# Systematic review on the use of machine learning to detect school learning difficulties

Gherson A. Monje-Castro[1]; Flavio S. Villanueva-Medina[2]; Walter R. Marzal-Martinez[3]; Luis C. Rada-Mota[4]
[1,2,3,4] Universidad Tecnológica del Perú, Perú, *U21230187@utp.edu.pe, U21201391@utp.edu.pe*, *C22314@utp.edu.pe*, *C18380@utp.edu.pe*

***Abstract* – This systematic literature review (SLR) analyzes the impact of machine learning on the early detection of learning difficulties in school settings. Using the PICO methodology and the PRISMA protocol, four key questions were articulated regarding types of difficulties, applied algorithms, comparison with traditional methods, and intervention improvements. A search of the Scopus database identified 306 documents, from which 36 relevant studies were selected after applying rigorous inclusion and exclusion criteria. The findings show that algorithms such as Random Forest, SVM, deep neural networks, and ensemble models allow the identification of complex patterns in academic, behavioral, and neuropsychological data, far exceeding the accuracy and agility of conventional methods. The main applications include the detection of dyslexia, dysgraphia, dyscalculia, and ADHD, as well as the prediction of academic risk and pedagogical personalization. Furthermore, it is observed that sensory and adaptive artificial intelligence tools strengthen educational inclusion for students with cognitive disabilities. However, significant challenges remain, such as the need for high-quality data, limited validation in real-life school settings, and the poor interpretability of some complex models. In conclusion, the use of machine learning represents an effective solution for improving the early detection of learning difficulties, overcoming the limitations of traditional approaches and opening up new opportunities for more accurate, timely, and inclusive educational interventions.***

***Keywords*-- machine learning, learning difficulties, artificial intelligence, academic challenges, risk prediction, traditional education**

## I. INTRODUCTION

Over the past decade, the incorporation of artificial intelligence into education has grown considerably. Machine learning (ML) models, such as artificial neural networks (ANNs) or algorithms such as Random Forest and Support Vector Machines (SVMs), [1], [2], [3], [4]are increasingly used to provide early identification of students at risk of developing learning difficulties such as dyslexia, attention disorders, or dyscalculia [2], [4], [5], [6]. These automated methods appear to have some advantages over traditional psychopedagogical testing and teacher observation alone, as they allow for timely action, which improves both academic outcomes and student well-being [7], [8]. For example, early warning systems are very good at detecting patterns in data, allowing action to be taken before problems become more serious [3], [5], [9], [10]. Furthermore, the fact that these systems can handle large amounts of information and make accurate predictions has been an important advance in how learning is improved [11], [12], [13].

This is essential because, being based on machine learning, these solutions have the ability to adapt much better to the specific needs of each educational environment [3], [6], [12]. However, despite these advances, significant limitations persist that prevent their full utilization in the school educational environment. Many traditional methods, such as standardized tests, observation sheets or psychopedagogical interviews, continue to predominate in schools, which makes the implementation of early pedagogical interventions difficult [2], [3], [6]. A clear example of these limitations is that some models, such as logistic regression, decision trees or random forests, are still not sufficiently validated in real educational environments [3], [7], [10], [13], and often do not consider key variables such as the family or emotional background of students [10], [12]. In addition to this, a major challenge is that educational materials are being created with machine learning without the active participation of teachers in their design, which makes it more difficult to apply them effectively in the classroom [3], [10], [12].

Although models such as neural networks or decision trees have worked well in some cases, they often operate separately and do not easily adapt to the variety of situations found in educational settings [6], [8], [9], [12], [13]. Furthermore, the lack of teacher training in the use of these technological tools highlights the urgent need to establish training and interdisciplinary collaboration protocols based on empirical findings [3], [12]. This clearly demonstrates the gap between advanced technology and what can actually be applied in the classroom. Furthermore, although studies [4], [5], [13]on the use of machine learning in education already exist, they tend to focus on very specific aspects, such as, the aforementioned, predicting students' academic performance [4], [5]or analyzing their behavior [13]. In this sense, it is necessary to conduct a new systematic review that thoroughly analyzes how machine learning can specifically contribute to the early detection of learning difficulties in schoolchildren. From this, the following research question arises: How does machine learning improve the early detection of learning difficulties in school education?

Consequently, it is necessary to conduct a LSR that synthesizes current knowledge on the early detection of learning difficulties using machine learning technologies, identifying good practices and guiding future research in this field. In this sense, this LSR aims to analyze the effect of using machine learning in optimizing the early detection of learning difficulties in school settings. With this in mind, this review article is structured into five sections. The first section explains the PICO method and the PRISMA protocol that guided the systematization of this review article. The second section is focused on a bibliometric analysis and findings of this study. A third section discusses the results. A fourth section is linked to the conclusions and recommendations of this study; and finally, a fifth section deals with the references used in this review.

## II. Methodology

### A. PICO Method

In Table 1, the PICO methodology was used [14] to design an effective information search focused on the use of machine learning to detect learning difficulties in school education. Through the components of this methodology, concise questions were formulated focused on identifying learning difficulties addressed through machine learning, machine learning algorithms and models, comparison of traditional methods and application of machine learning, and improvements in early detection, timely intervention and performance. This allowed for the precise determination of highly relevant data, generating a better review and stimulating good decision-making. In addition, the PICO method was used [14]to design an effective information search strategy focused on the application of machine learning to detect learning difficulties in school education.

A structure of search equations was established for each of the components of the PICO method [14], which were helpful in gathering information in this systematic literature review. It is relevant to mention that these equations were entered into the Scopus database, resulting in a general equation: ( "learning difficulties" OR "learning disabilities" OR "academic challenges" OR "cognitive impairments" OR "academic difficulties" OR "special educational needs" ) AND ( "machine learning" OR "ml" OR "algorithm" OR "data mining" OR "artificial intelligence" OR "AI" OR "predictive modeling" OR "neural networks" OR "supervised learning") AND ( "pedagogy" OR "education" OR "traditional education" OR "teaching" OR "student support" ) AND ( "early detection" OR "early identification" OR "diagnosis" OR "screening" OR "early intervention" OR "early recognition" OR "predictive diagnosis" OR "risk prediction" OR "proactive identification" ).

In this way, 306 documents were found, which were subsequently analyzed to provide answers to the questions posed using this method. The Boolean operators "OR" and "AND" were also used to ensure greater precision in the search, and the main keywords used included: "learning difficulties," "academic challenges," "machine learning," "artificial intelligence," "traditional education," "student support," "early detection," "risk prediction," among others.

TABLE I
PICO Method

| Component | Motivation | Ask | Search equation |
|---|---|---|---|
| P (Population / Problem) | Identification of learning difficulties addressed through machine learning in school education. | What types of learning difficulties have been addressed with the use of machine learning in school education? | ("learning difficulties" OR "learning disabilities" OR "academic challenges" OR "cognitive impairments" OR "academic difficulties" OR "special educational needs") |
| I (Intervention) | Identification of machine learning algorithms and models applied to learning difficulties in school education. | What types of machine learning-based tools are used to improve the early detection of learning difficulties in school education? | ("machine learning" OR "ml" OR "algorithm" OR "data mining" OR "artificial intelligence" OR "AI" OR "predictive modeling" OR "neural networks" OR "supervised learning") |
| C (Comparison) | Comparison of traditional methods and the application of machine learning for the early detection of learning problems in school education. | What is the effect of using machine learning techniques compared to traditional methods in the early detection of learning difficulties in school education? | ("pedagogy" OR "education" OR "traditional education" OR "teaching" OR "student support") |
| O (Outcome) | Improvements in early detection, timely intervention, and academic performance in school education. | What improvements have been reported in terms of early detection, timely intervention, or student academic performance in school education through the use of machine learning? | ("early detection" OR "early identification" OR "diagnosis" OR "screening" OR "early intervention" OR "early recognition" OR "predictive diagnosis" OR "risk prediction" OR "proactive identification") |

### B. PRISMA Protocol

Table 2 presents the flowchart developed according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol [15]. This diagram facilitated the methodical and transparent application of inclusion (IC) and exclusion (EC) criteria throughout the review. This cemented a rigorous procedure that allowed for the selection of the most relevant scientific literature on network device configuration automation for error prevention and correction.

TABLE II
Inclusion and Exclusion Criteria

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| **IC1:** Research articles in the range of 2021 to 2025. | **EC1:** Articles in the period 2021-2025 |
| **IC2:** Documents corresponding to articles and conference papers. | **EC2:** Articles in English or Spanish |
| **IC3:** Research articles in the English language. | **EC3:** Engineering Area |
| **IC4:** Open access research articles. | **EC4:** Open Access |
| **IC5:** Research articles related to the use of Machine Learning for | **EC5:** Original or conference papers |

| | |
|---|---|
| the early detection of learning difficulties in school students. | **EC6:** Review Articles<br>**EC7:** Unrelated articles<br>**EC8:** Access closed |

In this sense, in Fig. 1, the methodological rigor of this systematic review is based on strict adherence to the PRISMA protocol, ensuring transparency at every stage. Of the 306 records initially identified, a thorough filtering process was carried out, excluding 251 based on pre-established criteria such as language, area of study, and type of access. After exhaustive screening of the 55 preselected records, 21 articles were discarded (reviews, irrelevant, or restricted access), resulting in the evaluation of 34 reports. This meticulous process ultimately led to the identification and selection of two key studies, which, together with their detailed reports, constitute the basis of the 36 articles included in this critical analysis.

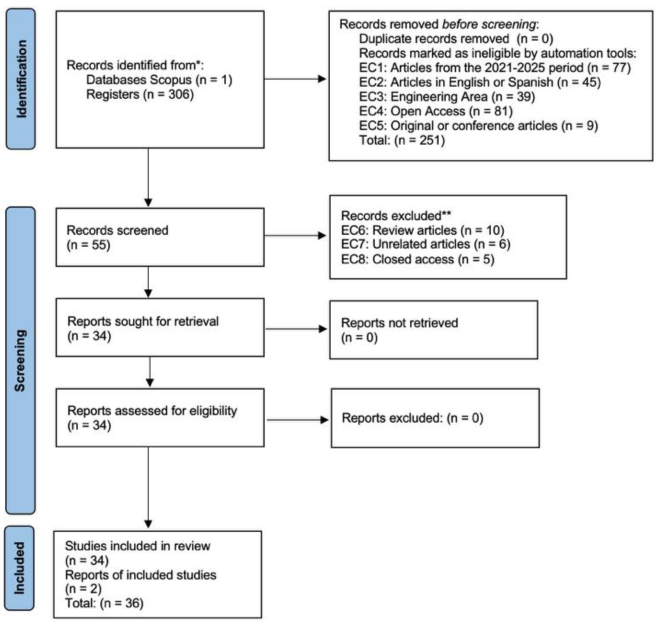


Fig. 1 PRISMA Protocol.

## III. Results

Machine learning in education is based on the application of advanced artificial intelligence models, including deep learning techniques, that allow for continuous analysis of academic, clinical, and behavioral data. Through these analyses, it is possible to identify complex patterns and early symptoms of learning difficulties, such as dyslexia and dysgraphia, predict students' future performance, and dynamically adapt both content and educational interventions. This personalization is based on individual histories and automatically generated prognoses, contributing to more timely and effective care [16], [17], [18], [19].

Along these same lines, learning pattern detection represents a fundamental application of machine learning in the school environment. This process involves the use of algorithms such as Random Forest and Support Vector Machines (SVM) to analyze both historical data and real-time information. These techniques allow for the recognition of phonological, orthographic, and behavioral correlations that would otherwise be difficult to perceive, thus facilitating the early identification of specific difficulties, such as dyslexia or dysgraphia, and promoting more timely and targeted educational interventions [16], [17], [19], [20], [21], [22].

Likewise, predictive models in the school setting extend the capabilities of machine learning toward a proactive and preventative perspective. By integrating data from clinical, academic, historical, and behavioral sources, algorithms such as deep neural networks, Random Forest, and SVMs generate highly reliable predictions about a student's future performance. As a result, potential cognitive difficulties are anticipated, enabling evidence-based pedagogical decision-making tailored to each student's individual needs [21], [23], [24], [25].

Fig. 2 shows a notable shift in scientific publications related to the use of machine learning algorithms to detect learning difficulties in school. While between 1984 and 2015, academic output was low and practically constant, a progressive and sustained growth has been observed since 2016. This growth accelerates significantly from 2020, reaching its peak in 2024 with around 70 registered documents. This increase, as can be inferred, could be motivated by the increasing availability of educational data, technical advances in deep learning algorithms, and the growing interest in applying artificial intelligence to the early treatment of learning disorders.

However, in 2025, a significant drop in production was evident, which, as seen in similar research, could be associated with a process of thematic reorientation or a phase of methodological consolidation within the field. It should be noted that this figure was developed from the results obtained through a structured search using the PICO method [14]in the Scopus database, which guarantees the validity and representativeness of the analyzed data. Therefore, this bibliometric behavior not only demonstrates the dynamism of the field but also justifies the development of this Systematic Literature Review.

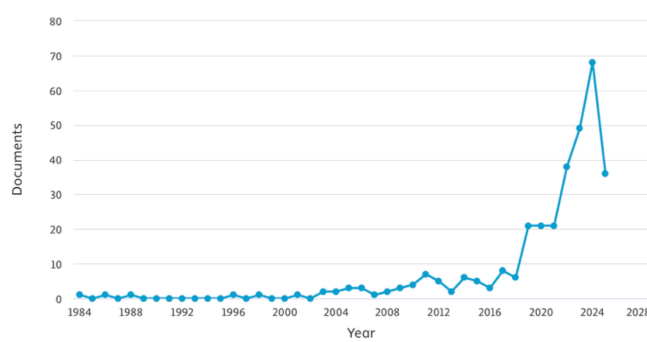


Fig. 2 Temporal trends in scientific production on the use of machine learning for the detection of school learning difficulties.

Fig. 3 represents a keyword co-occurrence map generated with VOSviewer software, based on the set of sources compiled from the Scopus database. As can be seen, the analysis reveals five well-defined thematic clusters. Among them, the green cluster stands out, associated with terms such as machine learning, artificial intelligence, dyslexia, and students, which demonstrates a method oriented toward diagnosing learning difficulties using intelligent techniques.

Likewise, the blue and yellow clusters group clinical terms such as controlled studies, neuroimaging, and Alzheimer's disease, reflecting the strong influence of the medical field. Meanwhile, the red cluster is linked to population-based and epidemiological studies. This map, constructed from a structured search using the PICO method [14], allows for the identification of established lines of research and reinforces the relevance of this Systematic Literature Review.

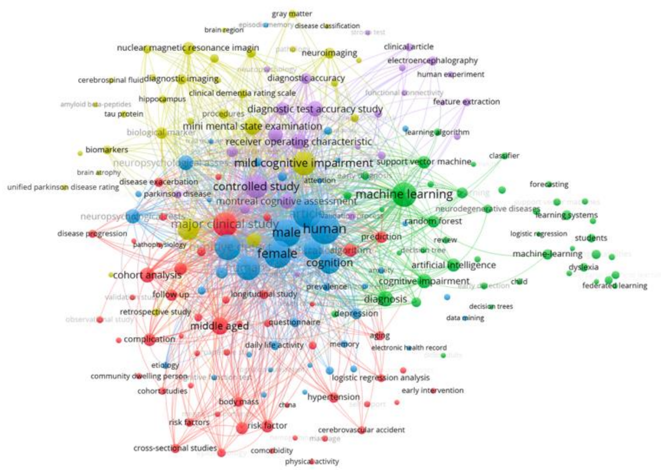


Fig. 3 Thematic map of keyword co-occurrence generated with VOSviewer from Scopus data.

Fig. 4 shows a keyword co-occurrence density map created with VOSviewer software, using the set of documents compiled from the Scopus database. In this type of visualization, brighter areas indicate greater frequency and thematic concentration. As can be seen, the densest terms located in the center of the map include machine learning, cognitive defect, humans, adult, education, and diagnosis, confirming the strong convergence between artificial intelligence, neuroscience, and education in the studies analyzed.

Likewise, the color distribution reveals well-defined thematic cores that connect medical concepts (Alzheimer's disease, biomarkers, controlled studies) with computational elements (support vector machine, prediction, data mining) and population-related elements (middle age, risk factor, cohort analysis). This visualization, based on a bibliometric analysis structured using the PICO method [14], clearly identifies the most researched areas, as well as the predominant conceptual interrelationships. Consequently, this overview reinforces the relevance of analyzing the use of machine learning in the early detection of learning difficulties in schools.

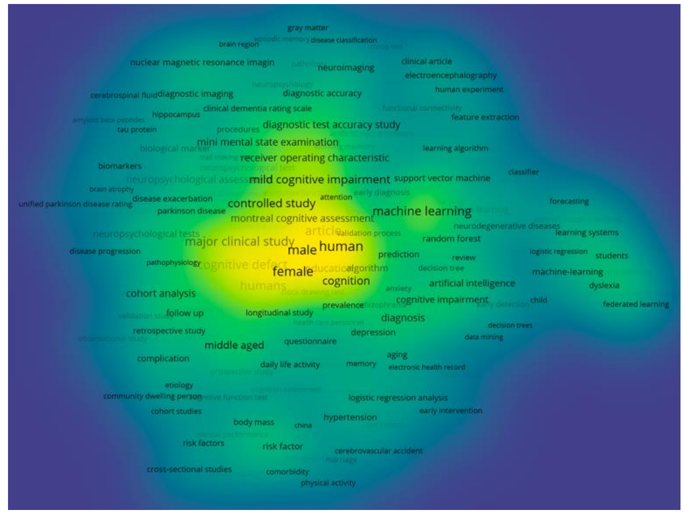


Fig. 4 Heat map of keyword co-occurrence generated with VOSviewer from data extracted from Scopus.

To rigorously structure this Systematic Literature Review, key research questions were defined according to the PICO method [14], which considers four fundamental dimensions: Population (P), Intervention (I), Comparison (C), Outcome (O). These questions were defined in Table 1. Therefore, the aim is to analytically delimit the scope of the study, facilitating the analysis of the findings and allowing a coherent organization of the reviewed evidence with respect to each PICO question developed.

**P: Types of learning difficulties that have been addressed with the use of machine learning in school education**

Several algorithms, such as neural networks and oculographic models, have demonstrated high accuracy in detecting dyslexia through the analysis of visual and linguistic patterns. This early identification allows for the implementation of adapted pedagogical strategies from the early school years [16], [17], [24], [26], [27], [28], [29], [30]. Similarly, neural networks applied to the automated analysis of handwriting have allowed the detection of motor and spatial characteristics associated with dysgraphia, facilitating rapid and objective interventions [17], [18], [31], [32].

Supervised algorithms have also been effective in identifying dyscalculia by detecting irregular patterns in numerical performance, allowing for the application of personalized reinforcements [33]. Likewise, monitoring behavioral variables in digital environments has allowed the identification of ADHD manifestations, facilitating interventions aimed at improving self-regulation [34].

Machine learning modeling of academic trajectories has revealed early signs of underachievement even without formal diagnosis, promoting preventive interventions [19], [20], [26], [30], [31], [32], [35], [36], [37], [38]. The integration of brief cognitive tests with classification models has strengthened the detection of mental deficits that affect school performance from early stages [25], [27], [38], [39].

Furthermore, personalized data analysis has allowed to identify cognitive and sensory barriers in students with disabilities, facilitating inclusive teaching, especially in STEM contexts [21], [28], [40], [41], [42]. Automated models have also anticipated undiagnosed difficulties from the recognition of academic and behavioral patterns [22], [23], [26], [36], while continuous behavioral analysis has identified amotivation and low engagement as key predictors of academic risk [29]. Finally, data mining techniques have detected deficiencies in fine motor skills, allowing physical activities to be adjusted to individual capabilities [43].

Table 3 shows the computational models used by type of difficulty. Neural networks and machine learning predominate, especially in dyslexia and poor academic performance. In contrast, other difficulties such as lack of motivation, dyscalculia, and motor skills barely appear. This behavior suggests a research method focused on visible academic aspects, which leaves potential gaps in behavioral, emotional, and psychomotor dimensions that require equally early detection and intervention.

TABLE III

TYPES OF DIFFICULTIES ACCORDING TO MACHINE LEARNING MODELS

| Type of difficulty | Number of studies | Applied model or tool |
|---|---|---|
| Dyslexia | 8 | Neural networks, oculographic models |
| Dysgraphia | 4 | Neural networks |
| Dyscalculia | 1 | Supervised algorithms |
| ADHD | 1 | Digital behavioral monitoring |
| Poor academic performance | 10 | Machine learning, academic paths |
| Undiagnosed mental deficits | 4 | Classification models, cognitive tests |
| Cognitive and sensory barriers | 5 | Adaptive systems |
| Undiagnosed difficulties | 4 | Recognition of academic and behavioral patterns |
| Lack of motivation/low commitment | 1 | Continuous behavior analysis |

Fig. 5 shows the relationship between types of learning difficulties and the machine learning tools used. Dyslexia and poor academic performance are the most widely covered, addressed primarily with neural networks and automatic modeling. In contrast, difficulties such as dyscalculia, ADHD, and motor skills are underrepresented. This reveals a prioritization of cognitive-linguistic aspects and presents opportunities for exploration in areas less addressed by current literature.

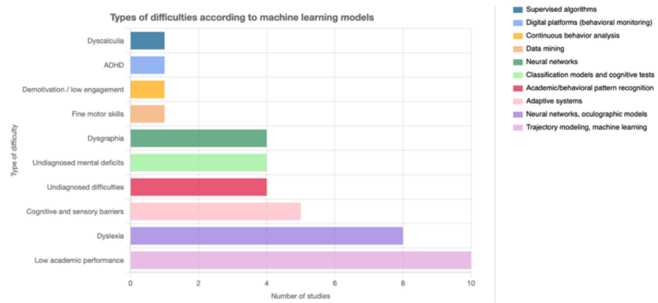



Fig. 5 Learning difficulties vs. machine learning tools.

**I: Type of machine learning-based tools used to improve the early detection of learning difficulties in school education**

Classification and prediction tools such as Random Forest, SVM, and neural networks have proven effective in the early detection of learning difficulties such as dyslexia and dysgraphia by analyzing patterns in reading and writing [24], [27], [31], [34], [37], [42]. These technologies, together with statistical models and deep neural networks, allow predicting cognitive challenges, which optimizes intervention times and improves pedagogical strategies by considering behavioral and linguistic aspects [16], [17], [18], [20], [25], [40], [44].

Multi-model systems that integrate ensemble algorithms improve diagnostic accuracy by combining academic, clinical, and emotional data, facilitating the detection of conditions such as dyslexia, autism, and ADHD [21], [22], [32], [35]. In the context of big data, predictive models allow analyzing large volumes of information to predict difficulties, enabling preventive interventions before they become significant obstacles [29], [30], [36], [45].

Furthermore, AI-based image and voice recognition tools capture expressive and linguistic patterns, being useful in STEM environments and with students with sensory limitations [28], [39], [41]. Intelligent tutoring platforms, such as DyslexiScan, personalize educational content according to student characteristics, promoting inclusion and early detection [33], [46], [47].

On the other hand, neural network and SVM-based models predict academic risks by analyzing performance, allowing individualized pedagogical interventions [35], [41], [48]. Deep learning tools adapt teaching to students with Down syndrome or other disabilities [49], [50], while affective decision trees analyze emotional responses to detect cognitive or emotional difficulties [23], [26], [29]. Finally, AI applied to reading improves comprehension in cases of dyslexia [33], [43], [50].

Table 4 shows ten tools organized by functional type. The predictive group leads with four tools, confirming its importance in the scientific literature. The sensory, adaptive, and emotional dimensions are less frequently represented. This organization reflects a research trend focused on anticipating difficulties rather than adapting to diversity or responding to emotional factors.

TABLE IV

MACHINE LEARNING TOOLS ACCORDING TO THEIR FUNCTIONAL TYPE

| ML Tool | Number of studies | Functional type |
|---|---|---|
| Random Forest / SVM / RN | 6 | Predictive |
| Statistical Models / Deep RN | 7 | Predictive |
| Ensemble / multimodel algorithms | 4 | Multimodal |
| Predictive models (Big Data) | 4 | Predictive |
| Image and voice recognition | 3 | Sensory/Cognitive |
| Smart tutoring platforms | 3 | Adaptive |
| Neural Networks and SVM | 3 | Predictive |
| Adaptive platforms (Deep Learning) | 2 | Adaptive |
| Affective decision trees | 3 | Emotional |
| Reading comprehension evaluators | 3 | Sensory/Cognitive |

Fig. 6 shows a bubble chart that classifies tools by functional type and frequency of use. Predictive functions clearly predominate, followed by sensory and adaptive applications. Emotional and multimodal dimensions are rare. This visualization highlights current methodological priorities and suggests new areas for the development of *machine learning-based educational solutions*.

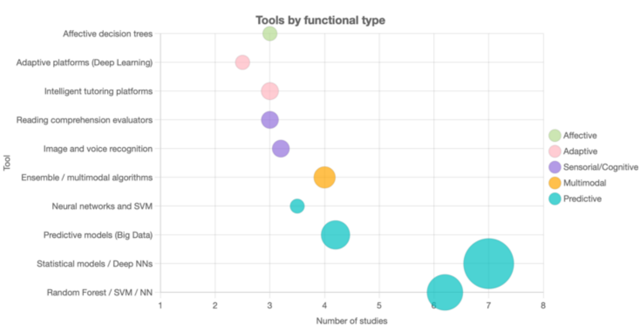



Fig. 6 Tools according to functional type.

### C: Effect of using machine learning techniques compared to traditional methods in the early detection of learning difficulties in school education

The use of *machine learning* has been shown to significantly improve the early detection of dyslexia by identifying complex patterns in writing and neurological signals more accurately than traditional methods, allowing for more effective pedagogical interventions [16], [24], [40]. Similarly, *deep learning has expanded the effectiveness of dysgraphia detection by analyzing handwriting strokes more quickly and accurately than manual assessments [18], [34]. Ensemble* models, by combining multiple algorithms and sources of information, increase diagnostic accuracy against the limitations of conventional approaches [21], [27].

*machine learning*'s ability to process large volumes of data enables dynamic pedagogical personalization, adjusting educational strategies based on individual performance, in contrast to the general observations of traditional methods [20], [36]. These techniques also outperform conventional methods in detecting cognitive impairment and neuropsychological disorders, offering faster and more accurate diagnoses [25], [27], [35].

Affective decision trees delve deeper into students' emotional and behavioral responses, enabling more sensitive and personalized instructional adaptation than conventional methodologies [23], [26]. Algorithms such as SVM and neural networks, on the other hand, optimize academic risk prediction by uncovering complex patterns in student performance, enabling timely and detailed interventions [31], [36].

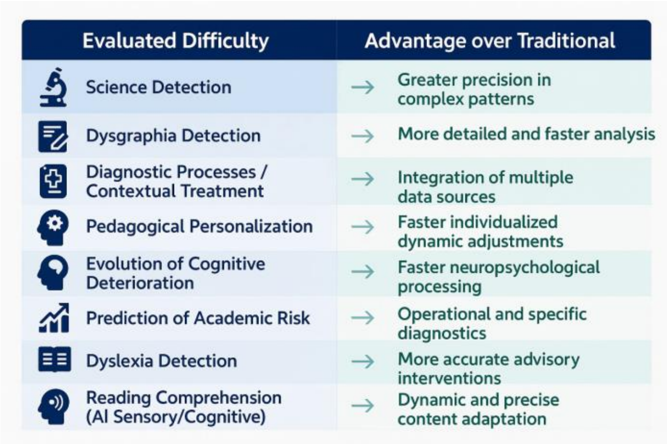
In the case of dyscalculia, *machine learning* allows detecting anomalies in numerical patterns with greater precision than traditional techniques [44]. Likewise, AI tools applied to reading comprehension, based on image and voice recognition, outperform conventional methods in the early detection of dyslexia [29], [34], [43]. Finally, *deep learning platforms dynamically* adapt educational content for students with Down syndrome or other disabilities, achieving a level of personalization that is faster and more precise than traditional approaches [49], [51].

Table 5 highlights benefits such as the integration of data sources, dynamic content personalization, and rapid processing of cognitive indicators, which is not common with conventional methods. Substantial improvements in the detection of dyslexia, dysgraphia, cognitive impairment, and academic risk are also highlighted. These advantages position *machine learning* as a key technology for achieving more timely educational interventions, tailored to each student's profile, and effective in increasingly complex school settings.

TABLE V
EFFECTS OF ML VERSUS TRADITIONAL METHODS

| Evaluated difficulty | Advantage over traditional methods |
|---|---|
| Dyslexia Screening | Greater accuracy in complex patterns |
| Dysgraphia Detection | More detailed and faster analysis |
| Diagnostic accuracy (ensemble models) | Integration of multiple data sources |
| Pedagogical personalization | Individualized dynamic adjustments |
| Detection of cognitive impairment | Faster neuropsychological processing |
| Emotional/behavioral assessment | Deeper emotional assessment |
| Academic risk prediction | Timely and specific diagnosis |
| Dyscalculia Screening | More accurate identification of anomalies |
| Reading comprehension (sensory AI) | A deeper examination of reading processes |
| Adaptation in cognitive disabilities | Dynamic and precise adaptation of content |

Fig. 7 presents a direct association between the educational aspects evaluated and the advantages observed when applying machine learning techniques. It is evident that, in most cases, these tools outperform traditional methods by offering greater diagnostic accuracy, greater depth of analysis, and more effective adaptive capacity. This visualization allows us to quickly identify the specific benefits that justify the growing interest in educational artificial intelligence.



| Evaluated Difficulty | Advantage over Traditional |
|---|---|
| Science Detection | → Greater precision in complex patterns |
| Dysgraphia Detection | → More detailed and faster analysis |
| Diagnostic Processes / Contextual Treatment | → Integration of multiple data sources |
| Pedagogical Personalization | → Faster individualized dynamic adjustments |
| Evolution of Cognitive Deterioration | → Faster neuropsychological processing |
| Prediction of Academic Risk | → Operational and specific diagnostics |
| Dyslexia Detection | → More accurate advisory interventions |
| Reading Comprehension (AI Sensory/Cognitive) | → Dynamic and precise content adaptation |

Fig. 7 Effects of using ML tools.

**O: Reported improvements in terms of early detection, timely intervention or academic performance of students in school education through the use of machine learning**

The application of machine learning allows for a more in-depth analysis of spelling. This improves the early detection of reading difficulties. Unlike traditional methods, these models offer more accurate diagnoses. They also facilitate targeted and timely educational interventions [16], [24], [40]. Similarly, the use of machine learning to analyze writing data helps identify complex patterns related to dyslexia and dysgraphia. Thus, interventions are faster and more effective, improving academic performance with personalized support [17], [18], [20], [34]. Similarly, machine learning-based tools allow for more effective personalized interventions than conventional methods. They predict academic success by analyzing data and identify at-risk students to adjust teaching to their needs.[20], [27], [29]

On the other hand, real-time predictive models analyze complex behavioral patterns. This allows for immediate interventions that significantly improve academic performance [26], [30], [32]. Likewise, the use of machine learning in the context of autism has improved the early detection of learning difficulties. The combined analysis of academic and behavioral data adapts learning to each profile, improving the academic performance of these students [22], [23], [39].

In parallel, rapid analysis of cognitive tests using machine learning has accelerated the identification of mental deficits. This enables timely actions that improve the performance of students with undiagnosed cognitive disabilities [25], [27], [35]. Furthermore, the use of SVMs and neural networks in academic risk prediction uncovers complex performance patterns. This facilitates faster, personalized interventions, improving academic outcomes [31], [36], [37].

Similarly, the integration of AI and deep learning into language teaching optimizes early intervention for dyslexia. These models dynamically adjust teaching strategies to each student's individual abilities, overcoming the rigidity of traditional methods [33], [43], [50]. Similarly, machine learning has improved educational intervention for ADHD. It personalizes attention and behavioral control activities, creating a more appropriate environment that boosts academic performance compared to traditional methods [45], [46], [47]. Furthermore, technologies such as Sankalpa and fuzzy neural networks have strengthened educational inclusion, effectively adapting content to cognitive and behavioral needs, promoting a sustainable increase in academic performance [41], [48], [49].

In Table 6, the most frequently reported improvements include personalized adaptation for students with autism and academic risk prediction, both geared toward performance. Meanwhile, the detection of dyslexia and undiagnosed deficits are key contributions to early detection. Personalized interventions, although less frequent, show a high impact. This distribution reveals a comprehensive approach that ranges from identifying difficulties to strengthening academic achievement.

TABLE VI
FREQUENCY BY TYPE OF IMPACT

| Improvement observed | Type of impact | Number of studies |
|---|---|---|
| In-depth spelling analysis | Early detection | 6 |
| Identifying patterns of dyslexia/dysgraphia | Early detection | 5 |
| More effective personalized interventions | Timely intervention | 7 |
| Immediate interventions with real-time data | Timely intervention | 4 |
| Personalized adaptation for students with autism | Academic performance | 8 |
| Detection of undiagnosed mental deficits | Early detection | 6 |
| Early prediction of academic risk | Academic performance | 7 |
| Early intervention in dyslexia | Early detection | 5 |
| Educational intervention in ADHD | Academic performance | 6 |
| Educational inclusion and content adaptation | Academic performance | 5 |

Fig. 8 shows that the most common type of impact reported in the studies is academic performance, with five associated improvements. Early detection is next, present in four interventions, while timely intervention appears in two. This indicates that machine learning applications prioritize sustained improvement in academic performance, without neglecting early diagnosis or immediate pedagogical action.

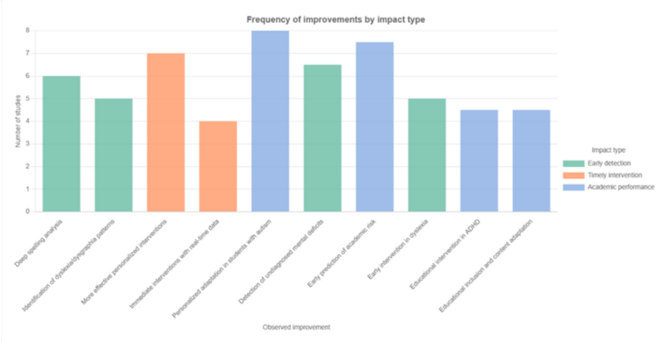



Fig. 8 Frequency of improvements by type of impact

## IV. Discussion of the Results

This SLR evidences the transformative potential of machine learning in the early identification of learning difficulties. The findings confirm superior accuracy in detecting dyslexia using neural networks and oculographic models [16], [17], [24], [33], [40], [42], [43], [50], as well as in the recognition of dysgraphia through automated handwriting stroke analysis [17], [18], [34], [50]. Supervised algorithms have also proven effective in identifying dyscalculia [44] and ADHD through behavioral monitoring [45]. Likewise, the early detection of poor academic performance [19], [20], [26], [30], [31], [32], [35], [37], [46], [47] and motor difficulties [51] surpasses traditional methods, which are often limited by slower procedures and high subjectivity [16], [18], [24], [34], [40]. These advantages demonstrate a greater diagnostic agility, allowing the implementation of personalized pedagogical interventions that mitigate negative effects on students' performance and well-being.

The results are consistent with the increasing integration of AI in educational contexts, highlighting the effectiveness of classifiers such as Random Forest and SVM in detecting error patterns and predicting academic risks [16], [17], [18], [20], [24], [25], [27], [31], [34], [37], [40], [42], [50]. Ensemble and multimodal models [21], [22], [32], [46], together with intelligent tutoring platforms such as DyslexiScan [33], [48], [50], exemplify the advances in personalization, enabling adaptive interventions aligned with students' cognitive and behavioral profiles. These findings reinforce the idea that machine learning can not only identify risks but also offer dynamic strategies to improve the learning process.

However, crucial limitations are recognized: the dependence on high-quality data and the interpretability of complex deep learning models [23], [26], [29]. Future research should address integration with virtual reality [28], [39], [41], data ethics and privacy, and applicability in diverse sociocultural contexts [21], [27]. Moreover, it is important to note the scarce empirical validation of many of these models in real classroom environments, which restricts their generalization and raises doubts about their effectiveness beyond controlled experimental settings [3], [7], [10], [13].

In addition, emotional and behavioral dimensions remain underrepresented in predictive models, despite their importance for holistic evaluations [29], [45]. Addressing these gaps would enhance ecological validity and generate interventions that better reflect the complexity of educational processes. Similarly, the lack of teacher training and interdisciplinary collaboration protocols limits pedagogical integration [3], [12], evidencing a gap between technological advances and their actual use in schools.

Finally, the ethical management of student data demands special attention. Safeguarding privacy, transparency, and equity is fundamental to avoid biases and promote responsible adoption [21], [27]. In this regard, machine learning applications must not only focus on accuracy but also ensure ethical commitment, contextual adaptation, and inclusiveness as guiding principles for their implementation in education.

## V. Conclusions

This SLR demonstrated that the application of machine learning represents a significant advance in the early detection of learning difficulties in school contexts. Algorithms such as deep neural networks, SVMs, Random Forests, and ensemble models enable more accurate and agile identification of dyslexia, dysgraphia, dyscalculia, and ADHD, clearly surpassing the limitations of traditional methods. These tools not only predict academic risk but also allow the design of personalized educational interventions adapted to each student's profile, strengthening learning processes and fostering inclusion.

Additionally, the review highlights the value of adaptive and sensory AI tools, which are especially relevant for students with disabilities in inclusive education contexts. However, the study also reveals persistent challenges: strong dependence on data quality, scarce empirical validation in real classroom environments, and limited interpretability of complex models. These constraints slow down large-scale implementation, particularly in regions with infrastructural and training gaps such as Latin America.

Therefore, future research should aim to standardize data collection procedures to increase comparability, broaden validation in diverse school environments to strengthen ecological validity, and develop interpretable or hybrid models that combine precision with transparency, thus increasing the trust of educators and policymakers [21], [23], [26], [27], [29]. Likewise, it is necessary to integrate emotional and behavioral variables into predictive models, complementing cognitive indicators to achieve holistic evaluations [29], [45].

At the same time, promoting teacher training and interdisciplinary collaboration is essential to bridge the gap between research and classroom practice [3], [12]. Equally important is addressing ethical and privacy issues, ensuring equity and transparency in the use of sensitive educational data [21], [27]. Finally, the exploration of emerging technologies such as virtual reality and augmented reality opens new possibilities for enhancing personalization and student engagement [28], [39], [41].

In conclusion, machine learning has the potential to transform educational practice through early detection and personalized interventions. However, its real impact will depend on overcoming the limitations identified and advancing toward contextualized, interpretable, and ethically responsible applications that respond to the diverse needs of students in real educational settings.

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