

Smart Education through Machine Learning: A Review of Trends, Benefits, and Risks

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Abstract

Machine learning (ML) is transforming the contemporary education by transforming it into smarter, data-driven and personalised learning. This review examines the key tendencies, advantages, and possible threats of applying ML in intelligent education. ML promotes adaptive learning, automatization of assessments, and student engagement, which is highly beneficial both to learners and educators. Nonetheless, issues like data privacy, algorithmic bias or unequal access are also a significant concern. The article emphasises the necessity of ethical and inclusive methodologies that would allow making sure that ML technologies can enhance the quality of education and make sure that the threats are contained. Digital technologies in education have resulted in the creation of smart education systems, which produce a lot of student data. These datasets provide an important source of data regarding the learning behaviour of students, academic achievement, and the levels of engagement. Machine learning can be used to give a potent tool in analysing educational data and predicting student outcomes. The early anticipation of the grades will help the teachers to detect the students with learning problems and support them accordingly. The study hypothesises a machine learning-centred system to forecast the academic performance of students through educational data including attendance, studying time, assignment grades, internal evaluation, and the past academic history. The system uses guided machine learning models such as Logistic regression, decision tree, random forest and support vector machine to identify levels of student performances. The experimental results prove that the Random Forest algorithm is the most accurate in making predictions in comparison to other algorithms. This paper emphasises the value of using data to make decisions in contemporary education or how predictive analytics can enhance teaching methods, boost student learning, and boost the success rates of students.

Keywords: Machine learning, education, adaptive systems, learning analytics, student performance prediction, personalized learning.

INTRODUCTION

I have witnessed the role of digital technology in changing education, which has led to smart education systems where ML is used to improve education and learning ML can be used to customise learning, intelligent tutoring, and data-based decision-making through the analysis of student performance and behaviour. These technologies improve the interaction process, adaptive teaching, and help teachers to tailor material to the needs of a particular student [1].

However, the drawbacks of implementing ML into education include the problem of privacy of personal data, algorithm bias, and unequal access to technology. There is a need to strike the balance between the innovation and ethical and equitable practices hence [2].

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Received Date: February 05, 2026

Accepted Date: June 13, 2026

Published Date: June 23, 2026

Citation: Mohit Sachan, Pankaj Jain, Laxmi Poonia. Smart Education through Machine Learning: A Review of Trends, Benefits, and Risks. Journal of Education Sciences. 2026; 3(2): 24–28p.

SCOPE AND METHODOLOGY

Here I will be excavating the most recent systematic and narrative reviews on machine learning in education, as well as some of the most important empirical studies. As an example, there is a systematic review that examines the ML techniques applied to education data in 2014-2022, which provides me with an idea of the frequency of various techniques and their applications [3].

The inclusion criteria that I am following are:

- (i) The studies using ML in education actually, i.e. think of student data, learning analytics, tutoring systems, adaptive learning, etc.
- (ii) Peer-reviewed articles or adequate systematic reviews.
- (iii) The research published not earlier than about ten years ago, and thus is up to date. I am omitting external education in the field of ML.

In my analysis, I will categorise the applications, calculate the methods, identify the advantages and obstacles, and conclude with a gap map, which would note where the future research would take [4].

Prediction and Risk of Student Performance and Drop-Out

This has been my most frequent use of ML in schools and universities. The aim is normally to predict the possibility of a person becoming an ace in their courses or flunking. The rapid search of studies published in 2014 to 2022 indicates that approximately 32 research addressed the issue of grades prediction and 30 studies examined the broader learning analytics. The thing is that the earlier the system notices that something goes wrong, the sooner the university will be able to intervene, identify who requires additional assistance and adjust study plans to each child [5].

Adaptive Tutoring and Intelligent Tutoring Systems (ITS)

ML operates learning platforms that are adaptive and as such, they result in the transformation of what you observe against your performance. Such adaptive or intelligent tutor systems fall under the first category of AI/ML in higher education profiling/prediction, assessment/evaluation, personalization, and intelligent tutors [6].

Behavioural Data Mining and Learning Analytics

In a nutshell, ML is all the logs that it collects, click- streams, response times, etc., and attempts to determine what learners are doing. You get feedback as to engagement, study plans, you can feed that into the system so that students get more constant feedback. One article even told that process-data review can provide you with diagnostic information through ML [7].

Recommendation of Content and Curriculum Personalisation

There is a lot of work suggesting the appropriate resources or optimization of learning paths. They are attempting to select the next best thing or forecast the knowledge level of a student to allow the course to keep pace. ML in education big review includes content recommendation as one of the leading themes.

Administrative and Institutional Decision Support

ML is not only being applied in the classroom, but is also being applied in scheduling, resource allocation, predicting admissions, identifying students at risk, and facilitating operations in schools.

The wider AI/ML scan in education is a separate category of institutional and administration services [8].

ORDINARY MACHINE LEARNING TECHNIQUES AND DATA

Methods

The most popular supervised algorithms, as per the literature that I have gone through between

2014 and 2022, are:

- Random Forest
- Decision Tree
- Support Vector Machine
- Logistic Regression

I also find the K-Nearest Neighbour and the Naive Bayes, but unsupervised stuff is quite rare.

Learning management system (LMS) logs: amount of time on it, clicks, how many times it has been logged in. Much-assessed evidence: quizzes, assignments, exams. Behavioural data interaction, engagement error sequences.

Data Types

The data which we normally use are:

- Demographic and background information on the students (age, previous grades and so on).
- The logs of the learning management system (LMS): time, clicks, frequency of access.
- Assessment materials: tests, assignments, quizzes.
- Behavioural insights: interaction levels, engagement.
- Process data: The processes, time spent working, pattern of error.

BENEFITS AND OPPORTUNITIES

Learning Individualisation

Machine learning will allow us to customise the content and the pace of learning to every learner, making the process more interesting and more effective. Many of the reviews note that teaching with the use of ML in fact enhances academic performance and retention [9].

The early warning and intervention would be encompassed in the fifth section

Predicting the possibility of drop-outs or learning problems means that universities will intervene at the earliest stage and provide the appropriate student with the necessary assistance. The prospects and challenges review emphasise the improvement of decision-making through the use of ML.

Efficiency and Scalability

Even with a very large number of students such as with MOOCs or blended courses, adaptive and intelligent tutoring systems can actually provide personalised assistance.

The following insights into Learning Behaviour are provided:

Learning analytics and machine learning enable teachers to observe how learning trajectories, approaches and difficulties of students change over time - to create instruction that is supported by concrete facts.

DIFFICULTIES, RESTRICTIONS AND MORAL IMPLICATIONS

Data Quality, Bias and Privacy

Practically, the ML models require tonnes of good data. Lost records, noisy records, biased samples, and unfair access among learners, we are far too often met with. There is also the privacy factor: there is the risk of storing sensitive student information and the chance of profiling. Other reviews even identify ethical threats of AI in higher education.

Interpretability and Integration of Educational Theory

Much of the research is on straight-up accuracy, not on connexion of the models to sound pedagogical theory. It implies that teachers could shoot out the output of a model without understanding how to use it, and the review of 2019 indicates that there is a poor connexion between

AI/ML work and classroom practice [10].

The researcher relies too heavily on supervised methods

Supervised learning is most commonly used in the majority of the studies and it may inhibit the exploration of unsupervised, semi-supervised or reinforcement learning in education. No wonder unmonitored learning is not used extensively.

Equity and Access

The issue of inequality increases with the use of ML- based systems when some groups of students are under-represented in the data or are deprived of resources. Algorithms can also create certain disadvantages to demographics without intent.

Implementation and Practical Integration

The application of ML research into the daily classroom life remains a challenge: teachers must be trained, the schools must have the appropriate technology and funding, individuals must spend money on it, and everyone must maintain the machine and see it in action. As an example, K-12 schools attempting to implement ML usually fail to provide their teachers with good professional development.

Ethical Risks

Robotized choices, black box algorithms, the freedom of students to make decisions, the ultimate ownership of the data, and concerns that the human element between the teacher and student will be diminished all bring up ethical concerns [11].

FUTURE RESEARCH FUTURE RESEARCH DIRECTIONS AND LACUNAE

- Research with greater geographical and institutional diversity: most studies are of some countries/institutions.
- Research in uncontrolled, semi-controlled, reinforcement learning and more advanced ML paradigms in learning.
- Rich Immediate Add further detail Add behavioural, multimodal, process information (e.g. eye-tracking, video, audio) to understand in more detail.
- Future studies in ML at early-educational level (K-12), non-STEM and in informal learning environments.
- Long-term studies to establish the implications of ML-based interventions over time and not cross-sectional images.
- Increased focus on interpretability, explainable AI (XAI) within the teaching and learning space to accomplish the goal of teachers and learners becoming confident in and cognizant of ML outputs.
- Discussing the issues of equity, impartiality, prejudice, and ethics specific to the education sphere in relation to ML.
- Implementation science researches on the ways the ML systems might be applied to the real classroom/institutional settings: teaching training, change management, cost-benefit, retained use.
- New directions Investigation in new directions including adaptive generative AI tutors, machine unlearning to adaptive systems, responsible AI systems in learning.

IMPLICATIONS FOR PRACTICE

- Technical performance is not the sole important factor, and the alignment of ML-based systems with the pedagogical theory and the workflow of a teacher.
 - The good data infrastructure, data cleaning and feature engineering: Bad data kills ML.
 - Provide training and support for educators to interpret and act on ML insights; build trust and transparency.
 - Take into account equity and access: make sure that all groups of learners are represented and that they are benefiting on ML-enabled systems; watch out bias.
 - Make human decisions more accurate through ML prediction, but do not remove the teacher-learner interaction.
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- Involve stakeholders (students, teachers, administrators) in design and implementation of ML systems in order to make them relevant and acceptable.
- Actual educational setting Pilot and test ML interventions, notice unexpected effects (e.g. over-reliance, less student agency).
- Create code of ethics, data-governance policies and privacy protection policy in processing educational data.

CONCLUSION

Machine learning in education is a fast and potentially effective field of application. ML has also been effectively applied to predict student performance, facilitate adaptive tutoring, individualise content and assist institutional decision-making as demonstrated in the literature. Nevertheless, other issues such as data quality, interpretability, equity, ethics and practical implementation are also a major challenge in this field.

ML provides potent tools to researchers and practitioners in the educational and technological field- however, success is achievable by careful consideration of how pedagogy, proper data practises, and stakeholder participation, and fairness are integrated. research needs to be done in unexplored settings and procedures, focus on longitudinal and real world research, and develop ML-based learning systems that are clear, just, and effective.

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