Artificial Intelligence in Inclusive Education: A Review of Opportunities and Challenges for Neurodivergent Learners

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The integration of Artificial Intelligence (AI) into education has opened new avenues for supporting students with neurodevelopmental disabilities (NDDs), including autism spectrum disorder (ASD), attention-deficit and hyperactivity disorder (ADHD), and dyslexia. This review examines current AI applications designed to enhance screening, learning, assessment, and behavioral support for students with NDDs, drawing on interdisciplinary research from education, neuroscience, and computer science. The paper examines how assistive technologies and AI-powered tools such as intelligent tutoring systems (ITS), speech and language technologies, chatbots, and gamified tools can cater to the diverse needs of neurodivergent students. While AI shows promise in creating more inclusive and adaptive learning environments, the review also highlights critical challenges, including ethical concerns, data privacy, algorithm bias, and unequal access to technology. By synthesizing findings from the current literature, this article provides a comprehensive overview of the opportunities and limitations of using AI in inclusive education.

AI; neurodiversity; inclusive education; ASD; ADHD; dyslexia.

1. Introduction

The concept of artificial intelligence (AI) has long been the subject of debate among scholars, researchers, and practitioners. As both a scientific field and a practical tool, AI resists simple categorization because its scope and applications continue to expand rapidly. Establishing a clear definition is essential for understanding its role in education and other domains, yet the very nature of AI makes such a definition elusive. As AI technologies become increasingly embedded in everyday tools, they often lose the explicit label "AI" and are instead regarded as conventional software or algorithms. This shifting boundary complicates a fixed definition. Additionally, AI encompasses contributions from diverse fields—including computer science, neuroscience, psychology, philosophy, linguistics, anthropology, and biology—each adding unique perspectives and terminology (Luckin et al., 2016).

Holmes et al. (2019) state that some researchers prefer the term augmented intelligence, which frames the human brain as the primary source of intelligence and views computers as sophisticated tools that enhance human cognitive abilities, especially by handling tasks that humans find difficult and time-consuming, such as identifying patterns in large datasets. They maintain that although this appellation may be more accurate or useful, the term artificial intelligence remains dominant in popular usage and discourse. In this paper, both the terms artificial intelligence and augmented intelligence are used interchangeably to refer to computer systems designed to interact with the environment through human-like capabilities such as visual perception and speech recognition, and to exhibit intelligent behaviors, including evaluating information, problem-solving, and making decisions aimed at achieving specific goals.

With the use of AI spreading across many fields, education is no exception. In fact, Artificial Intelligence in Education (AIED) has been the subject of research for over five decades, but recent years have seen a surge in investment and innovation. Tech giants like Amazon, Google, and Facebook have joined established AIED edtech companies such as Knewton and Carnegie Learning, channeling millions into AI-driven educational tools. Initiatives like the $15 million Global Learning XPrize have further promoted the development of technologies that enable learners to guide their own education. Simultaneously, AI is gaining ground in mainstream schooling not only as a tool for online tutoring and teacher training, but also as a subject within the curriculum itself. But despite the exponential growth of the AIED market, the application of AI in educational settings remains relatively unfamiliar to the wider public. The integration of AI raises significant implications for educational practices, including shifts in teacher roles, student agency, data usage, and broader ethical and social impacts (Holmes et al., 2019).

Luckin et al. (2016) proclaim that at its core, Artificial Intelligence in Education (AIEd) aims to make educational, psychological, and social knowledge computationally explicit, that is to say, transforming learning processes that are often implicit into structured, analyzable data. In other words, beyond powering smart educational technologies, AIEd serves as a tool for uncovering the complex, often hidden mechanisms of learning. It enables fine-grained insights into how learning unfolds, including the influence of socio-economic, physical, and technological factors. These insights can inform both the design of future AI-driven tools and non-technological teaching strategies, such as helping educators identify learning steps or the typical misconceptions that arise when trying to understand a complex concept.

Luckin et al. (2016) explain how AIEd systems rely on two key components: (i) knowledge about the world, which includes facts, concepts, skills, and educational content, and (ii) algorithms that use this knowledge to make intelligent, goal-oriented decisions that mimic human cognitive processes. This knowledge is organized into three central models within AIED systems:

The Domain Model: Encapsulates the subject matter or content knowledge the system is intended to teach. It includes the structure of concepts, their relationships, and the correct solutions to problems within a particular discipline.

The Pedagogical Model: Outlines strategies for effective teaching and learning. It determines how the system decides what to present, how to present it, and how to respond to learner errors—much like a human teacher adapting their instruction based on student needs.

The Learner Model: Represents the system's dynamic understanding of the individual learner. It includes data on the student's current knowledge, learning progress, behavior, preferences, and potentially even emotional states. The learner model allows the system to personalize content and adapt instructional strategies in real time.

The framework outlined by Luckin et al. (2016) holds considerable promise for supporting neurodivergent learners in inclusive classrooms as well as in the comfort of their homes. These three models allow AIEd systems to complement human instruction, enhancing engagement, accessibility, and equitable learning opportunities. When implemented simultaneously in a single system, they could even simulate the roles of a competent human teacher—delivering the right content, in the right way, at the right time, tailored to the needs of each learner—hence potentially limiting, or even obsoleting, the need for human instruction.

According to UNICEF (2021), nearly 240 million children worldwide live with some form of disability, a figure that reflects a broader and more inclusive understanding of functional domains, including psychosocial well-being. While most experience difficulties in only one domain, psychosocial challenges are the most prevalent across age groups. Children with disabilities face significant disadvantages compared to their peers, particularly in education. Despite the global commitment to inclusive education under Sustainable Development Goal 4, especially targets 4.5 and 4.a that emphasize equity for children with disabilities, data revealed that students with disabilities are more likely to be out of school—especially those with severe disabilities—and those who do attend are less likely to acquire foundational reading and numeracy skills. Limited access to learning opportunities and resources at home, together with other barriers such as stigma, untrained teachers, and inaccessible infrastructure further compound these disparities. This persistent exclusion not only limits their academic opportunities but also undermines their overall well-being and future prospects.

Recent developments in artificial intelligence (AI) have created new opportunities to support neurodivergent students within educational environments. AI-powered tools—

such as personalized learning systems, speech and language technologies, chatbots, and gamified applications—can cater to the diverse cognitive and learning needs of these students, promoting more inclusive and adaptive learning environments. However, alongside these opportunities, AI introduces challenges related to ethics, data privacy, algorithmic bias, and unequal access to technology. Guided by the following research questions—What are the main applications of AI for supporting neurodivergent learners, what opportunities do these tools present for inclusive education, and what challenges and risks accompany their use?—this review synthesizes current research to provide a comprehensive overview of both the potential and limitations of AI in inclusive education, particularly for students with dyslexia, ASD, and ADHD.

2. Understanding Neurodivergent Learners and Their Educational Support

The concept of neurodiversity, often attributed to Judy Singer in 1998—though some argue it did not originate from a single author but rather emerged collectively in the late 1990s through activists with ASD, online communities, and later the writings of Singer and journalist Harvey Blume (Botha et al., 2024)—is less a clinical term than a political and social one. Rooted in the disability rights and civil rights movements, it asserts that neurological differences such as ASD, ADHD, dyslexia, and Tourette's syndrome should be recognized as natural forms of human variation, deserving the same respect and inclusion as categories like race, gender, or ethnicity. Much like biodiversity strengthens ecosystems, neurodiversity is framed as vital to the resilience and creativity of human societies. The movement challenges deficit-based views by emphasizing rights, identity, and the value of neurological variation, extending the social model of disability into the realm of cognitive and perceptual difference (McGee, 2012).

This paradigm underscores that these variations represent natural differences in human cognition and information processing rather than diseases that need curing. This perspective highlights the value of diverse cognitive styles, recognizing that individuals may have unique strengths, talents, and ways of learning, while also acknowledging the support they may require to thrive in social, educational, and occupational contexts (Singer, 2016). By reframing cognitive differences as part of human diversity rather than deficits, the neurodiversity paradigm advocates for inclusive practices, personalized learning, and societal accommodations that allow neurodivergent individuals to reach their full potential. While the neurodiversity paradigm has gained strong traction in education, psychology, and advocacy, there are also critics and counter-arguments. Critics of the neurodiversity paradigm do not necessarily dismiss the importance of acceptance or dignity. Instead, they call for a balanced approach that recognizes the legitimacy of neurodivergent experiences and strengths while also acknowledging the lived realities and support needs of those with more complex challenges. They caution against oversimplified narratives that may unintentionally sideline vulnerable populations (Russel, 2019).

In this article, the term neurodiversity is employed as an umbrella construct encompassing a range of neurological and cognitive differences, including ASD, ADHD, dyslexia, and other specific learning disorders. Its use is neutral and deliberately disassociated from any negative connotation.

2.1. ASD, ADHD, and Dyslexia: Definitions and Educational Implications

Specific Learning Disorders (SpLDs), also referred to as Specific Learning Disabilities, represent a group of persistent, lifelong neurodevelopmental conditions that affect the way individuals acquire and use key academic skills. These conditions are not indicative of low intelligence but rather stem from differences in cognitive processing that interfere with particular domains of learning, such as reading, writing, spelling, or mathematics. Beyond academic performance, SpLDs can also influence everyday functioning, including organization, memory, and time management (American Psychiatric Association, 2022). Dyslexia, dyscalculia, and dysgraphia are commonly recognized as specific learning difficulties (SpLDs), reflecting challenges in academic skills and subskills, namely, reading and spelling; numerical reasoning and calculation; and written expression, respectively (McDonough et al., 2017). Despite this recognition, debate continues over how best to classify these conditions and differentiate them from other neurodevelopmental differences.

Some educators and researchers also include conditions such as ASD and Attention Deficit Hyperactivity Disorder ADHD within the SpLD framework, while others view them as broader developmental disorders or disabilities that often present with associated learning difficulties. This ongoing discussion highlights the complexity of understanding cognitive and learning differences and underscores the importance of nuanced approaches to diagnosis, support, and inclusive educational practice (Sewell, 2022). In this paper, specific learning disabilities/disorders (SpLDs), include dyslexia, dyspraxia, dyscalculia, and dysgraphia and is used interchangeably with the term learning disability, while ASD and ADHD are treated as separate neurodevelopmental conditions that may involve associated learning challenges. The term neurodiversity is therefore used as a superordinate term to encompass both SpLDs and other neurodevelopmental differences that result in learning difficulties (e.g., ASD and ADHD), highlighting the diversity of cognitive and learning profiles in educational contexts and the need for personalised support.

2.1.1. Autism Spectrum Disorder (ASD)

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition marked by persistent deficits in social communication and the presence of restricted, repetitive behaviors and interests. The DSM-5, published in 2013, revised the diagnostic criteria for ASD from the DSM-IV, simplifying the framework from three sub-criteria (the triad) to two (the dyad) and incorporating sensory symptoms as a core feature. Key changes include merging social and communicative impairments into a single social communication domain, while retaining restricted and repetitive behaviors as a separate criterion. The DSM-5 notes that symptoms emerge during early development, but they may not become fully apparent until social demands surpass the individual's abilities or are hidden by compensatory strategies. Compared to the DSM-IV, the updated criteria provide a more streamlined and developmentally sensitive approach, highlighting social-emotional reciprocity, nonverbal communication, relationship difficulties, and sensory reactivity as central features of ASD (American Psychiatric Association, 1994, 2013).

In DSM-5, the ASD diagnosis was redefined as a single "spectrum" to encompass previously distinct Pervasive Developmental Disorders (PDD), including autistic disorder, Asperger's disorder, childhood disintegrative disorder, and Pervasive Developmental Disorder – Not Otherwise Specified (PDD-NOS). Rett syndrome was excluded as it is now recognized as a separate neurological condition. A new diagnosis, Social (Pragmatic) Communication Disorder (SPCD), was created for individuals with social communication challenges but without restricted or repetitive behaviors. Severity level descriptors were also introduced to indicate the level of support required by individuals with ASD (Hodges et al., 2020).

The World Health Organization (WHO) estimates that ASD affects roughly 0.76% of the global population. This figure, however, represents only a small fraction—around 16%—of children worldwide (Baxter et al., 2015), highlighting both the variability in reported prevalence and the likelihood of underdiagnosis in many regions. Differences in diagnostic practices, access to healthcare, cultural perceptions of developmental differences, and availability of epidemiological data all contribute to this variation, suggesting that the true prevalence of ASD may be different than current estimates indicate (Salari et al., 2022). ASD is diagnosed more frequently in males than females, with girls often identified later. Females with ASD are more likely to present with co-occurring intellectual disability or epilepsy, while those without such impairments may remain undiagnosed due to subtler social and communication challenges. Compared to males, females may demonstrate stronger conversational reciprocity, greater ability to align verbal and nonverbal cues, and more situationally adaptive behaviors, sometimes masking autistic traits by imitating peers. Their repetitive behaviors may be less obvious, and special interests often center on socially normative themes, though pursued with unusual intensity (American Psychiatric Association, 2022).

The typical school environment can be highly stressful for students with ASD. In a survey, students with ASD highlighted five main areas of difficulty. The foremost challenge was navigating the social demands of school, including group work and coping with bullying or teasing. Managing anxiety and maintaining calm in the school environment was the second most common challenge, with classroom noise and peer interactions frequently cited as triggers. Third, students reported difficulties with executive function (EF) skills essential for managing impulses and resisting distractions, planning, organizing assignments, participating in assessments, and completing homework, with research indicating that deficits in these skills negatively impact cognitive, social, and academic performance and tend to worsen with age. Coping with frequent transitions and changes to routines was another significant challenge, as students with ASD often rely heavily on structure and predictability. Finally, handwriting demands, including producing neat and timely written work, presented ongoing difficulties. Addressing these needs through targeted classroom support not only benefits students with autism but also enhances the learning environment for all students (Saggers, 2016).

Fleury et al. (2014) synthesize a wide body of research showing that the unique cognitive style of individuals with ASD—particularly difficulties in Theory of Mind[1] (ToM), Weak Central Coherence[2] (WCC), and Executive Functioning (EF)—plays a significant role in shaping reading outcomes. Although these students acquire reading skills through formal schooling, their rate of progress is often significantly slower than that of peers with other learning disabilities. Across studies, a consistent pattern emerges: many demonstrate relative strengths in word decoding but face persistent challenges with comprehension, which remains the central area of difficulty despite mixed findings on word-reading ability. Further evidence highlights variability in how students approach text, with high-functioning adolescents showing three distinct comprehension profiles: text-bound readers who focus only on the text without accessing the background knowledge; imaginative readers who rely on visual support, background knowledge, but tend to oversubjectify the inference, and strategic readers who apply conventional comprehension strategies but struggle to make predictions. Collectively, these findings suggest that ToM, WCC, and EF deficits influence reading comprehension in varied ways, underscoring the heterogeneity of literacy development in ASD.

Moving on from reading to writing, Fleury et al. (2014) note that students with ASD often encounter writing challenges that involve both the mechanics of handwriting and the broader demands of written expression. Several studies have shown that difficulties with fine motor skills and visual-motor speed can make handwriting slow, laborious, and sometimes illegible, often resulting in shorter writing samples. Beyond these mechanical issues, problems with perspective can limit students' ability to adjust their writing for an intended audience, while weaknesses in executive functioning make it harder to plan, organize, generate, and revise text.

Science, Technology, Engineering, and Mathematics (STEM) careers are increasingly replacing traditional jobs, offering promising opportunities for individuals with ASD who have strong skills in math, science, or computing. In this regard, Fleury et

[1] Theory of Mind (ToM) is the metacognitive ability to understand and infer that others have their own thoughts, beliefs, desires, and emotions, which may differ from one's own (Brüne & Brüne-Cohrs, 2005).

[2] Weak Central Coherence (WCC) is a cognitive theory proposing that some individuals, especially those with autism, focus on details rather than integrating information into a broader context (Happé, 2021).

al. (2014) report that although overall college enrollment is low for this population compared to other disabilities, they show the highest participation in STEM majors among students with disabilities. Despite this, challenges linked to language comprehension and executive functioning—such as slower growth in calculation skills, difficulty recalling mathematical operations, and struggle with solving word problems—can affect performance. Mathematical achievement among individuals with ASD ranges from modest weaknesses to giftedness, highlighting, yet again, the heterogeneity of cognitive profiles and the need for tailored support.

With the increasing number of students diagnosed with ASD who are expected to achieve the same academic standards as their peers, there is a rising need for interventions aimed at improving their academic outcomes. Fleury et al. (2014) catalogue a range of instructional strategies shown to support students with ASD in general education settings:

Priming: it involves preparing a student for upcoming academic material by providing a brief (10–15 minutes) preview of the activity. This can include using the actual instructional materials, outlining the steps of a task, or describing what the student will be asked to do. The strategy helps reduce stress and anxiety by making new or challenging tasks more predictable, addressing executive function difficulties related to organization and planning. Research has shown that introducing assignments in advance can improve accuracy and decrease disruptive behaviors in class (Koegel et al., 2003).

Peer support: peers without disabilities can be trained to use targeted strategies that encourage the participation of classmates with ASD during both teacher-led and student-initiated activities. This may involve adjusting instruction, such as rephrasing questions or dividing tasks into smaller steps, facilitating communication between students with ASD and their peers, and offering regular feedback. Peer support interventions have been shown to decrease students' dependence on adult assistance while fostering social interaction and engagement with the curriculum for students with ASD. For example, Carter et al. (2005) found that pairing a high school student with ASD with two typically developing peers in English class led to more consistent participation in class activities and increased time spent interacting socially with classmates.

Video modeling: an instructional approach in which students learn by watching videos that demonstrate a specific skill or behavior. This can take several forms, including basic video modeling, where a student observes someone else performing the skill; video self-modeling, in which the student watches themselves successfully completing the task; and point-of-view modeling, which shows the task from the learner's perspective to clarify each step. The method is particularly effective for students with ASD, who often struggle to learn through observation in natural settings, because it provides clear, consistent, and repeatable demonstrations that support visual processing and observational learning. Video modeling also reduces confusion or anxiety that may arise from verbal instructions alone, strengthens observational learning, and can be adapted to teach social, academic, or behavioral skills. For example, Delano (2007) used video self-modeling to teach students the Self-Regulated Strategy Development (SRSD) approach for writing, resulting in increased word counts and more functional essay elements, highlighting the effectiveness of the approach in enhancing both skill acquisition and confidence.

Explicit strategy instruction: teaches students structured approaches to academic tasks, such as writing or math, by targeting both cognitive actions and metacognitive thinking. Students follow step-by-step routines that are often supported by mnemonics, which are memory aids—such as acronyms, rhymes, or visual cues—that help students remember the steps of a task more easily. This method capitalizes on visual strengths and strong rote memory to address everyday memory challenges.

Self-management: students are instructed to track their own behavior or performance and provide themselves with reinforcement at set intervals. The tasks and the steps required to complete them are clearly outlined, which reduces the teacher's need to give ongoing feedback and supports executive functioning skills related to self-management.

Graphic organizers: visual tools, such as Venn diagrams, Know, What, Learn (KWL) charts, flowcharts, or storyboards, used to help students organize and structure their knowledge or ideas. Because individuals with ASD often focus on details rather than the bigger picture, these tools support comprehension by helping them connect information meaningfully across a text, addressing central coherence difficulties. For example, Carnahan and Williamson (2013) found that students using keywords and Venn diagrams improved their understanding of expository science texts.

According to Sajid et al. (2024), teachers of students on the autistic spectrum can support academic success by combining formal academic strategies with behavioral interventions, often enhanced through technology. Students with ASD tend to be strong visual learners and generally respond well to computers and tablets, which can present course material in engaging, predictable ways. Technology can be integrated through individualized shared reading programs, structured training, and well-organized learning spaces. Research indicates that computer applications can also promote social and behavioral skills, while providing visual reinforcement and reducing stress by minimizing demands on interpersonal communication. Additionally, technology offers students a sense of control and predictability over their learning, increasing confidence and engagement while complementing traditional teaching methods (Jacklin & Farr, 2005, as cited in Sajid et al., 2024).

Students on the autistic spectrum can benefit from adapted shared reading activities to support literacy development. In this approach, an adult reads aloud while engaging the student with questions and discussion, tailoring the content to the child's interests and abilities. Shortened texts that maintain core concepts, themes, and plot can make literature age-appropriate while accessible. Research has shown that using visual aids, modified texts, and structured reading exercises increases both student engagement and reading comprehension, even for children with limited verbal communication skills (Muchetti, 2013, as cited in Sajid et al., 2024). These findings highlight that early, individualized literacy interventions can improve reading understanding and foster participation for students with ASD.

ASD is characterized by social communication difficulties, restricted behaviors, and sensory sensitivities, with diverse cognitive and learning profiles. Students with ASD often face challenges in social interaction, executive functioning, literacy, and written expression; however, evidence-based strategies—including priming, peer support, video modeling, explicit strategy instruction, self-management, graphic organizers, technology use, and adapted shared reading—can enhance engagement, comprehension, and independence. Emerging AI tools have the potential to further support these interventions.

2.1.2. Attention-Deficit/Hyperactivity Disorder (ADHD)

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental condition marked by significant difficulties with attention, organization, and/or hyperactivity-impulsivity. It can manifest as trouble sustaining focus, seeming inattentive, or often losing items required for tasks, in ways that surpass what is typical for one's age or developmental level. Hyperactivity and impulsivity may be expressed through constant movement, restlessness, difficulty staying seated, interrupting others, or impatience, also exceeding age-appropriate expectations. During childhood, ADHD commonly co-occurs with other externalizing disorders, such as oppositional defiant disorder or conduct disorder. The condition often continues into adulthood, where it can interfere with social relationships, academic achievement, and work performance (American Psychiatric Association, 2022).

Globally, ADHD affects about 8% of children and adolescents, with boys being diagnosed approximately twice as often as girls, with rates of 10% and 5% respectively, reflecting a notable gender disparity. The rates appear to be lower in adults compared to other age groups. Among the three recognized presentations of ADHD, the inattentive type (ADHD-I) emerges as the most prevalent, characterized by difficulties sustaining attention, forgetfulness, and disorganization. This is followed by the hyperactive-impulsive type (ADHD-HI), which involves restlessness, excessive activity, and impulsive behaviors, and the combined type (ADHD-C), where features of both inattention and hyperactivity-impulsivity are present. These differences in prevalence and symptom presentation highlight not only the heterogeneity of ADHD but also the importance of considering gender- and subtype-specific patterns in both research and clinical practice (Ayano et al., 2023).

Managing this lifelong condition generally involves two main approaches: non-pharmacological interventions (psychosocial treatments) and pharmacological treatment (American Academy of Pediatrics, 2001). In their account of these treatments, Wilens & Spencer (2010) synthesize several studies on ADHD medication. The results indicate that pharmacological management plays the most significant role in reducing core ADHD symptoms during the initial one to two years of multimodal treatment. The main drug classes include stimulants, noradrenergic agents, and alpha agonists, all of which demonstrate effectiveness across the lifespan. Stimulants are the first-line choice due to their strong evidence of efficacy and safety, with methylphenidate formulations and amphetamine formulations being the most widely used. Methylphenidate works by blocking dopamine and norepinephrine transporters, while amphetamines not only block these transporters but also release stored catecholamines, thereby boosting synaptic dopamine and norepinephrine levels. As for the non-pharmacological interventions, recommended approaches can be grouped into three categories: behavior management interventions, which include parent training, classroom strategies, and peer-based programs; training and cognitive interventions, such as cognitive training, neurofeedback, organizational skills training, and cognitive-behavioral therapy (CBT); and physiological treatments, including structured physical activity programs (for review see Shrestha et al., 2020).

Equipping parents with the tools to deal with their child's condition is crucial for effective intervention. Behavioral Parent Training (BPT) is one of the widely known effective therapies in treating ADHD; it typically follows the Antecedent–Behavior–Consequence (ABC) approach. This training can be delivered through multiple formats, including small or large group sessions, individualized family consultations, instructional videotapes, and interactive behavioral sessions that involve both parents and children. These diverse approaches allow parents to learn strategies for reinforcing positive behaviors, managing challenges effectively, and applying consistent behavioral techniques in real-life settings, thereby enhancing the child’s overall functioning (Van Den Hoofdakker et al., 2007).

Teachers can complement the effort done at home by implementing both individual and classroom-wide strategies using the ABC approach (Barkley, 2005). Antecedent interventions focus on identifying and addressing triggers of problematic behavior, such as boredom, peer provocation, or inconsistent rules. Interventions that combine antecedent and consequence strategies involve recognizing the causes of inappropriate behavior while reinforcing positive behaviors through rewards. Consequence-based interventions, on the other hand, use carefully applied disciplinary measures to promote appropriate behavior in the classroom (Wilens et al., 2010). A concrete application of the ABC model is found in the Behavioral Classroom Management (BCM), which is a structured evidence-based approach designed to improve the behavior and academic performance of children with ADHD and other behavioral challenges within the school setting. The BCM involves setting clear behavioral expectations, consistently monitoring student behavior, and providing immediate reinforcement for positive actions while applying predictable consequences for inappropriate behaviors. Key strategies include structured routines, token economies, contingent praise, and instructional modifications to support learning (Pelham Jr. & Gregory, 2008).

Peer-based interventions have demonstrated positive results in improving the social relationships of children with ADHD, who frequently experience significant difficulties in peer interactions, with more than half experiencing challenges in forming friendships. However, further research is needed to strengthen the evidence base supporting their effectiveness in ADHD management. These interventions are typically group-based and include three main approaches: peer involvement, where peers support each other through strategies like sharing, helping, or praising; peer-mediated interventions, in which trained peers provide instruction and guidance to the target child; and peer-proximity interventions, where skilled peers are placed in close proximity to model appropriate behaviors (Shrestha et al., 2020).

Beyond traditional psychosocial interventions that are known to benefit individuals with ADHD, tutors play an important role in supporting students by fostering academic skills, social development, and personal growth. They not only teach strategies for organization and prioritization but also serve as mentors and motivational figures, bridging the gap between emotional support and practical skill-building (Wilens et al., 2010). Most children with ADHD require individualized educational planning (IEP) tailored to their specific challenges, particularly since learning disorders frequently co-occur. Comprehensive support should include early screening, development of individualized education plans, and collaboration between parents, teachers, school counselors, and psychologists. Educational adjustments—such as structured routines, learning aids, additional resource support, and regular monitoring of homework—are vital for improving both academic and behavioral outcomes. Consistent communication between parents and schools further strengthens progress, and similar structured strategies at home can enhance the child's ability to manage tasks effectively (Wilens & Spencer, 2010).

2.1.3. Dyslexia

Dyslexia does not have a single agreed-upon definition, as scholars interpret it differently. Ried (2009) highlights that defining dyslexia is particularly challenging because of its complexity, and no definition can be regarded as universally accepted. He explains that people with dyslexia experience the condition in varied ways, which shapes their personal interpretations and perspectives. This implies that although certain contributing factors are commonly recognized, the manifestation of dyslexia can vary considerably from one individual to another. Despite the lack of universal agreement on its definition, the International Dyslexia Association (IDA) has, since 2002, defined dyslexia as "a specific learning disability that is neurobiological in origin. It is characterized by difficulties with accurate and/or fluent word recognition and by poor spelling and decoding abilities. These difficulties typically result from a deficit in the phonological component of language that is often unexpected in relation to other cognitive abilities and the provision of effective classroom instruction. Secondary consequences may include problems in reading comprehension and reduced reading experience that can impede the growth of vocabulary and background knowledge" (IDA, 2002). Its prevalence estimates vary widely—from under 5% to 20%—due to continuous variation in reading ability, differing diagnostic definitions, and the unreliability of identification methods (Wagner et al., 2020).

Snowling et al. (2020) criticize the discrepancy-based model of diagnosing dyslexia, arguing that it fails to distinguish clearly between children with dyslexia and those with broader learning difficulties, as both groups show similar reading and phonological deficits. They note that expanding the definition has created confusion around the diagnosis and even suggest that a new term may be necessary. The authors also emphasize the importance of recognizing comorbidities, with Moll et al. (2020) reporting that about 40% of children with dyslexia or reading disorders also have another neurodevelopmental condition. To reduce confusion surrounding the term *dyslexia*, the DSM-5 adopts the label *Specific Learning Disorder with impairment in reading*, classifying it as a type of neurodevelopmental disorder. Such disorders are typically heritable, often genetic, and lifelong in nature, with symptoms appearing early in development—dyslexia usually emerging in the preschool years. According to the DSM-5, this condition is defined as a persistent pattern of reading difficulties, including inaccurate or slow word recognition, poor decoding, and weak spelling, that continues for at least six months despite targeted intervention. Furthermore, a key indicator is notably low academic achievement relative to age, or performance maintained only through unusually high effort or external support.

Dyslexia is widely linked to deficits in phonological processing, which encompasses several interconnected skills. Phonemic awareness, the ability to identify and manipulate individual sounds, underpins early reading development. Extending this, phonological awareness includes broader abilities such as rhyming, blending, and segmenting, and tends to develop from larger sound units to smaller ones, with recognition typically preceding manipulation. This progression is not strictly linear but rather overlapping and fluid. In addition, phonological memory supports the temporary storage of sound sequences, while phonological processing speed enables rapid retrieval of phonological information. Collectively, weaknesses across these areas explain many of the reading difficulties associated with dyslexia (Anthony & Francis, 2005). Research indicates that individuals with dyslexia often demonstrate weak phonological awareness (Catts et al., 2005), along with limitations in verbal short-term memory (Szenkovits & Ramus, 2005) and slowed phonological processing speed (Wolf & Bowers, 1999). In addition, some studies report deficits in auditory discrimination despite otherwise normal auditory acuity (Orton, 1937; Bannatyne, 1974, as cited in Snowling et al., 2020).

In its resource kit for teachers, the IDA (2017) underscores a range of signs and symptoms that can indicate dyslexia, stressing the importance of early evaluation to ensure appropriate support. In general, individuals with dyslexia may struggle with speaking, learning letters and sounds, organizing language, memorizing number facts, reading fluently, comprehending longer texts, spelling, learning foreign languages, and performing math operations accurately. For elementary-aged children, more specific difficulties can include trouble remembering simple sequences (such as counting, days of the week, or the alphabet), recognizing rhymes or words with the same initial sound, pronunciation issues, clapping to rhythms, word retrieval challenges, and remembering names, places, or spoken instructions. However, the IDA cautions that experiencing these difficulties does not automatically mean a child has dyslexia, as formal testing is required for diagnosis.

Research has long emphasized the importance of early identification and intervention for dyslexia (Snowling, 2013), with studies showing that language and literacy precursors, such as letter-sound knowledge and phonemic awareness, can predict later outcomes at a group level (Muter et al., 2004), though predictions at the individual level remain challenging (Puolakanaho et al., 2007). Alternative approaches such as Response to Intervention (RTI) allow teachers to monitor children's progress and identify those who fail to respond to high-quality teaching (Fletcher et al., 2007), potentially enabling timely support without waiting for diagnostic thresholds. Evidence from the Early Years Foundation Stage Profile (EYFSP) in the UK shows that teacher assessments at year 2 are strong predictors of literacy achievement at the end of year 3, with communication, language, and literacy scores explaining about half the variance in later reading and writing outcomes. Follow-up studies further confirm that children identified as "at risk" through phonics monitoring display core dyslexic features, including deficits in phonological awareness, verbal memory, and processing speed. Collectively, these findings highlight that schools already collect sufficient data to identify children at risk of dyslexia and that embedding systematic teacher-led assessments and RTI frameworks provides an effective, cost-efficient approach to early detection and intervention (Snowling, 2013).

Snowling & Hulme (2011) highlighted the core components of evidence-based interventions for language and literacy challenges. They emphasize that effective programs should be structured, systematic, and multi-sensory, incorporating explicit instruction, opportunities for practice, and frequent review to accommodate children's limited attention and learning difficulties. For students with dyslexia, interventions should focus on teaching letter-sound relationships, phonemic awareness, and connecting letters and sounds through both writing and level-appropriate reading tasks to strengthen emerging skills. Conversely, children with comprehension difficulties require approaches tailored to oral language development, particularly vocabulary enrichment (Clarke et al., 2010). Since many learners experience difficulties with both decoding and comprehension, a blended approach is often necessary.

2.2. Etiological Factors of Neurodevelopmental Disorders

Although the precise causes of learning disabilities are unclear, research has identified several contributing risk factors and a high likelihood of a genetic basis. Notably, children with a family history of learning disability face a higher probability of developing one themselves. However, the absence of a hereditary history does not negate the genetic etiology of these neurodivergencies, as stated by Foster et al. (2015), who elaborate that evidence indicates that a wide range of environmental factors may contribute to the development of learning disabilities before, during, or after birth. These include prenatal infections; maternal health conditions; exposure to harmful substances like sodium valproate, prescription and recreational drugs; birth complications such as asphyxia; and issues related to prematurity. Maternal alcohol consumption during pregnancy has been shown to adversely affect cognitive development, including attention, memory, and mathematical skills (Mattson et al., 2011). Exposure to environmental toxins such as lead, even at low levels, is associated with impaired intellectual functioning and behavioral problems in children (Feldman & White, 1992; WHO, 2024). Nutritional deficiencies during infancy, particularly iron deficiency—which infants are highly vulnerable to—have been associated with lasting effects on cognitive, motor, and socio-emotional development. Longitudinal studies and animal research indicate that these outcomes result from disruptions in brain development, including altered neurometabolism, myelination, and neurotransmitter function, highlighting the critical importance of adequate early iron nutrition (Lazoff et al., 2006).

Similarly, the development of ASD is influenced by multiple factors, arising from intricate interactions between genetic susceptibility and environmental conditions. ASD is believed to be primarily influenced by genetic factors. This theory is substantiated with the results of twin studies that have shown high concordance rates for ASD in monozygotic twins, indicating a strong hereditary component. For reference, the concordance rate for ASD in monozygotic twins is reported to be between 70% and 90%, compared to up to 30% in dizygotic twins (Rosenberg et al. 2009; Hallmayer et al. 2011; Ronald & Hoekstra, 2014 as cited in Wiśniowiecka-Kowalnik & Nowakowska, 2019). Additionally, environmental factors also contribute to the risk of developing ASD. Prenatal exposures, such as maternal infections, advanced parental age, and complications during pregnancy, have been associated with an increased risk of ASD. Additionally, perinatal factors like low birth weight and prematurity may further elevate this risk (Hodges et al., 2020).

Akin to ASD, ADHD has a strong genetic basis. Family, twin, and adoption studies indicate that ADHD is highly heritable, with estimates of heritability ranging from 70% to 80% (Faraone & Larsson, 2019). Furthermore, studies indicate that ADHD is a polygenic condition, with multiple genes influencing brain development and function. Two frequently studied candidates are the brain-derived neurotrophic factor[3] (BDNF) and the dopamine transporter gene (DAT) (Núñez-Jaramillo et al., 2021). Environmental factors are also contributive in developing ADHD. Prenatal and perinatal influences, including

[3] A protein that supports neuronal survival and growth, modulates neurotransmitter activity, and facilitates neuronal plasticity, which is crucial for learning and memory (Bathina & Das, 2015).

premature birth, maternal malnutrition, immune activation, and prenatal exposure to toxins or high sugar intake, can disrupt neurogenesis and dopaminergic pathways. Early-life exposure to heavy metals and pesticides has also been linked to ADHD symptoms, while sleep disturbances can exacerbate or mimic core behavioral traits (Núñez-Jaramillo et al., 2021). Together, these findings highlight that ADHD results from complex interactions between inherited genetic vulnerabilities and environmental exposures, emphasizing the need for holistic approaches in both research and clinical practice.

In sum, learning disabilities, ASD, and ADHD arise from complex interactions between genetic predispositions and environmental factors. While heredity plays a central role, prenatal health, nutrition, and exposure to toxins also significantly shape outcomes. Raising awareness among parents, educators, and healthcare providers is essential for early recognition, while preventive measures—such as safeguarding maternal health, reducing environmental risks, and ensuring proper nutrition—can mitigate vulnerabilities.

3. Research on AI Tools for Neurodiverse Learners

Recent advances in artificial intelligence (AI) have opened new possibilities for supporting neurodiverse students in educational settings. Research increasingly explores how AI tools can assist learners with conditions such as ADHD, ASD, and dyslexia by providing personalized learning experiences, scaffolding attention and executive functions, and enhancing reading and comprehension skills. This section reviews studies that examine the effectiveness and implications of AI-assisted learning for these populations, highlighting how technology can complement traditional interventions and foster more inclusive classrooms.

3.1. AI Applications for Learners with Autism Spectrum Disorder

AI is increasingly used in autism diagnosis and support, with smartphone apps and tools aiding detection and helping improve social, communication, and emotional skills. While not a substitute for personalized treatment, AI models like ChatGPT provide accessible information and guidance for parents, therapists, and individuals. Beyond support for people with ASD, AI fosters acceptance and empathy by helping typically developing individuals better understand neurodiverse perspectives. Overall, AI offers practical benefits such as sensory management, structured routines, adaptive communication, and individualized support (Moraiti & Drigas, 2023).

Dechsling et al. (2022) conducted a scoping review of 49 studies exploring the use of virtual reality (VR) and augmented reality (AR) technologies in social skills interventions for individuals with autism spectrum disorder (ASD). Their review highlights that VR- and AR-based tools are promising, widely accepted by individuals with ASD, and particularly focused on children and adolescents, though very young children and adults remain underrepresented. The studies reviewed were generally small-scale, with limited female participation, reflecting a gap in inclusivity. While many interventions demonstrated potential for improving social skills, the paper emphasizes the need for more rigorous research designs that integrate VR/AR with evidence-based intervention strategies to establish stronger empirical support. Their general conclusion was that VR and AR hold considerable promise for enhancing social skills interventions in ASD, but future research must address methodological limitations, participant diversity, and scalability.

Traditional assessment methods (e.g., standardized tests, teacher-led evaluations, written examinations, and IQ-based measures such as the Wechsler Intelligence Scale for Children) often fail to account for the unique learning styles and cognitive and sensory profiles of learners with ASD. This limitation reduces their effectiveness in evaluating progress within AI-assisted education. To address this, researchers propose novel AI-specific metrics that combine quantitative indicators (e.g., task accuracy, completion rates, and response times adjusted for cognitive and motor differences) with qualitative measures (e.g., engagement, emotional responsiveness, and independent exploration). These metrics complement conventional assessments by leveraging real-time data and adaptive learning to provide more accurate, inclusive, and personalized evaluations (Adako et al., 2025). Practical examples include CogniAble, which uses facial recognition and behavior tracking for real-time screening, and AlterEgo, a wearable device that translates internal speech into text for non-verbal children. Other tools, such as Empowered Brain and Affectiva, employ augmented reality and emotion-recognition technologies to monitor social engagement and provide immediate feedback. Similarly, adaptive platforms like Jasper personalize social skills interventions by analyzing eye contact, speech, and reaction times. Collectively, these AI-driven systems illustrate how technology can enrich assessment practices beyond traditional methods by capturing both cognitive and socio-emotional dimensions of learning (Adako et al., 2025).

3.2. AI Tools for Students with ADHD

In their systematic review, Hardiani et al. (2025) state that preliminary studies on some AI-powered applications have demonstrated promise in supporting children with ADHD in their education. For example, EndeavorRx—an FDA-approved digital therapeutic game—employs AI to adapt gameplay based on a child's performance, specifically targeting attentional control. Similarly, programs like Cogmed Working Memory Training and NeuroPlus use AI to monitor and respond to user interactions, providing immediate feedback to maintain engagement. These tools leverage data-driven personalization to improve focus, a critical skill for learners with ADHD. The article concludes that despite encouraging early results of the reviewed studies, longitudinal research is still necessary to confirm sustained benefits of these tools.

Sun et al. (2025) carried out a scoping review of 52 studies to map how AI is being used for children with ADHD. They noted that most of the research focused on AI for diagnosis, often using brain imaging data (MRI). The review found that machine learning methods (ML)—especially support vector machines (SVMs)—were the most common, though deep learning (DL) approaches like Convolutional Neural Network[4] (CNNs) achieved the highest accuracy, with some models reaching over 98%. However, many studies relied on small datasets, and validation methods were fairly limited. They concluded that AI shows strong potential to improve diagnostic accuracy and support clinical decisions, but stress the need for larger, more rigorous studies before these tools can be widely adopted.

Somma et al. (2021) reviewed several studies conducted to evaluate AI-powered applications designed to support children with ADHD, highlighting their adaptive, gamified, and data-driven features. TALI Train™ adjusts task difficulty based on each child's abilities and provides visual, verbal, and motivational support, with progress tracked through achievement, accuracy, and reaction time. Studies reported modest improvements in selective attention and numeracy skills, though effects on sustained attention and behavioral attention were limited. Braingame Brian personalizes task difficulty in real time and uses gamified worlds to engage children, showing reductions in ADHD behaviors and gains in inhibition, but not consistently in working memory or set-shifting. Play Attention integrates neurofeedback to modulate theta/beta brainwave ratios, improving attention and executive function while reducing reliance on stimulant medication. ATENTIVmynd™ Games uses electroencephalography[5] (EEG)-based feedforward modeling to monitor attention and provide real-time feedback in gamified tasks, demonstrating improvements in attention and functional brain connectivity. Cogmed Working Memory Training® focuses on working memory exercises with adaptive difficulty and online monitoring; studies showed gains in nonverbal and verbal storage but limited impact on ADHD symptoms or academic achievement.

Aldakhil (2024) demonstrated that AI-based play activities significantly improve the quality of life for children with ADHD. In a study of 61 children aged 8–12, participants who engaged in twelve 45-minute AI-guided play sessions showed gains across all Pediatric Quality of Life Inventory (PedsQL) dimensions, which were sustained at a 7-week follow-up. The findings suggest that AI-driven interventions can enhance behavioral, social, and cognitive outcomes and highlight the potential of integrating such approaches into educational and therapeutic settings for children with ADHD. Additionally, Shpakivska Bilan et al. (2024) reported that an adaptive, game-based cognitive therapy, targeting 14 cognitive tasks based on neuropsychological paradigms (e.g., go/no-go, n-

[4] A type of deep learning model that automatically learns spatial hierarchies of features from input data, commonly used for tasks like image and pattern recognition. CNNs use layers of convolutions, pooling, and fully connected nodes to extract and classify features efficiently (Taye, 2023).

[5] A non-invasive technique for recording the brain's electrical activity. It involves placing small electrodes on the scalp to detect the electrical signals generated by neurons, which are then recorded as wave patterns reflecting neural activity (Rayi & Murr, 2022).

back) that were continuously adapted by AI according to each child's performance, not only reduced impulsiveness and inattention but also produced neurophysiological improvements, with progress in inhibitory control linked to normalized MEG spectral profiles and significant improvements in attention and impulsivity, alongside enhanced inhibitory control, cognitive flexibility, and spatial working memory in their experimental group.

3.3. AI Support for Students with Dyslexia: From Detection to Intervention

The integration of artificial intelligence (AI) has dramatically enhanced early dyslexia detection by introducing non-invasive, highly accurate diagnostic tools that outperform traditional methods. AI-driven models employing machine learning (ML) and deep learning (DL) algorithms have been used to analyze diverse behavioral data—such as eye movement patterns, handwriting characteristics, and speech signals—to identify markers of dyslexia in children (Yap et al., 2025). For example, researchers combining eye-tracking data with machine learning classifiers have achieved very high classification accuracies ranging between 88.58% using a random forest classifier (Cogan et al., 2025), 94% using multiple algorithms (e.g., logistic regression, support vector machine, k-nearest neighbor, and random forest) while taking into consideration the effect of color on the inter-subject variability (Vajs et al., 2022).

The influence of color on reading time has been supported by a study that measured electroencephalography (EEG) activity, heart rate variability (HRV), electrodermal activity (EDA), and eye movements in children with dyslexia and controls. The results revealed that children with dyslexia consistently demonstrated longer reading durations, with fewer and longer fixations and saccades, indicating that their reading was slower and less efficient than that of their non-dyslexic peers, regardless of colour condition. However, certain colours, specifically turquoise backgrounds and overlays and yellow backgrounds, significantly improved the reading performance of children with dyslexia, resulting in shorter reading times (Jakovljević et al., 2021).

Rangasrinivasan et al. (2025) address the need for early, efficient, and accessible screening tools for two common learning disabilities: dyslexia and dysgraphia. They argue that current screeners are limited because they are costly, time-intensive, and typically focus on either dyslexia or dysgraphia in isolation, often neglecting writing-based behaviors. Most dyslexia tools rely on oral and speech tasks, leaving out handwriting analysis, which can reveal important behavioral indicators for both conditions. The authors propose an AI-integrated screening framework that enhances handwriting evaluation by detecting dyslexia and dysgraphia indicators in children's writing. Grounded in the Dysgraphia and Dyslexia Behavioral Indicator Checklist (DDBIC), the framework integrates expert-defined criteria from speech-language pathology and occupational therapy—17 indicators, including four observed during writing (e.g., grip, pressure, speed, engagement) and 13 analyzed afterward, spanning dysgraphia-specific, shared, and dyslexia-specific markers—with machine learning trained on handwriting datasets. Using five analytical modules (Temporal, Structural, Handwriting Recognition, Semantic, and Post-processing/Fusion), the framework ensures a practitioner-aligned system for large-scale, explainable screening.

Aldehim et al. (2024) present another DL based approach for dyslexia detection using handwriting analysis. Their study employs a CNN model tailored for image-based handwriting analysis, focusing on accurately identifying the subtle features that differentiate dyslexic handwriting from typical writing. The model's performance is benchmarked against existing detection methods, showing superior accuracy and efficiency. These findings highlight the potential of CNN-driven handwriting analysis as a reliable tool for early dyslexia screening and intervention. Another use of CNN is Yogarajah and Bhushan (2021), who developed a DL based system for automated detection of dyslexia and dysgraphia using handwriting samples from 54 children aged 6–10. The system analyzed 267 images of selected Hindi words with a CNN, achieving an average accuracy of 86.14%. The study demonstrates that deep learning can effectively identify handwriting features indicative of dyslexia and dysgraphia, supporting automated screening and early detection.

Recent research underscores the transformative role of AI not only in screening and diagnosis but also in personalized learning for students with dyslexia, as intelligent systems adapt educational content and methods to individual cognitive profiles and evolving needs (Yap et al., 2025). Examples include Intelligent Tutoring Systems (ITS) tailored for learning disabilities (Ahuja et al., 2022); multimodal interactive applications for letter and color recognition (Al Omoush et al., 2023); and a Fuzzy Min-Max Neural Network[6] (FMMNN) based ITS that identifies learner characteristics to deliver customized experiences (Dutt et al., 2022). Further developments, such as language learning models with real-time feedback, demonstrate how AI-driven tools can provide responsive, engaging, and inclusive learning environments. Collectively, these innovations highlight AI's potential to improve engagement, accessibility, and learning outcomes for students with dyslexia by aligning instruction with each learner's trajectory (Yap et al., 2025).

Systematic reviews indicate that tools such as speech-to-text (STT), text-to-speech (TTS), and audiobooks positively impact reading and writing skills in students with learning disabilities, including dyslexia (Perelmutter et al., 2017). Studies also suggest that STT and TTS can foster greater independence, engagement in school activities, motivation, and learning satisfaction, especially when tailored to individual needs (Nordström et al., 2018; Svensson et al., 2021). However, research comparing text comprehension between audiobooks and printed text remains limited, which calls for further investigation into learner

[6] A neural network that combines fuzzy logic and neural learning by using hyperboxes to handle uncertainty, enabling adaptive, real-time pattern recognition while improving generalization and reducing overfitting (Nature, n.d.).

characteristics—such as motivation, perception, and attitudes—to better understand how these factors influence comprehension across different media (Singh & Alexander, 2022).

Anderle et al. (2025) conducted a pilot study exploring two gamified digital tools for supporting decoding and writing skills in students with diverse learning profiles, including those with special educational needs (SEN). Both neurotypical and SEN participants showed gains in decoding fluency, accuracy, and writing, alongside high engagement and acceptability. However, some improvements among SEN groups did not reach statistical significance, underscoring the need for personalized approaches and highlighting the potential of gamified tools as inclusive complements to traditional instruction.

Bäcka et al. (2023) conducted a five-year follow-up study to explore the long-term experiences of Swedish students with dyslexia using assistive technology (AT). They interviewed nine students using a semi-structured framework and analyzed the responses thematically. Three main themes emerged: contextual factors, emotional responses, and the development of meaningful strategies. The researchers found that audiobooks remained consistently helpful throughout the school years, text-to-speech (TTS) was mainly used for decoding, and speech-to-text (STT) showed mixed effectiveness. Sustained AT use was influenced more by school organization, students' acceptance of their dyslexia, and their attitudes toward AT, rather than by accessibility alone. Bäcka et al. (2023) concluded that effective AT support requires systematic training, attention to emotional responses in the classroom, and ongoing guidance to help students develop strategies for both basic and higher-level learning skills.

Kostadinovska-Stojchevska & Shalevska (2024) argue that AI tools like ChatGPT provide context-aware writing support that goes beyond basic spellchecking, offering real-time feedback on grammar, style, and vocabulary. By suggesting synonyms, improving arguments, and guiding text organization based on user input, ChatGPT helps students with dyslexia overcome challenges that extend beyond spelling, particularly in foreign language learning, where limited vocabulary and grammar knowledge can hinder writing development. They add that ChatGPT can address the challenges that students with dyslexia face with vocabulary retention by creating personalized, adaptive exercises aligned with each student's learning curve, curriculum, and preferences. These tools transform vocabulary practice into an interactive and engaging experience, fostering deeper language comprehension rather than simple rote memorization. Examples include interactive flashcards with audio pronunciations, contextual sentence generation, and gamified activities like crossword puzzles and word searches. However, while AI can offer valuable support, some researchers stress that these tools should be carefully integrated, educational institutions need to revise and modernize training for students and teachers, as well as policies and assessment methods in writing courses to address issues related to academic integrity, including plagiarism, AI-generated work, online or home-based exams, and challenges posed by automated error-correction (Imran & Almusharraf, 2023).

4. Challenges and Ethical Considerations in AI-Powered Support

The use of AI-based systems in education, while promising, also presents important limitations that must be acknowledged. First, equitable access remains a challenge, as not all families or schools possess adequate digital devices or reliable internet connections, potentially widening the digital divide and excluding disadvantaged learners from benefiting fully from these technologies. Second, prolonged and unsupervised use of AI applications may create risks of overreliance on technology, leading to reduced self-regulation skills, diminished face-to-face interactions, and excessive screen exposure, which can negatively impact physical and mental health. Third, privacy and data security concerns represent a critical barrier, particularly since many AI-based systems rely on collecting and analyzing sensitive personal and behavioral information. Without robust safeguards, there is a heightened risk of misuse, unauthorized access, or breaches of children's data, which can undermine trust and ethical implementation in educational settings (Hardiani et al., 2025). These limitations highlight the need for careful design, responsible use, and strong policy frameworks to ensure that AI tools support learning without introducing unintended harms.

In their review, Adako et al. (2025) emphasize that AI holds considerable promise for enhancing education for children with autism spectrum disorder (ASD), but its implementation faces multiple challenges. Ethical concerns, including consent, data privacy, and responsible use, are central, while algorithmic bias—often resulting from homogeneous training data—can misinterpret autistic behaviors or reinforce stereotypes. Accessibility barriers and the diverse learning needs of students with ASD further complicate effective implementation, highlighting the need for adaptive, inclusive, and transparent AI tools to ensure equitable and effective educational outcomes.

Similar limitations are evident in ADHD assessment and management. AI tools in this context face issues of bias and discrimination, particularly when training datasets are unrepresentative, which can reduce model accuracy for marginalized populations. Privacy concerns are also prominent, as these systems often collect sensitive personal information—including location, medical history, and behavioral data—that may be misused without proper consent. Additionally, the lack of transparency and interpretability in AI predictions can hinder clinicians' understanding of model outcomes. Incorporating clinician input and providing explanations through knowledge-based visualizations may improve both transparency and trust in AI-assisted ADHD detection (Rahman, 2023).

Extending these observations to dyslexia, a recent scoping review by Yap et al. (2025) identifies parallel challenges in AI-based dyslexia detection and support. Key issues include limited, imbalanced, or inconsistent datasets that reduce model accuracy and generalizability, particularly across diverse linguistic contexts. Accessibility challenges—such as inadequate infrastructure, high costs, and the digital divide—disproportionately affect learners in low-resource settings. Bias and validity concerns further complicate AI implementation, as homogeneous training data and poor image or text quality can lead to inaccurate or discriminatory outcomes. Moreover, balancing AI support with professional expertise is critical, since over-reliance on AI can undermine educators' nuanced judgment. Finally, transparency in AI decision-making remains a persistent barrier; the opaque processes of many deep learning models limit users' understanding and trust, challenging ethical accountability and effective integration in educational settings.

5. Conclusion

The integration of AI into inclusive education offers significant potential to transform learning experiences for neurodivergent students. AI-powered tools—including intelligent tutoring systems, speech and language technologies, chatbots, and gamified applications—can provide personalized, adaptive, and engaging support tailored to the diverse needs of learners with ASD, ADHD, and dyslexia. These technologies have the capacity to enhance screening, assessment, and behavioral interventions, promoting more equitable and effective educational outcomes. However, the promise of AI is tempered by substantial challenges, such as ethical considerations, data privacy risks, algorithmic bias, and disparities in access to technology. Addressing these issues requires careful system design, ongoing human oversight, and policy frameworks that prioritize inclusivity and equity. Future research should focus on refining AI interventions, ensuring transparency, and evaluating long-term outcomes to maximize their benefits while minimizing potential harm. Overall, AI represents a powerful tool for supporting neurodivergent learners, but its effective implementation depends on balancing technological innovation with ethical, practical, and educational considerations.

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