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Georgios P. Georgiou *

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Article

Machine Learning in Education

Georgios P. Georgiou [1,2]

[1] Department of Languages and Literature, University of Nicosia, Cyprus; georgiou.georg@unic.ac.cy

[2] Phonetic Lab, University of Nicosia, Nicosia, Cyprus

Abstract

Machine Learning (ML) is fundamentally reshaping education, offering tools to personalize instruction, automate assessment, and predict student outcomes. This paper provides a comprehensive overview of ML's role in education, tracing its evolution from early computer-assisted instruction to today's generative artificial intelligence (AI). We explore key applications, including intelligent tutoring systems, early warning systems for at-risk students, and automated essay scoring, highlighting their potential to address the long-standing challenge of individualized learning at scale. However, this technological integration is fraught with significant challenges. Ethical concerns regarding algorithmic bias, data privacy, and the "black box" nature of complex models threaten to exacerbate existing educational inequities. The recent proliferation of generative AI, exemplified by tools like ChatGPT, has further disrupted traditional paradigms of assessment and academic integrity, prompting urgent questions about the nature of learning itself. By synthesizing current research, this paper argues that while ML holds immense transformative promise, its successful and equitable implementation depends not on technological prowess alone, but on a concerted, ethically-grounded effort involving educators, researchers, and policymakers to ensure these tools augment human expertise and serve all learners.

Keywords: machine learning; education; historical development; applications; challenges

1. Introduction

Machine Learning (ML), a core subfield of artificial intelligence (AI), has emerged as a transformative force with the potential to fundamentally reshape educational practices, pedagogical methodologies, and institutional administration (Elbasi et al., 2025). Unlike traditional software systems that follow explicitly programmed instructions, ML enables computers to learn from data, identify patterns, and make predictions or decisions without being explicitly programmed for every conceivable scenario (Haenlein & Kaplan, 2019). In the educational context, this capability translates into systems that can analyze vast quantities of learner data, adapt instructional content in real-time, predict student outcomes, and provide personalized support at scale (Chen et al., 2020).

The integration of ML into education represents a paradigm shift that has been accelerating over the past decade. The global AI in education market was valued at USD 5.88 billion in 2024 and is projected to expand at a compound annual growth rate (CAGR) of 31.2% from 2025 to 2030 (Elbasi et al., 2025). This remarkable growth trajectory is driven by several converging factors: rising demand for personalized learning solutions, the rapid shift toward e-learning platforms accelerated by the COVID-19 pandemic, increasing investments in educational technology (EdTech) startups, and growing recognition of ML's potential to address long-standing challenges in educational access and quality (Alam, 2021; Zawacki-Richter et al., 2019). By technology segment, ML led the market with a 64.7% revenue share in 2024, underscoring its central role in enabling adaptive and personalized learning experiences (Elbasi et al., 2025).

The significance of ML in education extends beyond market metrics. For decades, educators have grappled with the fundamental tension between the need to provide individualized attention to each student and the practical constraints of classroom settings with limited resources (Bloom,

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1984). ML-powered systems offer a pathway to address this tension by automating routine administrative tasks—such as class planning and grading—thereby freeing educators to focus on high-impact activities, including mentorship, discussion facilitation, and personalized student support (Holmes et al., 2019). Furthermore, ML enables data-driven decision-making at unprecedented scales, allowing educators, administrators, and policymakers to derive actionable insights from the large volumes of student data now being generated through digital learning platforms (Kalita et al., 2025; Siemens, 2013).

Contemporary ML applications in education span the entire educational lifecycle, from student admissions and course scheduling to content generation, instructional delivery, performance assessment, and outcome prediction (Mallik & Gangopadhyay, 2023). Intelligent tutoring systems, powered by ML algorithms, can now imitate human tutors by providing real-time feedback and adapting instruction to individual learning preferences without human intervention (VanLehn, 2011). Learning analytics platforms leverage ML to identify at-risk students, predict dropout probabilities, and enable timely interventions (Romero & Ventura, 2020). Natural language processing (NLP) techniques, particularly transformer-based models such as BERT and GPT, are increasingly being deployed to provide automated feedback on student writing, power conversational agents, and support language learning (Devlin et al., 2018; Rodríguez-Ortiz et al., 2025).

However, the integration of ML into education is not without challenges and ethical considerations. Concerns regarding data privacy, algorithmic bias, the "black-box" nature of many ML models, and the potential for technology to undermine rather than enhance learning outcomes have been raised by researchers and practitioners alike (Akgun & Greenhow, 2022; Williamson & Eynon, 2020). The recent proliferation of generative AI tools, in particular, has introduced new complexities around academic integrity and the assessment of authentic student learning (Askari, 2025). These challenges underscore the need for careful, ethically-grounded approaches to ML deployment in educational contexts (see Georgiou, 2025a).

This paper provides a comprehensive overview of ML in education. It traces the historical development of ML applications in educational settings, examines the current landscape of ML applications across administrative, instructional, and assessment domains, critically analyzes the challenges and limitations facing ML adoption in education, and concludes with reflections on future directions. By synthesizing insights from the rapidly growing body of research in this field, this work aims to serve as a foundational reference for educators, researchers, policymakers, and technologists seeking to understand and shape the role of ML in the future of education.

2. Historical Development of ML in Education

2.1. Early Foundations: Computer-Assisted Instruction and Intelligent Tutoring Systems

The history of applying computational methods to education long predates the emergence of ML as a distinct field. The 1960s witnessed the development of computer-assisted instruction (CAI), which leveraged technology to deliver learning materials and provide feedback to users (Suppes, 1966). The Programmed Logic for Automatic Teaching Operations (PLATO), developed in 1960 at the University of Illinois, stands as the first large-scale CAI system, serving a diverse range of learners from school pupils to university students and even prison inmates across subjects including mathematics, Latin, and the sciences (Grimbley-Smith, 2025). PLATO's innovations included personalized learning paths, immediate feedback, and sophisticated student tracking capabilities, features that would later become central to ML-based educational systems (Bitzer & Easley, 1965).

The late 1960s and 1970s saw the emergence of more sophisticated intelligent tutoring systems (ITS). The Time-shared, Interactive Computer-Controlled Instructional Television (TICCIT) system, developed in 1968, delivered individualized, multimedia-based content to users and allowed learners to progress at their own pace (Merrill et al., 1980). These early systems were grounded in contemporary learning theories, particularly the work of B.F. Skinner on programmed instruction and Benjamin Bloom on mastery learning, which emphasized the importance of individualized

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tutoring and immediate feedback (Skinner, 1958). Bloom's influential "2 sigma" study, which demonstrated that one-on-one tutoring produced learning outcomes two standard deviations above conventional instruction, provided a compelling rationale for developing computer-based systems that could approximate the benefits of human tutoring at scale (Bloom, 1984).

2.2. The Emergence of AI and ML in Education (1980s–2000s)

The 1980s and 1990s witnessed the gradual integration of artificial intelligence (AI) techniques into educational systems. Early intelligent tutoring systems, such as SCHOLAR (teaching South American geography) and WHY (teaching causes of rainfall), incorporated knowledge representation and reasoning capabilities that allowed them to engage in dialogue with students and answer questions (Carbonell, 1970). The development of cognitive tutors at Carnegie Mellon University, grounded in John Anderson's Adaptive Control of Thought (ACT) theory, represented a significant advance by incorporating cognitive models that could trace student problem-solving steps and provide targeted hints and feedback (Anderson et al., 1985; Anderson et al., 1995).

The invention of the World Wide Web in 1989 fundamentally transformed the landscape for AI in education (Berners-Lee et al., 1992). Web-based learning environments could collect unprecedented amounts of data on user interactions, which could then be used to train software agents and improve system performance (Brusilovsky, 2001). The 1990s also saw the emergence of learning management systems (LMS) such as FirstClass and Blackboard, which organized content, tracked student progress, and managed online education (Watson & Watson, 2007). While early LMS platforms relied primarily on basic automation rules, they laid the groundwork for the data collection infrastructure that would later enable sophisticated ML applications (Coates et al., 2005).

The turn of the millennium brought advances in hardware capabilities, data mining techniques, and ML algorithms that accelerated the development of AI in education. The emergence of educational data mining (EDM) as a distinct research field in the early 2000s formalized the application of data analytics to educational questions (Baker & Inventado, 2014). Researchers began applying ML techniques to predict student performance, identify at-risk learners, and uncover patterns in learning behaviors (Koedinger et al., 2015; Peña-Ayala, 2014). The launch of Massive Open Online Courses (MOOCs) in the late 2000s created new imperatives for automated assessment and personalization, as courses with tens of thousands of students rendered traditional instructional methods infeasible (Pappano, 2012).

2.3. The Deep Learning Revolution and Modern Era (2012–Present)

The deep learning revolution, catalyzed by AlexNet's landmark performance in the 2012 ImageNet competition, profoundly impacted educational applications (Krizhevsky et al., 2012). Deep neural networks offered new capabilities for analyzing complex, high-dimensional educational data, including student writing, discussion forum posts, and multimodal learning interactions (LeCun et al., 2015). Related advances in speech-and-language ML—such as the use of biomarkers for early neurological detection—illustrate the broader maturation of ML methods that are increasingly transferable to educational language data and analytics (Georgiou, 2025b). The introduction of the Transformer architecture in 2017, with its self-attention mechanism, fundamentally transformed NLP and opened new possibilities for AI in education (Vaswani et al., 2017).

The release of BERT (Bidirectional Encoder Representations from Transformers) by Google in 2018 demonstrated the power of pre-trained language models for understanding context-dependent language, enabling more sophisticated analysis of student writing and more natural conversational agents for tutoring (Devlin et al., 2018). OpenAI's GPT series, introduced between 2018 and 2020, progressively expanded the capabilities of generative language models, with GPT-3 demonstrating remarkable few-shot learning abilities across diverse tasks (Radford et al., 2018; Brown et al., 2020). These developments laid the foundation for the integration of generative AI into educational applications, from automated feedback generation to intelligent tutoring (Bommasani et al., 2021).

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The COVID-19 pandemic served as a powerful accelerant for ML adoption in education. The rapid shift to remote learning created urgent demand for technologies that could support online instruction, maintain student engagement, and provide continuity in assessment (Hodges et al., 2020). Educational institutions that had previously been hesitant to adopt AI-powered tools found themselves compelled to explore digital solutions (World Bank, 2020). The pandemic also generated vast new datasets of online learning interactions, providing rich material for training and refining ML models (Lang et al., 2022).

The release of ChatGPT in November 2022 marked a watershed moment for AI in education (OpenAI, 2022). For the first time, generative AI capabilities became accessible to the general public through an intuitive interface, sparking widespread experimentation by students and educators alike (Baidoo-Anu & Owusu Ansah, 2023). Subsequent developments, including GPT-5 and specialized educational tools, have continued to expand the possibilities for ML in education while also raising profound questions about academic integrity, assessment practices, and the nature of learning in an AI-augmented world (Achiam et al., 2023; Choi & Chang, 2025; Mollick & Mollick, 2023). Figure 1 presents a timeline of ML-in-Education milestones.

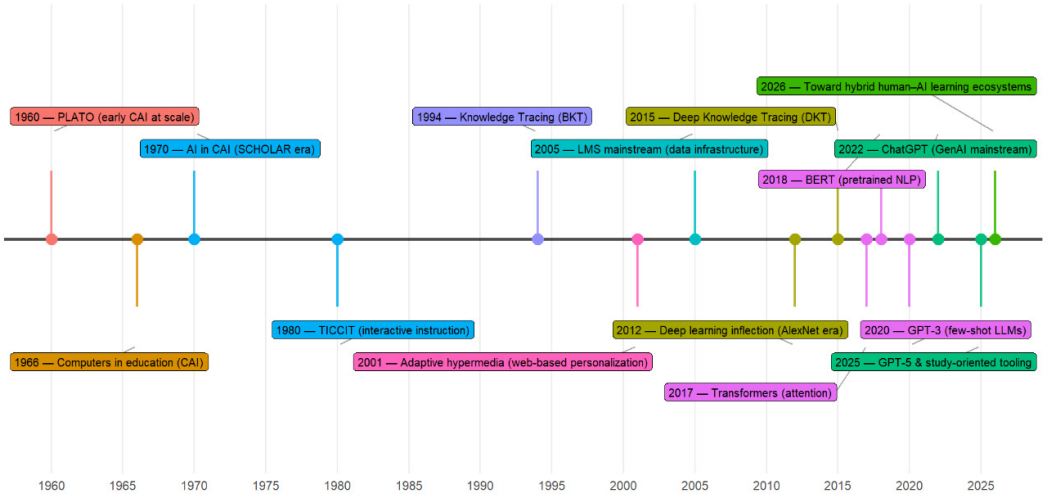

Figure 1. Timeline of ML-in-Education milestones (1960–2026).

2.4. Evolution of Research Themes

The research literature on ML in education has evolved significantly over the past two decades. Early work focused primarily on prediction tasks, forecasting student performance, identifying at-risk learners, and modeling knowledge acquisition (Shahiri et al., 2015). As ML techniques matured, researchers increasingly turned their attention to personalization and adaptation, developing systems that could dynamically adjust content and feedback based on learner characteristics (Xie et al., 2019). More recently, the focus has expanded to include affective computing (detecting and responding to student emotions), multimodal learning analytics (integrating data from multiple sources such as clickstreams, facial expressions, and physiological sensors), and the application of generative AI for content creation and feedback (D'Mello & Graesser, 2015; Blikstein & Worsley, 2016; Wang et al., 2025).

A systematic analysis of research published between 2003 and 2022 reveals the growing diversity of ML applications in education (Mallik & Gangopadhyay, 2023). Performance assessment has been the most extensively studied category, accounting for a substantial portion of published work, followed by content generation, learning content design, and student admission logistics (Ouyang & Jiao, 2021). The COVID-19 pandemic period (2020-2022) saw increased attention to online learning

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contexts and the challenges of maintaining educational quality in remote settings (Bozkurt & Sharma, 2020).

3. Applications of ML in Education

3.1. Student Performance Prediction and Early Warning Systems

One of the most extensively developed applications of ML in education is the prediction of student performance and the identification of learners at risk of academic difficulty or dropout (Hellas et al., 2018). Educational institutions at all levels face the challenge of identifying students who may need additional support before they fall irreparably behind (Arnold & Pistilli, 2012). ML models trained on historical student data, including demographics, prior academic performance, engagement metrics, and clickstream data from learning management systems, can predict outcomes with accuracy that often exceeds traditional methods (Arévalo-Cordovilla & Peña, 2024; Márquez-Vera et al., 2013; Sweeney et al., 2015).

A wide range of ML algorithms has been applied to performance prediction tasks. Logistic regression and decision trees provide interpretable models that can identify key risk factors (Bahadir, 2016; Bilal et al., 2022). Random forests and gradient boosting machines often achieve high predictive accuracy by capturing complex, non-linear relationships in the data (Beaulac & Rosenthal, 2019). Moreover, support vector machines and neural networks have been employed for more challenging prediction tasks involving high-dimensional data (Huang & Fang, 2013; Livieris et al., 2012). Finally, deep learning approaches, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, have proven effective for modeling temporal patterns in student learning trajectories (Piech et al., 2015; Xiong et al., 2016).

Early warning systems based on these predictive models enable timely interventions. When a model identifies a student as at-risk, institutions can trigger automated alerts to advisors, instructors, or the students themselves, prompting targeted support (Jayaprakash et al., 2014). Research has demonstrated that such systems, when properly implemented, can significantly reduce dropout rates and improve academic outcomes (Essa & Ayad, 2012; Krumm et al., 2014). However, the effectiveness of early warning systems depends critically on the quality of the underlying data, the appropriateness of the prediction horizon, and the availability of effective interventions to offer at-risk students (Ferguson & Clow, 2017).

3.2. Personalized and Adaptive Learning

Personalization stands at the core of ML's promise for education. The principle that instruction should be tailored to individual learner needs has deep roots in educational theory, but practical constraints have historically limited its implementation (Walkington, 2013). ML offers the potential to deliver personalized learning at scale by continuously adapting content, pacing, and pedagogical strategies based on individual learner characteristics and performance (Abeynayake et al., 2024; Peng et al., 2019).

Adaptive learning systems employ ML algorithms to build and continuously update models of student knowledge, often referred to as knowledge tracing (Corbett & Anderson, 1994). Bayesian Knowledge Tracing (BKT), one of the earliest and most influential approaches, models student mastery of individual knowledge components and updates probability estimates based on performance on related tasks (Corbett & Anderson, 1994). More recent deep learning approaches, such as Deep Knowledge Tracing (DKT), use recurrent neural networks to capture more complex patterns of knowledge acquisition and forgetting (Piech et al., 2015).

Content recommendation represents another key dimension of personalization. Collaborative filtering techniques, similar to those used by e-commerce and streaming platforms, can recommend learning resources based on what similar learners have found helpful (Bobadilla et al., 2009). Content-based recommendation systems analyze the characteristics of learning materials and match them to

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learner profiles (Pazzani & Billsus, 2007). Hybrid approaches combining multiple techniques often achieve the best results (Burke, 2002).

Personalized learning systems have been developed across diverse educational contexts and subject areas. In Sri Lanka, researchers developed an ML-powered personalized learning system for secondary mathematics that creates individualized learning paths, implements chatbot-based tutoring, and provides real-time feedback on student progress (Abeynayake et al., 2024). In Hong Kong, researchers applied recurrent neural networks to detect mindset states—including concentration, motivation, perseverance, engagement, and self-initiative—among secondary students in online courses, demonstrating the potential for real-time adaptation to affective as well as cognitive states (Wang et al., 2025).

3.3. Intelligent Tutoring Systems and Conversational Agents

Intelligent tutoring systems (ITS) represent one of the most mature applications of AI in education, with research spanning more than four decades. Modern ITS integrate multiple ML capabilities: they model student knowledge, track progress through curricula, generate appropriate problems and examples, provide targeted feedback, and offer hints when students struggle (Kestin et al., 2025; Ma et al., 2014). Cognitive Tutors, widely used in mathematics classrooms, exemplify this approach, having demonstrated significant learning gains in rigorous evaluations (Koedinger & Corbett, 2006; Koedinger et al., 1997).

Recent advances in NLP have enabled the development of increasingly sophisticated conversational agents for education (Winkler & Söllner, 2018; Wu & Yu, 2024). These agents can engage students in dialogue, answer questions, and provide explanations in natural language (Graesser et al., 2005). Early systems such as AutoTutor demonstrated the feasibility of tutorial dialogue systems, showing that conversational agents could produce learning gains comparable to human tutors in some domains (Graesser et al., 2004). Contemporary systems leverage large language models (LLMs) to engage in more flexible and contextually appropriate dialogue (Wollny et al., 2021; Pérez et al., 2020).

Chatbots have emerged as a scalable approach to providing on-demand support to learners. In higher education, chatbots are being deployed to answer administrative questions, provide academic advising, and offer course-specific tutoring (Prashant et al., 2025; Sandu & Gide, 2019). Research on chatbot effectiveness has shown positive effects on student engagement and learning outcomes, though results vary considerably depending on design and implementation (Winkler & Söllner, 2018). The RASA framework, an open-source platform for building conversational AI, has been employed to develop educational chatbots with natural language understanding capabilities (Bocklisch et al., 2017).

3.4. Automated Assessment and Feedback

Assessment represents both a significant opportunity and a significant challenge for ML in education. Automated assessment offers the promise of reducing the grading burden on educators, providing students with more immediate feedback, and enabling more frequent formative assessment (Shermis & Burstein, 2013). However, assessing complex student work—particularly writing and other open-ended responses—requires sophisticated natural language understanding (Burrows et al., 2015).

Automated essay scoring (AES) has been an active area of research and development since the 1960s (Page, 1966). Modern AES systems employ a variety of ML techniques to evaluate essays on dimensions including organization, argumentation, grammar, and style. While these systems have achieved sufficient reliability for use in high-stakes assessments such as the GRE and GMAT, concerns remain about their ability to validly assess authentic writing ability and their susceptibility to gaming (Perelman, 2014; Ramesh & Sanampudi, 2022).

ML is also being applied to provide more fine-grained feedback on student work. Systems can identify specific errors, suggest improvements, and provide explanatory comments (Dikli, 2006; Liu,

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2024). In programming education, automated feedback systems can evaluate code correctness, efficiency, and style, providing students with detailed guidance for improvement (Ihantola et al., 2010; Keuning et al., 2018). In mathematics, intelligent assessment systems can analyze student problem-solving steps, identify misconceptions, and generate personalized practice problems (Heffernan & Heffernan, 2014).

The emergence of generative AI has created new challenges for assessment. Students can now use tools like ChatGPT to generate convincing text, code, and problem solutions, potentially undermining the validity of traditional assessment formats (Susnjak, 2022; Georgiou, 2025c; 2026a). This has prompted calls for assessment reform, including a shift toward process-oriented assessment, oral examinations, and tasks that require integration of AI tools rather than their prohibition (Cotton et al., 2023; Lodge et al., 2023). Some institutions are exploring "AI-resilient" assessment designs that emphasize higher-order thinking skills and authentic performance (Bearman & Ajjawi, 2023).

3.5. Learning Analytics and Institutional Decision-Making

Learning analytics, defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimizing learning, has emerged as a distinct field at the intersection of education, data science, and ML (Siemens, 2013). Learning analytics platforms integrate data from multiple sources—learning management systems, student information systems, library usage, and other institutional data sources—to provide dashboards and reports that inform decision-making by educators, administrators, and students themselves (Ferguson, 2012; Gasevic et al., 2015).

ML plays an increasingly central role in learning analytics. Predictive models identify students who may benefit from additional support (Agudo-Peregrina et al., 2014). Clustering algorithms reveal patterns in student learning strategies and engagement (Kizilcec et al., 2013). Social network analysis maps patterns of interaction in online learning communities (Dawson, 2010). NLP analyzes discussion forum content to identify topics of interest, confusion, or concern (Crossley et al., 2015; Wise et al., 2017).

At the institutional level, ML-powered analytics support strategic planning and resource allocation (Norris & Baer, 2012). Enrollment management, curriculum planning, and program evaluation can all be informed by predictive models and pattern analysis (Picciano, 2012). However, researchers caution against over-reliance on analytics without appropriate human interpretation and contextual understanding (Selwyn, 2019). Ethical considerations, including student privacy, algorithmic fairness, and transparency, are central to responsible learning analytics implementation (Slade & Prinsloo, 2013; Prinsloo & Slade, 2017).

3.6. Content Creation and Curriculum Design

ML is increasingly being applied to the creation of educational content and the design of curricula (Rutecka et al., 2025). Natural language generation techniques can produce instructional texts, practice problems, and assessment items (Rus & Graesser, 2009). In language learning, ML-powered systems can generate exercises tailored to individual learner proficiency levels and interests (Heilman & Smith, 2010). In science and mathematics education, systems can generate problems with specified parameters and difficulty levels (Singh et al., 2012).

Generative AI, particularly LLMs, has dramatically expanded the possibilities for automated content creation (Cooper, 2023). Educators can use tools like GPT-4 to generate lesson plans, explanations, examples, and assessment items, significantly reducing preparation time (Trust et al., 2023). However, concerns about accuracy, appropriateness, and pedagogical quality require careful review and adaptation of AI-generated content (Zhai, 2022; Alfarwan, 2025).

Curriculum design, traditionally a labor-intensive process requiring extensive expertise, can be informed by ML analysis of learning trajectories, prerequisite relationships, and effectiveness data (Falmagne et al., 2006). Sequence mining techniques can identify optimal ordering of learning

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activities (Tang et al., 2016). Reinforcement learning approaches can optimize curriculum sequencing to maximize learning outcomes (Clement et al., 2015; Doroudi & Brunskill, 2019).

3.7. Supporting Diverse Learners and Inclusive Education

ML has significant potential to support diverse learners and advance inclusive education (Koutsouris et al., 2022). For students with disabilities, ML-powered tools can provide alternative means of accessing content and demonstrating learning (Seale, 2013). Text-to-speech and speech-to-text technologies, enhanced by deep learning, have become increasingly accurate and accessible. Computer vision systems can describe visual content to students with visual impairments (Bigham et al., 2010).

For students learning in a second language, ML-powered tools can provide real-time translation, simplified language, and vocabulary support (Simonnet et al., 2025). Adaptive systems can adjust linguistic complexity based on individual proficiency levels (Heift & Schulze, 2007). For students with learning disabilities, personalized learning systems can provide additional practice, alternative explanations, and multi-modal representations of content (Ok & Rao, 2019; Rose & Meyer, 2002).

However, researchers caution that ML systems must be carefully designed to avoid exacerbating existing inequities (Noble, 2018). If training data reflects historical biases—for example, if certain demographic groups are underrepresented or if assessment instruments contain cultural biases—ML models may perpetuate or amplify these biases (Benjamin, 2019; O'Neil, 2016). Ensuring that ML applications serve all learners equitably requires attention to diverse data sources, fairness-aware algorithms, and inclusive design processes (Holstein & Doroudi, 2021). Figure 2 displays a circular dendrogram of ML applications in Education.

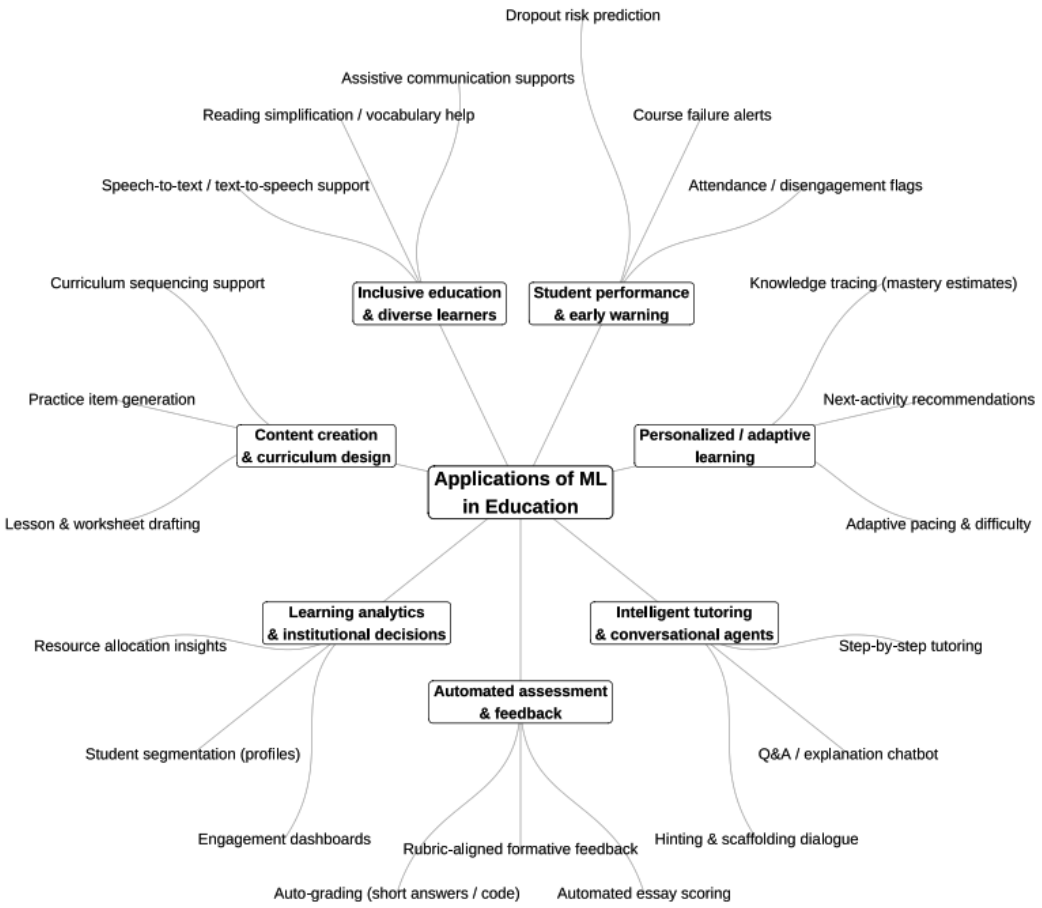

Figure 2. A circular dendrogram of ML applications in Education.

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4. Challenges of ML in Education

4.1. Ethical Challenges and Algorithmic Fairness

The deployment of ML in education raises profound ethical questions that must be addressed to ensure responsible innovation (Akgun & Greenhow, 2022; Georgiou, 2025d). Perhaps the most fundamental concern is algorithmic fairness: the risk that ML systems may produce systematically different outcomes for different demographic groups, potentially exacerbating existing educational inequities (Baker & Hawn, 2021). Research has documented instances where predictive models for student success exhibited bias based on race, socioeconomic status, or gender (Gardner et al., 2019; Georgiou, 2025e; Loukina et al., 2019). These biases often originate in training data that reflects historical patterns of inequality, but they can be amplified or obscured by algorithmic processing (Riazy et al., 2020).

Fairness in educational ML is complicated by the multiple, sometimes conflicting, definitions of what constitutes a fair algorithm (Barocas et al., 2023). Should a model aim for demographic parity (equal outcomes across groups), equal opportunity (equal true positive rates), or counterfactual fairness (outcomes that would be the same if sensitive attributes were different)? The choice among these definitions has substantive implications for system behavior and requires careful consideration of educational values and goals (Corbett-Davies & Goel, 2018; Kleinberg et al., 2016).

Beyond fairness, ethical challenges include transparency and explainability (Selbst & Barocas, 2018). Many of the most powerful ML models, particularly deep neural networks, operate as "black boxes" whose internal workings are opaque even to their developers (Castelvecchi, 2016). When these models influence consequential decisions about students—such as identifying at-risk learners or determining course placements—the inability to explain how decisions are reached undermines accountability and trust (Burrell, 2016). Explainable AI (XAI) techniques that provide interpretable explanations for model predictions are an active area of research with particular importance for educational applications (Conati et al., 2018; Khosravi et al., 2022).

4.2. Data Privacy and Security

ML in education depends on data—often large volumes of detailed data about students, their behaviors, and their performance (Reidenberg & Schaub, 2018). This data dependency creates significant privacy and security concerns (Zeide, 2017). Educational data may include personally identifiable information, academic records, behavioral traces from learning platforms, and increasingly, biometric data from facial analysis or other sensors (Regalia, 2020). The collection and analysis of such data raises questions about consent, data ownership, and the potential for misuse (Lupton & Williamson, 2017).

Student privacy is protected by legal frameworks in many jurisdictions, including the Family Educational Rights and Privacy Act (FERPA) in the United States and the General Data Protection Regulation (GDPR) in the European Union (Biegel, 2019). These frameworks impose obligations on educational institutions and technology providers regarding data collection, storage, and sharing (Hoofnagle et al., 2019). However, the rapid pace of technological change often outstrips legal frameworks, creating ambiguities about how existing regulations apply to novel ML applications (Crawford & Schultz, 2014).

Privacy-preserving ML techniques offer potential approaches to reducing privacy risks (Papernot et al., 2016). Federated learning enables model training across distributed data sources without centralizing raw data, reducing the risk of data breaches (McMahan et al., 2017; Kairouz et al., 2021). Differential privacy adds calibrated noise to query results to protect individual privacy while enabling aggregate analysis (Dwork, 2008). Homomorphic encryption allows computation on encrypted data without decryption (Gentry, 2009). However, these techniques involve trade-offs between privacy protection, computational efficiency, and model accuracy that must be carefully navigated (Abadi et al., 2016).

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4.3. Pedagogical Appropriateness and Effectiveness

A fundamental challenge for ML in education is ensuring pedagogical appropriateness—that systems are designed in ways that align with sound educational principles and actually enhance learning (Watters, 2021). Too often, ML applications are developed with primary attention to technical sophistication rather than pedagogical effectiveness (Selwyn, 2020). Systems may optimize for easily measurable outcomes (such as quiz completion or time-on-task) while neglecting deeper learning goals (Williamson, 2017). They may provide feedback that is technically accurate but pedagogically unhelpful (Pardo & Siemens, 2014).

The evidence base for ML effectiveness in education remains uneven. While some applications, particularly intelligent tutoring systems in well-defined domains like mathematics, have demonstrated significant learning gains in rigorous studies (Kulik & Fletcher, 2016), others have been subject to minimal evaluation (Du Boulay, 2019). Many published studies report positive results but suffer from methodological limitations, including small sample sizes, short intervention periods, and lack of appropriate control groups (Bulger, 2016; Reich, 2020). The rapid pace of technological change means that evidence often lags behind deployment (Luckin et al., 2016).

Integrating ML systems into existing educational practices presents additional challenges. Systems designed without adequate attention to teacher workflows and classroom contexts may be underutilized or misused (Hanshaw & Sullivan, 2025; Zhao, 2018). Teachers may lack the training and support needed to interpret ML-generated insights and translate them into effective action (Philipsen et al., 2019; Sailer et al., 2021). The most successful implementations treat ML systems as tools to augment, not replace, teacher expertise, and involve educators deeply in design and implementation (Holstein et al., 2019).

4.4. The "Black Box" Problem and Interpretability

The opacity of many ML models poses particular challenges in educational contexts where decisions affect students' educational trajectories and opportunities (Rudin, 2019). When a model identifies a student as at-risk or recommends a particular intervention, educators and students need to understand the basis for these determinations to respond appropriately (Kay & Kummerfeld, 2019). Without interpretability, it is difficult to verify that decisions are fair, to identify potential errors, or to build trust in the system (Miller, 2019).

Interpretability needs vary by stakeholder group (Abdul et al., 2018): educators benefit from knowing which features most influenced a prediction to guide pedagogical responses (Molenaar, 2022); students and families need understandable rationales to participate and advocate for support (Tsai et al., 2021); developers and researchers rely on interpretability to audit, debug, and refine models (Kizilcec & Lee, 2021); and regulators/policymakers use explanations to assess legal and ethical compliance (Yeung, 2017). Designing ML systems that can meet these diverse interpretability needs is an ongoing research challenge (Barredo Arrieta et al., 2020).

Posthoc explanation methods, such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), can provide approximations of model reasoning after the fact (Lundberg & Lee, 2017; Ribeiro et al., 2016). However, these explanations have limitations and may not faithfully represent actual model decision processes (Rudin & Radin, 2019). Some researchers advocate for inherently interpretable models—such as decision trees, logistic regression, or attention-based neural networks—over black-box models, even if they achieve slightly lower predictive accuracy (Rudin, 2019). The choice between accuracy and interpretability involves trade-offs that must be made with educational values in mind (Doshi-Velez & Kim, 2017).

4.5. Infrastructure and Implementation Barriers

Implementing ML in education requires substantial infrastructure that remains lacking in many contexts. Reliable internet connectivity, adequate computing devices, and robust data systems are prerequisites for most ML applications (Van Deursen & Van Dijk, 2019). Schools and institutions

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serving under-resourced communities often lack this infrastructure (Arias Ortiz et al., 2025), raising concerns that ML may exacerbate rather than reduce educational inequities (Dolan, 2016). The "digital divide" encompasses not only access to technology but also the capacity to use it effectively (Hargittai, 2002).

Data quality presents another significant barrier (Kitchin, 2014). ML models are only as good as the data they are trained on, and educational data is often messy, incomplete, or inconsistently recorded (Baker, 2016). Different systems may use incompatible data formats; historical data may be unavailable or of questionable quality; privacy concerns may limit data access for model development (Romero & Ventura, 2017). Building the data infrastructure needed for effective ML requires significant investment in data governance, cleaning, and integration (Bichsel, 2012).

Implementation challenges extend beyond technical infrastructure to include organizational capacity and culture (Weller, 2020). Educational institutions may lack personnel with the data science and ML expertise needed to develop, deploy, and maintain systems (Daniel, 2015). Existing staff may require substantial professional development to use ML tools effectively (Starkey, 2020). Institutional policies and procedures may need updating to address novel issues raised by ML deployment (Ahn & Chen, 2021). Sustained commitment from leadership is essential but not always present (Scherer et al., 2019).

4.6. Academic Integrity and Evolving Nature of Learning

The emergence of generative AI has fundamentally disrupted traditional conceptions of academic integrity (Nishihara et al., 2025). Students can now use tools like ChatGPT to generate essays, solve problems, and complete assignments in ways that are difficult to detect (Eaton, 2021). This has created what some describe as an "AI arms race" between students using generative tools and institutions attempting to detect misuse (Bretag, 2019). Traditional plagiarism detection systems, designed to identify copied text, are largely ineffective against AI-generated content (Georgiou, 2026b; Rogerson & McCarthy, 2017).

Institutions are grappling with how to respond. Some have attempted to ban or restrict AI tool use, though enforcement is challenging (Dawson, 2020). Others have chosen to embrace generative AI as a reality to be worked with rather than against, redesigning assessments to assume AI access and focus on higher-order skills (Morris, 2018; Swauger, 2020). These approaches include process-oriented assessment (evaluating drafts and revisions), oral examinations, collaborative projects, and authentic tasks that require integration of AI tools with original thinking (Bertram Gallant, 2017).

More fundamentally, the availability of powerful AI tools raises questions about the nature of learning and the goals of education (Williamson & Eynon, 2020). If AI can perform many of the tasks traditionally used to assess learning, what does it mean to be educated? How should curricula and pedagogy evolve to prepare students for a world where AI capabilities are ubiquitous? These questions lack simple answers and require ongoing dialogue among educators, students, policymakers, and the broader public (Cope et al., 2021; Peters, 2023). Figure 3 shows the main challenges of ML in Education. Figure 4 illustrates a suggested ML-in-Education pipeline with governance checkpoints.

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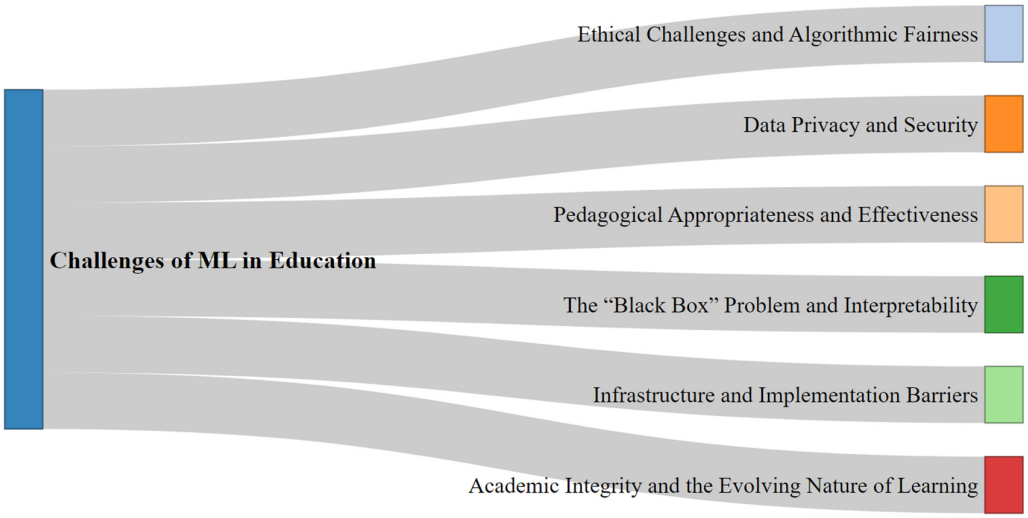

Figure 3. Main challenges of ML in Education.

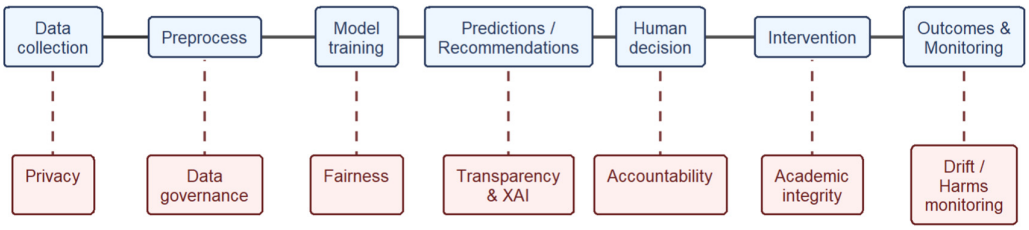

Figure 4. ML-in-Education pipeline with governance checkpoints.

5. Conclusions

ML has emerged as a transformative force in education, offering powerful tools for personalizing instruction, predicting student outcomes, automating assessment, and supporting institutional decision-making. The historical trajectory from early computer-assisted instruction to contemporary generative AI systems reflects decades of technological advancement and pedagogical innovation. Today, ML applications span the entire educational lifecycle, from admissions and course planning through instruction and assessment to outcome prediction and alumni engagement.

The potential benefits of ML in education are substantial. Personalized learning at scale can help address the long-standing challenge of providing individualized attention to every student. Routine administrative and assessment tasks can also be automated, allowing educators to devote more time to high-value work such as mentorship, discussion facilitation, and targeted student support. In addition, analysis of large-scale educational data can generate actionable insights that strengthen evidence-based decisions about curricula, pedagogy, and institutional policy. For learners, ML-enabled tools can deliver timely feedback, adapt the level of challenge, and offer support aligned with individual needs and circumstances.

Yet realizing this potential requires navigating significant challenges. Ethical concerns, including algorithmic fairness, data privacy, and transparency, demand careful attention. The pedagogical appropriateness of ML applications must be rigorously evaluated, with attention to whether they genuinely enhance learning rather than merely optimizing easily measurable proxies. Infrastructure and capacity barriers must be addressed to ensure that ML benefits all learners, not only those in well-resourced contexts. The disruption of generative AI to traditional assessment practices requires fundamental rethinking of how we evaluate and certify learning.

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Several directions for future development merit attention. First, advancing explainable AI techniques tailored to educational contexts can enhance transparency and trust, enabling educators and learners to understand and appropriately rely on ML systems. Second, developing privacy-preserving ML approaches, including federated learning and differential privacy, can enable valuable analysis while protecting student data. Third, creating robust evidence bases through rigorous evaluation of ML applications in diverse contexts can guide effective implementation. Fourth, fostering interdisciplinary collaboration among ML researchers, educators, learning scientists, and ethicists can ensure that technical development is guided by pedagogical wisdom and ethical reflection.

Ultimately, the integration of ML into education is not primarily a technical challenge but a human one. The question is not whether ML will be used in education—it already is, and its role will surely grow—but how. Will ML systems be designed to augment and empower educators, or to replace them? Will they serve all learners equitably, or exacerbate existing disparities? Will they promote deep learning and authentic understanding, or incentivize strategic compliance and gaming? The answers to these questions will be determined not by technology alone but by the values, choices, and actions of educators, researchers, policymakers, and technologists. The future of ML in education is not yet written; it is ours to shape.

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