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Application of Artificial Intelligence in Education: Models and tools to predict and improve academic performance towards an SDG perspective

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Abstract. The application of artificial intelligence (AI) in education is analyzed, focusing on how various models and algorithms can predict and improve academic performance, in line with the Sustainable Development Goals (SDGs). A documentary and comparative approach was used to analyze recent research on machine learning techniques or algorithms, such as neural networks, SVM, KNN and decision trees, among others that are applied to the detection of underachievement and school failure. Tools that allow monitoring and anticipating academic performance were also reviewed. AI has a high potential to identify academic risk patterns, facilitating early interventions. If implemented ethically and strategically, it can contribute significantly to inclusive and quality education, supporting the achievement of the SDGs.

Keywords: Artificial Intelligence, education, academic performance, failure, ODS, Algorithms, model, techniques.

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1 Introduction

Artificial intelligence, together with data mining techniques, has established itself as a key tool in the analysis of information in the educational field. Its ability to identify hidden patterns in large volumes of data has made it possible to generate predictive models that anticipate students' academic performance with high accuracy. This not only revolutionizes the way in which school data is managed, but also offers new possibilities for personalizing educational support, optimizing institutional processes and making better evidence-based decisions. Thus, technology becomes a strategic ally in the continuous improvement of education.

The academic trajectory of a student in an educational institution starts from the moment he/she enters until the completion of his/her studies in that institution, generating a large amount of information. Failure in school has a significant influence on academic trajectories and terminal efficiency. Failure and academic performance is a multifactorial situation seen from different perspectives (Rubiano Romero & Martínez Huertas, 2024; Sánchez Martínez et al., 2020).

Academic performance is evidenced through the performance that students demonstrate in the educational environment, particularly when they reach or exceed the minimum passing score in the subjects taken, which indicates the acquisition of the knowledge and skills proposed in each subject (Ji et al., 2024; Mora et al., 2021). Academic performance may be low, which is why it represents a topic of interest within the academy and the authorities in educational institutions. This performance may be associated with a lack of study techniques, poor study habits, lack of interest, among others. Academic, technological, personal, social, academic and health factors are an example of elements that influence school failure (Barrera-Cámara et al., 2022).

Artificial Intelligence (AI) is based on the application of mathematical algorithms, which are trained through machine learning processes (Ibáñez Martín, 2015). The goal is to achieve that AI can respond in a manner similar to human behavior, addressing tasks such as reasoning, perception, decision making and problem solving in an autonomous manner (Villota Hurtado, 2019). Artificial intelligence with historical data allows predictions that support decision making in various areas (Blanco, 2019; Casacuberta & Estany, 2019).

2 Artificial Intelligence and education

The United Nations Educational, Scientific and Cultural Organization (United Nations Educational, 2019), considers that artificial intelligence should be used to innovate in teaching and learning, under a framework of inclusion, equity and sustainable development, based on ethical principles. SDG 4 promotes inclusive, equitable and quality education; in this context, artificial intelligence becomes a strategic tool to personalize learning, reduce educational gaps and facilitate continuous access to knowledge. Among the benefits of artificial intelligence in the field of education, those that are aligned with the Sustainable Development Goals (SDGs) stand out:

- Optimization of educational processes: The use of intelligent systems helps to streamline activities such as homework correction, administrative management and individualized tutoring, allowing teachers to focus on more strategic pedagogical aspects (Ikhsan et al., 2025; Patel, 2024).
- Personalized and effective learning: AI technologies enable the adaptation of content and methodologies according to the characteristics of each student, which favors knowledge retention and improves the educational experience (Naseer & Khawaja, 2025; S & Arockia, 2025).
- Drives inclusion and equity: Artificial intelligence has the potential to reduce educational gaps and promote gender equity (Mittal et al., 2024; Nedungadi et al., 2024).
- Early detection of academic risks: AI tools enable accurate predictions of student performance, facilitating the implementation of preventive measures against the risk of school failure (Khoudi et al., 2025; Muniru et al., 2024).

On the other hand, a wide variety of applications and uses have been developed for the educational sector (Fuentes-Penna et al., 2025): Virtual assistants and tutoring, plagiarism detection tools, learning personalization, automatic assessment, video generators, text generators, image generators, visual and auditory recognition, conversational agents, among others. In (Wang et al., 2024), categories of applications are proposed: adaptive learning and personalized tutoring, intelligent assessment and management, performance profiling and prediction, and emerging technologies such as educational robots and virtual reality. One of the applications is to predict academic performance through data analysis (Pacheco-Mendoza et al., 2023). This allows the identification of patterns and trends for preliminary detection of learning problems (Yang, 2024), and to support the personalization of education (Wang et al., 2024).

3 Academic performance problems

In recent years, interest has been maintained in determining the origin of the problems of academic performance of students at the higher level (García & Furniel, 2019), this because it precedes one of the problems that has greater relevance in higher education which is school dropout (Mellizo-Soto & Constante Amores, 2020). Student dropout occurs when the student stops fulfilling his academic obligations and stops attending classes impacting terminal efficiency (Padua Rodríguez, 2019).

Academic performance is the result of the mental processes that enable students to acquire knowledge, understand ideas, solve problems, and make decisions (Ajisuksmo, 2023; Sandars, 2020). In turn, it also depends on the student's ability to be aware of how he or she learns and regulates his or her learning (Li, 2024; Torre & and Daley, 2023). The results are affected by social, cultural and economic factors, there are studies that indicate that there are factors with greater impact on students are those linked to their emotional intelligence such as self-esteem, self-concept, self-determination and motivation (Flores Ramírez et al., 2021). Along these lines, several investigations have been carried out to determine the variables, attributes or factors that have the greatest impact on the prediction of academic performance with the purpose of establishing strategies to increase permanence and terminal efficiency. Some strategies consider tutoring as a strategic element for academic performance (Ramos Ojeda et al., 2019).

The study developed in a private university, evidenced that women have a marked tendency to have a higher academic performance, on the other hand, it was observed that students who have a positive attitude towards the career they selected and their academic motivation are associated with better academic performance (Grimaldo & Manzanares-Medina, 2023).

The perception of university students on performance is analyzed by pointing out that personal, institutional and socioeconomic factors have an impact on this aspect. Self-concept, class perception and motivation are significant predictors of academic performance, with notable differences between students of different income levels. Students who come from homes with lower economic income give greater utility to the subjects, which is reflected in greater motivation (Herrera Rivera & Arancibia-Carvajal, 2022).

With (Rico Páez, 2023), machine learning techniques were applied to the prediction of academic performance based on the five most significant factors. This study proposes a methodology for the selection of the attributes that have the greatest impact on the academic results of students and that can be applied to any subject, educational modality and even proposes that data collection be systematized to obtain timely and efficient predictions. A similar initiative (Contreras et al., 2020), applied machine learning (ML) algorithms in the prediction of school performance and identified seven variables out of a total of thirty that have the greatest impact on academic performance, these being age, gender, the score obtained in the state exam for mathematical aptitude, the overall score of the exam, the enrollment value and the score of the exam for mathematical condition. The academic performance of first-year Psychology undergraduate students is analyzed, focusing on the role of extrinsic motivation and academic expectations (Curione & Fiori, 2024). The results indicate that when students are motivated only by external rewards, they tend to get worse grades and drop out more often. In contrast, students with high expectations improve performance and reduce dropout, while external motivation is associated with worse outcomes.

Academic and demographic variables are used to predict students' academic performance. For this purpose, several algorithms were used to identify patterns and more accurate predictions (Contreras Bravo et al., 2023). The study shows that the KNN is more effective and accurate

On the other hand, the academic performance of university students was analyzed through a systematic review of machine learning algorithms, with the purpose of identifying the most effective models for its prediction based on several variables. The results showed that the Decision Tree algorithm presented an outstanding performance, allowing the identification of factors that affect academic performance, including socioeconomic, family, demographic, personal, institutional and academic aspects (Barriga et al., 2024).

Educational institutions aim to improve student retention and degree completion over three years by analyzing student data to predict retention and completion rates through specific strategies (Cardona & Cudney, 2019). Every year (Mohamed Nafuri et al., 2022), more students enroll in bachelor's degrees, although not all of them graduate. Through predictions, the government seeks to increase graduation rates and thus improve the economic situation of students.

The high number of failures in the remedial course impacts performance and limits the availability of space and personnel at the institution. Because of this, a model was applied to estimate the probability of passing and to identify the students with the highest risk of not accrediting the course (Calva et al., 2021). The applied model evidenced a high capacity to anticipate cases of failure, while the logistic regression allowed recognizing the determining factors.

It is possible to predict the final performance of mathematics and Portuguese language courses, and thus design strategies for students with low performance (Alamri et al., 2021). In the study (Sabri et al., 2023), weekly data on self-efficacy and learning behavior are used to predict college performance. It is also possible to identify three behavioral patterns, which made it possible to anticipate underperformance from early stages with different time frames. Moreover, it is possible to predict student performance and discover patterns in social and academic characteristics (Borges et al., 2018).

In (Rojas Paucar, 2024), it contributes to enhance academic performance by facilitating the detection of patterns in student behavior and supporting decision making within educational environments. In engineering students, a significant relationship has been identified between the use of this type of algorithms and higher educational productivity, which indicates its usefulness to adapt training strategies according to the needs and characteristics of the students. It is possible to find relationships between students' grades, which allows suggesting master's degree programs that match their knowledge and skills acquired in the bachelor's degree (Carballo & Antunes, 2014).

To predict performance, identify students with difficulties or talents, and allow individualized training, student performance is evaluated, which can be used as a model in other educational institutions (Pronina & Piatykop, 2022).

4 AI algorithms applied to academic performance

Until a few years ago, the analysis of academic performance was mainly based on mathematical and statistical models. Nowadays, the trend is to take advantage of advances in artificial intelligence, which allow automating processes and analyzing large volumes of data more efficiently. Machine Learning is a field of Artificial Intelligence that focuses on the development of techniques, algorithms or statistical models to analyze data, find patterns and make decisions or predictions automatically, without the need to explicitly program each task (Russell & Norvig, 2020). ML techniques or algorithms developed to date are classified into supervised learning, unsupervised learning and reinforcement learning.

Supervised learning. Models that learn from input and output examples, allowing to predict or classify new data based on the information provided during the training process.

- Decision trees. Graphical representation of decision rules that are applied sequentially to classify a case into one of several classes. They start with the root node, which represents the most important variable in the classification. Decisions are made based on the values until reaching the leaf that corresponds to the final classification.
- Gradient Boosting Machine. Minimizes a loss function that represents the difference between the values predicted by the model and the real values of the training data.
- Naive Bayes. Based on Bayes' theorem and assumes that the characteristics of an example are independent of each other, known as naive assumption.
- Logistic regression. A statistical model used to predict the probability of occurrence of a binary event, i.e., an event that has only two possible outcomes.
- Support vector machine. Used for classification and regression. Model that represents data as points in a multidimensional space and uses the separation of these by hyperplanes to perform classification.

Unsupervised learning. Identifies new patterns and anomalies. Algorithms make sense of data by constantly searching for patterns and features. They do not collect external assumptions for training. These algorithms are made to perform more complex processing.

- Clustering. Groups similar data together, while the elements of other groups are different. It identifies patterns, structures or intrinsic relationships in the data without having prior information about the categories to which the objects belong.
- Principal component analysis. It reduces the dimension of a data set. Its main objective is to transform a set of correlated variables into a set of uncorrelated variables called principal components.
- Singular Value Decomposition. Mathematical technique that decomposes a matrix into three principal components: unit, diagonal and transpose. Useful in various applications such as dimensionality reduction, data compression and solving systems of linear equations.
- Independent component analysis. A statistical technique used to decompose a mixture of signals into their original independent components. It is often used in signal processing in the fields of neuroscience, signal engineering and computational biology, among others.

Reinforcement learning. Techniques that focus on regularized learning processes. When defining rules, attempts to explore different options and possibilities, observe and evaluate each outcome to determine which is optimal. Algorithms train through trial and error. They learn from past experience and begin to adapt their approach to the situation to achieve the best possible outcome.

- Dynamic programming. Decomposes a problem into smaller subproblems and solves them efficiently by combining storage of partial results and reuse of previous computations.
- Q-Learning. It is based on building a table of values, called Q-table, where each cell of the table represents the value or quality of an action in each state. These values are updated according to the reward received for performing the action and the discounted value is used to calculate the value of future rewards.
- SARSA. It is based on an iterative process where the agent interacts with the environment. In each iteration, it observes the current state of the environment, chooses an action to perform, receives a reward for that action, and observes the next resulting state.

Table 1. Shows a summary of research with the various techniques, models or algorithms used for the prediction of academic performance.

Classification	Model/technique/algorithm	Source
Supervised learning	Decision trees	(Aguilar-Reyes et al., 2025; Contreras Bravo et al., 2023; Contreras et al., 2020; Rico Páez, 2023)
	Random Forest	(Alamri et al., 2021)
	Gradient Boosting Machine	(Calva et al., 2021)
	Naive Bayes	(Rico Páez, 2023)
	Logistic regression	(Aguilar-Reyes et al., 2025)
	Support Vector Machine (SVM)	(Cardona & Cudney, 2019) (Alamri et al., 2021)
	Support Vector Classifier (SVC)	(Contreras Bravo et al., 2023)
	K-Nearest Neighbors (KNN)	(Contreras Bravo et al., 2023; Contreras et al., 2020; Rico Páez, 2023)
	Linear Discriminant Analysis	(Contreras Bravo et al., 2023)
Unsupervised learning	Clustering	(Pronina & Piatykop, 2022)
	k-means	(Mohamed Nafuri et al., 2022)
	Principal Component Analysis (PCA)	(Borges et al., 2018; Sabri et al., 2023)
	Singular Value Decomposition	(Carballo & Antunes, 2014)
Reinforcement learning	Q-Learning	(Rojas Paucar, 2024)

5 Tools for AI prediction

A variety of AI tools are available, from programming libraries to cloud services and integrated development environments. This variety offers researchers the flexibility to select according to their skills, with both free and commercial options (Barrera-Cámara et al., 2021). Some tools and their highlights are listed below:

- Amazon SageMaker. It has several ML models for the analysis and prediction of academic data.
- Apache Mahout. Free library designed for distributed environments, allowing mathematicians, statisticians and data scientists to quickly implement their algorithms. While beginners can use it for simple applications, more experience, especially in distributed environments, is needed for complex cases.
- Azure ML. Cloud computing service owned by Microsoft. It offers a set of tools that simplify the building, training, deployment and management of predictive analytics and ML models. It has visual tools that make tasks easier for beginners and experts.
- Brightspace (D2L). D2L Lumi uses AI to detect underperforming students based on learning patterns, provides personalized feedback, and proposes adaptive resources
- Civitas Learning. Platform Analyzes student data with AI to predict student attrition and propose academic interventions for the benefit of students and the institution.
- DataRobot. Automates the creation of ML models, which can be applied for educational analysis.
- ELKI. Open-source software, oriented to professionals and researchers interested in exploring data mining algorithms and techniques. Its focus on computational efficiency and its ability to handle large volumes of data demand experience in Java programming and data mining to be fully exploited.
- Google Cloud Vertex AI. Platform that has several ML models that can analyze academic data
- H2O.ai. AI tool that can support performance prediction.
- IBM Watson Education. Personalizes learning and uses NLP and ML models to predict academic outcomes.

- JSAT. Java library that offers a wide range of algorithms. Requires programming knowledge and experience as it does not have a graphical user interface.
- Jupyter Notebook. Free web environment for writing and running code in Python, Julia and R. Facilitates data exploration, experimentation with ML algorithms and presentation of visual results. With an interface that combines text and code, it is flexible for users of different experience levels.
- Knewton Alta. Platform that uses artificial intelligence to personalize learning, adapting content according to student performance and providing useful data for teaching intervention.
- KNIME. Free platform that facilitates the creation, execution, management and deployment of data analysis and ML processes. It stands out for its visual approach with nodes, facilitating intuitive workflows. It allows beginners to use algorithms without programming, while experts can implement scripts in various languages through pre-built integrations.
- Microsoft Azure ML. Platform for developing and training algorithms to predict failure risk.
- MOA. Java development environment that processes real-time, continuously generated and incoming data. It offers a graphical interface that allows users to experiment and work with algorithms visually.
- Orange3. Free tool that offers a graphical interface, allowing data analysis, predictive model building, data mining and visualization without requiring programming. Useful and simple for students, researchers and professionals.
- Power BI. Creation and integration of ML models for real-time academic analysis with interactive visualizations.
- Pythorch. Free library created by Facebook. Provides an API that allows the creation and manipulation of data structures (scalars, vectors, matrices), which is useful for image processing tasks, natural language processing, computer vision and other deep learning applications.
- RapidMiner. Commercial platform with a visual environment that simplifies data cleaning, model building, and results visualization. Offers a variety of algorithms and machine learning techniques for testing different approaches to problem solving.
- Salesforce Education Cloud. Support predicting student performance and academic risk.
- Scikit-Learn. Free library for implementation with Python. Known for its ease of use and syntax.
- Tableau. Allows the creation of interactive visualizations with models.
- ensorFlow. Free library created by Google. It integrates very easily with other high-level tools and offers a low-level API for experts. Versions for production models and a lightweight version for mobile or embedded devices are available.
- Weka. Free suite that provides a variety of tools for exploring data, preprocessing information, building models and evaluating their performance. It includes a graphical interface that allows developers to work visually but also provides a command line.

4 Conclusions

The use and application of AI in an ethical way in the educational field is currently of great help. The available data must be treated and processed by applying techniques and algorithms that allow to have a clear view of the academic performance of students and thus make decisions and strategies that improve performance by preventing school dropout.

It is essential to have a large amount of data and to consider several variables to predict students' academic performance. In addition, it is important to take advantage of advances in Artificial Intelligence and Machine Learning by exploring different algorithms. A variety of tools are available, both commercial and free, for beginners and experts; offering several options that facilitate experimentation. They range from specific libraries to comprehensive software suites, giving users the possibility to simplify and optimize resources in academic research.

The KNN model is more accurate in prediction (80%), followed by the prediction trees (Contreras Bravo et al., 2023). On the other hand, the best model predicting academic performance is Decision Tree with a value higher than 90% in almost all indicators (Barriga et al., 2024), and 96% accuracy in testing (Calva et al., 2021).

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