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Brief Survey of Ethical Artificial Intelligence and its commitment to Self-Regulated Learning

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Abstract. The increased use of Artificial Intelligence in education has created opportunities and concerns regarding its use, from an ethical perspective to the cognitive development of students. Various tools based on Artificial Intelligence, such as intelligent tutoring systems, generative models, intelligent assessment, personalised learning, and educational robotics, are transformative examples that promote individual student development. However, these same tools, or those that use Generative Artificial Intelligence, for example, raise questions about their ethical use. This article presents a brief overview of Educational Artificial Intelligence (EAI) and its integration into the teaching-learning process, considering ethical and cybersecurity issues in a self-regulated learning environment, where students must have the ethical capacity to use Artificial Intelligence-based tools to guide their learning.

Keywords: Educational Artificial Intelligence, Ethics, Self-Regulated Learning, Generative Artificial Intelligence.

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1 Introduction

Currently, advances in technology have led to a new conception of life, where the basic requirements for various everyday tasks are influenced by technology. Artificial Intelligence (AI) is a major driver of social, economic and cultural transformation, whose impact extends to everyday life and whose prominence has grown substantially.

The omnipresence of artificial intelligence manifests itself in multiple dimensions. In everyday life, its usefulness is evident in routine practices such as using a virtual assistant on the phone, receiving personalised recommendations on platforms, or relying on algorithms that organise our daily lives. Added to this is the fact that, without being fully aware of it, users interact with AI through automated financial systems, assisted medical diagnoses, weather forecasting models, and even security mechanisms. The impact is so widespread that it can be said that there is virtually no area of human life that is exempt from the influence of this technology.

In the economic and business spheres, AI has revolutionised ways of working and thinking about business. Process automation has improved simple mechanical systems, replacing them with intelligent networks capable of adapting to changing conditions, detecting trends in global markets, and generating predictions about consumer behaviour. This has led to increased efficiency, reduced costs, and the emergence of new ways of working on digital platforms, although it has also raised challenges regarding work ethics and the possible replacement of human jobs by machines. Artificial intelligence itself has become a new productive paradigm that shapes the role of the worker and redefines business competitiveness.

On the other hand, medicine has undergone a significant transformation. AI algorithms analyse diagnostic images with high precision, detect diseases early, personalise drug treatments and speed up research that previously required years of clinical study. This has led to exponential growth in the field of digital health, with clear benefits for patients and professionals, but also with ethical questions regarding data privacy and medical responsibility. The promise of saving more lives and improving collective welfare systems coexists with the need to establish regulatory frameworks that ensure the responsible use of sensitive information.

In the cultural and creative space, artists, writers, musicians, and other representatives of the arts have incorporated AI-based tools to create innovative works, musical compositions, and narratives. Paintings generated by machine learning systems, film scripts

written in collaboration with algorithms, and musical pieces composed by AI programmes are examples of a historic conceptual shift in which the boundary between human and artificial creation is now apparent.

On the other hand, social and political life has not remained immune to these changes. Artificial intelligence is involved in the administration of public services, cybersecurity, and infrastructure management. Governments around the world have begun to incorporate AI systems to predict emergencies, formulate policies based on big data, or strengthen citizen surveillance. AI is not simply a neutral tool, but a political factor that needs to be regulated with transparency and ethical guidance.

Amid this expansion into social areas, an essential question arises: how should AI be used in specific areas such as education? This field, which depends on the transmission of knowledge, the development of critical thinking, and the construction of values, represents a unique challenge for the integration of artificial intelligence. The possibility of incorporating algorithms into classrooms opens up a horizon of opportunities and, at the same time, a series of pedagogical dilemmas.

Specifically, educational AI is giving rise to increasingly concrete proposals, such as intelligent tutoring systems, interactive platforms that detect students' progress rates, and automated assessment tools, among others. These functions have the potential to personalise teaching like never before, overcoming the rigidity of traditional education and providing more opportunities for those facing conditions of inequality. Similarly, the collection and analysis of educational data facilitate the design of more comprehensive and effective public policies, with positive effects at the macro-educational level.

This article presents a brief survey related to the applications of Educational Artificial Intelligence as the synthesis of a technological era oriented towards the future of education. It has been shown to be capable of transforming established classroom practices, revolutionising not only the way students learn, but also the way society understands and values knowledge. Thinking about the future of education with AI means designing a tool that, when used ethically, can become the engine of fair, equitable learning tailored to the needs of each human being.

2 A Brief Survey of Algorithms, Techniques and Methods for Educational Artificial Intelligence

The application of artificial intelligence (AI) algorithms in education has evolved from traditional statistical models to machine learning and deep learning systems. These models make it possible to analyse large volumes of educational data such as grades, attendance, participation, interactions in virtual environments, among others, and generate predictions about student performance, dropout rates, motivation, or conceptual understanding (Pacheco-Mendoza et al., 2023).

Based on research into artificial intelligence algorithms and models applied to education, we present the following classification:

- Supervised learning
- Unsupervised learning and
- Reinforcement learning,
- Deep learning and hybrid models.

Supervised learning is based on the use of labelled data sets. In the case of the education sector, the input variables can be quantitative, such as students' study habits, access to virtual or face-to-face classrooms, partial or previous grades, etc., or qualitative data, such as preference for certain subjects (López Barriga et al., 2024). This data can be associated with an expected outcome, such as passing or failing a subject, or, for example, identifying trends, correlations between variables, predictions, among other results. The supervised learning approach allows for the generation of high-performance predictive models in education. In particular, the most used algorithms include the following examples:

- Decision trees: These allow students to be classified, for example, according to hierarchical rules based on significant variables. They have shown accuracies of over 90% in predicting academic performance (Barriga et al., 2024; Contreras Bravo et al., 2022).
- Random forests: This approach is based on combining multiple decision trees to improve accuracy and reduce overfitting. According to (Alamri et al., 2021), this algorithm is used in models for the early detection of dropout risk.
- Logistic regression: (Aguilar-Reyes et al., 2025) propose the use of logistic regression to predict the probability of success or failure in a subject, based on academic and personal factors.
- Support vector machines (SVM): These provide excellent results in the binary classification of student performance and retention (Cardona & Cudney, 2019).

- k-Nearest Neighbours (KNN): This classifies a student by comparing their characteristics with those of similar profiles. It is especially useful for small or medium-sized data sets and achieves an accuracy of approximately 80% (Contreras Bravo et al., 2022).
- Naïve Bayes: This model is classified as probabilistic, which assumes independence between variables. It is mainly used to detect patterns in student participation and thereby predict performance based on similar behaviours (Rico Páez, 2023).
- Gradient Boosting Machine (GBM): Optimises prediction models by combining multiple weak classifiers to improve accuracy. It is effective for analysing performance in online courses (Calva et al., 2021).
- Multiple linear regression: In the academic context, García & Furniel (2019) apply AI-enhanced multiple linear regression to identify the correlation between socio-economic factors, study habits and performance.
- Artificial neural networks (ANN): These allow for the modelling of non-linear relationships between multiple educational factors. Their generalisation capacity enables this model to analyse learning trajectories on e-learning platforms, according to Yang (2024).
- Extreme Gradient Boosting (XGBoost): An advanced variant of boosting that improves speed and accuracy. It has shown optimal results in predicting performance in mathematics and reading (Sabri et al., 2023).

The main purpose of this set of algorithms is to anticipate performance problems and guide personalized tutoring strategies, as they combine demographic, academic and behavioural information with automated predictive analysis.

The second classification is based on unsupervised learning. In these environments, there are no predefined labels or categories; unsupervised algorithms allow hidden patterns in educational data to be discovered. This type of analysis is used to segment students, identify learning styles, or analyse interaction in virtual environments. The main algorithms can be identified as:

- Clustering: Techniques such as k-means and DBSCAN group students according to similarities in their behaviour or performance, allowing the identification of groups at academic risk or with high potential (Mohamed Nafuri et al., 2022).
- Principal component analysis (PCA): Borges et al. (2018) describe how this model reduces the dimensionality of the data, highlighting the factors that most influence performance.
- Hierarchical cluster analysis (HCA): This allows students to be grouped into progressive performance levels, identifying learning trajectories (Rojas Paucar, 2024).
- Canonical correlation analysis (CCA) and multiple correspondence analysis (MCA): These are used to explore relationships between qualitative variables such as learning styles, satisfaction, and performance (Sandars, 2020).
- Kohonen self-organising maps (SOM): Visual data reduction that helps to discover relationships between patterns of academic behaviour. They have been applied in educational recommendation systems (Carballo & Antunes, 2014).
- These methods allow for the construction of more accurate learning profiles and the design of differentiated interventions that promote educational equity.

The third group of algorithms is based on reinforcement learning, which focuses on the interaction between an expert agent and its educational environment. The agent makes decisions based on rewards and penalties, learning from accumulated experience.

In the educational context, these algorithms allow activities to be dynamically adapted and the most effective teaching strategies for each student to be evaluated:

- Q-Learning: Learn optimal action policies through a reward system. It has been used in intelligent tutors that adjust the difficulty of content in real time.
- SARSA (State-Action-Reward-State-Action): Like Q-Learning but updates its values according to the policy followed by the agent, improving the stability of adaptive learning.
- Deep Reinforcement Learning: Combines neural networks with reinforcement learning, applied to educational robots, serious games, and pedagogical simulators (Mittal et al., 2024).
- Adaptive recommendation models: These use multi-armed bandits (MAB) to select the most appropriate resources or activities for the student based on their previous response (Wang et al., 2024).

These approaches allow AI systems to learn from continuous interaction with students, generating richer and more personalised learning experiences.

Finally, deep learning is considered the most widely used set of algorithms today, as they have a high capacity to process unstructured data such as text, voice, video, or images and have become the base model for virtual platforms:

- Convolutional neural networks (CNN): These are used to analyse students' facial expressions and gestures in video classes, identifying emotions and levels of attention (Ji et al., 2024).
- Recurrent neural networks (RNN) and LSTM: These analyse time sequences, such as weekly participation or progress in online courses, to predict dropout or demotivation (Sabri et al., 2023).
- Transformers and generative models (such as GPT or BERT): These enable the generation of personalised educational materials, the evaluation of students' textual coherence, and the provision of immediate feedback (Nedungadi et al., 2024).
- Hybrid models: These combine supervised and unsupervised methods (e.g., Decision Tree + PCA or KNN + SVM) to improve predictive robustness and reduce classification errors (Fuentes-Penna et al., 2025).

The rise of generative and multimodal models represents a new frontier in AI-based education, where platforms can adapt to multiple formats of cognitive and emotional interaction.

In summary, the models and algorithms applied in education allow us not only to predict academic performance, but also to understand how students learn and to personalise teaching strategies. The current trend points towards the integration of hybrid and multimodal systems that combine the power of predictive analytics with artificial emotional intelligence. However, their success will depend on the ethical, transparent and pedagogically oriented use of these technologies.

3 Examples and use of Educational Artificial Intelligence in Self-Regulated Learning

Artificial intelligence in education presents opportunities and risks, and ethical and accessibility regulations must be established for people (UNESCO, 2024). Due to the increasing development of artificial intelligence applications, there is a great variety of tools to support education, as well as their applications and uses in various contexts (J. Khurramov et al., 2025; Owan et al., 2023).

Simulation. Its application in various fields allows learning in controlled environments to resemble reality, being safe and even personalized. The health area can generate virtual patients that support training and education, equipment or dolls with intelligence, generation of clinical scenarios for diagnosis and medical decision making, as well as the possibility of improving medical treatments (Aguirre-Flórez et al., 2025; Lebo & Brown, 2022; Swan et al., 2025).

In engineering, it supports the creation of complex processes and systems, mathematical, mechanical, electronic, embedded systems or chemical models through experimentation in a safe, practical and interactive way (Kashokova et al., 2024; Mosqueda-Huerta et al., 2025). Artificial intelligence-based simulation in the social sciences and humanities, as an example in social studies, creates and designs interactive scenarios that allow students to experience historical events and explore different perspectives, thus helping to improve their understanding and critical thinking, as well as offering personalized learning experiences (Bernal Parraga et al., 2024).

Artificial intelligence LLM models allow simulating human subjects through human speech and behavior ((MacCormick, 2025):

- Academic and scientific research. It supports information search, literature review, text writing, data analysis, data visualization and streamlines research processes (Molina-Isaza, 2024; Khalifa & Albadawy, 2024). Also, it supports the detection of plagiarism and authenticity, improving the quality of research, as well as acquiring new skills in the use of new technologies (Vimos-Buenaño et al., 2024).
- Automated assessment and prediction of academic performance. AI can be used to support activities such as grading tasks, activities, exams, detecting errors in tasks (Fernández Manjón, 2024); also predicting students' academic performance (Barrera-Cámara et al., 2025; Herrmann & Weigert, 2024), optimizing learning (Orozco Morales & Osorio García, 2024).

Intelligent tutoring systems and personalization of learning. Intelligent tutoring systems designed with artificial intelligence guide students in a personalized way (Orozco Morales & Osorio García, 2024), adapting to the level, interests, pace and learning styles, stimulating motivation and autonomy in virtual or face-to-face environments (Hernández León & Rodríguez-Conde, 2024), 2024; Zapata-Ros, 2018), in this sense, the materials are designed considering the profile of the students for better understanding and motivation (Cordon García, 2023).

- Plagiarism detection and prevention. The generation of texts generated by artificial intelligence leads to the development of tools for the detection of plagiarism or AI-generated documents whose content may not be original (Diaz Arce, 2024). Plagiarism detectors and reference managers facilitate the identification of non-original content and help to promote ethical practices (Copado Rodríguez, 2023).
- Virtual assistants to support the generation of educational content. Virtual assistants, chatbots and intelligent speakers function as virtual assistants that support the creation of content, generate evaluations, evaluate student performance, resolve doubts, structure ideas, analyze data and research (Davar et al., 2025). They also support communication, management of administrative processes (Toapanta Caisabanda et al., 2024; Silva Payró et al., 2025).
- Gamification and immersive technologies. Through gamification, mechanical and game design principles are strategically applied in non-game environments through digital media, where people solve problems, contribute, increase their participation and competence (Christopoulos & Mystakidis, 2023). The combination of virtual reality and reality argued with artificial intelligence makes possible the creation of interactive learning environments, allowing us to simulate various situations, solve challenges (Kwemoi & Extension, 2024; Lampropoulos et al., 2022).

4 The Potential Impact of Educational Artificial Intelligence on Self-Regulated Learning

Educational action should help students to be aware of their thinking, to be strategic and to direct their motivation towards worthwhile goals (Lamas Rojas, 2008). Learning strategies that include student autonomy become an essential component of the academic process; that is, the absence of these strategies is reflected in a loss of control over the learning process, decreased motivation, responsibility, and behaviour, which negatively impacts established goals and other processes such as planning and managing educational resources.

Motivation plays a crucial role in self-regulated learning, where self-efficacy beliefs are essential for academic success. However, student motivation is currently unbalanced, which means that autonomous learning is increasingly rare. This is a problem that negatively impacts academic performance and learning, even with the use of integrated technological platforms that could significantly enhance student autonomy (Jin et al., 2023).

Various studies have been conducted to analyse the impact of AI in education. For example, (Sánchez Vera, 2023) proposes that AI is a tool for teachers in Spain, and the results show that conversational tools such as ChatGPT are currently the most widely used, both for preparing classes and for activities with students. Teachers highlight the need for training in its proper use and express concern about plagiarism. This study helps us highlight how AI can promote personalisation and autonomous learning, if used with proper training.

In turn, Ojeda et al. (2023) analysed the impact of ChatGPT on university education processes in Colombia, where they identified that ChatGPT facilitates personalised learning and immediate feedback, supporting both teachers and students in the creation of educational content and the improvement of classroom interaction. From this perspective, AI can be integrated into education, offering resources that enhance teaching practices and promote an adaptive, student-centred learning environment.

In the case of Alastruey Carlos (2021), they identified a relationship between AI and autonomous learning, given that AI emulates human capabilities, highlighting deep learning and the use of neural networks.

From the perspective of Aparicio and Aparicio Gómez (2024), they identified the importance of implementing AI-based adaptive learning systems to personalise teaching in education based on machine learning and deep learning to adapt content to each student's level and improve their motivation through real-time feedback. The results showed that these systems increase learning

effectiveness, promote student autonomy, and allow teachers to focus on value-added tasks. This approach offers technological strategies that optimise individualised learning in varied educational contexts.

Naseer et al. (2024) explore the implementation of an AI-driven educational platform to personalise learning experiences in university settings. The focus is on using deep learning techniques to adapt to educational content in real time, based on student performance data and engagement metrics. In turn, the AI-driven platform uses deep learning algorithms to analyse student data and generate adaptive learning paths. The key algorithms mentioned are:

- Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). CNN is used to process and extract patterns in complex data, such as student performance metrics, while RNN handles time series, such as student progress over time. These algorithms allow the content and difficulty of educational material to be adapted in real time, based on individual interactions.
- Personalised Learning Paths: Describes the process of collecting and analysing quantitative data. It initialises an empty list to collect student data (grades, engagement metrics, and test scores). It then analyses the data using the AnalyseCollectedData function, which includes grade comparisons (T-tests), engagement analysis, and test score distribution. The algorithm integrates loops to process data from multiple students and returns compiled analytical results.
- Statistical Tests in the Quantitative Phase. Structures the statistical analysis of the collected data. It includes the execution of T-tests to compare grades between groups, ANOVA tests to analyse engagement metrics and test scores by identifying significant differences between groups, and regression analysis to model the relationship between platform use and student performance.
- Complementary statistical methods: T-tests to compare results between control and experimental groups, ANOVA to evaluate interaction effects, and regression analysis to predict performance based on engagement metrics.
- The platform's central mathematical model is represented by the prediction equation of a basic neural network, which simulates the process of adapting educational content. This model allows for the dynamic prediction and adaptation of educational content based on patterns extracted from large data sets. In summary, the study demonstrates that these algorithms and the mathematical model achieve a 25% improvement in grades, scores, and engagement, empirically validating the effectiveness of AI in educational personalisation (equations 1–3):

$$Y_{predicted} = f(W \cdot X + b) \tag{1}$$

$$H_0: \mu_{control} = \mu_{experimental} \tag{2}$$

$$H_a: \mu_{control} \neq \mu_{experimental} \tag{3}$$

Where:

$Y_{predicted}$ Predicted learning outcome or content adaptation

X Input data vector (student performance metrics)

W y b Weights and biases of the neural network, adjusted during algorithm training

f Activation function applied in the layers of the neural network (CNN/RNN)

A second example is proposed by Pahi et al. (2024) based on an active learning approach that integrates teaching assistants and generative AI (ChatGPT) to provide feedback during class exercises in computer science courses. The results show that teaching assistants accurately detected common problems (backtracking) and that human-AI collaboration improved feedback in areas such as technical accuracy and conceptual clarity. This proposal relies on pre-trained generative AI to generate adaptive feedback. The key algorithms mentioned are:

- Large Language Models for the development of the main algorithm used to provide feedback to students. ChatGPT relies on transformer architectures and implicit recurrent neural networks to process student code and generate suggestions. It is integrated into the AI module to analyse student progress in real time, following specific guidelines such as positive reinforcement, avoidance of direct solutions, and identification of conceptual gaps. In the present study, it is used in four scenarios: uninfluenced feedback, guided feedback, feedback reviewed by teaching assistants, and feedback reviewed by ChatGPT itself.

- Real-Time Monitoring Systems: Monitoring algorithms are used to update student progress and allow teaching assistants to access workspaces for inline feedback, and an Integrated Development Environment with plugins for sharing code and receiving feedback, including simple labelling algorithms (Adequate, In Progress, No Progress, Incorrect) to evaluate submissions.
- To evaluate effectiveness, non-parametric statistical algorithms are used, such as the Mann-Whitney U test (compares the quality of feedback between teaching assistants and ChatGPT in uninfluenced and guided scenarios) and the Wilcoxon Signed Rank test (evaluates improvements in collaborative feedback by measuring paired differences in ordinal scores for effectiveness criteria).
- The mathematical model is based on personalised deep learning and pre-trained generative AI. However, descriptive and inferential statistical models are used for the quantitative evaluation of feedback and student progress. The main model for comparing groups is the Mann-Whitney U test represented in equation 4, where this model calculates differences in ordinal distributions without assuming normality, used for criteria such as technical quality.

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1 \quad (4)$$

Where:

n_1 and n_2 are the sample sizes of the two groups (e.g., feedback from TAs vs. ChatGPT).
 R_1 is the sum of ranks for the first group.

5 The Complexity of Ethics in the use of Educational Artificial Intelligence

Artificial intelligence (AI) has significantly transformed educational processes by integrating machine learning and data mining techniques to analyse large volumes of academic information, identify risk patterns and predict student performance. In the article presented by (Barrera-Cámara et al., 2025), it is argued that AI not only optimises institutional management, but also promotes more inclusive and personalised education, in line with the Sustainable Development Goals (SDGs), particularly SDG 4 on quality education.

The rapid development of artificial intelligence in educational settings offers enormous potential for personalising learning, improving teaching efficiency and supporting institutional decision-making. However, as (Barrera-Cámara et al., 2025) point out, its implementation requires a solid ethical framework that guarantees respect for human rights, algorithmic transparency and the protection of personal data. The ethical use of educational AI involves balancing the exploitation of its benefits with the prevention of risks associated with manipulation, bias or technological dependence.

According to UNESCO (2019), AI should be used under the principles of inclusion, equity and sustainability, as it is a key tool for pedagogical innovation. (Barrera-Cámara et al., 2025) highlight that its integration allows for personalized teaching, reduces educational gaps and facilitates evidence-based decision-making. Its ability to analyse historical data and predict academic performance has made AI a strategic ally for the development of educational policies aimed at continuous improvement.

Among the main benefits are the optimisation of educational processes, the early detection of school failure and the promotion of gender equality and educational inclusion (Ikhsan et al., 2025; Nedungadi et al., 2024). The aim is for AI to contribute to improving institutional efficiency and student well-being.

Furthermore, the use of intelligent systems to adapt content and methodologies based on student characteristics has been shown to improve knowledge retention (Naseer & Khawaja, 2025). To this end, AI facilitates the creation of adaptive environments that offer real-time feedback, generating continuous support that complements the work of teachers. This approach allows teachers to focus on activities of greater pedagogical value, while algorithms automate repetitive tasks.

UNESCO (2019) presented the basic principles for the ethical use of AI in education, shown in Figure 1. These principles seek to ensure that educational AI acts as a complement to, rather than a substitute for, human pedagogical judgement.

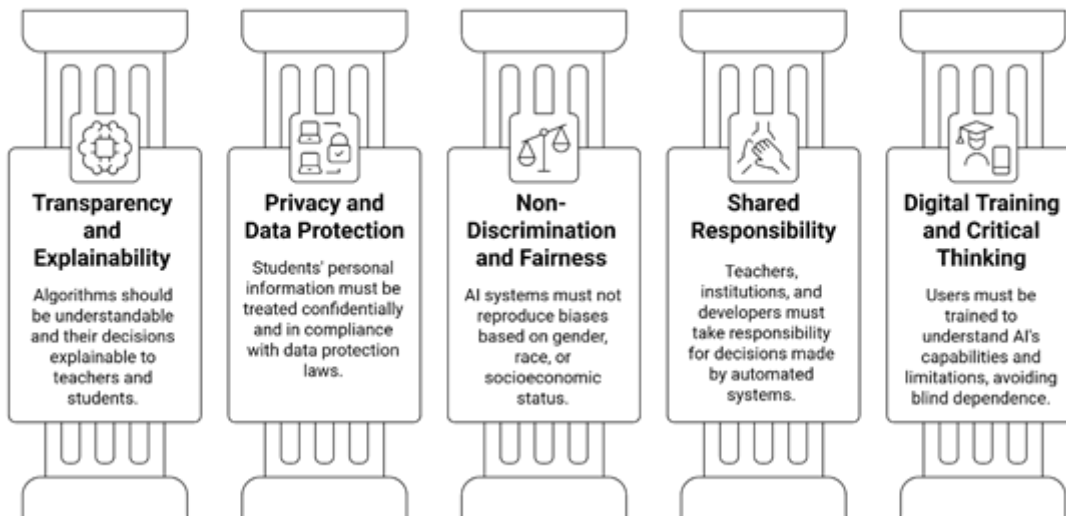


Fig. 1. Ethical principles for the use of AI in education (UNESCO, 2019)

In turn, we can highlight various practices for the ethical use of educational AI. For example:

- Responsible use of automated assessment systems: It is essential that teachers use complementary tools, such as Turnitin or Gradescope, to verify student results and avoid erroneous penalties due to algorithmic bias (Fuentes-Penna et al., 2025).
- Data protection on adaptive platforms: Systems such as Knewton Alta or Civitas Learning should be configured to anonymise personal data and share only aggregated information for institutional analysis purposes (Barrera-Cámara et al., 2025).
- Pedagogical explanation of predictions: Results generated by predictive models (e.g., dropout risk) should be communicated to students in a constructive manner, avoiding labelling or stigmatising their performance (Nedungadi et al., 2024).
- Teacher ethics training: Universities should offer training on digital ethics, privacy, and responsible use of AI so that teachers can integrate technology critically (Mittal et al., 2024).

Currently, the rise of generative tools such as ChatGPT, Copilot, Claude, among others, has increased the risk of students resorting to AI to complete tasks without real understanding. To counteract these practices, institutions can implement strategies:

- Designing authentic assessments: Include projects, debates, or case studies that require critical thinking and personal reflection that cannot be generated mechanically.
- Ethical authorship statements: Require students to explicitly declare the extent to which they have used AI in their work, promoting transparency and academic honesty.
- Pedagogical use of generative AI: Instead of banning it, students can be taught to use it responsibly, for example, to obtain feedback on drafts or structure initial ideas.
- Verification with anti-plagiarism and AI detection tools: Use software such as GPTZero or Turnitin AI Detection to identify automatically generated texts, always respecting due process and without criminalising the student.
- For their part, teachers must also avoid practices that are contrary to academic ethics, such as completely delegating the assessment or generation of teaching materials to unsupervised AI systems. Some preventive strategies are:
 - Human supervision: Ensure that all automated decisions about grades, tutoring, or educational interventions are validated by a teacher.
 - Avoid algorithmic bias: Periodically evaluate prediction models to identify possible discrimination based on gender, age, or origin (Khoudi et al., 2025).

- Transparency with students: Inform students when AI systems are used in the classroom and explain their purposes, limitations, and scope.
- Encouraging critical thinking: Promote discussions about the ethical limits of AI in class so that students learn to discern between responsible and fraudulent use.

The ethical use of AI in education does not depend solely on technical standards, but on the construction of a culture of shared responsibility. Institutions must establish codes of technological conduct, digital ethics committees, and oversight protocols to accompany the development and implementation of AI. As suggested by (Barrera-Cámara et al., 2025), AI should be conceived as a tool for the common good, aimed at improving educational quality, and not as an end.

Ethics in educational AI involves promoting the thoughtful, transparent, and fair use of technology, where both teachers and students understand its potential and risks. Only then will it be possible to ensure that artificial intelligence effectively contributes to a more humane, inclusive, and sustainable education.

6 Conclusions

The integration of Artificial Intelligence (AI) into education represents a transformative advance that redefines traditional teaching practices, promoting a more personalised, inclusive and efficient approach. Throughout this study, we have explored how AI, through supervised, unsupervised, reinforcement and deep learning algorithms, facilitates the prediction of academic performance, the early detection of dropout risks and the adaptation of content to the individual needs of students. Concrete examples, such as intelligent tutoring systems, virtual simulations, virtual assistants, and gamification tools, illustrate the potential of AI to enrich the teaching-learning process. However, this progress is not without significant ethical challenges, which must be addressed to ensure that AI contributes to the development of self-regulated learning, where students take an active role in managing their own knowledge, motivation, and educational goals.

One of the central ethical issues in the use of educational AI lies in the protection of privacy and personal data. As mentioned in the document, AI processes large volumes of educational information, including grades, interactions on virtual platforms, and behavioural data, to generate predictions and recommendations. This massive collection of data poses risks of vulnerability, such as the misuse or leakage of sensitive information, which could violate fundamental rights. Organisations such as UNESCO (2019) emphasise principles of inclusion, equity and sustainability, urging the anonymisation of data and the sharing of only aggregated information.

Without a robust regulatory framework, there is a danger that these systems will perpetuate inequalities, for example by discriminating against vulnerable groups based on algorithmic biases inherent in training data sets. Another critical ethical issue is the transparency and explainability of algorithms. Educational AI, which uses complex models such as convolutional neural networks (CNN) or recurrent neural networks (RNN), often operates as a 'black box,' where predictive decisions—such as the risk of academic failure—are not easily understandable to teachers or students. This raises dilemmas of responsibility: who takes the blame if a flawed algorithm stigmatises a student or generates inappropriate recommendations? The document stresses the importance of communicating results constructively, avoiding labels that demotivate, and training educators in digital ethics. In addition, the proliferation of generative tools such as ChatGPT or BERT increases the risk of plagiarism and technological dependence.

Students could delegate cognitive tasks to AI without developing critical skills, which contradicts the essence of self-regulated learning, defined by Lamas Rojas (2008) as the ability to be aware of one's own thinking, strategic and motivated towards valuable goals. To counteract this, strategies such as authentic assessments (projects, debates) that require personal reflection, ethical authorship statements, and detection tools such as GPTZero or Turnitin AI Detection are proposed, always respecting due process.

The importance of educational AI in the face of the need for self-regulated learning is evident in its ability to enhance student autonomy. In a context where motivation is unbalanced and autonomous learning is scarce, AI offers tools that adapt learning paths in real time, based on performance and engagement metrics.

This fosters self-efficacy by providing immediate feedback and resources tailored to individual learning styles, stimulating intrinsic motivation and independent management of educational resources. In fields such as health or engineering simulation, AI creates safe, personalised environments that allow risk-free experimentation, promoting critical thinking and problem solving.

Likewise, in academic research, it facilitates searches, data analysis and visualisations, empowering students to direct their own research process.

However, this importance is conditioned by ethical balance. AI should act as a complement, not a substitute, for human pedagogical judgement, as UNESCO warns. Without ethics, it could foster a dependency that erodes autonomy, turning students into passive consumers of machine-generated knowledge. The document highlights ethical practices such as human supervision in automated assessments and the promotion of classroom discussions on the ethical limits of AI, cultivating critical thinking that reinforces self-regulated learning. In gamification and immersion environments, AI can motivate through adaptive rewards, but it must avoid manipulations that prioritise superficial engagement over deep development.

EAI is emerging as a catalyst for more equitable and effective self-regulated learning, aligned with the Sustainable Development Goals (SDGs), particularly SDG 4 on quality education. Its importance lies in personalisation that empowers students, overcoming traditional rigidities and addressing inequalities. However, ethical issues—privacy, bias, transparency, plagiarism, and dependency—require a responsible approach: institutional codes of conduct, ethics committees, and oversight protocols. Only through a culture of shared responsibility, where teachers and students understand potential and risks, can AI contribute to a humane, inclusive, and sustainable education. Future research should focus on hybrid models that integrate AI with student-centred pedagogies, evaluating long-term impacts on autonomy and equity. In this way, AI will not only transform education but elevate it to a paradigm where self-regulated learning is the norm, benefiting entire societies in an increasingly technological world.

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