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ARCHITECTURES AND APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN MODERN EDUCATION [3]

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Abstract: *This article offers an analytical review of the basic architectures of artificial intelligence (AI), which are used or have the potential for application in educational environments, as well as the key realizations and their effects on the learning process. The text views the classic symbolic approaches, the methods of machine and deep training, as well as the transformer-based large language models (LLMs). A comparative analysis of criteria such as accuracy, adaptability, transparency and technical resistance has been presented, ethical and regulatory challenges have been discussed and guidelines for future studies, including the role of neuro-sybolic hybrids, have been formulated. The key findings point to the increasing value of hybrid solutions and increasing challenges caused by generative models in terms of academic honesty and reliability of automated assessments.*

Keywords: *Artificial Intelligence in Education; Intelligent Tutoring Systems; Large Language Models; Neuro-symbolic; Learning Analytics; Ethics.*

INTRODUCTION

The use of Artificial Intelligence in Education (AIED) has expanded rapidly in recent years, from early expert systems and intelligent tutoring systems to modern adaptive platforms and generative language models capable of dialogue and content creation. This dynamic evolution is driven by two parallel forces: advances in computational architectures and algorithms (including transformers and large-scale neural models), and the accumulation of extensive educational datasets coupled with growing demand for personalised learning. Despite promises for improved outcomes and broader access to high-quality education, AI deployment introduces complex challenges related to transparency, fairness, privacy and academic integrity.

Summary of recent peer-reviewed studies and systematic reviews (2023–2025) investigating AI and LLMs in education is given in Table 1.

Table 1

Study (year)	Context / Domain	Sample Size / Type	Outcome(s) Measured	Reported Effect (metric)
Filippi, S., & Motyl, B., 2024	Engineering education (systematic review)	20 studies selected	Adoption context, pedagogical recommendations	Narrative synthesis
Liu et al., 2025	EFL / Critical Thinking (systematic review)	15 studies	Critical thinking development	Mixed outcomes; 66.7% positive
Zhang & Zhang, 2024	Teacher education	202 students; 68 staff	Perceptions; digital literacy	Questionnaire statistics (p-values)
Traga Philippakos & Rocconi, 2025	K-12 teacher AI literacy	292 teachers	AI competence scale, PD needs	Scale validation, ANOVA

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Seo et al., 2025	LLMs as evaluators	Varied experiments	Consistency and accuracy of LLM feedback	Precision/recall, F1, AUC in some studies
Kosmyna et al., 2025	Student cognitive engagement	n=54 experimental	EEG measures, essay performance	Group differences reported

Ensuring responsible and ethical integration requires a systematic analysis of architectures, applicable scenarios and limitations. This article provides such a systematic review and comparative analysis.

EXPOSITION

Architectures of AI Systems in Education

AI architectures relevant to education can be classified into four main categories: symbolic (rule-based) systems, classical machine learning, deep learning (including transformer-based models), and neuro-symbolic hybrids. Each offers trade-offs in terms of interpretability, adaptability and resource requirements. Cognitive models (for example, model tracing and knowledge tracing) inform many ITS designs by linking learner states to pedagogical decisions.

The classic symbolic architectures were among the first used in educational technologies. These systems, including expert and rule-Based approaches, work through formalized knowledge of knowledge and removal rules that allow explanatory solutions and easy validation by subject experts. Approaches in this category are used in early intelligent training systems and educational assistants, where transparency and causal explanation are important. However, the restriction of symbolic systems is their dependence on handmade rules and the difficulty of scaling for rich, informal domains.

With the development of machine learning (ML) and the accessibility of empirical data, approaches based on statistical models and neural networks have begun to dominate. The supervised and uninvited training allowed the extraction of behavior patterns and presenting students from interaction data. Deep neural networks have expanded the ability to process text, speech and images and have led to a significant improvement in tasks such as automatic evaluation, speech recognition and emotional analysis. However, these methods often suffer from a shortage of transparency and require large sets of labeled data for good performance (Guo, L., Lu, L., et al., 2021).

In 2017, the transformer architecture changed the landscape of NLP through the mechanism of attention, which allowed more efficient modeling of long-term dependencies in ranks of symbols and created the basis for large language models (LLMs). Transformers have proven high flexibility and adaptability in many tasks and have generated GPT, Palm, etc. models, which are already used as interactive assistants, educational generators and dialogue tools in a learning environment. However, LLMs also demonstrates specific weaknesses, including "Hallucinations" (inventing facts), lack of real understanding and problems with reliability in evaluating training results (Peters, J., 2024), (Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I., 2017).

Neuro-Symbolic hybrids are a prospective direction for combining the benefits of the symbolic and neural approach: combining the explanatory logic and structured knowledge with the ability of neural networks to extract noisy data. Trends in literature show increased interest in such integrations in order to increase the explanability, reliability and suitability for complex educational tasks (Colelough, B. C., & Regli, W., 2025), (Garcez, A. d'Avila, & Lamb, L. C., 2020).

A comparison of characteristics of these four AI architectures relevant to educational applications is given in Table 2.

Table 2

Architecture	Core Mechanism	Typical Educational Use	Strengths	Limitations
Classic Symbolic (Rule-Based)	Relies on manually defined logical rules, symbolic representations, and expert systems that model domain knowledge using if–then logic, ontologies, and inference engines.	Used in early Intelligent Tutoring Systems (e.g., SHERLOCK, GUIDON, WHY) and automated assessment tools focused on structured domains such as mathematics, physics, and formal grammar.	High transparency and interpretability; deterministic reasoning process; reliable and consistent behavior in well-defined domains; easy to audit and explain feedback; low computational cost.	Poor generalization and flexibility; cannot learn from data; requires manual rule encoding and continuous expert intervention; scales poorly across open-ended or ill-structured domains.
Neural / Deep Learning	Based on multi-layer artificial neural networks trained on large datasets through optimization algorithms such as gradient descent; relies on statistical pattern recognition and representation learning.	Applied in adaptive learning systems (e.g., Carnegie Learning MATHia), handwriting or speech recognition in e-learning, emotion detection in classrooms, and automated grading systems.	High adaptability to data-driven personalization; capable of identifying subtle behavioral or performance patterns; scalable to large populations; strong predictive accuracy and performance in multimodal learning environments.	Limited interpretability ("black box" issue); requires extensive, high-quality labeled data; costly model training and maintenance; weak reasoning capability; risk of bias in educational decisions.
LLM-Supported Learning Agent	Employs transformer-based large language models (e.g., GPT, Gemini, Claude) that leverage self-attention mechanisms and contextual embeddings to understand and generate natural language adaptively.	Used in conversational tutoring assistants (e.g., Khanmigo, ChatGPT tutors) for personalized Q&A, essay feedback, and simulation of Socratic dialogues; supports dynamic content creation and multilingual instruction.	High linguistic versatility; strong contextual understanding; can simulate human-like teaching dialogue; cross-domain flexibility; supports scalable, individualized learning experiences; reduces teacher workload.	Factually inconsistent or hallucinated outputs possible; only moderately interpretable; dependent on external APIs or high-end computing; potential ethical and privacy concerns; requires robust fact-checking and pedagogical alignment.
Hybrid Neuro-Symbolic Model	Combines neural networks' perceptual and adaptive capabilities with symbolic reasoning's logical and explainable	Emerging in intelligent tutoring research and explainable AI education systems integrating logical curriculum reasoning with	Balances adaptability and explainability; improves logical consistency while maintaining flexibility; offers interpretable	Complex system design and integration; higher implementation cost; requires expertise across symbolic and neural paradigms;

	structures; neural modules handle feature extraction, symbolic modules ensure rule-based reasoning.	personalized student modeling; used in concept mapping and cognitive reasoning tutors.	feedback grounded in both rules and data; adaptable to complex domains requiring both structured knowledge and learning from experience.	not yet widely adopted in mainstream educational platforms.

The four main AI architectures in education represent distinct paradigms of intelligent instruction and learner interaction. Classic symbolic or rule-based systems rely on explicit expert-defined rules, providing high transparency and reliability but limited adaptability and scalability. Neural or deep learning architectures excel in data-driven personalization and pattern recognition, yet they remain opaque and resource-intensive. LLM-supported learning agents extend adaptability through natural language understanding, enabling conversational tutoring and content generation, though they face challenges of factual accuracy and ethical management. Hybrid neuro-symbolic models aim to integrate the interpretability of symbolic reasoning with the adaptability of neural systems, offering a balanced approach to explainable and flexible learning support. Together, these architectures outline an evolutionary continuum from rigid expert-driven models to adaptive, language-based, and hybrid intelligent educational systems.

A Comparative Analysis of Architectural Approaches

In order to evaluate the applicability of the different AI architectures in an educational context, a comparison using four criteria: effectiveness (in the sense of improving learning results), adaptability (ability to personalize against the student), transparency/explanatory and technical/financial resilience is made. The results of the study are shown in Table 3.

Table 3

Architecture Type	Effectiveness (Improving Learning Results)	Adaptability (Personalization to the Learner)	Transparency / Explanatory Power	Technical / Financial Resilience
Classic Symbolic (Rule-Based)	Generally effective for well-defined educational tasks such as testing procedural knowledge, grammar correction, or logical reasoning drills. However, its effectiveness is limited when facing complex, ambiguous, or creative learning situations due to rigid rule sets.	Low adaptability, since personalization depends on explicitly programmed rules. It can tailor feedback only within predefined conditions, making it less effective for dynamic learner profiles.	High transparency: rules and decision chains are explicitly coded, making explanations easily understandable by educators and students.	Technically stable and financially affordable due to low computational demands, but costly in terms of maintenance and rule authoring when scaling up across subjects.
Neural / Deep Learning Architecture	Highly effective at detecting patterns in large datasets and improving prediction-based tasks such as performance forecasting, adaptive assessments, and automatic grading. However, effectiveness	High adaptability through continuous learning from data, enabling personalized feedback, recommendation systems, and adaptive tutoring based on student	Low transparency: decision-making processes are often opaque, resulting in limited interpretability and difficulty in explaining why	Technically demanding and financially intensive due to high training costs, computing resources, and the need for frequent

	depends heavily on data quality and size.	behavior and engagement.	certain feedback is generated.	retraining, but scalable when integrated into cloud-based systems.
LLM-Supported Learning Agent	Very high effectiveness in producing contextually rich, conversational, and domain-adaptive feedback. Capable of assisting students across multiple subjects and languages, simulating human-like tutoring.	Extremely adaptive because it can dynamically adjust tone, difficulty, and explanations according to the student's responses and prior knowledge inferred from dialogue.	Moderate transparency: while it can generate textual justifications, the underlying reasoning is probabilistic and non-deterministic, so interpretability remains partially limited.	Technically complex and resource-intensive due to large model sizes and inference costs, though financially viable in shared infrastructure or API-based deployment models.
Neuro-Symbolic (Hybrid)	Demonstrates balanced effectiveness by combining symbolic reasoning (structured logic, domain rules) with neural adaptability (pattern recognition). Performs strongly in complex educational tasks requiring both factual precision and contextual understanding.	Very high adaptability, as the symbolic module ensures logical consistency while the neural component personalizes interactions and feedback to individual learners.	High transparency compared to purely neural models: the symbolic layer enables interpretable reasoning chains, while the neural layer manages nuanced contextual adjustments.	Moderately high resilience: although more complex to design, it offers better long-term sustainability, as symbolic components reduce retraining needs and neural modules can be updated independently.

Applications and Realisations in Educational Practice

Intelligent Training Systems (ITS) are a classic example of AI application in education and include components such as domain model, student model, pedagogical model and interface. When these components are designed correctly, ITS can offer adaptive learning paths and provide targeted feedback similar to personalized human mentoring. Platforms such as Aleks and Cognitive Tutors present is empirical evidence of the efficiency of such systems in specific subject domains, especially mathematics and natural sciences, where the structure of tasks allows formalization (Koedinger, K. R., & Aleven, V., 2007), (Sun, S., Else-Quest, N. M., Hodges, L. C., French, A. M., & Dowling, R., 2021).

Automatic evaluation and feedback generation use a combination of NLP and classification models. In addition, computer vision is applicable to evaluating graphic or handwritten content. The generative models allow for the compilation of explanatory texts, suggested solutions and adapted content, but their statements must be controlled according to accuracy and reliability, especially in formative and summaries. Automatic evaluation shows promising results, but it remains a source of debate due to possible bias and lack of complete transparency (Graesser, A. C., et al., 2004), (Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z., 2024).

Learning Analytics and academic analytics use data on the interaction of trainees with platforms to predict the risk of dropping, identify problem areas in curricula and support adaptive support. The approaches here range from simple regression models to sophisticated time models and ensemble schemes. The key advantage is the possibility of preventive intervention, while the main risks include misinterpretations of data and potential confidentiality disorders (Long, P., & Siemens, G., 2011).

Large language models and chatbots have already been introduced into commercial and educational platforms such as interactive assistants. These systems facilitate dialogue, personalization and access to explanations in natural language. Practical examples such as Khanmigo and Duolingo Max demonstrate that LLM-based solutions can improve engagement and create personalized exercises, but at the same time enhance the issues of the reliability of content and academic honesty. Regulators and institutions are already discussing the restriction or restructuring of the forms of evaluation due to the difficulty of detecting trivial abuses of generative AI (Peters, J., 2024).

Ethical, Regulatory and Social Aspects

The integration of AI into education requires systematic attention to ethical issues. Algorithmic bias can lead to unequal opportunities for students, especially when learning data reflect historical or demographic inequalities. The confidentiality of student data and compliance with regulations such as GDPR are critical, especially when analytical systems collect and process sensitive information. The emergence of generative models that make it impossible to reliably detect unlicensed use in asynchronous evaluations, forced regulatory authorities and accreditation institutions to recommend changes to evaluation methods, such as the introduction of Secure Assessment Points, examined exams and emphasis on the public presentation. These discussions emphasize that technological capabilities do not on their own do not guarantee their ethical implementation without clear policies, technical measures and vocational training of teachers (Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z., 2024).

The role of the teacher in the AI era has changed from a source of facts to the facilitator of critical thinking, evaluation and socio-emotional support. This transforms the requirements for professional development: teachers need both technical literacy to work with AI instruments, as well as ethical and pedagogical training for interpretation and control of automated recommendations.

Prospects and Guidelines for Future Research

The most likely mid-term trajectory in AIED is the development of integrated and hybrid solutions that combine neural presentations with formal, symbolic structures of knowledge to achieve a balance between efficiency and explanability. Studies should focus efforts on methods of verification and validation of generative systems, mechanisms for detecting and restricting Hallucinations, techniques for fair and representative training, as well as the design of teaching assessments that are resistant to automated and semi -automatic fraud means.

From a technical point of view, priority areas are the development of resource-efficient models that can work offline or in educational contexts with limited infrastructure, as well as standardized interfaces for integration with LMS systems. From a pedagogical point of view, further empirical work is needed to determine the conditions under which the AI instruments most effectively improve long-term learning results, not just short-term indicators.

CONCLUSION

AI offers significant opportunities for personalization, automation and expansion of access to training, but at the same time imposes complex requirements for reliability, ethics and regulation. The choice between symbolic, neural, transformer-based and neuro-symbolic architectures is not unilateral. It should be based on clear pedagogical purposes, data available, infrastructure capabilities and ethical frameworks. In the short and medium term, hybrid architectures and the careful integration of LLM as supporting tools seem to be the most productive. The academic honesty, confidentiality and professional development policies will be the critical factors of whether technology will really serve to improve educational results.

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