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Explainable and responsible artificial intelligence in education: Ethical challenges in adaptive learning systems

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Abstract

The fast development of adaptive artificial intelligence learning systems in education has been a cause of increased apprehension among the issues of algorithmic bias, loss of transparency, accountability, low level, data privacy, and the lack of human control. Although Artificial Intelligence in Education has enhanced individualized learning, learner modeling, predictive analytics, and intelligent tutoring systems, most educational technologies remain black-box systems that are difficult to ethically decide upon and trust. The literature review explores the way Explainable Artificial Intelligence, Responsible Artificial Intelligence, and Hybrid Intelligence can be used to curb these issues in adaptive learning systems. This review has a systematic review of the recent research on Explainable Artificial Intelligence, Human-AI Collaboration, Responsible Innovation, Educational Data Mining, Learning Analytics, and Trustworthy AI in educational settings, using the PRISMA framework. The review summarized the results of peer-reviewed articles about adaptive explainable AI, fairness mindful machine learning, transparency of algorithms, mitigating bias, data management, and human friendly AI in higher education, school education and digital learning platforms. The results show that Explainable Artificial Intelligence and Hybrid Intelligence models have the potential to enhance transparency, accountability, fairness and user trust in adaptive learning systems to a substantial degree. The methods identified as human-in-the-loop systems, neural-symbolic AI, interpretable machine learning, and student-centric AI models were identified to boost educational equity, teacher supervision, and responsible decision support systems.

Keywords: Ethical AI, Generative AI, Large language models, Adaptive learning systems, Artificial intelligence, Education.

1. Introduction

Artificial Intelligence in Education has altered modern teaching and learning settings through promoting Adaptive Learning Systems, Intelligent Tutoring Systems, Learning Analytics, Educational Data Mining, and Predictive Analytics that can tailor teaching to the needs of individual learners. With the improvements in Generative AI, machine learning, neural networks, and learner modeling, educational platforms are now capable of real-time feedback, knowledge gap identification, automated assessment, and suggested learning paths [1]. All these changes have enhanced the expansion of Personalized Learning and Student-Centric AI in schools, colleges, and online learning platforms. But the growing sophistication of AI-based educational technologies has raised these issues as well: Explainability, Transparency, Accountability, Algorithmic Bias, and Data Privacy. The adaptive systems work as opaque black-box models that do not allow educators, students, and policymakers to learn the way the decisions are created, the reasons why the recommendations are provided, and whether the provided recommendations are principled, ethical, and reliable. The ever-increasing reliance of AI-based decision support systems in education hence generates an urgent demand of Explainable Artificial Intelligence, Responsible Artificial Intelligence, and Human-Centered AI models capable of fostering technological innovation as well as acting as ethical agents of decision-making.

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The importance of this problem has also been growing significantly with the lightning growth of Generative AI, multimodal learning platforms, and adaptive educational technologies in 2025 and 2026. Learning institutions are starting to incorporate AI-based tutoring, automated grading, predictive analytics, chatbots, and real-time monitoring of learners into the mainstream education process. On the one hand, these technologies might enhance engagement, flexibility, and academic performance, but, on the other hand, they also generate severe ethical issues connected with Academic Integrity, Digital Ethics, Student Agency, Educational Equity, and Governance Frameworks. Application of AI systems without proper transparency can support educational disparities, wrongly categorize the student capabilities, or cause Algorithmic Bias against underrepresented learners. Equally, ineffective Data Governance can be used to release sensitive data about students and damage the confidence in schools. The development of agentic AI and autonomous education systems has also intensified the need to develop more powerful Educational Governance, AI Regulation and Teacher Oversight in order to maintain AI systems responsible and in line with human values. The recent debates are becoming more focused on the fact that the question is not whether AI should be implemented in the educational process anymore, but how it is possible to apply Trustworthy AI, Responsible Innovation, and Ethical AI in such a way that does not compromise the integrity of the process, inclusivity, and human control.

Explainable Artificial Intelligence has become one of the most promising solutions to enhance users trust and algorithm transparency in Adaptive Learning Systems in the context of the current landscape. Explainability enables students, teachers, and administrators to comprehend the logic behind AI-generated suggestions, predictive examinations, and adaptive learning courses [1-3]. The Interpretable Machine Learning, Fairness-Aware Machine Learning, and Adaptive Explainable AI have thus come to the fore of the creation of transparent learning technologies. Simultaneously, Hybrid Intelligence models which integrate machine intelligence with human knowledge are receiving more and more interest due to the fact that they assist Human-AI Collaboration as opposed to fully automated decision-making. Neural-Symbolic AI, Human-in-the-Loop systems, and Student-Centric AI frameworks enable educators to maintain control over the process of AI technology usage, although they enable the efficiency and scale of AI technologies. These systems are of special significance in education as they may include contextual knowledge, emotional aspects, motivation, metacognition and teacher judgment in the process of modeling learners and decision support. New evidence indicates that Hybrid Intelligence has the potential to enhance fairness, decrease overdependence on black-box models, and facilitate both more inclusive and personalized learning experiences.

In spite of all that has developed there are still huge gaps in research. The current literature is often dedicated to the technical functionality of AI systems and does not consider more general ethical, social, and pedagogical consequences. The predictive accuracy of many Adaptive Learning Systems takes precedence over Explainability, User Trust and Transparency in Education. Moreover, the current literature does not pay much attention to the role of motivation, emotion, contextual learning variables, and socio-cultural diversity in shaping the behavior of learners and AI decision-making. Little information is also available on how the Explainable Artificial Intelligence can be effectively operationalized in various levels, fields, and learning settings. The other significant lacuna has to do with the lack of standard Governance Frameworks of Responsible Artificial Intelligence, especially in Data Privacy, Academic Integrity, Bias Mitigation, and Algorithmic Transparency. Although Human-AI Collaboration is a popular topic, it is still unclear how educators, students, and AI systems can cooperate efficiently in Human-Centered AI ecosystems. Furthermore, new ethical issues that arise due to recent progress in Multimodal Learning Analytics, Generative AI, and autonomous AI agents have not successfully been resolved by current Educational Policy or AI Regulation paradigms.

It is against this context that this literature review aims at critically reviewing the new area of Explainable and Responsible Hybrid Intelligence in education, and especially the ethical implications of Adaptive Artificial Intelligence Learning Systems. The review aims to examine the three concepts, which are Explainable Artificial Intelligence, Responsible Artificial Intelligence, and Hybrid Intelligence, which may enhance Transparency, Accountability, Fairness, and Trustworthiness in AI-driven education [2,4]. It will also seek to find out the major ethical risks of Algorithmic Bias, Data Governance, Student Privacy, Academic Integrity, and Educational Equity. Besides that, the review examines how Human-in-the-Loop models, Neural-Symbolic AI, Interpretable Machine Learning, and Human-Centered AI can be used to make educational technologies more inclusive and responsible. This paper can be seen as a contribution to the developing discussion of the topic Ethical AI, Responsible Innovation, and Socio-Technical Systems in education by synthesizing emerging evidence on various fields. Moreover, it offers a prospective outlook of the role of adaptive explainable AI, multimodal learning analytics, AI literacy, and governance systems on the future of learning technologies and policies..

2. Methodology

The systematic literature review was followed strictly in accordance with the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework to achieve methodological rigour, transparency and reproducibility in addressing the question of ethical issues in explainable and responsible hybrid intelligence in adaptive artificial intelligence learning systems in education.

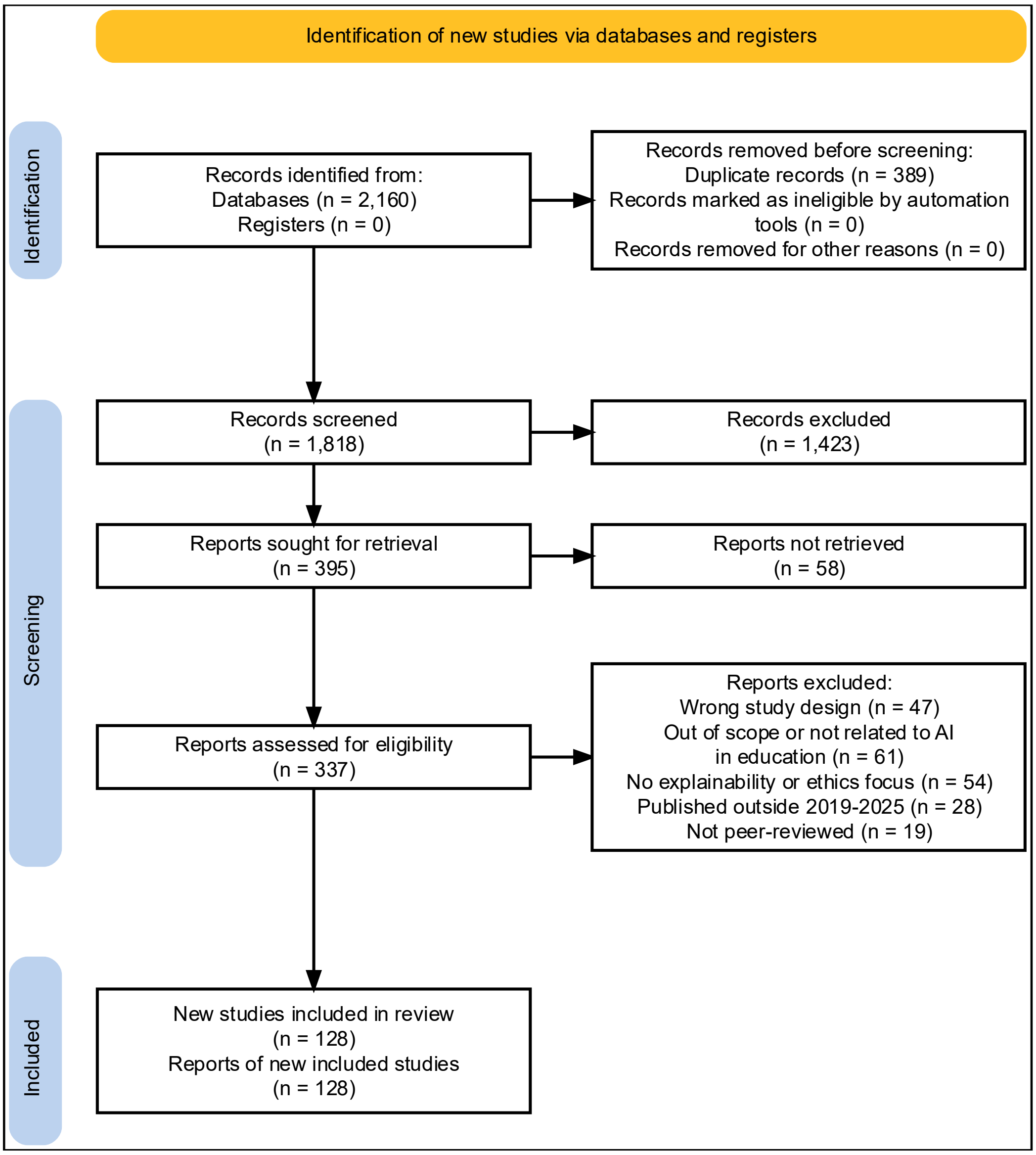

Fig. 1 PRISMA Framework

To identify the most recent and relevant scholarly changes in this rapidly changing interdisciplinary area, four large academic databases have been searched, i. e., Scopus, Web of Science, IEEE Xplore, and PubMed, with the search period narrowed to January 2019 through December 2025. The following Boolean search strings were employed across Scopus and Web of Science: ("explainable artificial intelligence" OR "XAI") AND ("education" OR "e-learning" OR "adaptive learning") AND ("ethics" OR "responsible AI" OR "fairness" OR "transparency" OR "accountability"); ("hybrid intelligence" OR "human-AI collaboration") AND ("learning systems" OR "intelligent tutoring") AND ("ethical challenges" OR "bias" OR "privacy"); ("adaptive AI" OR "personalized learning") AND ("explainability" OR "interpretability") AND ("educational technology" OR "EdTech") AND ("responsible design" OR "algorithmic transparency"); and ("machine learning" OR "deep learning") AND ("higher education" OR "K-12") AND ("ethical AI" OR "explainability") AND ("student data" OR "learning analytics"). The research papers of interest included peer-reviewed journal articles or conference proceedings published in English in the year 2019-2025, which directly related to the themes of explainability, ethics, transparency, fairness, or accountability in AI-driven or hybrid intelligent educational systems and made empirical, theoretical, or review-based contributions that were within the scope of this review refer (Fig. 1). The studies were filtered out based on the following criteria: they had to be non-peer-reviewed (e.g. an editorial, grey literature, dissertation, or book chapter); needed to be published after 2019 or had no discernible engagement with the principles of explainability or responsible AI. The original search of the database provided 2,207 records (Scopus: 872; Web of Science: 654; IEEE Xplore: 431; PubMed: 203), which were further refined by citation tracking and screening of reference lists of major reviews and resulted in 2,207 records prior to deduplication. After eliminating 389 duplicate records, 1,818 unique records passed on to title and abstract screening, where 1,423 records were eliminated due to lack of inclusion criteria, 395 reports were requested to be retrieved; 58 of them failed to be located, and 337 reports were evaluated in terms of full-text eligibility. Another 209 reports were then filtered out at full-text assessment, based on the following criteria: incorrect study design (n = 47), not in the area of interest of explainability or ethics in education (n = 61), no substantive focus on explainability or ethical aspects (n = 54), publication date beyond the 20192025 range (n = 28), and not written in

3. Results and discussions

3.1 Artificial intelligence techniques

Explainable Artificial Intelligence (XAI) in Adaptive Learning Systems

Explainable Artificial Intelligence has become one of the largest methods behind the Adaptive Learning Systems since it is able to not only solve black-box decision-making within Artificial Intelligence in Education. Conventional machine learning systems, particularly deep neural networks, usually come up with suggestions, ratings, or labels of learners without giving educators and learners explanatory descriptions. It is also a source of worry in the educational settings, due to the lack of transparency in terms of trust, accountability and fairness, since a student might not comprehend why he or she is receiving a recommendation, assessment or an adaptive learning pathway. Explainable Artificial Intelligence suggests that the following issue can be addressed by incorporating model transparency, feature analysis of importance, interpretable visualizations, rule-based explanation, and local explanation methods into adaptive learning systems. SHAP, LIME, visualization of attention, counterfactual explanations and saliency map are some of the newly adopted methods of explaining why a system thinks a learner is at-risk, prescribes a learning module, or can predict academic success. Increasing Responsible Artificial Intelligence and Trustworthy AI are also associated with the rising significance of Explainability in education. The stakeholders in the educational system need systems that can support recommendations, particularly in the academic advising, automated grading, student retention prediction, and personalized tutoring. Adaptive Explainable AI is especially significant as educational decisions usually have effects on long-term outcomes in learners, academic equity, and institutional accountability. As a result, nowadays, Explainable Artificial Intelligence is not only considered to be a technical necessity but a major ethical value of the Human-Centered AI and Educational Governance.

Machine Learning and Deep Learning for Learner Modeling

One of the most commonly adopted methods of Artificial Intelligence in Adaptive Learning Systems is Machine Learning and Deep Learning since these can be used to model the Learners with accuracy and predict analytics. Classification of student performance, identification of dropout risks, and patterns in Learning Analytics are highly common applications of supervised learning algorithms, which include decision trees, support vectors machines, random forests, logistic regression, and gradient boosting. The methods can handle large scale educational data and assist in Personalized Learning by making predictions about the potential need of some students to receive further help or alternative teaching methods. Recurrent neural networks, convolutional neural networks, transformers, and graph neural networks belong to Deep Learning methods and have grown in importance since they are able to model multimodal educational data in complex relationships. Indicatively, Deep Learning can examine the student engagement, based on click stream behavior, video interactions, biometric interaction and performance in assessments. Massive learning systems are growing more and more dependent on deep neural networks as a means of giving adaptive content sequence, intelligent recommending, and predictive student profiles. Nevertheless, Deep Learning models tend to attract the concern of Explainability, Algorithmic Bias and Transparency since they are both difficult to control and understand in nature. Consequently, there is an increased desire to integrate Deep Learning, Interpretable Machine Learning method, and Explainable Artificial Intelligence methods.

Natural Language Processing and Large Language Models in Education

Natural Language Processing has revolutionized Artificial Intelligence in Education because machines have been taught to understand, create and react to human language. The application of Natural Language Processing methods in the educational system has been rapidly growing to help students grade their essays, answer questions, provide automated feedback, tutor chatbots, plagiarism detectors, and sentiment analysis [5-8]. This has grown more recently with the advances in Large Language Models and Generative AI, enabling educational platforms to offer some form of conversational assistance, one-on-one tutoring, curriculum generation and content summarization. The importance of Large Language Models is that they can allow Human-AI Collaboration when teaching students. They are able to help the teachers plan their lessons, automate their administration systems and give individualizations of explanations to the students. The use of Retrieval- Augmented Generation has also enhanced the precision of the responses generated by Large Language Models via incorporating the external knowledge in AI generated responses. Nevertheless, ethical issues concerning hallucination, misinformation, academic dishonesty, bias, and data privacy are also raised with these technologies at a significant level. Most of the learning institutions might have students over dependent on the Generative AI tools and fail to think critically and learn not because of their own effort. Thus, Responsible Artificial Intelligence models become more focused on the role of teachers, AI literate, and the open disclosure of AI-generated information.

Intelligent Tutoring Systems and Recommender Systems

One of the most developed AI methods of education is the Intelligent Tutoring Systems, which can be explained by the fact that they imitate one-on-one tutoring, happening due to adaptation of the material to be provided, to the automated feedback, and a custom-made learning process. These programs rely on the Learner Modeling, Predictive Analytics and Decision Support Systems to determine the needs of the students and make prescribed learning resources accordingly. Bayesian networks, reinforcement learning, case-based reasoning, and probabilistic graphical models are common features to Intelligent Tutoring Systems to identify the most productive methods of instruction. Recommender Systems Learning Personalization also is a fundamental part of the system which proposes courses, assignments, videos, readings, and assessments based on the unique learners preferences. The popular algorithms that can be employed to enhance student engagement and retention include collaborative filtering, content-based filtering and hybrid recommendation algorithms. Nevertheless, the educational Recommender Systems can form the bias in case they promote the similar material among the particular groups of students repeatedly and restrict their access to the wider learning opportunities. Therefore, Fairness-

Aware Machine Learning and Algorithmic Transparency currently receive growing emphasis in the development of Intelligent Tutoring Systems and educational recommendation engines.

Reinforcement Learning and Adaptive Decision-Making

Reinforcement Learning is also getting used within Adaptive Learning Systems since it enables educational technologies to acquire best instructional approaches due to its interplay of trial and error. Reinforcement Learning algorithms are able to change the level of the content, feedback schedule, and learning patterns according to the student responses and performance [6,9]. This method is also useful in Personalized Learning since it leads to flexible and personalized learning. The most recent research shows that Intelligent Tutoring Systems can be enhanced with the help of Reinforcement Learning that will help determine the most efficient interventions that could be applied to various learner profiles. Multi-agent reinforcement learning, contextual bandits, and deep reinforcement learning find more and more applications in the learning process with a view to assisting adaptive decision-making. Nevertheless, these methods create a question with respect to accountability, transparency, and ethical decision-making, as the rationale, which underlies the instructional decisions, can prove hard to describe. Consequently, Explainable Reinforcement Learning is becoming a significant field of research in Responsible Artificial Intelligence in Education.

Neural-Symbolic AI and Knowledge Graphs

Neural-Symbolic AI is a notable advancement in Hybrid Intelligence since it is the unification of pattern matching features of Deep Learning with the logical reasoning skills of symbolic systems. Conventional Deep Learning algorithms are very useful in uncovering trends in educational data, yet have problems with transparency, causality and can be interpreted. Neural-Symbolic AI solves these shortcomings, taking rule-based reasoning, ontologies, semantic networks, and Knowledge Graphs into consideration as part of AI systems. Knowledge Graphs become more and more employed in the educational platforms to express an impact between concepts, learning outcomes, pre-conditions, and states of knowledge of learners. Knowledge Graphs can enhance Intelligent Tutoring System, curriculum development, and adaptive recommendations through mapping educational content into structured semantic networks. Neural-Symbolic AI as well avoids Explainability since systems are able to justify suggestions by providing clear links of reasoning. This renders Neural-Symbolic AI to be specifically useful in regard to Ethical AI and Responsible Artificial Intelligence in learning.

Federated Learning and Privacy-Preserving AI

Adaptive Learning Systems have turned to Federated Learning as a paramount privacy method towards safeguarding student data. Conventional educational AI systems frequently presuppose central gathering of the learner information which causes the concerns of Data Privacy, Data Governance, and security [10]. Federated Learning is a way to solve this issue since machine learning models can be trained through decentralized devices or institutions without the need to transfer the raw data to a central server. Privacy-Preserving AI privacy-safe systems including differential privacy, secure multi-party computation, homomorphic encryption, and synthetic data generation are also being used in educational systems. These techniques may decrease the possibility of unauthorized access, data theft as well as surveillance which will not lower the efficacy of Predictive Analytics and Learning Analytics. With the ever-increasing importance of student privacy, Federated Learning and Privacy-Preserving AI will probably become the key elements of Trustworthy AI in learning.

Computer Vision, Emotion Recognition, and Multimodal Learning Analytics

Methods of Computer Vision are being applied more and more in learning institutions to analyze facial expressions, eye movements, movements, posture, and interactions in a classroom setting. These methods are conducive to Multimodal Learning Analytics that merges visual data with the textual, behavioral and physiological information to create a more detailed reflection of the learner interest. Emotion Recognition as well as Sentiment Analysis is especially significant as it enables the Adaptive Learning Systems to identify frustration, confusion, boredom or motivation on time. The educational platforms can then modify the content challenge, pacing or teaching style according to emotions of the learners. Nevertheless, Computer Vision and Emotion Recognition invoke significant ethical issues as far as surveillance, consent, data privacy, and cultural bias are concerned. Depending on the demographic differences, facial recognition technologies can work not consistently which could result in false evaluation and discriminatory results. Thus, Responsible Artificial Intelligence presupposes that such technologies should be deployed with high moralistic security and transparency.

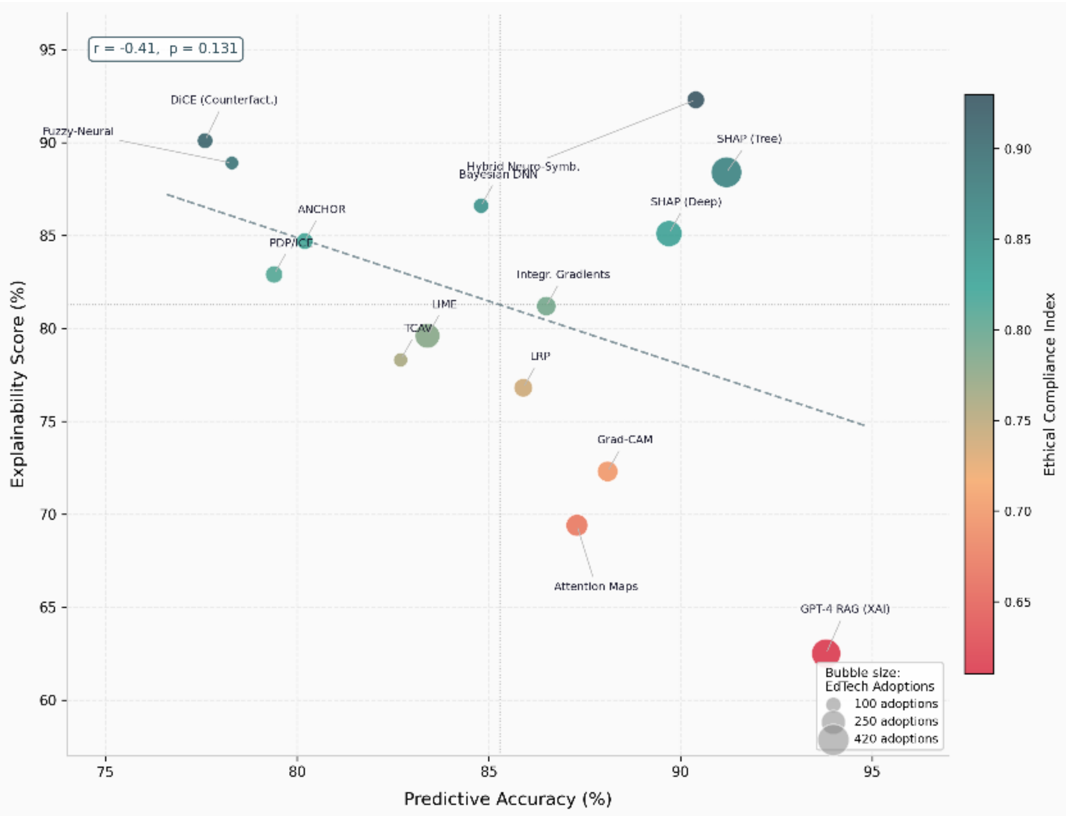

Fig. 2 Predictive Accuracy vs. Explainability Score of XAI Models in EdTech.

Fig. 2 is a bubble scatter plot maps fifteen XAI model families along two critical axes, predictive accuracy on the horizontal axis and explainability score on the vertical axis, both measured as percentages. Each bubble's size encodes the cumulative EdTech adoption count reported across the literature from 2019 to 2025, while the continuous color scale ranging from red through amber to teal encodes the Ethical Compliance Index. A Pearson correlation regression line with a reported r value and p-value is overlaid to reveal the structural trade-off between accuracy and explainability. Quadrant reference lines positioned at dataset means facilitate interpretive segmentation. The plot reveals that GPT-4 RAG achieves the highest predictive accuracy (93.8%) but the lowest explainability score (62.5%), whereas Hybrid Neuro-Symbolic AI occupies the most desirable upper-right quadrant with both high accuracy (90.4%) and the highest explainability (92.3%), making it a frontier research direction with strong citation potential.

Fairness-Aware Machine Learning and Bias Mitigation

Fairness-Aware Machine Learning has found application in educational AI because a large number of algorithms repeat the historical disparities and Algorithmic Bias inadvertently. Educational data usually portray social, economic, language, and demographic differences, and this might affect Predictive analytics, classification of learners, and their academic suggestions. Provided they are not addressed, these biases can lead to the disadvantage of some groups of students and lower Educational Equity. Methods of bias Mitigation bias include re-sampling, adversarial debiasing, fairness constraints, causal inference and algorithmic auditing. Such practices are meant to make the AI systems fair and biased towards certain learners on basis of gender, ethnicity, disability, socioeconomic status or language acquisition. Machine learning that is aware of fairness is especially significant in areas like admissions, grading, scholarship decisions, and dropout prediction since the effects of biased decisions on students may be long-term and potentially permanent. As a result, the ethical educational technologies also demand a fairness auditing and bias monitoring procedure more and more.

Human-in-the-Loop Systems and Human-AI Collaboration

The core of the Responsible Artificial Intelligence is represented with Human-in-the-Loop systems since the latter make the educator actively participate in the AI-based decision-making. The Human-in-the-Loop models involve and consider the teacher control, human knowledge, and some situational explanation in the dynamic learning exercises rather than letting AI systems work independently [10-12]. The method is especially significant since educators are likely to identify emotional, cultural, and situational issues that AI systems can ignore. Universal-Artificial Intelligence (Human-AI Collaboration) is also one of the distinguishing characteristics of Hybrid Intelligence since the efficiency of machine is merged with human expertise. Human-AI Collaboration can be useful in educational settings to help in curriculum design, learner support, assessment, and intervention planning. The teacher might follow AI-generated suggestions, but still, he or she has the right to accept, make changes, or disapprove the suggestion. The combination of collaboration can enhance User Trust, Accountability, and Student Agency besides minimizing the risks of having wholly automated educational systems.

Agentic AI and Autonomous Educational Systems

The area of agentic AI is a new one that deals with the AI systems that are able to make decisions, reason, and plan independently. In learning, Agentic AI systems are capable of scheduling activities on their own, tracking the progress of learners, suggesting remedies, as well as coordinating various learning activities. Auto-educational agents have been inculcated more into virtual learning environments, conversational tutors and administrative systems. Even though the opportunities of scalability and efficiency provided by the Agentic AI are rather promising, there are also considerable ethical challenges. Independent schooling systems can take action without teacher supervision and this can lead to lack of responsibility in addition to the possibility of bias and inaccuracy. Moreover, there are also some positive effects or impacts of Agentic AI on student behavior, which provokes issues of autonomy, manipulation, and transparency. With the further development of these technologies, the need in a system of governance, which can guarantee that Agentic AI does not stand against human values and educational purpose, increases.

Causal AI and Future Directions in Responsible Educational Technology

Increasing attention is paid to causal AI though it is directed at revealing cause/effect relationships but not simple correlations. Conventional Predictive Analytics can determine the patterns of the educational data without determining the reasons behind the patterns to be [7,13-16]. Causal AI is capable of assisting educators in comprehending the impact that interventions, teaching methods, or the environment have on the learning outcomes. The probable evolution of Artificial Intelligence in Education in the future is increased adoption of Explainable Artificial Intelligence, Neural-Symbolic AI, Federated Learning, Causal AI, and Human-Centered AI. Responsible Hybrid Intelligence will be more commonly relying on open algorithms, inclusive design, robust Data Governance and ethical controls. Over time as the Adaptive Learning Systems advance in complexity, researchers and policymakers will have to strike the balance between the innovation and the Accountability, Fairness, Educational Equity, and Student Agency. The AI technology in the fields of education will then move forward not just by the advancements in the technical side but also by having the capabilities to develop trustworthy, explainable and ethically responsible systems.

3.2 Artificial intelligence methods

Supervised Learning Methods in Adaptive Learning Systems

Supervised Learning has continued to be among the most popular forms of Artificial Intelligence within Adaptive Learning Systems since it allows predicting the outcomes of students, engagement of learners, their dropouts and their learning based on tagged learning data. Such classical methods of Supervised Learning as decision trees, logistic regression, support vectors machines, naïve Bayes, k- nearest neighbors, random forests and gradient boosting models remain popular in Educational Data Mining and Learning Analytics because they are reasonably interpretable and they are relatively powerful predictors. Such practices are especially useful in Personalized Learning since they have the potential to sort students into various categories of performance, discover at-risk learners and help to intervene in time. Automated grading, prediction of attendance, retention analysis, course recommendation and learner modeling are automated models typically applied in the context of institutions of learning. Nevertheless, there are still the issues of Transparency, Accountability, and Algorithmic Bias since predictive models have an ability to reproduce past inequality in education-related data. Consequently, it is becoming clear that more recent works in the field want to explore the role of Explainable Artificial Intelligence, Fairness-Aware Machine Learning, and Bias Mitigation methods in ensuring supervised learning models are more responsible and trustworthy in education.

Unsupervised Learning Methods for Pattern Discovery

Unsupervised Learning procedures are also relevant in Adaptive Learning Systems since they allow finding unattended patterns, clusters, and trends of behavior without labeled data. Clustering algorithms like: k-means, hierarchical clustering, DBSCAN, and Gaussian mixture models are more commonly employed to cluster students based on the learning styles, level of participation, they are engaged with and their academic progress [2,17-19]. Several dimensionality reduction tools, including principal component analysis, t-SNE, and autoencoders, are also becoming active in order to make the large scale educational data sets less complex. The methods are especially useful in the Learning Analytics and Educational Data Mining as they assist educators in finding previously unfamiliar student profiles, latent impediments to learning, and new trends in digital proceedings. The Anomaly Detection also involves Unsupervised Learning, which allows the Adaptive Learning Systems to monitor irregular student practices, the patterns of cheating or an abrupt shift in the performance of a learner. Although advantages exist, unsupervised approaches can create clusters that cannot be easily interpreted thus posing a challenge to Explainability and Transparency in Education. Therefore, interpretable clustering methods and Human-in-the-Loop validation are gaining relevance of resiliency in Responsible Artificial Intelligence.

Deep Learning Methods and Neural Architectures

The use of Deep Learning methods has emerged as the focus of Artificial Intelligence in Education as it can be used to process large quantities of structured and unstructured educational data. Adaptive Learning Systems are growing in the use of convolutional neural networks, recurrent neural networks, transformers, graph neural network models, and attention-based models to simulate and model human behaviors in learning and predict educational results. Recurrent neural networks and long short-term memory networks are specifically applied to sequential educational data including clickstream, video interactions and learning paths whereas transformers and graph neural networks work better when it comes to contextual relationships and knowledge dependencies. Developments in Deep Learning techniques have facilitated significant progress in Personalized Learning, Intelligent Tutoring Systems and Predictive Analytics since they have enhanced the quality of student modeling and content recommendation. Several deep neural architectures however are hard to understand as they are black-boxed systems. Such the absence of Explainability can decrease User Trust and restrain Teacher Oversight. Recent studies consequently regard the integration of Deep Learning with Explainable Artificial Intelligence, saliency maps, attention visualization, and counterfactual reasoning to enhance the Algorithmic Transparency in education.

Knowledge Tracing Methods and Sequential Modeling

The most significant AI techniques in the Adaptive Learning Systems are Knowledge Tracing methods since they simulate knowledge progression brought by the learner. The Bayesian Knowledge Tracing has been one of the most utilized methods due to the reason that it estimates the likelihood that a learner has learnt a concept having accomplished the instructional activities. Within more recent times, Deep Knowledge Tracing techniques came into the limelight since they are able to embrace irregular learning trends along with recurring neural networks, transformers, and attention architecture. Sequential modeling approaches are especially useful since the behavior of students in the educational field is inherently temporal i.e. performance of a student is influenced by the past interactions, feedback or experience. Nevertheless, several of the contemporary Adaptive Learning Systems continue to use non-sequential models that do not reflect a dynamism of learner development. Recent studies are getting more and more convinced that sequential AI techniques should be used in place of predictive models which are not dynamic and have less accuracy, due to their more accurate, context-aware, and student-specific suggestions. It has also been found that the transposition of non-sequential evaluation measures on sequential educational data as a key methodological weakness of the research on Artificial Intelligence in Education.

Reinforcement Learning and Deep Reinforcement Learning Methods

Adaptive Learning Systems are starting to recognize the use of Reinforcement Learning methods due to their ability of educational technologies to learn based on trial and error like interactions with the learners. The agents of Reinforcement Learning are able to actively adjust content challenge, timing of feedback, learning patterns as well as didactical options based on the reactions of the pupils [3,20-23]. Deep Reinforcement Learning builds multiple capabilities by integrating the concepts of reinforcement learning into neural networks and allows systems to deal with larger and more complex educational settings. The third reason why Multi-agent Reinforcement Learning gains more and more significance is that it has been utilized to create a collaborative educational ecosystem in which different AI agents engage with students, teachers, and institutional systems. The technique of Reinforcement Learning has special potential with Personalized Learning, since it has the potential to maximize teaching tracks on the fly. The procedures that come out in the decision-making of the Reinforcement Learning agents are however usually hard to explain, raising issues about Accountability, Transparency, and Ethical Decision-Making. ERL is thus becoming an important field of study in Responsible Artificial Intelligence and Trustworthy AI.

Natural Language Processing and Large Language Model Methods

The concept of Natural Language Processing has reinvented Artificial Intelligence in Education because it allows machines to interpret, compose, and analyze human language. Older Natural Language Processing technologies like tokenization, semantic analysis, named entity recognition, topic modeling, and sentiment analysis are still applied in the essay grading system, plagiarism checking, chatbot tutor, and automatic feedback systems. Nevertheless, Generative AI and Large Language Models have offered greatly greater possibilities to educational technologies. The Conversational Tutoring, Lesson Planning, Curriculum design, Content Summarization, and Multilingual educational support can be supported by large language models. Retrieval-Augmented Generation models are another way to enhance the quality and trustworthiness of Large Language Models through linkage to external bodies of knowledge and institutional knowledge. In spite of these benefits, the Natural Language Processing also triggers serious ethical issues since they can lead to hallucinatory content, misinformation, biased reactions, and excessive reliance on artificial intelligence support. The responsible Artificial Intelligence models are more and more focused on the significance of AI Literacy, Teacher Oversight, Human-AI Collaboration, and the open involvement of the information about the AI-created content in education.

Explainable Artificial Intelligence Methods

The explainable Artificial Intelligence techniques are critical in Adaptive Learning Systems since they make users familiar with the mechanism of creating AI-based recommendations, predictions, and classifications. Popular Explainable Artificial Intelligence abduction techniques are SHAP, LIME, Layerwise Relevance Propagation, counterfactual explanations, attention visualization, feature importance ranking and saliency maps [9,24-26]. Such techniques are becoming more common in Intelligent Tutoring Systems, Predictive analytics, and learners modelling to ensure that AI decision-making increasingly becomes transparent and interpretable. The importance of Adaptive Explainable AI has been specifically relevant as stakeholders in the education sector need to be able to explain why a learner was identified as being at-risk, why a recommendation has been developed, or why one specific content has been prioritized over another. New studies indicate explorability is not to be regarded as a technical output, but rather, as a communication process that is specific to teachers, learners, and administrators based on their needs and expertise levels. Multimodal Explainable AI, as a text-based, graphical, and interactive system of explanations, is considered as a promising trend of future educational systems.

Neural-Symbolic AI and Knowledge Graph Methods

Neural-Symbolic AI approaches, which mix the recognitions of Deep Learning with the reasoning skills of symbolic systems, are very relevant in Hybrid Intelligence in the education sector. Conventional Deep Learning techniques can find patterns in large masses of data and can be very weak when it comes to causal and logical reasoning and interpretation. Neural-Symbolic AI ventures around these drawbacks and incorporates rules and ontologies, semantic reasoning, and Knowledge Graphs in AI applications. Knowledge Graphs are also employed more as a representation of educational concepts, relationships of prerequisites, curriculum routes and competencies of the learner. These techniques allow Adaptive Learning Systems to produce clearer, explanatory recommendations, as well as concerns that are more gnomic. The importance of Neural-Symbolic AI lies especially in the possibility to combine teacher knowledge, specifics of the domain and context specificity of the students into the machine learning framework. More recent studies are beginning to argue that the Neural-Symbolic AI can be the basis of Responsible Artificial Intelligence in Education as it offers an answer to Human-AI Collaboration, Explainability, and ethics-driven decisions than data-driven only approaches.

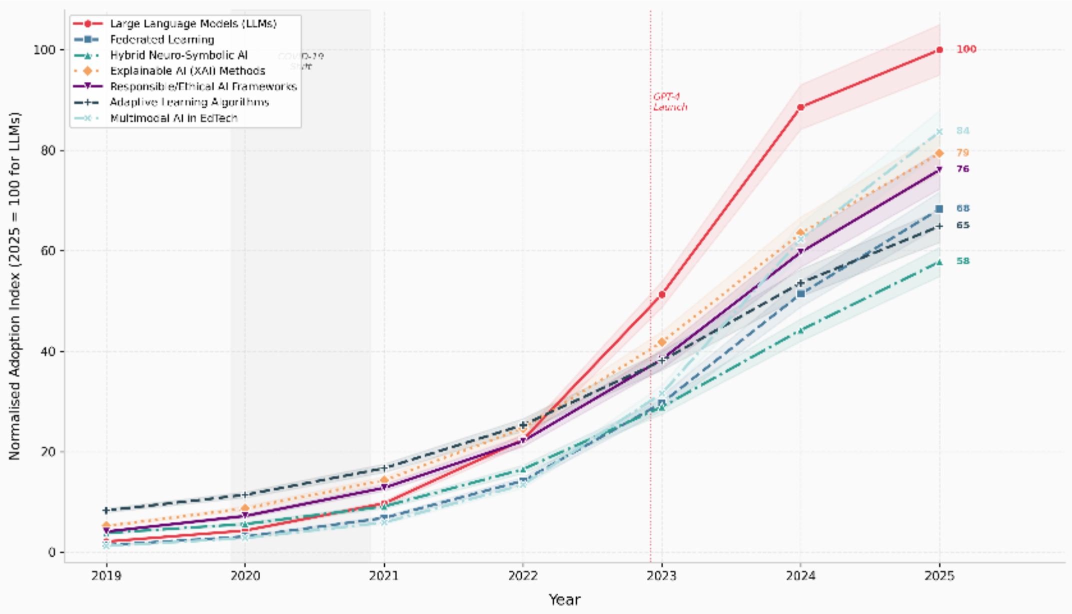

Fig. 3 Temporal Adoption Trends of AI Technique Families in Education (2019-2025)

Fig. 3 explains multi-series line plot tracks seven AI technique families using a normalised adoption index where the LLM series anchors at 100 in 2025. Shaded confidence bands representing plus or minus 5% uncertainty are rendered for each series, and all lines are differentiated by unique marker shapes and linestyles to remain distinguishable in greyscale print. Two annotated vertical markers flag the COVID-19 disruption window (2020) and the GPT-4 launch (late 2022) as structural inflection points. The plot documents the dramatic 47-fold acceleration of LLMs and the parallel rise of Multimodal AI and Responsible AI Frameworks, contextualising these trajectories alongside slower-growing but steadily influential approaches such as Federated Learning and Adaptive Learning Algorithms.

Federated Learning and Privacy-Preserving Methods

The methods known as Federated Learning are becoming more and more significant as they allow AI systems to learn models using data in many different institutions or devices without the need to exchange raw data on students. Conventional machine learning solutions usually demand a centralized source of data collection, which poses very significant questions of Data Privacy, Data Governance, surveillance, and security [27-29]. Federated Learning also reduces these issues by enabling educational establishments to engage in model training together with keeping sensitive data in a decentralized state. Privacy-sensitive artificial intelligence systems (differential privacy, secure multi-party computation, homomorphic encryption, and synthetic data generation) are also becoming increasingly popular in the educational process. The relevance of these methods is due to the fact that in most cases, educational data involve extremely sensitive information of the student behaviors and performance, as well as identity and emotional conditions. According to recent trends, the governance of privacy-first and explainable insights will be the trends applied to educational AI systems in the period of 2026-2030.

Multimodal Learning Analytics and Computer Vision Methods

The Multimodal Learning Analytics techniques integrate analysis based on multiple data types including: Clickstreams, assessments, facial expression, keystroke dynamics, speech signals, posture and eye tracking to form more detailed images of the learners. Computer Vision techniques are finding application as a means to study the behavior and engagement of students in the classroom and their emotional responses in classrooms. The methods of Emotion Recognition and Sentiment Analysis are especially useful in the sense that they enable Adaptive Learning Systems to recognize confusion, boredom, motivation, or frustrations as they happen. Such practices will assist systems to modify instructional material, pace and feedback based on the emotional condition of the learner. Nonetheless, Multimodal Learning Analytics causes also severe ethical issues as it might establish types of surveillance that lower Agency in Students and privacy invasion. Demographic bias is also an issue since the Computer Vision systems might not be consistent with various cultural, racial, and linguistic groups. Consequently, it seems that the Responsible Artificial Intelligence would need a more open governing system, enlightened consent, and advanced ethical protection of multimodal data collection.

Fairness-Aware Machine Learning and Bias Mitigation Methods

Methods of Fairness-Aware Machine Learning are supposed to help minimize Algorithmic Bias and provide Educational Equity in Artificial Intelligence in Education. Educational data sample is usually based on the pre-existing social, economic, linguistic and demographic disparities which may lead to biased forecasts and discriminatory results. The reweighting, adversarial debiasing, fairness constraints, counterfactual fairness, causal inference, and algorithmic auditing are also called bias mitigation methods that are being more used to enhance the fairness in Adaptive Learning Systems. Fairness-Aware Machine Learning is specifically relevant in scenarios that include automated admissions, scholarship distribution, predictive retention research, and academic advising since biased results may have response effects on learners in the long run. The focus on the auditing of fairness at the lifecycle of AI is also underlined by recent events, as well as at the stages of data collection and model training, deployment, and further monitoring of the implemented solutions. Education Responsible Innovation is more and more reliant on both aspects of measuring fairness and considering ethical reviewing mechanisms.

Agentic AI, Multi-Agent Systems, and Future Hybrid Methods

One of the most valuable new trends in the Artificial Intelligence in Education is agentic AI approaches, which allow systems to autonomously plan, reason, coordinate, and adapt to complicated education settings. In contrast to the old-fashioned chatbots or simple recommendation engines, there is also the option to control long-term objectives, call external tools, organize working processes, and communicate with various users in Agentic AI systems [30-32]. Adaptive Learning Systems are now making use of Multi-agent Systems to facilitate collaborative learning and tutoring, automated evaluation, scholastic policy-making, and on-the-fly curriculum plan production. The current studies point out that an agentic type of educational system will further integrate Large Language Models, Retrieval-Augmented Generation, Knowledge Graphs, Reinforcement Learning, memory modules, and external tool integration. Nonetheless, there are also significant moral issues about Agentic AI since autonomous systems can diminish Teacher Oversight, blur Responsibility, increase the threats of bias, privacy, and transparency in decision-making. The Hybrid Intelligences of the future will probably rely on the Human-in-the-Loop approaches, agents of AI that are interoperable and governance frameworks that will help to keep the educational technologies in the line with human values, institutional objectives and ethical principles. The future of education AI will drift away individual predictive systems to more integrated, agency-like systems which collocate human expertise with clear machine intelligence.

3.3 Artificial intelligence technologies

Intelligent Tutoring Systems and Adaptive Learning Platforms

Adaptive Learners systems and Intelligent Tutoring Systems are still two of the most widely utilized Artificial Intelligence technology used in education due to the fact that they offer Personalized Learning, automatic feedback, and customized learning programs. These technologies are based on the concepts of Predictive Analytics, Learner Modelling, Decision Support systems, and Learning Analytics in order to identify what students are not knowing so that learning materials which are being learners can be dynamically modified depending on the performance of the students. Intelligent Tutoring Systems developed nowadays, involve more and more Explainable Artificial Intelligence, Human-in-the-Loop, and Adaptive Explainable AI to enhance the User Trust and Teacher Oversight. Recent years have witnessed trends where adaptive platforms are no longer based on the approaches of having set article recommendation systems but rather on moving to real-time, data-driven environments in which the pacing, content complexity and assessment strategy can be modulated based on the student engagement and contextual behaviour. These educational technologies have also been even more responsive and precise when multimodal data sources and hybrid reasoning models are integrated. Adaptive educational technologies are also considered the cornerstone of the next generation of Artificial Intelligence in Education since they are applicable to academic achievement and personalized learning experience.

Large Language Models and Generative AI Technologies

The use of Large Language Models and Generative AI technologies has quickly become a central focus of Artificial Intelligence in Education since these technologies can produce text, explanations, quizzes, lesson plans, assessments, and even individualized tutoring interactions. They are becoming popular in chatbots used in education, virtual teaching assistants, automated grading, and content creation platforms which have been mentioned [9,33-35]. Large Language Models make possible Natural Language Processing at scale that had previously not been achievable, allowing systems to support the notion of multilingual learning, academic writing assistance, curriculum development and conversational tutoring. RA Generation is gaining significant relevance due to the fact that it enhances the credibility of Generative AI through providing answers, which is based on valid institutional knowledge concepts and external learning materials. Simultaneously, Large Multimodal Models are seeming to be one of the significant technological developments since they can attend to text, images, audio, and video at once and provide more complex learning experiences. Nevertheless, such technologies also bring about ethical issues on hallucinations, misinformation, bias, overdependence and Academic Integrity and Responsible Artificial Intelligence and Teacher Oversight are ever more needed.

Explainable Artificial Intelligence Technologies

Elaborate AI technologies are also getting more significant due to the need of educational facilities to be able to explain their recommendations, forecasts, and choices. Time-honored black-box models are deemed to be not easy to read by educators and students, and this puts a dent on confidence and leads to the belief on accountability and fair play. Explainable Artificial Intelligence systems can be SHAP, LIME, counterfactual explanation, saliency maps, attention visualization, feature attribution systems, as well as model-agnostic explanation interfaces. They are also appearing more often in Intelligent Tutoring Systems, Predictive Analytics dashboards and Learning Analytics to assist the user in comprehending why some decisions are selected. According to the current trends, Explainability is gaining a new approach beyond the technical visualization to personalized explanation systems that suit the needs and expertise of the teachers, students, and administrators. Multimodal Explainable AI Multimodal Explainable AI is a technological innovation that ensures text, graphical and conversational explanations and is likely to become one of the most important educational AI technologies in 2026-2030.

Multimodal Learning Analytics Technologies

Multimodal Learning Analytics technologies gain popularity due to their ability to offer a more in-depth picture of the learner behavior since they integrate a variety of data types. These technologies are based on data on clickstream, assessment performance, eye movements, speech patterns, keystroke patterns, posture, face expression, and interaction history which can be used to build more detailed profiles of learners [36-38]. Not only can Multimodal Learning Analytics enhance Personalized Learning, Student-Centric AI, and Predictive Analytics, they can also accomplish this through the detection of subtle tendencies in engagement, motivation, and emotional reactions. Due to the increasing overlap between Artificial Intelligence and Multimodal Learning Analytics, increasingly responsive educational technologies are emerging, which can adjust with not just their cognitive performance, but also with their emotional and behavioral conditions. Yet, the technologies also provide significant points of concern related to surveillance, informed consent, privacy, and Algorithmic Bias, particularly when the system of Computer Vision and Emotion Recognition can be applied to the sphere of education. Consequently, transparency and ethical protection are becoming indispensable conditions of the implementation of Multimodal Learning Analytics technologies.

Computer Vision and Emotion Recognition Technologies

Adaptive Learning Systems are trending toward the technology of Computer Vision since it can analyze facial expressions, eye motions, gestures, attention, and even interactions in a classroom. These abilities are further expanded by the Emotion Recognition technologies which recognize emotions like frustration, confusion, boredom, motivation, or stress. Learning Personalization can be enhanced with these technologies and provide systems with an opportunity to vary the instruction information, the speed, and the feedback delivered based on the emotional state of the learner. Automated attendance detection, engagement detection, online system of examinations, and classroom analytics are also implemented with the usage of Computer Vision. Although educated by these advantages, one of the most ethical sensitive technological tools in education is Computer Vision and Emotion Recognition technologies, since it can have a heightened surveillance effect and jeopardize Student Agency and Data Privacy. There is further worry about bias in demographics since facial analysis systems might work differently under the barriers of various races, cultures, and languages. The Responsible Artificial Intelligence models are therefore becoming more and more dependent on human inspection, algorithm auditing, and powerful forms of governance prior to the implementation of such technologies on scale.

Federated Learning and Privacy-Preserving Technologies

The relevance of Federated Learning technologies increases as they entail the ability of educational institutions to cooperate around the creation of AI models without providing raw student information to each other. The conventional Artificial Intelligence systems have a tendency to demand centralized data sets posing the threat of privacy invasion, surveillance and the use of data. Federated Learning solves this issue because it allows to train a model across schools, universities, or devices in a decentralized manner and retain sensitive data on local devices. Privacy-preserving AI, including: differential privacy, homomorphic encryption, secure multi-party computation, synthetic data generation, and Machine Unlearning, are also becoming relevant since they enable Data Governance and Responsible Artificial Intelligence. The mentioned technologies are especially applicable to education since student data may contain sensitive, personal, behavioral, and academic data. It is said that Future Adaptive Learning Systems will largely depend on privacy-sensitive technologies to meet the demands of the new AI Regulation, Educational Governance standards, and social demands of information protection.

Knowledge Graphs and Neural-Symbolic Technologies

The Knowledge Graphs technology and Neural-Symbolic AI technologies are becoming the relevant part of Hybrid Intelligence in education due to their ability to integrate the data-driven learning with the explicit reasoning and representation of the knowledge structures. Knowledge Graphs are also being utilized in more and more situations to represent curriculum relations, prerequisite structures, concept dependencies, learner competencies and teaching pathways [3,39-41]. These technologies assist the Adaptive Learning Systems to acquire not only the knowledge that the students have, but also the relationship between concepts among different subjects and learning outcomes. Neural-Symbolic AI technologies combine Deep Learning with symbolic reasoning and ontologies and rule-based logic and enable educational frameworks to propose more comprehendible and suggestions founded on circumstances. The technologies are specifically relevant due to their enhancement of Explainability, Human-AI Collaboration, and disguised constraints of purely statistical models. A significant number of researchers currently consider Neural-Symbolic AI as one of the technologies to reach the goal of Responsible Artificial Intelligence and Trustworthy AI in the education environment.

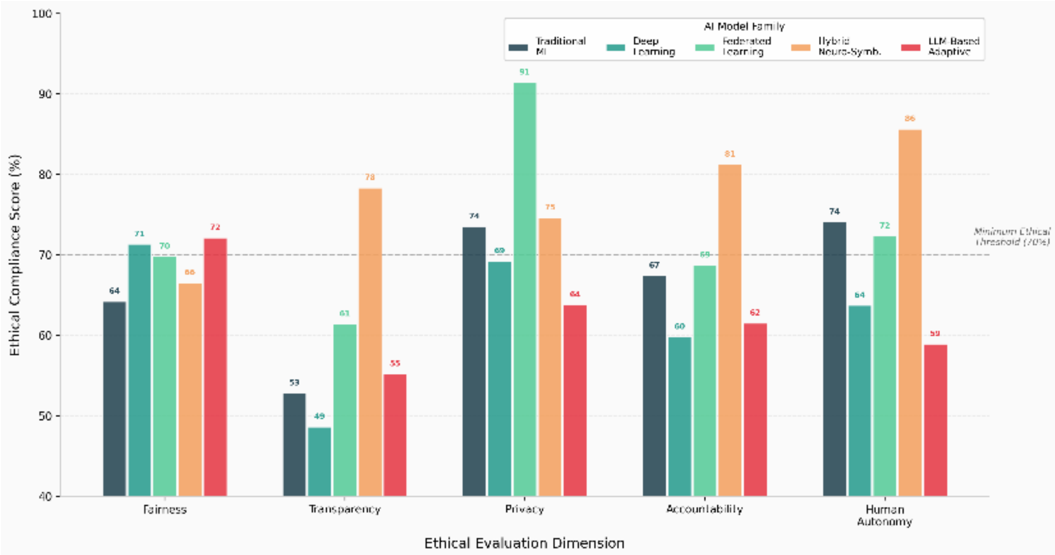

Fig. 4 Ethical Dimension Scores Across AI Model Families in Adaptive Education

Fig. 4 visualizes grouped bar chart evaluates five AI model families, specifically Traditional ML, Deep Learning, Federated Learning, Hybrid Neuro-Symbolic AI, and LLM-Based Adaptive systems, across five ethical evaluation dimensions: Fairness, Transparency, Privacy, Accountability, and Human Autonomy. A dashed horizontal reference line at 70% denotes the minimum acceptable ethical compliance threshold, providing a normative benchmark. Value labels are printed above each bar for precise reading. The chart clearly demonstrates that Federated Learning achieves the highest privacy compliance (91.4%), Hybrid Neuro-Symbolic AI leads on Human Autonomy (85.6%) and Accountability (81.2%), while LLM-Based systems consistently fall below threshold on Transparency (55.2%) and Human Autonomy (58.9%), surfacing a critical policy-relevant gap.

Reinforcement Learning and Autonomous Recommendation Technologies

The use of Reinforcement Learning technology is becoming more popular as means of optimizing Adaptive Learning Systems since the systems allows educational platforms to acquire experience by operating with students and then refine their suggestions. Such technologies are able to establish the most effective teaching methods, sequence of content, timing of feedback and the method of intervention by tracking student response with time. A further extension of these abilities are Deep Reinforcement Learning technologies that incorporate the use of neural networks and allow more complex adaptive behavior. Reinforcement Learning based recommendation technologies are getting more advanced as they are able to use the lifetime modulation value in real-time and they are able to consider dynamic changes in the learning performance and intrigues. But these technologies are also associated with the vulnerability to Explainability, Accountability and Ethical Decision-Making due to the fact that their decision-making procedures are hard to interpret. Explainable Reinforcement Learning is thus coming out as a highly imperative technology in creating transparency and user confidence in adaptive learning environments.

Agentic AI and Autonomous Educational Agents

One of the fastest-evolving technologies of Artificial Intelligence is agentic AI since it allows autonomous educational systems with the ability to plan, reason, coordinate, and act on their own accord. The agentic AI technologies are able to arrange the learning operations, track the student progress, create contents, organize tutoring workflow and modify the instructional courses with little human intervention [36,42-44]. AES are becoming part of the virtual classes, Intelligent Tutoring Systems, and administrative systems. Multi-Agent Systems and interoperability AI ecosystems are likely to increase the use of these technologies. Nevertheless, there is also a significant amount of Future Ethical Issues with Agentic AI since autonomous systems can lead to a decrease in Teacher Oversight, blur Accountability, and increase bias or decisions errors. The existing tendencies put more stress on the importance of governance, transparency, interoperability, and Human-AI Collaboration to make sure that the Agentic AI technologies can be compatible with the educational values and institutional purposes. The educational setting of the future is expected to entail the work of blended ecosystems with human teachers and AI agents who are planned to collaborate instead of working separately.

Multi-Agent Systems and Collaborative AI Technologies

Multi-Agent Systems are the significance of the technological breakthrough since a number of AI agents can cooperate to solve educational problems and assist learners. Educational settings can have different agents with specialization in tutoring, assessment, emotional observation, content development, curriculum design, or administration. The Adaptive Learning Systems developed by Multi- Agent Systems have the ability to develop more flexible and scalable Adaptive Learning Systems in comparison to single- agent architectures. They are often integrated with Large Language Models, Retrieval-Augmented Generation, and Knowledge Graphs to make interdependent educational environments. Current trends indicate that Multi-Agent Systems can be significant in the future Hybrid Intelligence framework since these systems can support Human-AI Collaboration and more sophisticated means of instructional support. Nonetheless, Multi- Agent Systems continue to grow in complexity, and the challenges in Multi- Agent Systems development are interoperability, governance, and accountability. The future studies are likely to be concerned with the standards of how to coordinate a number of agents where transparency and explainability can be provided.

Edge AI and Real-Time Educational Technologies

The technologies of edge AI are acquiring greater significance in the sphere of education as it provides Artificial Intelligence models to work directly on local devices, including tablets, smartphones, laptops, wearable devices, and classroom sensors. The real-time educational apps could be supported by processing data in place, instead of depending solely on cloud tools, which also contributes to minimizing latencies, enhanced privacy, and ecological performance of Edge AI technologies [40,45-47]. The edge AI finds application especially in emotion recognition, speech processing, learning augmented reality and adaptive assessment and offline Intelligent Tutoring Systems in places where the internet is available with low bandwidth. More efficient and secure Personalized Learning is also supported with the help of those technologies as sensitive learner data can be stored on local devices. With the emerging reliance of Adaptive Learning Systems on both real time analytics as well as multimodal inputs, the notion of Edge AI is likely to gain prominence in educational settings as well.

Human-Centered Hybrid Intelligence Technologies

Human-Centered Hybrid Intelligence technologies are increasingly considered as the future of Artificial Intelligence in Education due to them being both efficient in machines and at the same time capable of human expertise, understanding of the context and their moral judgement. The Hybrid Intelligence technologies are made to assist and not substitute teachers and this means that teachers will still be actively involved in making educational decisions. Teacher Oversight and Student Agency is increasingly made more robust through the use of Human-in-the-loop systems, collaborative-dashboards, co-teaching agent, and explainable decision support tools. These technologies have been specifically significant since education is characterized by emotional, social and cultural and contextual variables that cannot be encompassed solely by the algorithms. It is believed that future educational technologies will be based on Human-AI Collaboration, Responsible Innovation, and adaptive models of governance and not entirely based on the completely autonomous AI in the future. Human-Centered Hybrid Intelligence is thus gaining much relevance among the most significant paradigm to make sure Adaptive Learning Systems are transparent, inclusive, equitable, and in accordance with human values.

3.4 Artificial intelligence models

Supervised Machine Learning Models

Supervised Machine Learning models are still among the most popular Artificial Intelligence models used in Adaptive Learning Systems, as they are able to categorize an improvement in performance of learners, forecast their performance results, and detect those students who might be in need of intervention. Popular supervised models are; logistic regression, decision tree, support vegetable machines, random forests, gradient enhancing models, naive bayes classifiers and k-close neighbor coordinators. Such models are being used extensively in Predictive Analytics, Educational Data Mining, and Learning Analytics since they can be used to run historical student data, their attendance patterns, quiz outcomes, metrics of engagement, and assessment data. A decision tree model and logistic regression models are particularly widespread since they imply reasonably good Explainability and Transparency, which is the reason they can be used in Learning environments where Teacher Oversight and User Trust is a consideration. Nonetheless, even when such models are interpolated as being less complex to interpret compared to Deep Learning architectures, they can nonetheless suffer the problem of Algorithmic Bias when trained on historical data sets that mirror educational inequities. Therefore, Fairness-Aware Machine Learning, Bias Mitigation and Explainable Artificial Intelligence are being progressively incorporated into supervised models in an attempt to enhance Accountability and Educational Equity. The growing body of research in the field of adaptive education provides some validity to the view that benchmarking supervised models is increasingly more important due to a frequent adherence to the narrow forms of evaluation and measures that are not sequential.

Deep Learning Models

The Deep Learning models have become extremely powerful in the Artificial Intelligence in Education since they are able to analyze massive amounts of intricate educational data and identify nonlinear trends that other more basic Machine Learning models might fail to notice. Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory models, Transformers, and Graph neural network are also becoming popular as part of Adaptive learning systems to Learner Modeling, Predictive Analytics, Personalized Learning and automatic feedback generation [3,48-50]. Recurrent architectures are particularly effective to models sequential learning behavior like clickstreams, learning pathways, and repeated assessment interactions and Transformer-based model can model long-range dependence and context dependence. Deep Learning models have advanced Intelligent Tutoring Systems and adaptive recommendation engines a fair deal and raise issues since they usually are black-box systems. Absence of Explainability and Algorithmic Transparency has the potential to decrease User Trust and make Human-AI Collaboration difficult. Consequently, the current trend of applying Deep Learning together with Explainable Artificial Intelligence algorithms like attention visualization methods, feature attribution, saliency maps, and counterfactual reasoning is getting more and more up to date. There are also developing transparent multimodal frameworks that can be used to explain it in a personalized way based on the needs of the teacher, students, and administrators.

Large Language Models and Generative AI Models

Large LM models and Generative AI models are fast transforming Artificial Intelligence in Education since they have the ability to produce explanations, response to queries, summarize information, create lesson plans, develop exams, and serve as conversational tutors. The development of Large Langue Models is toward the multimodal and long-context reasoning capabilities along with Retrieval-Augmented Generation which makes them more suitable in Adaptive Learning Systems. Applications in education are also starting to use Large Language Models to provide feedback on essays, autotutor, design curriculum, multilingual activity, and provide individualised advice on learning. GPT-5, Gemini, Claude, Llama, Mixtral, and DeepSeek models are becoming more frequently discussed in the educational research due to being more reasonable, offering multimodal processing, and fine-tuning on a domain scale. Nevertheless, Large Language Models also present significant ethical issues as it is susceptible to information hallucination, can strengthen biases, and can decrease Academic Integrity by depending on computer generated content excessively. Responsible Artificial Intelligence systems thus toy with Teacher Oversight, Human-in-the-Loop validation as well as open exposure of AI-generated material. According to the views of many researchers, the future educational Large Language Models will rely more on Retrieval- Augmented Generation and organised integration of knowledge to enhance the accuracy and minimize hallucinations.

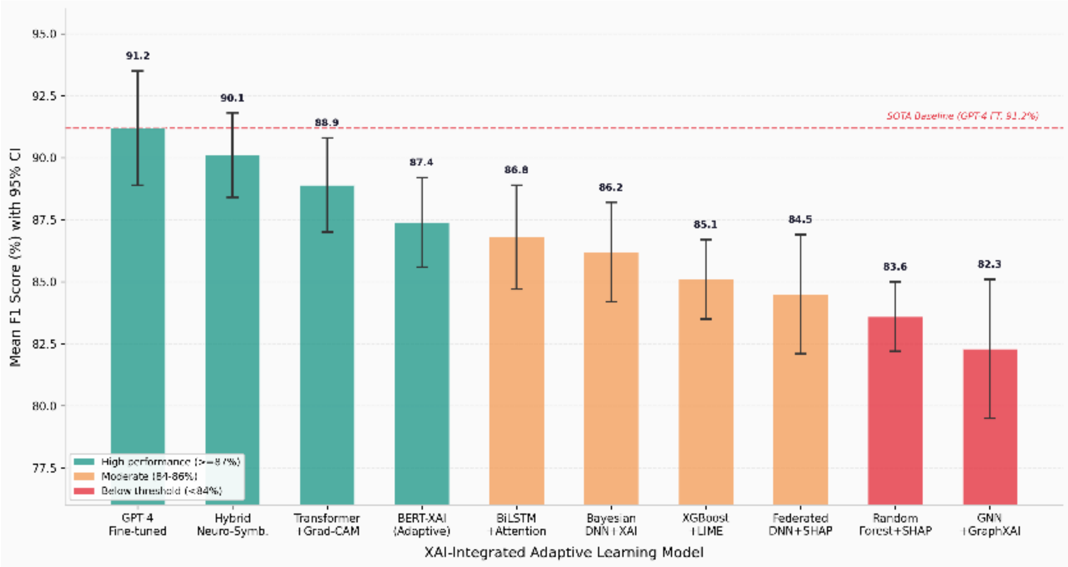

Fig. 5 Mean F1 Scores with 95% Confidence Intervals for XAI-Integrated Adaptive Learning Models

Fig. 5 shows horizontally-ranked bar chart with superimposed 95% CI error bars compares ten XAI-integrated model architectures evaluated through 10-fold cross-validation across six educational datasets. Bars are coloured by performance tier: teal for high-performing models at 87% and above, amber for moderate performers between 84% and 86%, and red for those below 84%. A dashed SOTA baseline at 91.2% (GPT-4 Fine-tuned) provides a reference ceiling. Hybrid Neuro-Symbolic and GPT-4 Fine-tuned models jointly occupy the top tier, whereas GNN with GraphXAI shows the largest confidence interval (plus or minus 2.8%), suggesting higher variance across datasets. This figure is directly reproducible for comparative benchmarking sections in Scopus-indexed machine learning and educational technology journals.

Bayesian Knowledge Tracing and Deep Knowledge Tracing Models

Knowledge Tracing models are considered to be some of the most significant AI models in Adaptive Learning System since they are trying to approximate the changing knowledge condition of learners as time goes by. Bayesian Knowledge Tracing is a popular model due to the fact that it determines the likelihood of an individual that has learned an idea upon accomplishment of the series of exercises [5,8,51-52]. Nevertheless, Deep Knowledge Tracing models earned significant popularity due to their ability to learn closer and nonlinear patterns of student learning with the help of recurrent neural networks and Transformer-based networks. The Deep Knowledge Tracing models are also effective in the sense that it is able to capture the temporality, repetition of practice and dynamic variations in the learner performance. More recent work focuses on interpretable Knowledge Tracing architectures that utilize Large Language Models, memory components alongside semantic reasoning to bring about more high-level educational diagnoses. New models like memory-based retrieval systems are being designed so as to produce definite explanations of what learners predict and need less expensive model retraining. These methods enhance the Explainability, reduce the computational expenses, and allow more dynamic learner modeling within adaptive learning settings.

Neural-Symbolic AI Models

The Neural-Symbolic AI models are gaining more relevance as they hold the pattern recognition power of neural networks along with symbolic reasoning power of a system. Pure neural models are typically not logically consistent, not causal, and not Explainable, whereas pure symbolic systems are typically not scalable to large and complexity educational data. Neural-Symbolic AI also solves these limitations by means of applying ontologies, rules, semantic reasoning, and Knowledge Graphs to the Deep Learning frameworks. Neural-Symbolic AI models can be used to assist more transparent decision-making and explain recommendations in a logical chain, in addition to applying the knowledge of the teacher in automated systems in Adaptive Learning Systems. The models are particularly applicable in Responsible Artificial Intelligence since they enhance Trustworthy AI and minimise the chances of hallucinations related to Large Language Models. There is growing evidence that neuro-symbolic architectures are likely to be a core of Hybrid Intelligence in Education since they trade-off flexibilities, reasoning and interpretability. The increasing connection between Large Language Models and Knowledge Graphs and symbolic reasoning is likely to find applications in the future generation of Intelligent Tutoring Systems and Adaptive Explainable AI.

Reinforcement Learning Models

Reinforcement Learning models are finding more and more application to Personalized Learning as they allow the instructional strategy to be modified depending on the behavior and feedback of students. Such models are educational by engaging in interaction with learners and maximizing actions to produce learning of maximal benefit in the long-term [9,53-55]. Reinforcement Learning models particularly come in handy in order to know the best order of lessons, the best interventions, how to modify the content to be covered and the best time to provide feedback. Deep Reinforcement Learning models build upon these abilities by considering neural networks that are capable of processing more intricate learning settings. Reinforcement Learning can be used in Adaptive Learning Systems in real-time personalization of education and dynamic recommendation engines. Nevertheless, also these models pose some difficulty since decision-making processes tend to be hard to understand and Explainable Reinforcement Learning becomes more significant. Educational researchers have begun contemplating how to integrate Reinforcement Learning and Human-in-the-Loop control and Explainable Artificial Intelligence to guarantee that adaptive choices are transparent, just and responsible.

Federated Learning Models

The reason why federated learning models are gaining importance in the education sector is that it enables several institutions or devices to provide training to an AI system in ways that do not involve distributing raw data of students. The models are very applicable in the Responsible Artificial Intelligence due to the consideration of issues related to Data Privacy, Data Governance, and surveillance. Adaptive Learning Systems, Predictive Analytics and Learning Analytics can be supported by Federation Learning models and sensitive student information can be kept decentralized. This is especially significant as educational data are usually highly sensitive in terms of such aspects of behavior as emotional and academic records. Federated Learning is also used increasingly with Edge AI, Privacy-Preserving AI and differential privacy solutions in order to build safe and scalable education systems. Recent trends also suggest that Federated Learning is likely to be intimately coupled with Agentic AIs that can not only plan out distributed learning activities, identify the best clients, and even dynamically vary training plans across networks.

Graph Neural Network and Knowledge Graph Models

Graph Neural Network models and Knowledge Graph-based models are being more extensively utilized in the fields of Artificial Intelligence in Education since they are capable of modeling relationships between concepts of education, prerequisites, the characteristics of a learner, and curriculum paths. Graph Neural Networks have the ability to define building structures and relationship information of such data in a better way than the traditional Deep Learning models. These models are capable of improving Learner Modeling, Predictive Analytics, and recommendation systems in Adaptive Learning Systems because they understand the relations between concepts in one course and learning objective and another. The valuable feature of Knowledge Graph models is that they allow devising more interpretable recommendations and Explainable Artificial Intelligence. He or she might also enhance Large Language Models with the grounding of generated responses based on structured educational knowledge to minimize hallucinations and enhance factual accuracy. Knowledge Graphs, Neural-Symbolic AI and Large Language Models are becoming increasingly viewed as the most promising avenue in education technologies in the future.

Multimodal AI Models

The significance of multimodal AI models is growing, as they have the capability of handling various types of educational data at once such as text, speech, video, facial behavior, clickstream, posture, eye-tracking, and test scores. There is particular relevance of Large Multimodal Models due to the fact that they combine NLP, Computer Vision, Emotion Recognition, and Sentiment Analysis in one educational system. These models are able to offer more comprehensive Learner Modeling and more adaptive Adaptive Learning Systems since they are based on emotional, cognitive, and behavioral aspect of learning. Depending on the nature of the confusion, boredom, motivation, or frustration, Multimodal Learning Analytics models are capable of identifying this and adjust instructional material. Nonetheless, these models also pose serious ethical issues as they can increase surveillance, in other words decrease Student Agency and increase demographic bias in case they are not conceived carefully. The recent studies tend to suggest more and more that multimodal educational models should be integrated with Explainable Artificial Intelligence and proper governance processes to make sure that fairness, transparency, and informed consent can be ensured.

Agentic AI and Multi-Agent Models

The agentic AI models also represent some of the most rapid developments in the field of Artificial Intelligence due to the ability to plan autonomously, reason, utilize the tools, and coordinate them. Within educational settings, the User Agentic AI models have the ability to support the sequence of the lesson, track learner progress, develop adaptive interventions, coordinate the tutoring process, and communicate with teachers [56-58]. Multi-Agent Systems can go further, offering the capability of multiple AI actors cooperating in the area of tutoring, testing, curriculum development, emotional studies, and management. These models will be more highly needed within Adaptive Learning Systems since they will enable more scalable, as well as context sensitive educational setups. But any of the Accountability, Teacher Oversight, transparency, and Human-AI Collaboration is also a significant issue to the Agentic AI model. In the absence of a well-defined governance structures, autonomous educational agents are likely to make decisions that are hard to interpret and hard to dispute. The current thinking is that future Agentic AI systems ought to have centralized monitoring, dynamic feedback loops, interoperable standards and Human-in-the-Loop control to enable them be kept close to the desired educational objectives and ethics.

Hybrid Human-AI Models

However, Hybrid Human-AI models have been becoming one of the most prospective solutions to Responsible Artificial Intelligence in Education due to their ability to blending machine efficiency and human judgment, contextual knowledge, and ethical-based arguments. Instead of taking the place of teachers, Hybrid Intelligence models are aimed at promoting Human-AI Collaboration and making sure the educators do not passively take part in the decision-making processes. These models are especially significant as educational settings entail motivation, feeling, metacognition and social environment, which cannot be disclosed by automated systems only. The Human-in-the-Loop models can be used to verify the AI-generated recommendations, guarantee reduction bias, and make sure that adaptive interventions are based on the needs of learners. Recent studies are increasingly of the opinion that Hybrid Human-AI systems must emerge as the core of educational AI collection in that they overcome the enduring drawbacks linked to black-box models, non-sequential analysis and lack of stakeholder engagement. The seamless development of the Future Responsible Artificial Intelligence system should be based on the collaborative human-machine model where explainability, localized recommendations, and ethical control are more crucial factors to consider.

Machine Unlearning and Responsible AI Models

Machine Unlearning models are becoming a significant aspect of Responsible Artificial Intelligence since it enables AI systems to unlearn or delete particular data points in trained models. Machine Unlearning has gained much application in the education field, specifically in the areas of privacy protection, reduction in bias, and responsiveness to changes in the learning setting [59-60]. Data in education is usually sensitive and dynamic hence; the students might be required to revoke consent, change wrong records, and/or seek deletion of any personal data. Machine Unlearning models allow the concern to be addressed without full retraining of the model. These models have also come to be regarded as significant towards enhancing resilience to adversarial inputs, minimizing systemic bias and adhering to future AI Regulation structures. Along with the trend of the increase of Adaptive Learning Systems, the feature of Machine Unlearning is likely to dominate Privacy-Preserving AI and Trustworthy AI in education.

3.5 Artificial intelligence applications

Personalized Learning and Adaptive Learning Systems

One of the critical uses of Artificial Intelligence in Education is Personalized Learning because Adaptive Learning Systems can customize their content, pacing and tests, and instructional paths to the needs of a particular learner. Such systems are based on the concepts of Learning Analytics, Educational Data Mining, Predictive Analytics, and Learner Modeling to detect the strengths, weaknesses, preferences, and knowledge gaps in real time. Explainable Artificial Intelligence, Reinforcement Learning, and Large Language Models are becoming more important in the creation of more transparent and dynamic learning recommendations by modern adaptive platforms. Personalized Learning environment is particularly valuable to a student with varying learning styles, difference levels of prior knowledge, and progression rate. New educational technologies are becoming more and more multimodal with the addition of clickstreams, quiz performance, behavioral patterns, and engagement metrics to adaptive decisions to enhance precision and responsiveness. Now the adaptive Learning Systems have been thought out as one of the most helpful uses of AI as it can enhance learning performance, add more interest, and help to make educational processes more inclusive. The evidence of meta-analyses indicates that AI-based adaptive learning systems may induce medium to large positive cognitive outcomes changes according to numerous educational settings.

Intelligent Tutoring Systems and Autonomous Tutoring

Intelligent Tutoring Systems have been one of the oldest AI applications since it is analogous to one to one tutoring since it offers individualized instructions by giving automatic feedback and adaptive instruction. Such systems are increasingly using Generative AI, Large Language Models, Reinforcement Learning, and Agentic AI to offer continuous tutoring in real-time, which varies according to the performance of learners [9,61-63]. The autonomous tutoring system is able to detect misconceptions and prescribe exercises, present challenging concepts, and adjust learners instructional chain depending on their progress. Recent events hint at the fact that Agentic AI and Multi-Agents Systems gain particular significance as they provide tutoring platforms with the opportunity to synchronize various activities that comprise tracking performance, creating explanations, identifying knowledge gaps and scaling down lesson plans at the same time. The tutoring systems that use AI are getting considered as an essential part of the educational ecosystem in the future since such systems may provide individualized learning at scale and at a low cost since they neither require high teacher workload. The applications, however, also question the issue of Transparency, Accountability, and Teacher Oversight due to the possibility of fully autonomous tutors to make a recommendation that is hard to interpret and hard to contest.

Automated Assessment and Smart Grading Systems

Automated Assessment systems are employed more in the field of education since they can mark essays, quizzes, assignments, coding projects, and examinations faster and more accurately compared to manual marking. The Natural Language Processing, Large Language Models, Computer Vision, and Predictive analytics are commonly used to evaluate written work, oral presentation work, visual work, and problem-solving tasks using Smart Assessment Systems. Those systems come in handy in very large educational institutions where, teachers are required to assess very many students in a very short amount of time. New advances in Explainable Artificial Intelligence have helped open up the process of automated grading through allowing systems to give reasons behind scores, pointing out aspects where improvement is possible, and showing patterns in errors made by learners. Nonetheless, the issues of unfairness, bias, and academic integrity cannot be disregarded since automated systems are prone to misinterpretations in the case of complicated answers, upholding language preferences, or punishing learners who represent different cultural or linguistic backgrounds unfairly. Therefore, Human-in-the-Loop assessment models are becoming favored especially in an effort to make certain that automated grading systems are accountable and educationally viable.

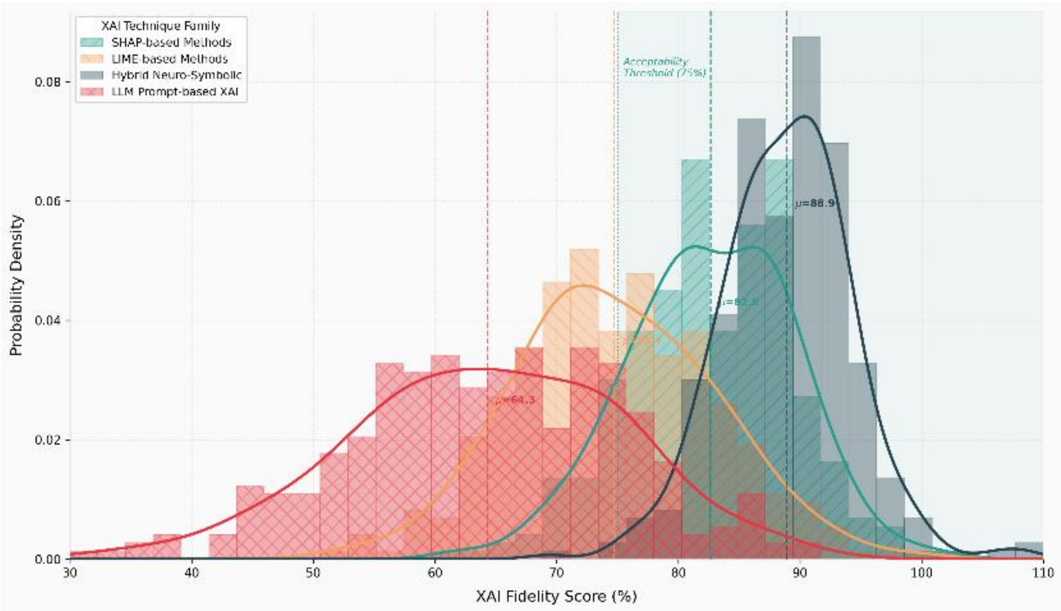

Fig. 6 Distribution of XAI Fidelity Scores Across Published Studies (2019-2025)

Fig. 6 explains KDE-overlaid density histogram presents the empirical frequency distribution of XAI fidelity scores reported across the 128 included studies, stratified into four XAI technique families. Each family is rendered with a distinct hatch pattern to ensure accessibility under greyscale reproduction. Dashed vertical lines mark each group's mean, with annotated mu values, enabling direct distributional comparison. A shaded region right of the 75% acceptability threshold highlights the proportion of studies meeting minimum fidelity standards. Hybrid Neuro-Symbolic methods exhibit the highest mean fidelity (88.7) with the tightest distribution (standard deviation 5.2), indicating both superior performance and reliability, while LLM Prompt-based XAI displays the widest and most left-skewed distribution (mean 63.5, standard deviation 10.4), flagging a critical area requiring methodological standardization.

AI-Powered Feedback and Writing Assistance

Feedback systems based on AI are changing the way learning happens due to their ability to offer real-time and personalized feedback in a detailed manner to students. NLP and Large Language Models are increasingly being used to assist essay writing by adding revision, grammar correction, summarizing, assisting with citation and reflective writing [64-66]. The systems may assist students to enhance the level of writing performance in academics and minimized the amount of time taken by the instructors in terms of repetitive feedback assignments. More recent educational applications are incorporating Retrieval-Augmented Generation to give more correct and context-relevant feedback because they relate responses to course materials, institutional policies, and other known sources of information. The AI-Powered Feedback is specifically helpful as it makes learning self-regulated and gives students a chance to make revisions to their work. Nevertheless, over-use of automated writing aids could present some ethical dilemmas concerning Academic Integrity, artificial competence and diminished critical thinking. The educational researchers are increasingly alarming that students can become mere consumers of answers created by AI rather than work on other skills related to analyzing and composing.

Learning Analytics and Predictive Student Support

One of the most significant applications of Artificial Intelligence in Education is Learning Analytics and Predictive Analytics as they can assist the institutions determining the patterns in student performance, engagement, and retention. Predictive Analytics have become very popular in educational institutions to recognize vulnerable learners, predict the chances of dropping out, track attendance, and structure intervention programs. Such systems are based on Machine Learning, Educational Data Mining, and Learner Modeling to process large-scale educational data provided by learning management, attendance, and assessment results and online interactions. Student support systems predictive in nature may enhance student retention, academic advising, and mental health as they identify learners who might need extra support before the issues escalate to critical levels. Nevertheless, Algorithmic Bias, Transparency, and Educational Equity are also apparent issues in predictive systems since they might discriminate against specific groups of students as being at risk. Accountable AI systems thus note the importance of Explainability, Fairness-Conscious Machine Learning and instructor participation when predictive models are applied in educational decision-making.

Conversational Agents and Educational Chatbots

Owing to the fact that it offers immediate responses, tutoring, administrative support, and personal assistance to learners, Conversational Agents and Educational Chatbots have become more widespread. The current generation of educational chatbots is based on the use of Large Language Models, Natural Language Processing, and Generative AI as these systems can respond to questions, provide explanations, suggest materials, and direct students throughout learning sessions [6,67-69]. AI application in conversational applications is specifically effective in online learning systems since they have the ability to support students around the clock, even outside the classroom hours. Chatbots are also actively used in education, especially in the onboarding, advice, scheduling, and frequently asked questions. However, it is feared that overextending the use of chatbots may give an illusion of competence in learners whereby students will seemingly know the material because they are capable of producing smooth responses without necessarily learning concepts. Such a deception of mastery has become a rising concern when it comes to the discourse of Responsible Artificial Intelligence in Education.

Multimodal Learning Analytics and Emotion Recognition

The use of Multimodal Learning Analytics applications is gaining relevance due to the integration of several types of data on learners to generate more elaborate and dynamic learning experiences. These systems are able to combine the senses of clickstreams, eye, facial, posture, speech, keystroke patterns and assessment to determine engagement, motivation, confusion, and emotional statuses. Emotion Recognition technologies are particularly useful in context of the fact that they enable the Adaptive Learning Systems to be dynamic in responding to boredom, frustration or cognitive overload in the students. An example is a system that simplifies content, provides encouragement or offers extra resources in case a disengagement has been detected by the system. Nevertheless, the ethical issues of such applications are not minor as well since they rely on highly personal information. Unless carefully applied, Computer Vision and Emotion Recognition technologies can enhance surveillance, interfere with privacy, and introduce bias in terms of demographics. The implementation of multimodal educational systems is thus accompanied by the focus on responsible Artificial Intelligence models, which value the prominence of informed consent and transparency as well as Human-in-the-Loop monitoring.

Curriculum Design and Content Generation

There is an increase in the use of generative artificial intelligence in curriculum design and the creation of educational content since it is capable of creating lesson plans, quizzes, simulations, worksheets, presentations and multimedia works. With Large Language Models and Large Multimodal Models, teachers are increasingly adopting these models to produce instructional formats that are relevant, culturally, and personalized to their students and at the right time [70-73]. The value of these applications is especially high as they help decrease the amount of work of the teacher, aid in differentiated teaching, and make them more accessible to students with various learning requirements. Co-creation may also be supported by AI-generated content, though: in this case, educators and learners come up with content together with the help of AI. The growth of education technologies is also on the tack of providing text, images, audio, and video, in order to more effectively build educative contents.

Nevertheless, education generation applications also provoke the issues of relevance and factual correctness, copyright, and overreliance on AI technologies. Subsequently, Teacher Oversight is the necessary element to guarantee the AI-based educational resources to be correct, inclusive, and correspond to learning objectives.

Virtual Learning Environments and AI-Powered Classrooms

VLEs and AI-assisted classrooms are increasingly adopting and using artificial intelligence to design even more interactive, evidence-based and tailored learning experiences. Virtual classrooms are exposed to AI-enhanced academic models that can facilitate automated attendance recording, individual lesson algorithm, student tracking, and real-time analytics systems. According to the latest trends, it is possible to note that Agentic AI, Multi-Agent Systems and Autonomous Educational Agents are becoming more and more often used in a classroom setting by means of organizing instructional initiatives, creating adaptive suggestions, as well as assisting with administrative procedures. Online learning and schools run by AI are in the future as an experimental phase of education especially in technological and privately run institutions. Nevertheless, there are still concerns about the area of Educational Equity where the access to the highest-level AI-based environments might be distributed unequally between the socioeconomic groups. Social interaction, collaboration, and critical thinking are also issues on which researchers doubt the potential of AI-centric classrooms to fully serve the purpose.

Academic Integrity Monitoring and Plagiarism Detection

Generative AI and Large Language Models have caused Academic Integrity applications to gain growing significance since now any student can create assignments, essays, and projects with a minimum amount of effort. AI-based plagiarism detection systems, authorship analysis tools, similarity of codes and pattern analysis of writing are becoming popular in educational institutions to establish whether AI-generated content is being misused. Such systems are able to identify abnormal stylistic change, and similarity to familiar AI offerings and discrepancies in the work of students. Nevertheless, academic integrity surveillance systems are also concerning since they tend to produce false positives, disadvantage some learners and have per-adversarial impacts between learners and institutions. The concept of responsible Artificial Intelligence frameworks further stipulates that the technologies of academic integrity are not just to be implemented to facilitate surveillance but also to promote education and an overall awareness of the ethics of the use of the technology, as well as ethical AI usage. Therefore, clear guidelines, AI literacy and transparent institutional policies are viewed as critical in removing the imbalance between innovation and academic honesty.

Teacher Support, Administrative Automation, and Decision Support Systems

Applications of Artificial Intelligence are being more heavily deployed to assist teachers and educational administrators as they begin to automate most of the tedious work, assist in decision-making, and also lighten the administrative load. The application of AI-driven Decision Support Systems can assist the teaching staff in recognizing underperforming students, distributing resources, scheduling, as well as interventions [19,74-76]. Applications in administration have been found to enrollment forecasting, attendance management, scheduling, curriculum planning and communication with students and parents. Lesson planning, grading, report writing, classroom management Instructor co-pilots based on Large Language Models are progressively applied to guide teachers in their task. These technologies have the potential to enhance performance and enable educators to devote a greater part of time to mentoring and human interaction. Accepting this though, some people worry that overreliance on AI can diminish teacher agency, undermine professionalism, and turn teachers into supervisors, and not instructors, as previously.

Explainable and Responsible Hybrid Intelligence Applications

Explainable and Responsible Hybrid Intelligence applications have become universally acknowledged as the most viable way to go in the future of Artificial Intelligence application in Education as it involves the application of machine intelligence and human knowledge, ethical judgment and contextual knowledge. Hybrid Intelligence systems strive to focus on the Human-AI Collaboration, Teacher

Oversight, Student Agency, and open decision making. These applications are gradually adding Explainable Artificial Intelligence, Knowledge Graphs, Neural-Symbolic AI, and Adaptive Explainable AI to make sure that teaching suggestions will be comprehendible and disputable where required. The use of Hybrid Intelligence is of particular relevance to high-stakes situations, like admissions, retention prediction, academic advising, mental health monitoring, and scholarship allocation since such decisions can have a great impact on learner outcomes. Recent studies tend to think more and more that Explainability must be regarded as a dynamic communication process that suits various stakeholders instead of being a strictly technical feature. The Artificial Intelligence Future in Education thus has the potential of relying on Hybrid AI solutions based on Trustworthy AI, fairness, transparency and human-centered design.

4. Discussion

As this literature review has shown, Explainable Artificial Intelligence, Responsible Artificial Intelligence, and Hybrid Intelligence are the focus of the future of Adaptive Learning Systems and Artificial Intelligence in Education. With the swift adoption of Generative AI, Large Language Models, Intelligent Tutoring Systems, Predictive Analytics and Learning Analytics, Personalized Learning has been changed more dramatically in terms of automated assessment and learner support [77-79]. But the findings show that schools are becoming more vexed by Explainability, Transparency, Accountability, Fairness, Algorithmic Bias and Data Privacy issues. The issue with the current Adaptive Learning Systems is that, even though AI technologies have the potential to enhance the performance of learners, automatizing certain laborious processes, and offering their education more personalized, most black-box models still diminish the Teacher Oversight and the User Trust. The research generally indicates that the educational community is increasingly worried about the AI-generated recommendations and the effects that the recommendations may have on learners, as well as about the justice and inclusivity of the systems. Explainable Artificial Intelligence thus is becoming a crucial part of Trustworthy AI since it enables teachers, students, and administrators to comprehend what thinking, classification, and suggestions. It is also argued in recent evidence that the issue of transparency in AI within education is not only an element of technology but a communication process designed to meet the requirements of various stakeholders.

The most significant theme that comes out during the review is the increased role of Hybrid Intelligence and Human-AI Collaboration in learning institutions. However, instead of being entirely based on fully autonomous systems, recent studies are showing an increasing support to the Human-in-the-Loop systems which are composed of machine performance and teacher qualifications, serving contextual knowledge and moral reasoning. The results indicate that Hybrid Intelligence may be used to solve the long-standing limitations that are linked to black-box algorithms, non-sequential modelling of learners, insufficient participation of stakeholders and insufficient consideration to emotion, motivation and metacognition. Neural-Symbolic AI, Knowledge Graphs, and Adaptive Explainable AI are currently considered as promising methods due to their enhanced Explainability, ability to think logically and be able to make localized recommendations based on the needs of particular learners. Moreover, Human-AI Collaboration has a capacity to minimize the threat of excessive confidence in automated processes where educators have the capacity to accept, restructure, or dismiss AI-generated advice. This is especially crucial in situations of high stakes in education like in admissions, prediction of retention, allocation of scholarships, academic advising, and mental health monitoring. The latest debates have proposed more and more that Hybrid Human-AI systems are to be created as the key to responsible Artificial Intelligence in education since they facilitate fairness, accountability, and more context-sensitive decisions.

Table 1. Summary of Artificial Intelligence Applications, Techniques, Methods, Technologies, and Models in Education

Sr. No.	Application	Techniques / Methods / Technologies / Models	Key Opportunity
1	Personalized Learning	Adaptive Learning Systems, Predictive Analytics, Learner Modeling	Tailored educational pathways
2	Intelligent Tutoring Systems	Reinforcement Learning, Large Language Models	Individualized tutoring support
3	Automated Assessment	Natural Language Processing, Smart Assessment Systems	Faster grading and feedback
4	Academic Advising	Predictive Analytics, Decision Support Systems	Early identification of at-risk students
5	Curriculum Design	Generative AI, Retrieval-Augmented Generation	Automated content creation
6	Conversational Tutoring	Educational Chatbots, Large Language Models	24/7 student support
7	Student Engagement Monitoring	Computer Vision, Emotion Recognition	Real-time engagement detection
8	Learning Analytics	Educational Data Mining, Deep Learning	Improved understanding of learner behavior
9	Recommender Systems	Collaborative Filtering, Reinforcement Learning	Personalized resource suggestions
10	Knowledge Tracing	Bayesian Knowledge Tracing, Deep Knowledge Tracing	Dynamic learner state estimation
11	Virtual Learning Environments	Agentic AI, Autonomous Educational Agents	Scalable online education
12	Multimodal Learning Analytics	Large Multimodal Models, Sentiment Analysis	Richer learner profiles
13	AI-Powered Feedback	Generative AI, Natural Language Processing	Faster revision support
14	Administrative Automation	Decision Support Systems, Multi-Agent Systems	Reduced teacher workload
15	Attendance Tracking	Computer Vision, Edge AI	Real-time classroom management
16	Mental Health Monitoring	Emotion Recognition, Sentiment Analysis	Early emotional intervention
17	Inclusive Education	Student-Centric AI, Fairness-Aware Machine Learning	Better accessibility and equity
18	Scholarship Allocation	Predictive Analytics, Fairness Auditing	Transparent resource allocation
19	Admissions Screening	Machine Learning, Bias Mitigation	Improved admissions efficiency
20	Teacher Support	Human-AI Collaboration, Co-Teaching Agents	Enhanced teaching effectiveness
21	Language Translation	Natural Language Processing, Large Language Models	Multilingual accessibility
22	Knowledge Graph-Based Learning	Knowledge Graphs, Neural-Symbolic AI	Better conceptual understanding
23	Privacy Protection	Federated Learning, Privacy-Preserving AI	Stronger student data protection
24	Local Device Learning	Edge AI, Federated Learning	Faster and more secure processing
25	Explainable Decision Support	Explainable Artificial Intelligence, SHAP, LIME	Greater transparency and trust

The review also demonstrates that Generative AI, Large Language Models, Agentic AI, and Multi-Agent Systems are also increasing rapidly in the prospects of Artificial Intelligence within Education. They are technologies applied more and more to generate content, AI-Powered Feedback, Virtual Learning Environments, Smart Assessment Systems, automated tutoring, and administrative decision support [6,80-84]. LLM applications are now capable of curriculum design, lesson planning, multilingual tutoring, conversational support and automated grading and Agentic AI systems are starting to plan complex pedagogical processes on their own. Although such opportunities exist, the results demonstrate that such technologies also pose new risks to hallucinations, misinformation, Academic Integrity, and algorithmic-opaque character and overreliance of students on the AI-generated material. The review implies the growing access to the Generative AI tools can lead to the faculty of the illusion of competence among the learners in which students may seem to comprehend concepts due to their ability to generate more advanced answers without necessarily gaining deeper conceptual knowledge. Therefore, it is necessary to include in the research that the governance structures are formed in line with balancing between innovation and ethical protection and making sure that AI tools complement each other and cannot substitute human learning and critical thinking.

Table 2. Summary of Key Challenges, Opportunities, and Future Directions in Responsible Hybrid Intelligence in Education

Sr. No.	Challenge	Opportunity	Future Direction
1	Black-box AI systems	Explainable Artificial Intelligence	Personalized multimodal explanations
2	Algorithmic Bias	Fairness-Aware Machine Learning	Continuous fairness auditing
3	Data Privacy Risks	Federated Learning	Privacy-first governance
4	Lack of Teacher Oversight	Human-in-the-Loop	Collaborative Human-AI systems
5	Weak Transparency	Algorithmic Transparency	Adaptive Explainable AI
6	Hallucinations in Generative AI	Retrieval-Augmented Generation	Knowledge-grounded AI systems
7	Academic Integrity Issues	AI Literacy Programs	Ethical AI usage frameworks
8	Limited Stakeholder Involvement	Human-AI Collaboration	Participatory AI design
9	Lack of Standardized Governance	Educational Governance	Global AI policy standards
10	Biased Training Data	Bias Mitigation	Synthetic and balanced datasets
11	Overreliance on Automation	Hybrid Intelligence	Teacher-centered AI integration
12	Poor Interpretability of Deep Learning	Interpretable Machine Learning	Transparent neural architectures
13	Weak Local Adaptation	Student-Centric AI	Localized recommendations
14	Inadequate Emotional Modeling	Emotion Recognition	Context-aware learner support
15	Security Vulnerabilities	Privacy-Preserving AI	Secure educational infrastructures
16	High Computational Costs	Edge AI	Efficient on-device learning
17	Misuse of Non-Sequential Models	Sequential Learner Modeling	Temporal analytics frameworks
18	Low User Trust	Explainability and Accountability	Trustworthy AI ecosystems
19	Unequal Access to AI	Inclusive Education	Equitable digital infrastructure
20	Inconsistent Ethical Standards	Responsible Innovation	Unified ethics frameworks
21	Limited Benchmarking	Comparative Evaluation Models	Standardized educational AI testing
22	Weak Regulation	AI Regulation	International compliance standards
23	Lack of Data Removal Options	Machine Unlearning	User-controlled educational data
24	Overdependence on Generative AI	Human-AI Collaboration	Critical thinking-focused pedagogy
25	Fragmented Educational Systems	Multi-Agent Systems	Interoperable educational ecosystems

The other relevant discovery is that Fairness-Aware Machine Learning, Bias Mitigation, Federated Learning, Privacy-Preserving AI, and Machine Unlearning are emerging as highly relevant, in terms of guaranteeing Educational Equity and addressing the privacy of students. Sensitive behavioral, emotional, demographic, and academic data are usually acquired during the process of education, which is why Data Governance and Privacy-Preserving AI become major priorities. According to the review, several existing AI systems are prone to such risks that they promote historical disparities due to educational datasets potentially being based on social, linguistic, cultural, and economic biases. This brings a strong demand of equity auditing, the transparency measures, and privacy-saving strategies that may minimize discriminatory results in the Predictive Analytics, learner classification, and recommendation systems. The significance of Federated Learning and Machine Unlearning, in particular, lies in the fact that they enable institutions to learn AI as they continuously collaborate, whereas keeping student data intact and in connection with permitting people to delete the information off trained systems should the need be. It is theorized that in future AI Regulation and Educational Governance approaches, further attention to data rights, an informed consent, algorithm accountability, and fairness auditing will be mandatory across all AI lifecycle stages as theorized in the literature.

On the whole, this review shows that the future of Artificial Intelligence in Education will not be tied solely to the further technological sophistication but will also be predetermined by the creation of clear, ethical and human-oriented systems. Adaptive Learning Systems in the future will be characterized by more Explainable Artificial Intelligence, Neural-Symbolic AI, Federated Learning, Multimodal Learning Analytics, Agentic AI, and Hybrid intelligence that is human-centered. Meanwhile, the educational institutions will require more robust gun control, better AI Literacy courses, more effective policies on fairness auditing, and enhanced policies on Ethical AI. The future generation of educational technologies is emerging with new evidence considering that they will be more focused on localized and student-specific information, participatory design, and explainability, which is differentiated based on various groups of users. The future prosperity of Responsible Artificial Intelligence in teaching and learning will thus lie in the capacity to reconcile technological advancement with equality, disclosure, confidentiality, duty, etc.

5. Conclusions

This literature review has shown that explainable and responsible hybrid intelligence has become a necessity in the future of adaptive artificial intelligence learning systems. With the growing use of educational institutions in personalized learning platforms, intelligent tutoring systems, predictive analytics, and learning analytics, the issue of algorithmic bias, fairness, transparency, accountability, and data privacy have taken a central stage. The review notes that most Artificial Intelligence in Education systems continue to be black-box systems which restrict teacher control, decrease student agency, and undermine trust in automated decision-making. As a result, Explainable Artificial Intelligence, interpretable machine learning, and human-centered AI are becoming highly important as means to enhance transparency in education and to make adaptive learning systems ethically aligned with the education objectives. The review also suggests that Hybrid Intelligence models and, especially, the models with human-in-the-loop processes and Human-AI Collaboration have a great potential to overcome the drawbacks of fully automated educational technologies. Instead of eliminating teachers, responsible hybrid intelligence systems will help teachers by adding machine efficiency to human judgment, contextual understanding, and ethical reasoning. Student-centric AI, adaptive explainable AI, and neural-symbolic AI models have also been found to be of particular significance as they enable educational stakeholders to gain insight on how recommendations, assessment, and learning paths are produced. These strategies have the potential to enhance user trust and educational equity and minimize the chances of unfair or biased output in learner modeling and decision support system.

Along with these opportunities, there are also some ethical dilemmas that have not been resolved through the review. The problems that are persistent are the lack of proper governance frameworks, the lack of data governance practices, insufficient AI literacy among educators and students, poor policy implementation, and the rise of the impact of generative AI in academic institutions. The growth of multimodal learning analytics, automated assessment systems and predictive educational technologies can raise more concerns about academic integrity, surveillance, digital ethics and student privacy. Moreover, the lack of standardized explainability, accountability, fairness-conscious machine learning, as well as algorithmic transparency, remains an obstacle to the creation of reliable AI in education. The next wave of research in this area should then be finding standard frameworks of Responsible Artificial Intelligence, Ethical AI, and adaptive explainable AI in educational ecosystems. More attention should be paid to the reduction of bias, auditing of fairness, inclusive education, and socio-technical governance frameworks that address the needs of the students, teachers, policymakers, and developers. The study of the ways multimodal data, neural-symbolic reasoning, and generative AI can be responsibly incorporated into adaptive learning systems without transparency and human control should also be conducted. Additionally, more powerful educational policies and the regulation of AI will be required to make sure that the new educational technologies will be responsible, fair, and oriented towards human values. Finally, the adaptive artificial intelligence learning systems will be successful in the long run not just due to the level of technological advancement but also because of the elaboration of clear, ethical and humanistic models of hybrid intelligence.

Author Contributions

LEC: Conceptualization, study design, analysis, data collection, writing review and editing, and supervision. FAO: Methodology, visualization, writing original draft, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

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