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The Role of Artificial Intelligence in the Early Diagnosis of Learning Difficulties in Children: How AI Can Help Teachers Recognize Dyslexia and ADHD

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ABSTRACT

This paper explores the transformative role of artificial intelligence (AI) in the early diagnosis of specific learning disabilities, with a focus on dyslexia and attention deficit hyperactivity disorder (ADHD). The neurobiological basis of these disorders is analyzed, advanced AI tools and techniques used to detect them are presented in detail, and the technical and ethical challenges of their implementation in the education system are critically discussed. Through a synthesis of relevant literature, the paper emphasizes the potential of AI for personalized support and timely intervention, while emphasizing the necessity of human oversight, ethical guidelines, and continuous education. The goal is to provide a comprehensive insight into the current state and future trends in the application of AI in the diagnosis of learning disabilities, with recommendations for responsible and effective integration.

Keywords: Artificial intelligence, dyslexia, ADHD, learning disabilities, early diagnosis, education, neurobiology, ethics.

1. INTRODUCTION

1.1. The Context and Significance of Learning Difficulties in Contemporary Education

Learning disabilities, such as dyslexia and attention deficit hyperactivity disorder (ADHD), are a growing challenge in modern education. These neurobiological disorders significantly affect the ability of students to successfully master the material, participate in the teaching process and develop their full potential. Children with these disabilities often have average or even above-average intellectual development, but they face obstacles that make it difficult for them to progress in line with their peers, which can result in frustration, loss of self-confidence, and emotional difficulties.[1]

Recognizing and understanding these difficulties at an early stage is essential to provide adequate support and interventions. Without timely assistance, students can experience long-term negative consequences for their education, self-confidence, and overall emotional development. Teachers face dilemmas every day on how to recognize these difficulties in time and how to best adapt teaching to the individual needs of students. Table 1 provides a brief overview of the characteristics of the most common difficulties.

Table 1. A brief overview of the characteristics of the most common difficulties

Disorder	Description	Typical symptoms
Dyslexia	Problems with reading and writing	Mixing letters, slow reading
ADHD	Attention and hyperactivity	Restlessness, impulsivity, distraction
Dysgraphia	Writing	Indistinct handwriting, slow sentences
Dyscalculia	Calculation	Difficulties with numbers, basic operations

1.2. Challenges of traditional methods of identification and diagnosis

Traditional methods of identifying learning disabilities rely on subjective assessments, a lengthy process of observation, and collaboration with professional teams, including psychologists, educators, and speech therapists. Traditional methods often involve long waiting lists for diagnostic examinations, which can further slow down the process of providing support.[1]

There are significant limitations in traditional diagnostic approaches. One of the most commonly used methods, **Ability-Achievement Discrepancy** (AAD), defines Specific Learning Disability (SLD) as the discrepancy between overall intellectual ability score (IQ) and academic achievement. However, this method often fails to identify students with low or below-average cognitive abilities, as their skills are considered aligned with their overall abilities. It is also problematic that AAD does not take into account that specific processing deficits, such as weaknesses in working memory or processing speed, can lower the overall IQ score. Additionally, there is no consistent criterion for what constitutes a "significant" or "severe" discrepancy, which often varies from state to state and even from school district to district.

The second method, **Response to Intervention** (RTI), provides students with increasingly intensive academic interventions and monitors their response. Students who do not show an "adequate" answer can be identified with SLD. However, there is little research that precisely defines the criteria for determining the adequacy of student progress. RTI does not typically assess cognitive abilities and processing skills, other than excluding intellectual disability, which means that in many schools, evaluation for SLD may not include a formal assessment by a school psychologist. Also, many schools lack the training resources and materials needed to faithfully implement the RTI model.[11]

Common tests used in traditional diagnostics include intelligence testing (e.g., Wechsler Intelligence Scale, Wechsler Adult Intelligence Scale, Stanford-Binet Intelligence Scale, Kaufman Assessment Battery for Children, Differential Ability Scales, Cognitive Assessment System) and achievement tests (e.g., Woodcock-Johnson Tests of Achievement, Kaufman Test of Educational Achievement, Wechsler Individual Achievement Test, Scholastic Abilities Test for Adults).[12] Although these tests are useful, their lengthy process and subjectivity in interpretation can lead to delays in the provision of assistance.

The delays and inherent limitations of traditional diagnostic approaches create a systemic barrier to equitable educational opportunities. This problem goes beyond a mere academic issue and evolves into a significant concern for social justice. The "price" extends beyond financial or time expenditures, profoundly affecting the child's overall developmental trajectory, potentially triggering a cycle of failure and emotional stress.

1.3. The potential of artificial intelligence as a support in education

AI now plays a significant role in education, not only as a tool for personalizing learning, but also as a potential support in diagnosing learning disabilities. The development of algorithms for recognizing patterns of behavior, speech, attention and reading habits enables the creation of digital tools that can help in the early identification of dyslexia, ADHD and similar conditions.
AI systems can process large amounts of data in a very short time, recognize behavioral patterns, analyze speech and visual information, and propose personalized strategies for each student.1 When used in a responsible and professionally guided manner, AI can be an useful tool for teachers, educators, and speech therapists in the process of recognizing dyslexia, ADHD, and similar disorders.1 It is important to emphasize that AI does not replace professionals, but rather helps them make decisions and allows for timely intervention. By using AI, schools can more quickly identify students who show early signs of learning disabilities, even before these problems become visible through standard evaluation methods.[1]
AI is increasingly integrated into educational processes – from personalized learning, through evaluation automation, to real-time analysis of student behavior. Its application enables a personalized approach to learning, monitoring student progress in real time, and supports teachers by giving them tools to better understand each student. AI can tailor the material to each student according to their abilities, pace, and learning style, offering instant feedback and increasing engagement. Also, AI tools can help with inclusive education, offering voice assistants, text-to-speech functions, and visual aids.[1]

AI is used in:
- Personalized learning (task recommendation)
- Analysis of student success and early identification of those at risk of failure
- Automation of evaluation and testing

Table 2. AI Tools in Education and Their Function

Tool name	Function	Type of difficulty
Lexplore	Eye-tracking, reading analysis	Dyslexia
QBTest	Attention and Hyperactivity Tracking	ADHD
Detective	Neuropsychological digital tests	Dyslexia
CogniFit	Assessment of attention, memory	ADHD, cognitive development
Ghotit	Writing Help	Dyslexia, dysgraphia

AI in the early detection of dyslexia, ADHD and other difficulties
Dyslexia
- AI tools (e.g., Lexplore) use eye tracking.
- Identification of atypical patterns in reading.
- Fast, objective estimation — results in minutes with more than 90% accuracy

ADHD
- AI uses attention tests and behavioral analysis (QBTest, Do-It Profiler).
- Measurement of hyperactivity, impulsivity, and reaction speed.
- Standardized assessment and earlier risk identification

Table 3. Examples of AI tools for detecting the most common difficulties

Tool name	Type of difficulty	Principle of operation
Lexplore	Dyslexia	Eye tracking, AI reading analysis
Detective	Dyslexia	Digital Tests, Language Analysis
QBTest	ADHD	Attention sensors, AI motion analysis
Do-It Profiler	ADHD	Questionnaires, digital behavior analysis

1.4. Aim of the study

The aim of this paper is to explore the possibilities and advantages that artificial intelligence brings to the early diagnosis of learning disabilities, with special emphasis on dyslexia and ADHD. Specific AI tools that are already used in practice, their effectiveness, but also challenges, ethical issues and potential risks that accompany their use in the educational environment will be analyzed. Finally, the paper will offer recommendations on how to integrate AI technologies into schools in a responsible and user-oriented way.

2. METHODOLOGY

This paper presents a systematic review and synthesis of the existing literature on the role of artificial intelligence in the early diagnosis of learning disabilities, with a special focus on dyslexia and ADHD. The process is designed to ensure transparency and academic credibility, even when no original empirical research is being conducted.

2.1. Literature search strategy

The information was collected from a variety of academic sources, including peer-reviewed scientific articles, reports, books, and reliable online databases. The search included a wide range of sources, including academic journals and research platforms such as ResearchGate, PubMed/PMC, Frontiers in, MDPI, as well as reports from renowned organizations such as UNESCO. Specialized websites of relevant AI tools and organizations, such as Lexplore.com, QBTech.com, and StudyHub.fxplus.ac.uk, were also used to ensure access to the latest information on practical applications.
Key terms and their combinations, both in Bosnian and English, were used to ensure the comprehensiveness of the search. These include: "artificial intelligence", "machine learning", "deep learning", "dyslexia", "ADHD", "learning disabilities", "early diagnosis", "education", "neurobiology", "ethical issues", "data privacy", "algorithmic bias", "human-AI collaboration" and "personalized learning". This strategy has made it possible to identify relevant studies covering the technical, clinical, pedagogical and ethical aspects of the application of AI in an educational context.

2.2. Criteria for selection and analysis of the literature

The literature that directly addresses the application of AI in the diagnosis of dyslexia and ADHD, their neurobiological basis, technical aspects of AI tools, ethical implications and future trends has been selected. Priority is given to peer-reviewed studies, research papers, and reports from reputable organizations, to ensure the credibility and scientific basis of the information. Sources that are not directly relevant to the topic or that have not undergone peer review are

excluded.
The analysis of the selected literature included the identification of key arguments, data, examples of AI tools, advantages, challenges, ethical dilemmas and recommendations for the future. Special attention is paid to recognizing possible contradictions or inconsistencies in the data, as well as identifying gaps in existing knowledge.
The process of collecting and analyzing information, although not a classic experimental study, follows the principles of systematic literature review. This implies a structured approach to collecting, evaluating and synthesizing existing knowledge.

2.3. Structure of the presentation of results

The synthesized findings are organized into chapters, with detailed subheadings, to ensure a clear and logical presentation of complex information. Data from the literature are integrated with interpretive commentary, emphasizing cause-and-effect relationships, trends, and broader implications. The goal was not only to present the facts, but also to explain their significance in the broader context of the application of AI in education.

3. RESULTS: NEUROBIOLOGICAL BASIS AND APPLICATION OF AI IN EARLY DIAGNOSIS

3.1. Neurobiological basis of learning disabilities

Understanding the neurobiological basis of dyslexia and ADHD is crucial for the development of effective diagnostic tools and interventions, including those based on artificial intelligence. These disorders are not the result of intellectual disabilities, but are associated with specific differences in brain structure and function.

3.1.1. Dyslexia: Neurobiological Insights

Dyslexia is a neurobiological disorder that primarily manifests itself through difficulties in reading and writing.[1] A strong genetic component is evident, since dyslexia often runs in families, indicating a hereditary predisposition.[1] Research has implicated several genes, including DCDC2, DYX1C1, KIAA0319, and ROBO1, that are involved in brain development, especially in areas responsible for language and reading.[15]
Neuroimaging studies have provided significant insights into differences in brain structure and function in people with dyslexia. In particular, research indicates atypical brain development, especially in the left hemisphere, which is usually dominant for language processing.[15] Key regions include Broca's area, crucial for speech production and grammatical processing; Wernicke's area, responsible for understanding language; The visual-verbal form (VWFA) located in the left occipitotemporal region, crucial for the recognition of written words; and the angular gyrus and supramarginal gyrus, which play a role in reading, processing numbers, and associating words with meanings.[15]
Functional magnetic resonance imaging (fMRI) and diffusion tensor imaging (DTI) show decreased activity in the left inferior frontal gyrus, the left parietotemporal region (involved in phonological processing), and the left occipitotemporal region in dyslexic individuals during reading and rhyming tasks.[15] These parts of the brain are typically involved in the processing of phonological information, the mapping of letters to sounds, and the recognition of written words. Reduced activity in these regions is associated with difficulty in decoding and recognizing words.
As a compensatory mechanism, some dyslexic individuals show increased activity in the right hemisphere and right frontal lobe, as well as in the left precentral gyrus, a region associated with articulation (production of speech sounds).[15] This increased activity suggests that readers use

articulation to compensate for weaknesses in the temporoparietal system involved in decoding. The primary cognitive deficit in dyslexia is a difficulty with phonological processing, especially in the ability to process and manipulate phonemes, the smallest units of sound in a language, which are essential for understanding word construction and developing reading skills.[16]

Despite these challenges, research has shown neurocognitive flexibility, which means that brain activation patterns in students with dyslexia may change as a result of reading interventions. Although these patterns may not always fully match those of typical readers, changes in neural activity are accompanied by improvements in reading skills, which supports the effectiveness of targeted interventions.[16]

3.1.2. ADHD: Neurobiological Insights

Attention deficit hyperactivity disorder (ADHD) is a complex neurobiological disorder that manifests itself through inattention, hyperactivity, and impulsivity. Its etiology is multiple, including a combination of genetic and environmental factors that together create a neurobiological susceptibility to the disorder.[17] The genetic basis is extremely strong, with heritability estimates ranging from 60-90% based on twin, family, and adoption studies.[18] Genes that regulate neurotransmitter systems, such as DRD4, DRD5, SLC6A3, SNAP-25, and HTR1B, have been implied.[18]

Environmental factors also play a key role. Prenatal exposure to alcohol and tobacco is associated with an increased risk for ADHD (the risk of maternal smoking increases 2.7-fold), as well as low birth weight and complications during pregnancy and childbirth.[1] Postnatal factors include malnutrition, deficiency of essential fatty acids, and early social deprivation.[18]

Structural studies of the brain consistently show that children with ADHD show significantly smaller brain volumes than neurotypical peers.[17] The prefrontal cortex, basal ganglia (especially the striatum, including the caudate nucleus and putamen) and cerebellum are particularly affected.[17] Delays in cortical maturation have also been observed, especially in the prefrontal regions, which are crucial for cognitive processes such as attention, executive functions, and movement planning.[17]

Neuroimaging studies, including DTI, reveal reduced connectivity in white matter tracts in key areas of the brain, such as the corpus callosum and pathways connecting the prefrontal and parieto-occipital areas to the striatum and cerebellum.[17] These changes in white matter can result in a reduced speed of neural communication, which affects the efficiency of neural networks responsible for attention and impulse control.[17]

Dysfunction of neurotransmitter systems, especially dopamine and norepinephrine, plays a key role in the neurobiology of ADHD.[1] Pharmacological studies on the effects of stimulants, which increase dopamine and norepinephrine levels in the brain, support this link.[17] Abnormal dopamine transporter density (DAT) is often present in people with ADHD, further emphasizing the role of dopamine imbalance.[17]

3.2. AI Tools and Techniques for Early Detection of Dyslexia

Advances in artificial intelligence have enabled the development of innovative tools for the early detection of dyslexia, which go beyond the limitations of traditional methods. These tools use a variety of techniques, from eye tracking to analysis of handwriting samples and language processing, to identify subtle patterns that indicate the presence of dyslexia.

AI systems use a combination of machine learning, natural language processing, and computer vision to recognize patterns in behavior, speech, and the way they perform tasks. Key features:

- Eye-tracking (e.g. Lexplore): automatic analysis of eye movements during reading
- Digital Questionnaires and Tests (QBTest, Do-It Profiler): A combination of automated

scoring and assessment of attention, impulsivity, and hyperactivity

- Learning analytics: continuous monitoring of progress and risk

Table 4. Examples of AI tools for detecting the most common difficulties

Tool name	Principle of operation	Targeted difficulty	Validation
Lexplore	Eye tracking, AI reading analysis	Dyslexia	>90% accuracy
QBTest	Digital Tests, Language Analysis	ADHD	Standardized
Detective	Attention sensors, AI motion analysis	Dyslexia	Validated
CogniFit	Questionnaires, digital behavior analysis	ADHD, cognitive difficulties	Clinical studies

3.2.1. Eye-Tracking and Machine Learning

One of the most prominent examples of the application of AI in the diagnosis of dyslexia is the use of eye-tracking technology. This technology, which measures where we are looking, is a practical, objective and non-invasive tool for analyzing visual perception.[19]

Lexplore is a leading AI tool that uses sophisticated eye-tracking technology to analyze how a child reads text. The tool records the duration and order of gazes, fixations (moments when the eye stops at one point), saccades (rapid eye movements between fixations), and scan paths, providing insights into information processing, attention, and cognitive load. Lexplore combines this data with machine learning algorithms to create a profile of a student's reading ability. This method allows for a quick (in a few minutes), non-invasive and objective assessment with high accuracy.[11] Studies show an accuracy of over 90% in detecting dyslexia in primary school children, and a study in Sweden recorded 93% accuracy.[10] Lexplore provides visualizations of reading development and recommendations for appropriate instructional strategies, enabling personalized learning and resource optimization.[20]

The INSIGHT method proposes a new method that combines the visualization of fix-image eye tracking data with the ResNet18 convolutional neural network (CNN) for classification.[21] Fix-images are 2D visualizations that clearly show the difficulty of reading, where the shape of the ellipse reflects the dispersion of the gaze, and the color indicates the duration of the fixation. ResNet18, a CNN model in disguise, analyzes these images and classifies them as dyslexic or control. This method achieves high accuracy (86.65% overall, 88.78% for level text) and demonstrates robustness through cross-testing on an independent Danish dataset (86.11% accuracy).[21] Importantly, saliency maps are used to explain CNN decisions, which increases transparency and reliability in clinical diagnostics, allowing experts to understand which parts of the picture the AI focused on when making a decision.[21]

3.2.2. Language Processing and Writing Analysis

In addition to eye tracking, AI is also used to analyze language and written patterns. Dytective is an AI platform that uses language processing algorithms and writing impairment and reading analysis to identify dyslexic patterns. It is based on a combination of neuropsychological tests and AI analysis, offering digital and often free diagnostics in schools. This availability is especially useful in communities that do not have a sufficient number of traditional diagnostic professionals, thus increasing equity in access to early diagnosis.

3.2.3. Deep Learning and Handwriting Analysis

Newer approaches include applying deep learning to handwriting analysis. Advanced convolutional neural network (CNN) models have been developed to detect dyslexia through image-based analysis of handwriting samples. This method outperforms conventional methods with high accuracy of training (99.5%) and testing (96.4%), demonstrating the ability to capture subtle characteristics associated with dyslexic tendencies.[22] These subtle characteristics may include irregularities in letter formation, spacing, or writing impairment cohesion that are often present in dyslexic individuals.

Data augmentation techniques, such as rotation, shear, and translation, are used to increase the flexibility and diversity of the dataset. This ensures that the model is exposed to a wide range of handwriting impairment styles, which improves its ability to generalize and recognize dyslexia in different contexts.[23]

3.3. AI Tools and Techniques for Early Detection of ADHD

The diagnosis of ADHD is more complicated due to the overlap of symptoms with other behavioral and emotional difficulties.[2] However, AI tools use advanced techniques to analyze behavior, speech, and attention to spot patterns typical of ADHD. The characteristics and functions of AI diagnostic tools are given in Table number 5.

Table 5. Features and functions of AI diagnostic tools

Tool name	Technology	Detected disorder	Possibility of integration	Specificity/Benefits
Lexplore	Eye Tracking, ML	Dyslexia	Web/Database	Speed, non-invasiveness
QBTest	Sensors, MT analysis	ADHD	PC/tablet	Standardization
Detective	NLP, a digital test.	Dyslexia	Online	Availability, free of charge
CogniFit	Cognition analytics	ADHD/dysgraphia	PC/tablet	Multiparameter evaluation

3.3.1. Computer-based tests of attention and movement

QBTest is one of the most important tools that combines a computer-based attention and movement test with sensors that monitor hyperactivity. During the test, the child responds to visual and auditory stimuli, while the AI system records the frequency of errors, reaction speed, and body movements.[Based] on this data, the system generates a report that can help psychologists and pediatricians assess the existence of ADHD.[24] Studies show significant positive correlations between QbTest scores and parent-teacher ratings for hyperactivity and impulsivity.[5] One study found that of those identified as ADHD by QbTest, 76-86% actually had ADHD, while of those with a negative result, 37-50% did not have a diagnosis.[2] Nevertheless, it is emphasized that QbTest is only one part of a comprehensive assessment and that its usefulness may be limited in complex cases involving additional needs such as mental disabilities, learning disabilities, and trauma.

3.3.2. Questionnaires and digital assessment

Do-It Profiler uses questionnaires and digital assessment that includes parents, teachers, and the students themselves.[4] AI processes the collected data and compares it with norm databases to identify potential cases of ADHD and suggest further steps. It is important to understand that Do-It Profiler is primarily a screening tool and does not provide a formal diagnosis.[25] Its purpose is to indicate potential signs of dyslexia, dyspraxia, or ADHD, facilitating early identification and referral for further, more detailed evaluations.

3.3.3. Natural Language Processing (NLP) and Stylometry

Research explores the potential of natural language processing (NLP) and stylometry to identify linguistic markers in the narratives of adolescents with ADHD, especially in their "Self-Defining Memories" (SDM).[26] Studies have shown that adolescents with ADHD produce shorter, less lexically diverse, and less cohesive narratives compared to the control group.[26] These linguistic patterns may be associated with difficulties in pragmatic language skills, executive functions, and working memory, all of which are characteristics of ADHD.[27]
Stylometric analysis, using classifiers such as the Support Vector Machine (SVM), can differentiate between ADHD and control groups with high accuracy, reaching up to 100% accuracy with 3-gram characters.[26] Various linguistic markers have been identified; for example, in the ADHD group, there was a greater use of the neutral pronoun "he" (in French) instead of the expected pronoun "I", potentially reflecting difficulties in regulating emotions or the need to distance oneself from one's own feelings. These approaches offer objective measures through the analysis of textual and speech characteristics, mitigating the inherent subjectivity of traditional scales and reducing the time, cost, and infrastructure required for diagnostics.[26]

3.3.4. Multimodal systems

Multimodal systems are also being developed around the world that use a combination of technologies to identify ADHD and even autism spectrum disorders early. Examples include software that analyzes speech processing, video motion analysis, and even facial expression tracking. The AI in these systems can recognize signs of stress, lack of social interaction, or unusual speech patterns, providing a more comprehensive view of a child's behavior.

3.4. Case studies and examples of implementation of AI tools in practice

The implementation of AI tools in education and health systems has already shown significant results in the early recognition of specific learning disabilities. Case studies provide concrete examples of how AI can improve the diagnostic and educational process.

Lexplore in Sweden and the United Kingdom: Lexplore, a tool based on eye-tracking technology, has been implemented in several primary schools in Sweden and the United Kingdom. In a primary school in Sweden, Lexplore assessed all students in the first grades and was able to identify students who were later diagnosed with dyslexia with 93% accuracy. These data enabled timely referral of students to additional speech therapy and adjustments in teaching, which resulted in a significant improvement in their reading abilities. The use of Lexplore also reduced stress among students and parents, as it allowed for an objective and quick assessment of the problem, thus greatly reducing the waiting time for a diagnosis.[1]
QBTest in London: In a London primary school, teachers used QBTest to assess students who were showing symptoms of ADHD. The results showed that students with high scores on attention and reaction tests were later diagnosed with ADHD.[1] After diagnosis, students began receiving

adapted learning strategies and methods, including reducing time spent in the classroom, using assistive technology, and guided breaks to maintain focus. The biggest success of this initiative was in reducing stress among parents, as data on children's behavior was available immediately, allowing them to get help for their children more quickly.[5]

Do-It Profiler in Belgium: A technical school in Belgium has implemented the Do-It Profiler AI tool to diagnose ADHD among its students. The tool was useful in identifying students with possible ADHD, who were later referred for further diagnostic tests. Although the tool was useful in the initial phase of identification, educators emphasized the importance of the human factor in the final diagnostic process. A key benefit was increased efficiency in diagnosis and a reduction in stress and uncertainty among students and their parents, as students received support much faster than would have been possible in a traditional process.[4]

Combination of tools in the US: In a specific school district in the US, a combination of multiple AI tools has been implemented for the purpose of early diagnosis and monitoring of students with learning disabilities, including dyslexia and ADHD. Using Lexplore for dyslexia and QBTest for ADHD, teachers were able to gain a comprehensive insight into each student. The tools are integrated into the existing education system, allowing teachers to monitor the progress of their students in real time and adjust the curriculum and strategies based on this. This approach has enabled students with disabilities to be identified much faster, and intervention measures have been implemented earlier, significantly improving the academic performance of children with specific learning disabilities.[1]

The application of AI in the diagnosis of learning disabilities represents a significant step forward in the practical application of neurobiological insights. AI tools act as a kind of "neuro-cognitive translators", enabling the recognition of complex, internal neurobiological differences through the analysis of subtle, external behavioral manifestations. For example, Lexplore's eye tracking detects unusual patterns in reading that are characteristic of dyslexia, thus linking the behavior to an underlying neurobiological condition. Similarly, NLP identifies language patterns in ADHD that are associated with cognitive and emotional dysfunctions. This ability to "translate" enables objective, data-driven indicators that bypass the often lengthy and subjective traditional diagnostic processes. This significantly reduces delays in diagnosis and mitigates negative impacts on children's development, virtually democratizing access to advanced neurobiological insights that were previously limited to highly specialized clinics or expensive medical equipment. This enables the application of cutting-edge neuroscience in everyday educational settings.
However, it is important to emphasize that AI tools, while useful in screening and identifying risks, do not replace experts. The final diagnosis must always be the result of a comprehensive professional evaluation by clinical psychologists or psychiatrists.[1] AI may indicate the existence of risk, but the human factor remains indispensable in making the final decision, taking into account all the nuances of the child's development and context. This clear distinction between AI-screening and human diagnosis is crucial for setting realistic expectations, ensuring ethical implementation, and optimizing the diagnostic workflow. AI's real value lies in expanding the capabilities of human diagnosticians by providing highly efficient, objective, and early screening data. This allows human experts to allocate their limited resources more efficiently, focusing their comprehensive assessments on high-risk cases identified by AI. Such a collaborative model optimizes the entire diagnostic process, making it faster and more accessible.
Table 6 summarizes the key AI tools mentioned in this paper, their technology, mechanisms, and recorded effectiveness.

Table 6: Overview of Key AI Tools for Early Diagnosis of Dyslexia and ADHD

Tool	Targeted difficulty	Technology/Mechanism	Recorded accuracy/efficiency	Examples of implementation
Lexplore	Dyslexia	Eye-tracking, machine learning	>90% accuracy in detecting dyslexia; study in Sweden: 93% [1]	Primary Schools in Sweden and the UK [1]
INSIGHT	Dyslexia	Eye Movement Tracking (Fix-images), Convolutional Neural Network (ResNet18)	86.65% overall accuracy; 88.78% for level text; cross-testing on the Danish dataset: 86.11% [21]	Research studies, potential for clinical diagnosis [21]
Detective	Dyslexia	Language processing, writing and reading analysis, neuropsychological tests	Provides free and digital diagnostic [1]	Schools in Resource-Constrained Communities
Deep Learning (Handwriting)	Dyslexia	Convolutional Neural Network (CNN), image-based handwriting analysis	Training accuracy: 99.5%; Test accuracy: 96.4% [22]	Research Studies [22]
QBTest	ADHD	Computer-based attention and movement tests, hyperactivity sensors	76-86% chance of ADHD with a positive result; 37-50% chance of absence of ADHD with a negative result	Primary Schools in London [1]
Do-It Profiler	ADHD, Dyslexia, Dyspraxia	Questionnaires, digital assessment (parents, teachers, students)	Screening tool, indicates signs [25]	Technical School in Belgium, Universities (for screening) [1]
NLP and Stylometry	ADHD	Natural Language Processing, Stylometric Narrative Analysis (SDMs)	Up to 100% accuracy with 3-gram characters; 85% with function words [26]	Research Studies [26]

Multimodal systems	ADHD, Autism	Speech processing, video analysis of movements, facial expression monitoring	Recognizes signs of stress, lack of social interaction, unusual speech patterns [1]	Development systems

4. CHALLENGES AND ETHICAL ISSUES

The introduction of artificial intelligence (AI) in the diagnosis and support of students with learning disabilities brings many benefits, but it also poses significant challenges, both technical and ethical. While AI has the potential to revolutionize the education system, enabling faster, more accurate, and fairer diagnostics, the use of these technologies requires careful consideration of various challenges and potential risks.[6]

4.1. Technical challenges in the implementation of AI tools

One of the biggest challenges in the implementation of AI in education is the development and optimization of AI tools.[7] Using AI to diagnose dyslexia and ADHD requires the development of complex algorithms that can accurately identify behavior patterns and difficulties in children, but these algorithms are not always perfect.

4.1.1. Precision and errors of algorithms

AI diagnostic tools, such as Lexplore and QBTest, use student behavior data, such as eye movements, response speed, and impulsivity, to generate assessments. Although these tools often exhibit high accuracy, they are not immune to errors. Misinterpretation of data or incorrect algorithms can lead to false positives or false negatives. For example, a child who shows symptoms of ADHD due to stress or anxiety may be misdiagnosed, while a child who has ADHD but behaves more calmly due to various factors may be missed. Therefore, it is important that AI tools are always based on broad and representative data sets, to ensure the accuracy and fairness of the diagnosis.[5]

4.1.2. Data access and interoperability of systems

A bigger challenge is access to the data needed to effectively deploy AI technologies.[7] In many cases, data on students and their behavior must be integrated from a variety of sources, including teachers, parents and professionals, and systems to monitor academic performance. This is where the problem of interoperability arises, as many school systems do not have common databases or technical standards that allow data to be exchanged between different AI systems. In many educational institutions, student data is kept in a variety of formats and locations, which can make it difficult to use AI tools effectively.[7]

4.1.3. Data quality

Data quality is critical to the success of an AI system. If the data used to train AI algorithms is not of high quality, the results will be inaccurate. In the context of dyslexia and ADHD diagnostics, data must be accurate, up-to-date, and based on the actual needs of students. Poorly collected data or data that does not take into account all behavioral variants can reduce the effectiveness of AI systems. For example, if the data does not reflect the diversity of students' linguistic or cultural backgrounds, the AI tool may have disorder identifying difficulties in certain groups, leading to low diagnosis accuracy.[8]

4.2. Ethical issues and risks

When it comes to ethics, the use of AI in education raises a number of questions related to privacy, access to information, fairness and data security.[28] The use of AI to diagnose learning disabilities must be carefully balanced with the rights of students, parents, and other parties involved.[29]

4.2.1. Privacy and security of student data

One of the biggest ethical issues when using AI diagnostic tools is the privacy and security of student data.[10] AI systems often collect sensitive information about students, such as their behavior, abilities, and even emotional states. This may include data about a child's classroom behavior, test data, information about peer interactions, and other personal information.[The] use of this data must be strictly regulated to protect the privacy of students, while respecting data protection laws, such as the General Data Protection Regulation (GDPR) in Europe.[10] Free versions of generative AI tools (GenAI) are particularly risky because they can use user interactions to further train models, thus exposing sensitive data.[9]

The issue of consent also poses challenges. In many cases, children and parents may not be fully aware of what data collection through AI systems entails, nor do they have complete control over that data. Educating parents and students about privacy rights, as well as implementing clear privacy policies, are key to reducing the risk of data misuse. Schools should retain full ownership of all student data and ensure that contracts with AI tool vendors explicitly prohibit the resale of data or its use to train unrelated AI models.[31]

4.2.2. Algorithmic bias and discrimination

AI systems can rely on historical data to train their algorithms, and if that data is biased, it can lead to discrimination. Algorithmic bias is defined as inequality in the outcomes of algorithmic decision-making between two groups of different morally relevant reference classes, such as gender, race, or socioeconomic status.[32] For example, if the data used to train AI algorithms has historically favored children from certain socioeconomic groups or ethnic communities, AI may unconsciously prefer or ignore children from other groups. This form of prejudice can lead to unfair diagnoses and a lack of resources for children who need support the most.[33]

Bias can arise from a number of sources, including unbalanced coaching data (lack of diversity or underrepresentation of minority groups), problematic algorithm design (use of proxy variables such as zip code for race), technical biases (where detection features are less reliable for some groups), and feedback loops that reinforce existing biases.[33] The consequences of algorithmic bias in education are significant, as they can amplify existing inequalities and create new forms of systemic barriers, affecting students' educational trajectories and opportunities.[32]

4.2.3. Over-reliance on technology and the role of the human factor

While AI can provide useful information and guidance, there are also concerns that over-reliance on technology could reduce the human factor in education.[34] Professionals, such as teachers, educators, psychologists, and speech therapists, have an irreplaceable ability to perceive nuanced aspects of a child's behavior and development that cannot always be captured through AI-collected data.[35]

Excessive use of AI for diagnostics can lead to reduced personal contact and reduced attention to the emotional and social needs of the child. AI should support, not replace, clinical judgment, especially in cases where data is incomplete or ambiguous.[34] Human intuition, empathy, and the ability to make contextual reasoning remain essential for a comprehensive assessment and decision-making that affects a child's well-being. UNESCO's AI Competency Frameworks emphasize a humanistic approach, promoting critical thinking, ethical considerations, and the responsible use of AI technologies, with an emphasis on the need for AI to support human decision-making and intellectual development, not undermine or replace it.[29]

4.2.4. Application ethics and supervision

AI technologies, while useful, can also raise the question of ethics regarding their application in education systems. If AI tools recognize learning disabilities and automatically direct children to certain educational paths, the question arises as to how this data is used and who has access to it. Also, the question arises whether the application of these tools in education is justified in the context of their ability to shape the educational path of children, without sufficient human supervision. Algorithmic transparency is needed, which means it is necessary to understand how the AI model works, its data sources, and general decision-making processes. Explainability is also crucial, making it possible to understand why AI made a certain recommendation in an individual case.[30] Without that, there is a risk of a 'black box' where decisions are taken without a clear understanding or possibility of challenge.

5. RECOMMENDATIONS FOR THE FUTURE

In order for AI to be responsibly and effectively integrated into the educational system for diagnosing learning disabilities, it is necessary to adopt a comprehensive approach that includes collaboration, education, ethical guidelines and continuous monitoring.

5.1. Cooperation between the education and technology sectors

Further cooperation between educational institutions, psychologists, educators and experts in AI technologies is recommended. This multidisciplinary collaboration is crucial to ensure the proper implementation and evaluation of AI-based tools. The development of AI tools should be guided by the needs and experiences of educational experts, while technology experts should ensure technical robustness and security. The goal is to create a symbiotic partnership where humans and AI work together to achieve common goals, such as improving the efficiency and accuracy of diagnostics, and advancing learning.[34]

5.2. Continuous education of teachers, trainers and experts

Educators need to be trained to use AI tools effectively, but also to understand their limitations. This training must enable teachers to better interpret the results of AI assessments and provide the necessary support to students. UNESCO's AI Competence Frameworks for Educators emphasize lifelong professional development, ensuring that educators are equipped to use AI responsibly and effectively, minimizing potential risks.[29] Education should cover the ethics of AI, the basics of AI and its applications, and AI pedagogy, supporting teachers in using AI for innovative teaching methods.[29]

5.3. Developing ethical guidelines and privacy policies

Clear and strict ethical guidelines for the use of data and the protection of students' privacy need to be developed. This includes complying with relevant data protection laws, such as GDPR, and ensuring transparency and security when using AI systems in education.[10] Ethical guidelines should include the principles of proportionality (AI must not go beyond what is necessary for legitimate purposes), safety, fairness and non-discrimination, and human oversight.[30] It is also crucial to ensure informed consent from parents and students about data collection and use.

Schools must retain full ownership of student data and require AI tool providers to have clear policies for data retention and deletion.[30]

5.4. Regular update and evaluation of AI systems

To ensure the accuracy and relevance of AI systems, it is important that these tools are regularly updated and evaluated based on new data and research. This includes checks for algorithmic bias and ensuring that AI models adapt to the diversity of the student population. Continuous valuation should ensure that AI tools remain effective and equitable, and that their application is based on the latest scientific knowledge.

5.5. Timely intervention and personalised learning

One of the key benefits of AI is the ability to diagnose and identify learning disabilities faster. Therefore, educational institutions should use AI tools for early identification and intervention, which can significantly improve students' educational success.[13] AI enables personalized learning at scale, adapting content, pace, and assignments to the individual needs of students. These include predictive insights, process automation, and intelligent decision-making that make education more adaptable and data-driven. Using AI to provide instant feedback and early intervention can significantly improve student engagement and ownership of the learning process.[14]

6. CONCLUSION

AI has considerable potential to improve the education system, especially in the field of diagnosing learning disabilities such as dyslexia and ADHD. Traditional methods of diagnosis, while useful, are often slow and time- and resource-intensive, which can slow down timely intervention, which is crucial for the successful development of children with learning disabilities. Given the ability of AI tools to accurately analyze large amounts of data and recognize behavioral patterns, their application can significantly improve the ability to recognize these difficulties, thus enabling faster and more efficient diagnostics and interventions.

The application of AI tools such as Lexplore for dyslexia and QBTest for ADHD provides an opportunity for educators, parents, and educators to spot students' specific difficulties and implement personalized support strategies. These tools allow for faster problem identification, reducing waiting times for the appropriate diagnosis and the resources needed to get help. Also, the use of AI technologies can help reduce the stress that children and parents experience due to slow and often unsafe traditional diagnostic methods.

However, while AI brings significant improvements, its application in education is not without its challenges. Technical problems, such as the accuracy of algorithms, data quality, and interoperability of different systems, can affect the efficiency and accuracy of diagnosis. At the same time, ethical issues related to data privacy, discrimination due to algorithmic bias, and over-reliance on technology remain key challenges. Strict guidelines need to be developed to ensure the protection of learners' rights and to ensure transparency regarding how data is collected, analyzed and used.

Also, it is important to understand that AI is not a substitute for the human factor in education. While AI can provide valuable information and analysis, the final decision on diagnosis and intervention should always be in the hands of professionals who are able to look at all aspects of a child's development. The combination of AI tools with human intuition and expertise can be the key to successfully implementing these technologies into the educational process. Experts have an irreplaceable ability to spot nuanced aspects of a child's behavior and development that cannot always be captured through the data collected by AI.

In the future, the development and application of AI in education will continue to be in focus, and will require careful management to ensure their maximum positive impact while minimizing potential risks. Learning from the experiences we have already had in implementing AI tools in education systems will continue to be of great importance for shaping future guidelines and strategies. Given the rapid development of technology, it is important that the education and healthcare sectors continuously adapt to the new opportunities offered by AI, and that all aspects of it - from technical solutions to ethical guidelines - are carefully considered. Only in this way can AI truly become a useful tool that improves education, helps children with learning disabilities and allows them to reach their full potential.

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