changes are taking place. The decisions on technology are a balance between innovation and the need to support it in the long term. Pedagogical sustainability makes sure that methods are educationally valid with the increase in understanding. Research-practice Partnerships bridge the gap between system development and learning sciences research. The findings of educational research and practice are included in the iterative improvement. Evidence-based design basis the decisions made on legitimate principles but not trends. Technological resilience entails adjusting to change in infrastructure, development of the platform and the advent of new standards. Core logic is protected against dependency modifications by abstraction layers. Interoperability and migration are made easy with the help of standards compliance. Redundancy and failover mechanisms ensure that operation will go on even in case of components failure. Testers on disaster recovery are done on a regular basis to ensure contingency plans.

Flexible learning objectives are able to support various curricula and standards. Domain cover extensions are possible with the use of pluggable content modules. There are various pedagogical approaches that facilitate different educational philosophy. This flexibility provides life cycle adaptability of systems over the cycles of educational reform. Sustainability of the environment is taken into account in terms of energy consumption and carbon footprint of AI systems. Model efficiency studies are those in which a small model with low-computational intensity is constructed and performs well. The data centers that are operated through renewable energy will decrease carbon emission. Unnecessary processing is reduced through green practices. Lifecycle analysis measures the overall effects of environment.

3.17 Policy and Regulatory Landscape

In the context of this chapter, the policy and regulatory landscape will require exploration, and the particular programmatic aspects of the Regulatory Barrier Analysis (Head-On 2004) will be of significant concern [58-61]. The policies on educational technology put in place governance systems that regulate the use of AI tutoring. The regulations on data protection such as GDPR and FERPA limit the collection, storage, and sharing of data. The protection of student privacy is offered with special provisions of student data privacy laws. The measures needed to ensure compliance should include a design of a careful system that contains privacy-preserving measures and drawing of suitable consents. The regulations on accessibility require the education technologies to cover learners with disabilities. Web Content Accessibility Guidelines is developing technical standards of accessibility of digital media. Principles of universal design of learning inform the formation of a flexible learning experience that can serve the needs of any variety learning needs requirements. Integration of assistive technology facilitates the use of screen readers and alternative input devices, etc. Accountability systems ensure that failures and harms of systems are attributed responsibility. An example of these certification programs is ensuring that the systems are of quality and safe. Third party auditing gives impartial review of system functionality as well as the compliance. The requirements of reporting the incidents need to disclose failures that involve learners. Liability frameworks define the person to whom care was taken in the occurrence of harm when systems lead to damages.

The procurement policies direct the institutional choices concerning the adoption of AI tutoring systems. This is because of the evidence requirements that require being proved to be effective before purchase. Interoperability standards guarantee system incorporation with the current infrastructure. Transparency requirements of the vendors force the disclosure of algorithms, practices of data and assessment outcomes. TCOA does not only focus on the acquisition costs but on the implementation, training and maintenance costs as well. Equity policies eliminate digital inequities and unequal access to AI-enhanced education. Universal access efforts will offer technology and connectivity to underserved communities. Multilingual services mean that systems are available to the linguistically diverse learners. Cultural responsiveness transforms content and interactional styles to various cultural situations. Disability inclusion is not an add-on at the end of the design process, but included in the first design. There exist professional guidelines to AI-mediated teaching that present competencies that educators should have to integrate properly. Artificial intelligence, data-driven teaching, and human-AI relationships are included in teacher preparation programs. These skills are acquired through professional development opportunities that are offered to the practicing teachers. The programs on certification acknowledge the knowledge on AI-enabled teaching. The use of AI tools in the sphere of professional responsibilities is determined by ethical guidelines.

Those studies that assess the effectiveness of the tutoring systems are also subjected to research ethics procedures. The threats and safeguards of research are evaluated by institutional review boards. Informed voluntary processes provide the participants with the knowledge on study processes. Special segments put up extra measures on vulnerable populations including those that protect children and other vulnerable groups. Information about the participants of the research is secured by data security.

3.18 Cross-Cultural Considerations

The cultural differences between different educational practices and expectations are significant, and culturally responsive AI tutoring systems are needed. The pedagogical traditions are characterized by the differences in the focus on the individual or collective learning, the direct instruction or discovery, teacher/student authority or autonomy, rivalry or collaboration [62-64]. Systems that are created to work within one cultural setting might not work or can be offensive in another setting. The linguistic diversity requires the use of multilingual assistance which is not based on the mere translation. The pedagogical approaches are language dependent considering the system of writing, grammatical frameworks and the difficulty arising during language learning. The cultural allusions that are made in the examples and situations should appeal to the various learners. Code-switching recognition enables the learners to speak the way they want as opposed to making them use one language or dialect. Cultural knowledge presentation abstracts culturally-particular ideas, values and modes of knowing. The indigenous knowledge systems can have different structures of concept arrangements as compared to Western scientific models. Knowledge depends on historical and social contexts as it determines what knowledge should be valued and the method of its transfer. Cultural knowledge can be integrated in a respectful manner that does not entail appropriation of any kind and at the same time accepts the existence of different epistemologies. This is based on communication norms which shape proper behaviors of agents and the interaction style. Different cultures have different behavioral norms of directness of feedback, use of earthy language, acceptable humor, and criticism. The cultural allowability is influenced by avatar looks and naming. Embodied agents should also have their gesture and proxemics in accordance to the cultural expectations. According to evaluation, competition, and recognition, the assessment practices outline cultural values. Other cultures focus on the demonstration of mastery by tests with high stakes whereas some value the use of portfolio assessment. There are situations where public performance displays are appreciated whereas in others it creates anxiety. Feedback is culturally different in terms of the level of directness and emphasis on strengths and weaknesses. In the participatory design, the involvement of different cultural stakeholders assists in designing culturally responsive systems. Pedagogical skills based on values of the community are offered by local educators. The prototypes are tested by learners belonging to target groups, and the mismatches between cultures are detected. The respectful representation is guaranteed within community review processes. This participative style generates systems, which are acceptable within varying situations.

3.19 Impact on Educational Ecosystems

The systems of AI tutoring impact the whole educational ecosystem rather than just interaction of one person and one system. The role of teachers is changing where AI takes care of routine teaching and teachers on the other hand, get to do the complicated facilitating role, social emotional support and creative instruction [1,65,66]. The change in professional identity should be handled with a delicate change management that aids the teachers in these transitions. There are educators who accept AI as empowering but those who view it as threatening which should be addressed carefully. The adoption of AI is associated with institutional changes. Organizational designs can rearrange around hybrid educational experiences that look at models of blended learning involving human and AI teaching. The redistribution of resources is seen with an increased budget on technology, maybe an increase in the classes. The use of data analytics created by AI systems becomes more important in decision-making. The competencies of addressing technology strategy and data governance are added to the list of leadership competencies.

AI mediated learning modifies curriculum and assessment systems. The method of continuous AI evaluation making one capable of showing the mastery anytime it proves possible facilitates competency-based progression to a higher level. Individualized learning plans cut off the necessity of age-based grades [67-70]. The standard of performance could go up because AI tutoring will enhance the average performance. The evaluation process changes to evaluation of more profound ability that is uniquely acquired by humans. There is a response of higher education and workforce preparation to the prevalence of AI in learning. Universities repackage programs teaching skills that work alongside AI abilities as opposed to competing against them. AI enhanced learning is becoming part of professional training. Credential systems are modified to reflect skills that are presented in various situations such as AI tutoring spaces.

The approaches to learning research are changing with AI systems producing more information than ever before. Analytics of learning make it possible to study the learning processes on a fine basis. Pedagogical hypotheses can be tested quickly by means of A-B testing. The large-scale experimentation is possible. Nevertheless, these are limited by the ethical issues that restrict what one can conduct research on the students. The policy in education is changing with regard to AI tutoring opportunities and challenges. The funding process can evolve directing towards technology infrastructure and professional development. AI-generated data on achievement is in the accountability systems. According to equity policies, there is a difference in access. The laws that govern privacy are flexible

4. Conclusions

This has been a robust literature review of the changing scene of agentic systems of artificial intelligence which is utilized in the form of tutoring systems of personalized adaptive learning by utilizing multi-agent cognitive architectures. The process of synthesizing the current studies has identified a sphere that is technologically developing faster, becomes more sophisticated in terms of pedagogical application, and recognizes both opportunities and challenges in the field of AI-mediated education ever-increasing. The bottom line is that AI tutoring systems via multi-agents are a qualitative advance to the previous educational technologies. These systems employing autonomous agents with different specialization accomplish complex tutoring skills that are similar and sometimes even higher than the human performance in tutoring. The cognitive architecture based on learning sciences makes them pedagogically acceptable and the computational capacities permit them to make decisions about students in a way that humans can never accomplish. The integration of machine learning, natural language understanding, affective computing, and learning analytics results in systems that think through what is going on with learners in an all-encompassing manner, rationally decide on which instructions to give, and dynamically respond to the learner in real-time. The uses in varieties of educational fields show high levels of applicability. In elementary mathematics as in professional training, in language learning as in scientific inquiry, agentic AI tutors have been found to enhance learning outcomes, boost engagement and equitably deliver high-quality education. The ability of multi-agent architectures to support the flexible needs of different pedagogical requirements without sacrificing fundamental adaptive learning concepts can be demonstrated by domain-specific implementations.

The technical advancement of the current systems is impressive but in the state of continuous improvement. The deep learning makes sensitive pattern detection in behavior of learners possible. Reinforcement learning identifies optimal policies of tutoring by searching in a systematic manner. Knowledge graphs facilitate complex concepts with respect to conceptual relationships. The emotional intelligence of artificial tutors is literally to be added by the advent of affective computing. Conversational interfaces with the appearance of naturalness ranging close to human ones are made possible through natural language processing. These technologies are synergistically compatible and thus the capabilities achieved are beyond what any one of the techniques can perform. Enthusiasm is however bottlenecked by serious challenges. Scalability is still an issue. Since advanced cognitive architecture requires a lot of computing power. Evaluation practices are not yet standard which poses a challenge on cross-system comparison and the accumulation of knowledge. Authoring of content is a challenge that requires an expert and effort in content covering, which is restricted to long-tail educational topics. There are cold-start issues due to initial personalization, until there are adequate learners data. The incorporation into functioning learning situations is faced with institutional, technical, and social impediments. Ethical factors require a long-term care. Protection of privacy is to the fore since these systems record very extensive data concerning learners. Algorithms are threatening to propagate or exacerbate educational inequity. Complex deep learning models do not have transparency and explainability. Agency among learners should be retained whereby learners have an effective control over their learning experiences. Automated systems should not be used to make important decisions about education because human control will inhibit over-reliance. The identified opportunities are promising new directions in the future. Neuroadaptive interfaces hold out the promise of previously never before seen cognitive state responsiveness. AR and VR establish learning experiences. Lifelong learning companions promote lifelong learning. Federated learning supports joint model enhancement and the privacy protection. In learning causal discovery methods go beyond correlation to comprehend the workings. Hybrid human-AI instructions are an integration of the complimentary human and machine capabilities.

The sustainability and resiliency requirements shown above demonstrate the fact that technical excellence is not enough. The economical viability of systems is necessary to achieve the access by a large number of people instead of focusing on privileged groups. Technical sustainability mandates sustainability of architectures that endure technological change. The sustainability of pedagogy requires the basis on the proven learning principles instead of the educational trends. Environmental sustainability is one that regards energy consumption and carbon footprint. These dimensions are guaranteed of the long-term positive influence compared to the short-term newness. Regulatory and policy environment defines the course of action of this area. Data protection laws limit the type of information that can be gathered and in what manner the information will be applied. Inclusive design is required by the accessibility requirements which target learners with disabilities. Accountability systems will provide responsibility in case of failures in the systems. The Procurement policies govern the adoption of institutions. Equal opportunities policies deal with the inequality of access and corresponding results. Educator competency in employing AI is determined by professional standards. Ethics in research provide guidance to the study designs and protection of the participants. The reason is that cross-cultural remind us of the fact that the world is diverse in terms of education practices and values. Systems that have been adapted to fit in a single cultural setting might not be effective or offensive in another setting. It is not only translation that is needed to address linguistic diversities but culturally-responsive pedagogical procedures are also required. The practice of evaluation can be based on cultural values concerning assessment. The communication norms impact the proper agent behaviors. Active design processes that involve various stakeholders are useful in development of culturally-acceptable systems.

The effects of the educational ecosystems are way beyond the personal learner-system interaction. The role of a teacher should change to include complex facilitation as AI takes care of daily chores. Instead of just relying on traditional institutional structures, blended models of learning are reorganized using institutional structures. The systems of curriculum and assessment evolve according to the ongoing AI-mediated evaluation. Education and training Workforce The increase in AI is met by higher education. The approaches to educational research turn the possibilities of using unparalleled data. The policy develops with regards to new opportunities and challenges. A number of important implications can be made by the researchers, developers, educators, and policymakers. Researchers must emphasize on the long term effects studies, causal inference techniques, and uniform assessment models that will allow the compounding of knowledge. It is necessary to have cross-disciplinary collaboration which includes AI, cognitive science, learning sciences, and education. Human-centered design, the involvement of the educators in co-design, and the focus on accessibility, and cultural responsiveness should be prioritized by the developers even at the early phase. Modular architectures, because of their support of maintenance and evolution, evolve with the development of technologies and pedagogies. Professional development that educators obtain in favor of effective AI implementation will assist them in acquiring awareness of the possibilities and constraints, cultivating complementary skills, and ensuring that they retain proper control. Leadership in the institutions needs to plan AI implementation thoroughly and not only think about procurement of technology but also the change of the organisation, professional growth, and investment in the infrastructure. The policymakers ought to introduce governance systems based on a balance between innovation and protection, equitable access without resulting in algorithmic discrimination, research infrastructure benefiting the field. There are a number of potential lines of research that are promising in the future. To begin with, designing coherent theoretical frameworks between cognitive architectures and learning outcomes would allow designing systems with greater false another principle and predicting their performances with greater certainty. Second, the development of standard benchmarks and evaluating protocols would be able to compare and speed up the progress because of the competitive development. Third, exploring the best models in human-AI cooperation would provide answers regarding how to merge and integrate complementary advantages instead of making AI replace teachers. Fourth, the explainable AI methods in the educational settings should be advanced to provide greater trust and pedagogical visibility. Fifth, creating privacy-sensitive learning analytics that retrieve knowledge without compromising confidential information would be a solution to one of the key tensions. Sixth, the development of culturally-adaptive systems that can be of service to the global populations in a dignified manner would not only help to extend its benefits to those who are already benefited, but also include the rest of the world. Seventh, research into the long-term effects in the domain of educational transitions would provide the insight into the possibility of the benefits obtained early to be sustained.

The picture that is formed as a result of this review is the picture of low key optimism. The agentic AI-based tutoring systems involving multi-agent cognitive structures have the real potential to solve long-term educational issues. Individualized adaptive learning scale would decrease achievement disparities, support a variety of learning requirements and extend high-quality education to disadvantaged groups. Nevertheless, to achieve this potential, it is important to put in constant effort that will resolve technical, pedagogic, ethical, and social issues. Success requires the interdepartmental and intersectoral cooperation. Scientists should proceed with the development of the science basing the work on the real educational situations. The developers have to design effective, usable systems that are not distracted by the pedagogical principles and ethical stipulations. Teachers no longer can be passive users of technology and require to be active collaborators in designing and implementing new technologies. Any policy maker should put in place enabling governance structures that support innovations and prevent casualties. Students and the society have to be involved in the development of these technologies that will affect millions of lives. Technical sophistication is not the final indicator of success, but the influence of education. Do they work in increasing the learning of diverse masses? Is it that they boost instead of debased human agency? Are they fair or are they increasing the inequalities? Have they built what is important to prosperous lives? These are basic questions that are to be used in further development and deployment. This general overview has sketched the present situation, determined the obstacles and new opportunities and suggested the ways of the field development further. The synthesis that is presented in the form of detailed tables is a structured source of documentation on certain areas of the system design, implementation and evaluation. The suggested gaps indicate the areas where it is most needed to do research. The implications made imply tangible steps of actions to different stakeholders. Since the artificial intelligence capabilities are developing, their use in education can be expected to increase further. The base that is presently on the market through agentic AI tutoring systems with multi-agent cognitive architectures gives a starting point towards more advanced educational technologies. Nevertheless, improvement will have to come not only with technical innovation, but with prudence regarding what the success of education actually possesses, and about the complexity of the learning process of human beings. The way forward requires an ideal mix of excitement about technological possibility and practical acceptance of the reality about challenges and an unswerving dedication to address all learners fairly, efficiently as well as respectfully. The redefinition of education in the context of agentic AI is something new that is still under development. It will be seen in the coming years, whether this technology will deliver on its promises to democratize access to personalized high-quality instruction or will recreate the historic patterns of educational inequality.

Author Contributions

NG: Conceptualization, study design, resources, visualization, writing original draft, writing review and editing, and supervision. SH: Methodology, software, resources, visualization, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

References

[1] Todupunuri A. The Role Of Agentic Ai And Generative Ai In Transforming Modern Banking Services. American Journal of AI Cyber Computing Management. 2025 Sep 26;5(3):85-93. https://doi.org/10.64751/ajaccm.2025.v5.n3.pp85-93

[2] Gosmar D, Dahl DA. Hallucination mitigation using agentic ai natural language-based frameworks. arXiv preprint arXiv:2501.13946. 2025 Jan 19.

[3] Yamada Y, Lange RT, Lu C, Hu S, Lu C, Foerster J, Clune J, Ha D. The ai scientist-v2: Workshop-level automated scientific discovery via agentic tree search. arXiv preprint arXiv:2504.08066. 2025 Apr 10.

[4] Kshetri N. Transforming cybersecurity with agentic AI to combat emerging cyber threats. Telecommunications Policy. 2025 Jul 1;49(6):102976. https://doi.org/10.1016/j.telpol.2025.102976

[5] Huang L. Ethics of artificial intelligence in education: Student privacy and data protection. Science Insights Education Frontiers. 2023 Jun 30;16(2):2577-87. https://doi.org/10.15354/sief.23.re202

[6] Kamalov F, Santandreu Calonge D, Gurrib I. New era of artificial intelligence in education: Towards a sustainable multifaceted revolution. Sustainability. 2023 Aug 16;15(16):12451. https://doi.org/10.3390/su151612451

[7] Huang J, Saleh S, Liu Y. A review on artificial intelligence in education. Academic Journal of Interdisciplinary Studies. 2021 May;10(3). https://doi.org/10.36941/ajis-2021-0077

[8] Su J, Ng DT, Chu SK. Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities. Computers and Education: Artificial Intelligence. 2023 Jan 1;4:100124. https://doi.org/10.1016/j.caeai.2023.100124

[9] Idroes GM, Noviandy TR, Maulana A, Irvanizam I, Jalil Z, Lensoni L, Lala A, Abas AH, Tallei TE, Idroes R. Student perspectives on the role of artificial intelligence in education: A survey-based analysis. Journal of Educational Management and Learning. 2023 Jul 24;1(1):8-15. https://doi.org/10.60084/jeml.v1i1.58

[10] Tapalova O, Zhiyenbayeva N. Artificial intelligence in education: AIEd for personalised learning pathways. Electronic Journal of e-Learning. 2022;20(5):639-53. https://doi.org/10.34190/ejel.20.5.2597

[11] Alam A. Possibilities and apprehensions in the landscape of artificial intelligence in education. In2021 International conference on computational intelligence and computing applications (ICCICA) 2021 Nov 26 (pp. 1-8). IEEE. https://doi.org/10.1109/ICCICA52458.2021.9697272

[12] Limna P, Jakwatanatham S, Siripipattanakul S, Kaewpuang P, Sriboonruang P. A review of artificial intelligence (AI) in education during the digital era. Advance Knowledge for Executives. 2022 Jul;1(1):1-9.

[13] Doroudi S. The intertwined histories of artificial intelligence and education. International Journal of Artificial Intelligence in Education. 2023 Dec;33(4):885-928. https://doi.org/10.1007/s40593-022-00313-2

[14] Nguyen A, Ngo HN, Hong Y, Dang B, Nguyen BP. Ethical principles for artificial intelligence in education. Education and information technologies. 2023 Apr;28(4):4221-41. https://doi.org/10.1007/s10639-022-11316-w

[15] Paek S, Kim N. Analysis of worldwide research trends on the impact of artificial intelligence in education. Sustainability. 2021 Jul 16;13(14):7941. https://doi.org/10.3390/su13147941

[16] Chiu TK, Xia Q, Zhou X, Chai CS, Cheng M. Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. Computers and Education: Artificial Intelligence. 2023 Jan 1;4:100118. https://doi.org/10.1016/j.caeai.2022.100118

[17] Akgun S, Greenhow C. Artificial intelligence in education: Addressing ethical challenges in K-12 settings. AI and Ethics. 2022 Aug;2(3):431-40. https://doi.org/10.1007/s43681-021-00096-7

[18] Pratama MP, Sampelolo R, Lura H. Revolutionizing education: harnessing the power of artificial intelligence for personalized learning. Klasikal: Journal of education, language teaching and science. 2023 Aug 10;5(2):350-7. https://doi.org/10.52208/klasikal.v5i2.877

[19] Tan X, Cheng G, Ling MH. Artificial intelligence in teaching and teacher professional development: A systematic review. Computers and Education: Artificial Intelligence. 2025 Jun 1;8:100355. https://doi.org/10.1016/j.caeai.2024.100355

[20] Abbasi BN, Wu Y, Luo Z. Exploring the impact of artificial intelligence on curriculum development in global higher education institutions. Education and Information Technologies. 2025 Jan;30(1):547-81. https://doi.org/10.1007/s10639-024-13113-z

[21] Baig MI, Yadegaridehkordi E. Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education. International Journal of Educational Technology in Higher Education. 2025 Feb 3;22(1):5. https://doi.org/10.1186/s41239-025-00506-4

[22] Yang Z, Wu JG, Xie H. Taming Frankenstein's monster: Ethical considerations relating to generative artificial intelligence in education. Asia Pacific Journal of Education. 2025 Aug 8;45(4):1330-43. https://doi.org/10.1080/02188791.2023.2300137

[23] Abulibdeh A, Zaidan E, Abulibdeh R. Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions. Journal of Cleaner Production. 2024 Jan 15;437:140527. https://doi.org/10.1016/j.jclepro.2023.140527

[24] Qiu J, Lam K, Li G, Acharya A, Wong TY, Darzi A, Yuan W, Topol EJ. LLM-based agentic systems in medicine and healthcare. Nature Machine Intelligence. 2024 Dec;6(12):1418-20. https://doi.org/10.1038/s42256-024-00944-1

[25] Li Y, Zhou X, Yin HB, Chiu TK. Design language learning with artificial intelligence (AI) chatbots based on activity theory from a systematic review. Smart Learning Environments. 2025 Mar 10;12(1):24. https://doi.org/10.1186/s40561-025-00379-0

[26] Markauskaite L, Marrone R, Poquet O, Knight S, Martinez-Maldonado R, Howard S, Tondeur J, De Laat M, Shum SB, Gašević D, Siemens G. Rethinking the entwinement between artificial intelligence and human learning: What capabilities do learners need for a world with AI?. Computers and Education: Artificial Intelligence. 2022 Jan 1;3:100056. https://doi.org/10.1016/j.caeai.2022.100056

[27] Sudarshan M, Shih S, Yee E, Yang A, Zou J, Chen C, Zhou Q, Chen L, Singhal C, Shih G. Agentic llm workflows for generating patient-friendly medical reports. arXiv preprint arXiv:2408.01112. 2024 Aug 2.

[28] McIntosh TR, Susnjak T, Liu T, Watters P, Xu D, Liu D, Halgamuge MN. From Google Gemini to OpenAI Q*(Q-Star): a survey on reshaping the generative artificial intelligence (AI) research landscape. Technologies. 2025 Jan 30;13(2):51. https://doi.org/10.3390/technologies13020051

[29] Ladak A, Loughnan S, Wilks M. The moral psychology of artificial intelligence. Current Directions in Psychological Science. 2024 Feb;33(1):27-34. https://doi.org/10.1177/09637214231205866

[30] Teo ZL, Thirunavukarasu AJ, Elangovan K, Cheng H, Moova P, Soetikno B, Nielsen C, Pollreisz A, Ting DS, Morris RJ, Shah NH. Generative artificial intelligence in medicine. Nature medicine. 2025 Oct;31(10):3270-82. https://doi.org/10.1038/s41591-025-03983-2

[31] Hanna MG, Pantanowitz L, Dash R, Harrison JH, Deebajah M, Pantanowitz J, Rashidi HH. Future of artificial intelligence-machine learning trends in pathology and medicine. Modern Pathology. 2025 Apr 1;38(4):100705. https://doi.org/10.1016/j.modpat.2025.100705

[32] Habler I, Huang K, Narajala VS, Kulkarni P. Building a secure agentic AI application leveraging A2A protocol. arXiv preprint arXiv:2504.16902. 2025 Apr 23.

[33] Sperling K, Stenberg CJ, McGrath C, Åkerfeldt A, Heintz F, Stenliden L. In search of artificial intelligence (AI) literacy in teacher education: A scoping review. Computers and Education Open. 2024 Jun 1;6:100169. https://doi.org/10.1016/j.caeo.2024.100169

[34] Sabri H, Saleh MH, Hazrati P, Merchant K, Misch J, Kumar PS, Wang HL, Barootchi S. Performance of three artificial intelligence (AI)-based large language models in standardized testing; implications for AI-assisted dental education. Journal of periodontal research. 2025 Feb;60(2):121-33. https://doi.org/10.1111/jre.13323

[35] Kamila MK, Jasrotia SS. Ethical issues in the development of artificial intelligence: recognizing the risks. International Journal of Ethics and Systems. 2025 Jan 30;41(1):45-63. https://doi.org/10.1108/IJOES-05-2023-0107

[36] Nemorin S, Vlachidis A, Ayerakwa HM, Andriotis P. AI hyped? A horizon scan of discourse on artificial intelligence in education (AIED) and development. Learning, Media and Technology. 2023 Jan 2;48(1):38-51. https://doi.org/10.1080/17439884.2022.2095568

[37] Su J, Yang W. Artificial intelligence in early childhood education: A scoping review. Computers and Education: Artificial Intelligence. 2022 Jan 1;3:100049. https://doi.org/10.1016/j.caeai.2022.100049

[38] Zadorina O, Hurskaya V, Sobolyeva S, Grekova L, Vasylyuk-Zaitseva S. The role of artificial intelligence in creation of future education: Possibilities and challenges. Futurity Education. 2024 Apr 30;4(2):163-85.

[39] Bobula M. Generative artificial intelligence (AI) in higher education: A comprehensive review of challenges, opportunities, and implications. Journal of Learning Development in Higher Education. 2024 Mar 27(30). https://doi.org/10.47408/jldhe.vi30.1137

[40] Masters K. Ethical use of artificial intelligence in health professions education: AMEE Guide No. 158. Medical teacher. 2023 Jun 3;45(6):574-84. https://doi.org/10.1080/0142159X.2023.2186203
[41] Linderoth C, Hultén M, Stenliden L. Competing visions of artificial intelligence in education-A heuristic analysis on sociotechnical imaginaries and problematizations in policy guidelines. Policy Futures in Education. 2024 Nov 13;22(8):1662-78. https://doi.org/10.1177/14782103241228900
[42] Erduran S, Levrini O. The impact of artificial intelligence on scientific practices: an emergent area of research for science education. International Journal of Science Education. 2024 Dec 11;46(18):1982-9. https://doi.org/10.1080/09500693.2024.2306604
[43] Borger JG, Ng AP, Anderton H, Ashdown GW, Auld M, Blewitt ME, Brown DV, Call MJ, Collins P, Freytag S, Harrison LC. Artificial intelligence takes center stage: exploring the capabilities and implications of ChatGPT and other AI-assisted technologies in scientific research and education. Immunology and cell biology. 2023 Nov;101(10):923-35. https://doi.org/10.1111/imcb.12689
[44] Moradbakhti L, Schreibelmayr S, Mara M. Do men have no need for "feminist" artificial intelligence? Agentic and gendered voice assistants in the light of basic psychological needs. Frontiers in psychology. 2022 Jun 14;13:855091. https://doi.org/10.3389/fpsyg.2022.855091
[45] Hosseini S, Seilani H. The role of agentic ai in shaping a smart future: A systematic review. Array. 2025 Jul 1;26:100399. https://doi.org/10.1016/j.array.2025.100399
[46] Murugesan S. The rise of agentic AI: implications, concerns, and the path forward. IEEE Intelligent Systems. 2025 Apr 10;40(2):8-14. https://doi.org/10.1109/MIS.2025.3544940
[47] Gridach M, Nanavati J, Abidine KZ, Mendes L, Mack C. Agentic ai for scientific discovery: A survey of progress, challenges, and future directions. arXiv preprint arXiv:2503.08979. 2025 Mar 12.
[48] Chan A, Salganik R, Markelius A, Pang C, Rajkumar N, Krasheninnikov D, Langosco L, He Z, Duan Y, Carroll M, Lin M. Harms from increasingly agentic algorithmic systems. InProceedings of the 2023 ACM conference on fairness, accountability, and transparency 2023 Jun 12 (pp. 651-666). https://doi.org/10.1145/3593013.3594033
[49] Wei J, Yang Y, Zhang X, Chen Y, Zhuang X, Gao Z, Zhou D, Wang G, Gao Z, Cao J, Qiu Z. From ai for science to agentic science: A survey on autonomous scientific discovery. arXiv preprint arXiv:2508.14111. 2025 Aug 18.
[50] Jiang F, Pan C, Wang K, Michiardi P, Dobre OA, Debbah M. From large ai models to agentic ai: A tutorial on future intelligent communications. IEEE Journal on Selected Areas in Communications. 2026 Feb 2. https://doi.org/10.1109/JSAC.2026.3660010
[51] Mohammed A. Agentic AI as a Proactive Cybercrime Sentinel: Detecting and Deterring Social Engineering Attacks. Journal of Data and Digital Innovation (JDDI). 2025 Jun 16;2(2):109-17.
[52] Belcak P, Heinrich G, Diao S, Fu Y, Dong X, Muralidharan S, Lin YC, Molchanov P. Small language models are the future of agentic ai. arXiv preprint arXiv:2506.02153. 2025 Jun 2.
[53] Bousetouane F. Agentic systems: A guide to transforming industries with vertical ai agents. arXiv preprint arXiv:2501.00881. 2025 Jan 1. https://doi.org/10.32388/2DKDCK
[54] Sapkota R, Roumeliotis KI, Karkee M. Vibe coding vs. agentic coding: Fundamentals and practical implications of agentic ai. arXiv preprint arXiv:2505.19443. 2025 May 26.
[55] Floridi L. AI as Agency without Intelligence: On Artificial Intelligence as a New Form of Artificial Agency and the Multiple Realisability of Agency Thesis: L. Floridi. Philosophy & Technology. 2025 Mar;38(1):30. https://doi.org/10.1007/s13347-025-00858-9
[56] Meng L. From Reactive to Proactive: Integrating Agentic AI and Automated Workflows for Intelligent Project Management (AI-PMP). Frontiers in Engineering. 2025 Nov 26;1(1):82-93. https://doi.org/10.63313/FE.9003
[57] Shavit Y, Agarwal S, Brundage M, Adler S, O'Keefe C, Campbell R, Lee T, Mishkin P, Eloundou T, Hickey A, Slama K. Practices for governing agentic AI systems. Research Paper, OpenAI. 2023 Dec 14.
[58] Singh A, Ehtesham A, Kumar S, Khoei TT. Enhancing AI systems with agentic workflows patterns in large language model. In2024 IEEE World AI IoT Congress (AIIoT) 2024 May 29 (pp. 527-532). IEEE. https://doi.org/10.1109/AIIoT61789.2024.10578990
[59] Townsend DM, Hunt RA, Rady J, Manocha P, Jin JH. Are the futures computable? Knightian uncertainty and artificial intelligence. Academy of Management Review. 2025 Apr;50(2):415-40. https://doi.org/10.5465/amr.2022.0237
[60] Singh A, Ehtesham A, Kumar S, Khoei TT. Agentic retrieval-augmented generation: A survey on agentic rag. arXiv preprint arXiv:2501.09136. 2025 Jan 15.
[61] Acharya DB, Kuppan K, Divya B. Agentic AI: Autonomous intelligence for complex goals-A comprehensive survey. IEEe Access. 2025 Jan 22;13:18912-36. https://doi.org/10.1109/ACCESS.2025.3532853

[62] Hughes L, Dwivedi YK, Malik T, Shawosh M, Albashrawi MA, Jeon I, Dutot V, Appanderanda M, Crick T, De' R, Fenwick M. AI agents and agentic systems: A multi-expert analysis. Journal of Computer Information Systems. 2025 Jul 4;65(4):489-517. https://doi.org/10.1080/08874417.2025.2483832

[63] Vanneste BS, Puranam P. Artificial intelligence, trust, and perceptions of agency. Academy of Management Review. 2024 Mar 22(ja):amr-2022. https://doi.org/10.2139/ssrn.3897704

[64] Schneider J. Generative to agentic ai: Survey, conceptualization, and challenges. arXiv preprint arXiv:2504.18875. 2025 Apr 26.

[65] Karunanayake N. Next-generation agentic AI for transforming healthcare. Informatics and Health. 2025 Sep 1;2(2):73-83. https://doi.org/10.1016/j.infoh.2025.03.001

[66] Borghoff UM, Bottoni P, Pareschi R. Human-artificial interaction in the age of agentic AI: a system-theoretical approach. Frontiers in Human Dynamics. 2025 May 9;7:1579166. https://doi.org/10.3389/fhumd.2025.1579166

[67] Plaat A, van Duijn M, Van Stein N, Preuss M, van der Putten P, Batenburg KJ. Agentic large language models, a survey. Journal of Artificial Intelligence Research. 2025 Dec 30;84. https://doi.org/10.1613/jair.1.18675

[68] Xiao Y, Shi G, Zhang P. Toward agentic ai networking in 6g: A generative foundation model-as-agent approach. IEEE Communications Magazine. 2025 Sep 8;63(9):68-74. https://doi.org/10.1109/MCOM.001.2500005

[69] Qu Y, Huang K, Yin M, Zhan K, Liu D, Yin D, Cousins HC, Johnson WA, Wang X, Shah M, Altman RB. CRISPR-GPT for agentic automation of gene-editing experiments. Nature Biomedical Engineering. 2025 Jul 30:1-4. https://doi.org/10.1038/s41551-025-01463-z

[70] Kolagani SH. Agentic Automation and Work Flow Orchestration in Enterprise SaaS: Effects on Ticket Resolution Time and Employee Productivity in IT Service Management. IJSAT-International Journal on Science and Technology. 2024 Nov 8;15(4). https://doi.org/10.71097/IJSAT.v15.i4.9876