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Artificial Intelligence Applications for Students with Learning Disabilities: A Systematic Review

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ABSTRACT

This review study endeavors to elucidate the utilization of artificial intelligence (AI) in assisting students with learning disabilities (SWLDs). Among the 16 studies examined, dyslexia was the primary focus in 10 instances, with only one study concentrating on dyscalculia, and the remainder addressing learning disabilities in a broader context. Notably, only half of the studies targeted school-age children. Across these studies, seven distinct categories of AI applications were identified, encompassing adaptive learning, facial expression analysis, chatbots, communication aides, mastery learning systems, intelligent tutoring systems, and interactive robots. Among these, adaptive learning emerged as the most prevalent. Employing the SAMR-LD (Substitute, Augment, Modify, Redefine - Learning Disability) model, it was discerned that AI has been applied in diverse capacities to support SWLDs, with instances observed across substitution, augmentation, modification, and redefinition levels. While the findings underscore the potential of AI in aiding SWLDs, the limited number of empirical studies also highlights substantial gaps, indicating the necessity for further research into AI's broader role beyond mere identification and diagnosis of learning disabilities in this population.

Key words learning challenges, synthetic intelligence, developmental reading disability, number dyslexia, tailored education, technology integration model for learners with disabilities

INTRODUCTION

The global prevalence of learning disabilities has surged to approximately 79.2 million individuals, a figure that continues to rise steadily (UNICEF, 2021). These disabilities significantly impact various cognitive domains including listening, speaking, scientific reasoning, reading, writing, spelling, and mathematical abilities, necessitating substantial provisions for special education. In the United States alone, over 15% of public school students, around 2.3 million, are enrolled in special education programs due to learning disabilities, with even greater demands in countries with lower socio-economic development (National Center for Education Statistics, 2022). Students with learning disabilities consistently face challenges in academic performance, evidenced by their lower scores across subjects such as reading, science, and mathematics (Asghar et al., 2017). In addition to academic struggles, individuals with learning disabilities encounter emotional and social difficulties (Ouherrou et al., 2019). Research underscores heightened negative emotional experiences, including depression and loneliness, among students with learning disabilities compared to their non-disabled peers. Thus, addressing the academic needs of students with learning disabilities is pivotal for fostering their social and emotional well-being. Particularly in STEM disciplines, the impact

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of learning disabilities is pronounced due to the complex cognitive demands involved in processing multimodal information essential for learning (Asghar et al., 2017). While educators strive to support these students, meeting the diverse needs of each individual with a learning disability presents formidable challenges. Advanced tools such as Artificial Intelligence (AI) applications offer promising avenues for identifying students' unique requirements and devising tailored strategies to address them effectively. The integration of AI in supporting individuals with learning disabilities has been a subject of research for several years, primarily focusing on diagnosis and intervention (Drigas & Ioannidou, 2013). Notably, AI has demonstrated utility in screening for dyslexia and other learning disabilities, as well as in automating tasks such as essay scoring and identifying reading and writing difficulties (Drigas & Ioannidou, 2012). However, existing studies predominantly concentrate on diagnostic aspects, underscoring the need to expand AI applications towards interventions tailored to the specific learning needs of individuals with disabilities (Rauschenberger et al., 2019; Rello et al., 2018; Zvoncak et al., 2019). Intelligent tutoring systems, for instance, offer potential avenues for providing personalized feedback, speech therapy, and fostering social skills development (Drigas & Ioannidou, 2012, 2013). As advocates for equitable educational opportunities emphasize, further exploration into the integration of AI technologies to support learning for individuals with disabilities is imperative (Zhai & Nehm, 2023). This study endeavors to systematically explore the existing literature to elucidate the diverse applications of AI in supporting individuals with learning disabilities beyond mere screening and diagnosis. Specifically, the study aims to delineate how AI can facilitate tailored support for students already identified as having learning disabilities, addressing the following research inquiries:

- What AI advancements have arisen over the past 15 years to assist students with learning disabilities?
- How have these AI innovations been implemented within classroom environments to provide support for students facing learning disabilities?

INDIVIDUALS EXPERIENCING LEARNING DISABILITIES

Learning disabilities do not include any learning issues that may be caused by visual, auditory, emotional, or motor disabilities. Instead, learning disabilities, also referred to as neurodevelopmental disorders, are caused by genetic or neurobiological factors that change brain functions. It excludes any learning difficulties that might result from adverse cultural, environmental, or financial circumstances (Learning Disabilities Association of America, n.d.; Individuals with Disabilities Education Act, 2007). One important piece of American legislation, the Individuals with Disabilities Education Act, defines learning disability precisely.

Impairment in one or more of the fundamental psychological processes involved in comprehending or using language, either spoken or written, which can show up as an imperfect capacity for listening, thinking, speaking, reading, writing, spelling, or performing mathematical computations. These disorders include dyslexia, minimal brain dysfunction, brain injury, perceptual disabilities, and developmental aphasia. (Paragraph 10 of the Individuals with Disabilities Education Act, 2007). According to the Learning Disabilities Association of America (n.d.), learning disabilities are processing issues that affect not only fundamental learning abilities like reading, writing, and math but also organizational skills, scientific reasoning, attention, and long- or short-term memory. Learning disabilities that affect various learning domains have also been classified according to domains. For example, dyslexia (which impacts reading and related language-based processing skills), dysgraphia (which affects and enhance their emotional and social development. Büttner and Hasselhorn (2011) discovered that these performances related to learning disabilities cannot be explained by outside causes. Researchers have also discovered that illnesses other than learning difficulties can cause learning problems. For instance, attention deficit disorder (ADD), autism spectrum disorder (ASD), and Learning disabilities does not include Attention Deficit Hyperactivity Disorder (ADHD). On the other hand, kids that fit under both categories may also have a learning problem. Academic performance is clearly impacted for SWLDs, and this impact cannot be attributed to outside variables like inadequate education or a physical impairment. This suggests that students with SWLDs do not require a physical accommodation and that their difficulties in the classroom cannot be attributed to subpar teaching. Rather, SWLDs require customized.

ARTIFICIAL NEURAL NETWORKS FOR LEARNING DISORDERS

The field of artificial intelligence (AI) has been under discussion for decades, yet there is still no consensus on its definition, leading to a multitude of interpretations across different domains. To address this ambiguity, Samoili et al. (2020) conducted a qualitative analysis of over 50 documents that define AI, culminating in an operational definition established by a high-level expert group. According to their findings, AI refers to software and hardware created by humans, which operate in either physical or digital realms. These systems perceive their environment through data acquisition, interpretation, reasoning, or information processing, ultimately making decisions to achieve specific goals (Samoili et al., 2020). The recent surge in interest and attention towards AI, particularly in academia and industry, can be attributed to the emergence of machine learning, a subcategory of AI. Machine learning enables machines to "learn" from "experience" and apply acquired knowledge to solve novel problems, akin to human learning processes. This advancement has garnered significant interest, leading to the development and application of various AI technologies and tools across numerous sectors, including education (Thompson et al., n.d.). In the realm of education, different AI technologies such as natural language processing, computer vision, chat robots, communication assistants, adaptive learning devices, facial expression recognition, intelligent tutors, interactive robots, and mastery learning devices are being developed and implemented. The diverse array of AI applications in education empowers educators to identify and address the unique challenges faced by students with learning disabilities, providing tailored support to meet their specific needs. In recent years, there has been a noticeable increase in literature focusing on the utilization of artificial intelligence (AI) to enhance outcomes for students with learning disabilities. A review study conducted by Poornappriya and Gopinath (2020) explored machine-learning applications aimed at predicting dyslexia and utilizing e-learning methods for learning and cognitive disorders. Among the 24 studies analyzed, six incorporated external AI-based tools to enhance learning outcomes. Specifically, four studies concentrated on providing personalized or customized learning experiences, one examined the impact of online learning activities, and one investigated general machine learning interventions. Notably, the majority of the reviewed studies (13 out of 24) primarily focused on screening, predicting, or diagnosing learning disabilities or difficulties. Poornappriya and Gopinath's (2020) findings highlight a significant emphasis in AI research for students with learning disabilities on predictive, screening, or diagnostic approaches, with comparatively less attention directed towards enhancing the learning experiences of these students, despite its paramount importance albeit complexity. This literature review diverges from the focus of Poornappriya and Gopinath's (2020) study by specifically examining research utilizing artificial intelligence (AI) to support students with learning disabilities (SWLDs) in areas beyond predicting, screening for, or diagnosing learning disabilities. While three studies reviewed by Poornappriya and Gopinath (2020) met the inclusion criteria for this review and are consequently included, the scope of this review extends to encompass a broader range of AI applications. Moreover, the level of integration or depth of intensity of AI technology varies across the studies examined.

The literature reviewed in this study reveals diverse AI applications and levels of integration, as delineated by Puentedura's (2006) SAMR Model.

Model for Integrating Technology in Learning for Individuals with Disabilities Technology alone cannot improve learning outcomes; rather, it is the users and the manner in which technology is utilized that drives change for learners. When employed purposefully and meaningfully, technology has the potential to support both students with and without disabilities in achieving higher academic success in the classroom. Conversely, if technology is not integrated or implemented correctly within a lesson or educational environment, it fails to enhance or support learning (Zhai, 2021). Therefore, it is essential to examine how AI technologies are integrated into specific learning activities to aid students with learning disabilities. Puentedura (2006) introduced the SAMR model, which stands for Substitute, Augment, Modify, and Redefine, as a valuable framework for comprehending the integration of technology in learning. Originally designed to assess the transformative nature of online learning, the SAMR model has proven to be effective in analyzing technology integration across various educational contexts, including mobile learning (Zhai et al., 2019). By offering clear definitions of technology integration levels, the SAMR model enables educators to discern the extent to which technology can transform and enhance learning experiences, moving beyond mere replication of traditional teaching methods (Terada, 2020). The SAMR model, developed by Puentedura (2006), posits that higher levels of technology integration correlate with increased student achievement. This model delineates technology integration into four progressive levels: substitution, augmentation, modification, and redefinition. In the substitution level, technology serves as a direct replacement for a traditional learning practice without altering its functionality. Augmentation involves technology substituting for a learning practice while enhancing its functionality. Modification occurs when technology significantly redesigns a learning practice. The highest level, redefinition, represents technology's ability to facilitate the creation of entirely new learning tasks that were previously unattainable in a traditional classroom setting. It is at the modification and redefinition levels where learning undergoes transformative changes with technology. Here, technology not only substitutes traditional learning tasks but also enables innovative and more integrated approaches to learning in the classroom. The SAMR Model served as the foundational framework for our study, enabling us to examine the integration of technology, particularly AI technology, within learning activities aimed at supporting and enriching the learning experiences of students with learning disabilities (SWLDs). We specifically tailored the SAMR model to the context of SWLDs by developing the SAMR-LD model, which focuses on how technology, particularly AI, is integrated to transform learning for this specific student population. Unlike the conventional SAMR model, SAMR-LD explicitly addresses the integration of technology for the benefit of SWLDs. Given the diverse learning needs of students, the integration of technology for learning may differ between students with and without learning disabilities. SAMR-LD is specifically designed for the latter group, enabling us to analyze how AI technologies are employed to enhance learning experiences for SWLDs. While we retained the same level names from the original SAMR model, the significance of these levels has been redefined within SAMR-LD to better suit the context of supporting SWLDs. At the substitution level of integration within SAMR-LD, AI technology may replace existing learning practices without offering significant functional improvements to support SWLDs. For instance, this could involve using AI to analyze facial expression data of SWLDs, providing educators with surface-level insights such as student engagement levels (Abdul Hamid et al., 2018b). At the augmentation level of integration within the SAMR-LD model, AI serves as a substitute for existing learning practices, but with notable functional enhancements tailored to support SWLDs. For instance, AI technologies can enable SWLDs to customize the format of text, such as chunking or reading aloud (Rajapakse et al., 2018). While this may initially appear as a substitution, it's crucial to consider the specific needs of SWLDs. For students without learning disabilities, having text read aloud might be a mere substitution. However, for SWLDs who encounter challenges in reading decoding or comprehension, this functionality constitutes augmentation, as it offers additional support that is particularly beneficial for their learning needs. In essence, the substitution and augmentation levels within the SAMR-LD model are viewed as enhancements to the learning process (Terada, 2020). At the modification level, AI is utilized to redesign learning activities with substantial functional improvements specifically aimed at supporting SWLDs. For example, AI can analyze the specific type of learning disability a SWLD has and subsequently recommend personalized learning strategies (Sharif & Elmedany, 2022). This could involve the AI system generating a comprehensive report outlining strategies that educators or students could employ to support learning. Such an approach represents a significant advancement in learning activities, as without this technological intervention, identifying personalized learning strategies would require extensive teacher support and time to understand the student's disability and devise tailored approaches. At the redefinition level, which represents the pinnacle of integration within the SAMR-LD model, AI is utilized to not only redesign learning activities but to do so in a manner that transcends what is achievable in a traditional learning setting, specifically to support SWLDs. An instance of AI functioning at the redefinition level involves its use in identifying a SWLD's personalized learning style and subsequently adapting the learning material accordingly as an output to the SWLD (Zingoni et al., 2021). Both modification and redefinition levels of AI involve identifying the personalized learning style and sometimes even the disability of the user. However, the distinction lies in the actions taken by AI at each level. At the modification level, AI provides strategies that either the user or the teacher must implement, whereas at the redefinition level, AI autonomously adapts the material to match the user's needs, offering content and activities that have been tailored accordingly. For example, at the modification level, AI may suggest the incorporation of visuals to support student learning, while at the redefinition level, it would go a step further by adapting the content material to include visual support directly. Modification and redefinition represent transformative stages of learning (Terada, 2020). As one progresses through the levels of integration in both the SAMR and the modified SAMR-LD model, technology becomes increasingly ingrained within the learning process, ultimately leading to a total transformation of learning that surpasses what would be feasible without technology.

Methodology to conduct this systematic literature review, we followed a structured three-stage procedure: a) Initial Identification: In this stage, we identified relevant literature based on their titles and abstracts, ensuring that they aligned with the scope of our review. b) Detailed Examination: Once the initial selection was made, we thoroughly read the selected literature to gain a deeper understanding of their content and relevance to our study. c) Analysis: After comprehensively reviewing the literature, we analyzed each piece using a predefined coding scheme. This scheme facilitated the systematic categorization and evaluation of the key findings, themes, and methodologies presented in the literature. This systematic approach ensured the rigor and consistency of our literature review process, enabling us to effectively synthesize and interpret the findings from a diverse range of sources.

LITERATURE REVIEW

To identify relevant literature, we initially gathered articles from three databases: Web of Science, ProQuest, and Google Scholar. The search terms used were: ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND ("learning disabilit*" OR "learning disorder" OR "learning difficult*" OR "dyslexia" OR "dyscalculia" OR "dysgraphia"). We focused on the last fifteen years, extending slightly to ensure all significant studies were captured. The search was conducted in June 2022. Web of Science yielded 375 articles, while ProQuest returned 6246. From Google Scholar, we included the first 100 results sorted by relevance, considering the significant overlap with the other databases. This process resulted in a total of 6,721 articles, including their titles and abstracts, for the initial screening phase.

Selection of Relevant Literature: Screening Process

Establishment of Selection Criteria: Focusing Scope and Targeting Research. In order to address our research inquiries effectively, we devised a set of seven inclusion and exclusion criteria aimed at refining our focus and pinpointing relevant research (refer to Table 1). We specifically concentrated on scrutinizing journal articles and conference proceedings to ensure comprehensive coverage of substantial contributions within the field. Moreover, our review exclusively considered publications available in English, ensuring accessibility to the authors. Additionally, we emphasized the incorporation of AI technology in the studies under examination. Furthermore, we delimited our investigation to studies that primarily addressed the support of students with learning disabilities, excluding those focusing on other types of disabilities. Furthermore, we stipulated that the educational content related to reading, writing, or mathematics, catered to by the studies, must be in English. This criterion is crucial given the considerable variability in the challenges faced by students with learning disabilities across different languages. Notably, English exhibits a particularly intricate orthography with numerous irregularities and complexities, contributing to a comparatively slower learning pace (Seymour et al., 2003).

Table 1. Inclusion and Exclusion Criteria

Aspect	Study Inclusion Criteria
Publication Language	English
Type of Study	Review Study
Involvement of Artificial Intelligence	Present
Target Population	Students with learning disabilities
Language of Content Being Studied	English
Field of Study	Education
Focus of Study	Supporting, instructing, or assessing students with learning disabilities

English content, we ensured more precise comparisons among research findings. This approach is crucial because the manifestations of learning disabilities can vary depending on the language used, underscoring the importance of considering language-specific classifications (Poornappriya & Gopinath, 2020). Additionally, we excluded literature pertaining to the medical field or studies conducted in medical or clinical settings, as well as those necessitating medical equipment or personnel. This exclusion was intended to maintain the focus on identifying research applicable to classroom settings, where teachers or students with learning disabilities could benefit. Lastly, any literature solely focused on screening, diagnosing, or predicting learning disabilities was omitted for two main reasons. Firstly, a prior review has already explored the use of artificial intelligence in screening or diagnosing learning disabilities (Poornappriya & Gopinath, 2020). Secondly, our study's objective was to support learning and teaching for students already diagnosed with learning disabilities. Therefore, identifying or diagnosing a student's disability would not align with the goals of this study. Following the outlined inclusion and exclusion criteria, the primary author conducted a screening of the titles and abstracts of the 6721 sources initially identified. This screening process yielded a selection of 45 potential sources. Subsequently, these 45 studies underwent thorough examination, resulting in the identification of 16 studies that aligned with the inclusion and exclusion criteria established for this literature review. A graphical representation of the search procedure is presented in Figure 1.

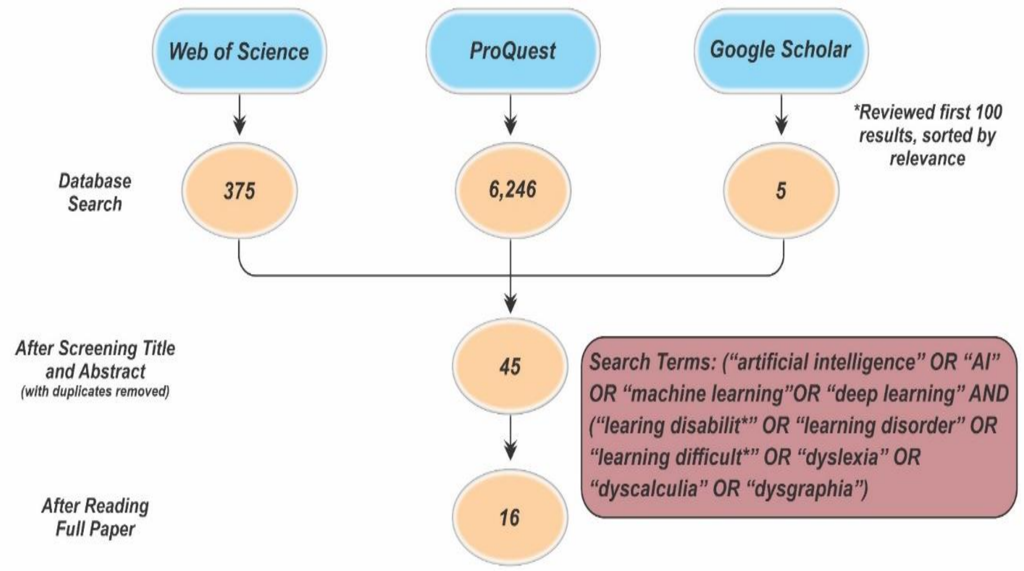


Figure 1. Literature search procedures

Examining the Literary Landscape: Key Insights and Findings

Analyzing the literature in this review involved both inductive and deductive approaches to address the research questions. To explore the landscape of AI applications developed over the past 15 years to support students with learning disabilities (SWLDs), an inductive approach was employed for the first research question. Collaboratively, the two authors, each bringing expertise in special education and AI, determined the codes representing various AI applications or uses. These codes were derived from the reviewed literature and categorized into seven distinct applications: adaptive learning, communication assistant, chat robot, mastery learning, facial expression analysis, interactive robot, and intelligent tutor. Although different papers may use varied terminology to describe these AI applications, the authors established consistent names based on the underlying technology described in the literature. Thus, the identified AI applications may not be explicitly labeled as such in every relevant article, but rather inferred from the descriptions provided. To address the second research question, which focused on integrating AI technologies, a deductive approach was adopted. Codes were assigned using the adapted SAMR Model of Technology Integration (Puentedura, 2006). Each study underwent classification based on the SAMR model, with the level of integration determined by the description of the AI technology employed. Both authors collaborated to assign the codes. These examples illustrate how the reliance on and necessity of AI technology in teaching practices increase with each level of integration. At the substitution level, AI technology is not essential and can be easily managed by a classroom teacher. Conversely, practices at the redefinition level heavily depend on AI technology and are nearly impossible to execute without it.

RESULTS

Out of the 16 studies meeting the inclusion and exclusion criteria, ten specifically targeted dyslexia, a learning disability characterized by reading difficulties like decoding or comprehension. Only one study focused on dyscalculia, a learning disability affecting mathematical skills, while the remaining five addressed learning disabilities more broadly. The reviewed studies predominantly centered on school-age children, constituting 50% of the total. The remaining studies focused on individuals aged 18 and above, including university students, or did not specify age groups. Geographically, the studies spanned various countries, including the United States, Malaysia, Pakistan, Italy, China, Greece, India, Morocco, Slovenia, Saudi Arabia, South Africa, Sri Lanka, the United Kingdom, and Switzerland. A comprehensive analysis of the literature has revealed seven distinct types of AI applications tailored to support students with disabilities: adaptive learning, facial expression analysis, chat robot assistance, communication aids, mastery learning platforms, intelligent tutoring systems, and interactive robots. This section provides an overview of each application type. Adaptive Learning: Students with learning disabilities (SWLDs) exhibit diverse learning needs, presenting additional challenges in educational support. Addressing this challenge effectively requires personalized learning assistance or adaptive learning materials. Among the 16 studies reviewed, five incorporated adaptive learning AI technologies designed for a wide age range (from under 5 years old to adulthood) and various disabilities (e.g., dyslexia, dysgraphia). Researchers have devised adaptive learning strategies utilizing AI to deliver tailored learning support through intelligent educational games (Flogie et al., 2020), intelligent tutoring systems (Kaser et al., 2013), and e-learning management platforms (Yaqoub & Hamed, 2019). For instance, Zingoni et al. (2021) developed the BESPECIAL software platform, integrating AI to comprehend the challenges faced by dyslexic students and offer personalized digital support methods and adapted learning materials. By leveraging inputs such as clinical reports, surveys, and psychometric test data, BESPECIAL's AI algorithms predict the individual needs of SWLDs (e.g., concentration levels, memory impairments) and recommend tailored strategies (e.g., concept maps, highlighted keywords) to address specific student requirements. Furthermore, the system equips teachers with student-specific strategies and best practices. Facial Expression Analysis: Fostering student engagement is a pivotal aspect of effective classroom support, particularly for students with learning disabilities (SWLDs). Utilizing facial expression analysis, researchers have explored methods to predict student engagement with educational content. Among the 16 studies reviewed, three incorporated AI technologies for facial expression analysis, all aiming to predict student engagement. These studies, involving students aged 7 to 12, employed various AI techniques such as bag of features (BOF) (Abdul Hamid et al., 2018b), speed-up robust features (SURF) combined with support vector machines (SVM) (Abdul Hamid et al., 2018a), and convolutional neural networks (CNN) (Ouherrou et al., 2019). The focus of these studies was on frontal face detection to assess SWLDs' engagement with educational content, with some employing deep learning to detect subtle facial cues. By analyzing facial expressions, these AI applications offer valuable insights to educators regarding student engagement levels and the effectiveness of different instructional activities. Chat Robot Assistance: With the widespread integration of chat robots in various digital platforms, students have become increasingly familiar with interacting with these AI-driven assistants. Inspired by the success of chat robots in customer service and troubleshooting, their application in education has gained traction. Two studies in this review employed chat robots to support SWLDs. One study utilized a smart assistant named Sammy, which engaged students through chat interactions to offer accessibility resources and personalized feedback (S. Gupta & Chen, 2022). Another study introduced a mobile application named ALEXZA, designed to support individuals with dyslexia by providing features such as text-to-speech, text chunking, highlighting, and other text manipulation tools (Rajapakse et al., 2018). ALEXZA's chatbot feature could also respond to user queries directly. Both studies leveraged chat robot technology with AI capabilities to enhance accessibility and support for students with reading-related learning disabilities. Communication Assistance: Students with learning disabilities often face challenges in verbal and written communication, which can impact their confidence and ability to express themselves effectively. Communication assistants serve as valuable tools in supporting these students in interacting with their peers and adults. Two of the 16 studies reviewed in this paper employed AI technology as communication assistants to aid students, specifically those with dyslexia. Wang et al. (2021) integrated AI into an Augmentative and Alternative Communication (AAC) device to facilitate verbal communication for students with dyslexia. Another study utilized Neural Machine Translation (NMT) to develop a tool called Additional Writing Help (AWH), which aimed to "translate" text with common dyslexia-related writing issues into more accessible formats while preserving elements commonly found in social media platforms, such as slang abbreviations and hashtags (Wu et al., 2019). Mastery Learning: AI-driven mastery learning focuses on leveraging machine learning algorithms to monitor user progress and provide targeted support to facilitate mastery of learning objectives through iterative practice and assessment. Two of the 16 studies examined in this review utilized mastery learning approaches to support students with dyslexia. Latif et al. (2015) employed machine learning to implement a relearning process for writing skills, allowing learners to practice similar skills until they achieved mastery before progressing to new learning segments. Similarly, Ndombo et al. (2013) proposed the Intelligent Assistive Dyslexia System (IADS), which leveraged machine learning to support reading and writing skills among students with dyslexia by continuously evaluating their learning progress. Machine learning facilitates targeted skill improvement among students with learning disabilities through iterative practice and evaluation processes. Intelligent Tutoring: Intelligent tutor technology employs dynamic machine learning models to identify an individual's learning difficulties and proficiency level, offering personalized learning strategies. Among the 16 studies reviewed, only one study (Sharif and Elmedany, 2022) explored this technology, presenting a proposed approach that is still under development. Sharif and Elmedany (2022) proposed leveraging machine learning to detect patterns in learners' reading, writing, typing, and other skills to provide feedback on their progress and suggest specific strategies for support. While the study is in its preliminary stages and the strategies offered by the technology are still being developed, it holds promise for supporting educators in delivering tailored assistance to students with learning disabilities. Interactive Robot: Interactive robots also employ machine learning methodologies to enable social interaction with students. Only one of the 16 studies incorporated an interactive robot as an AI technology to support students with learning disabilities. This study (Papakostas et al., 2021) focused on assessing student engagement using the interactive robot. Unlike chat robots, the social robot physically interacted with students and utilized multimodal machine learning techniques to predict their engagement levels in the classroom (Papakostas et al., 2021).

Revolutionizing Support: Integrating AI Technologies for Students with Disabilities AI Integration Levels for Students with Learning Disabilities: A SAMR Model Analysis"According to Puentedura's (2006) SAMR model, our examination indicates that AI applications have been utilized to enrich and revolutionize learning experiences for students with learning disabilities (SWLDs). Our review identified four studies categorized at the substitution level, six at the augmentation level, two at the modification level, and four at the redefinition level. The SAMR model suggests that higher levels of technology integration correlate with increased student achievements (as noted by Zhai et al., 2019). Therefore, it is anticipated that greater AI integration levels would be advantageous for student outcomes. This section delves into each integration level and provides illustrative examples. Table 3 presents a summary of the four integration levels along with an example. Of the four studies classified at the substitution level, artificial intelligence (AI) was employed to supplant or substitute an existing learning activity with technological assistance using AI technologies like facial expressions or an interactive robot to anticipate student engagement (Abdul Hamid et al., 2018a, 2018b; Ouherrour et al., 2019; Papakostas et al., 2021). While this data is crucial for educators to maintain the involvement of students with learning disabilities (SWLDs) in the lesson, these methods offer limited functional enhancements to conventional learning activities. For instance, Papakostas et al. (2021) involved ten elementary SWLDs in learning activities using a social chat robot NAO. They devised ten scenarios (e.g., Meet/greet, story listening and telling, and sentence structuring) to engage SWLDs in experiencing the respective activities in each scenario. The scenarios encompassed eight activity types: a) Meet/greet; b) Text decoding, comprehension, and reading; c) Phonology composition, decomposition, discrimination, and addition; d) Memory; e) Robot-child relaxation game; f) Story listening and telling; g) Sentence structuring; h) Strategic visual representation. On average, students spent 35 minutes on each scenario. Researchers gathered students' multimodal data (e.g., visual sensing, audio sensing, and feature extraction) and assessed the engagement levels of the 10 SWLDs during learning. Figure 2 below outlines the methodology employed by the researchers in this study. The researchers achieved a 93% accuracy rate in predicting student engagement, yet they also discovered the variability in definitions of engagement. This study utilized AI to gather data on and forecast student engagement. While this information is valuable for educators supporting SWLDs, it did not offer any functional enhancements specifically tailored to SWLDs or to the educators assisting them, such as providing precise methods to enhance engagement for SWLDs. Therefore, according to the SAMR-LD model, this level of AI application is classified at the substitution level.

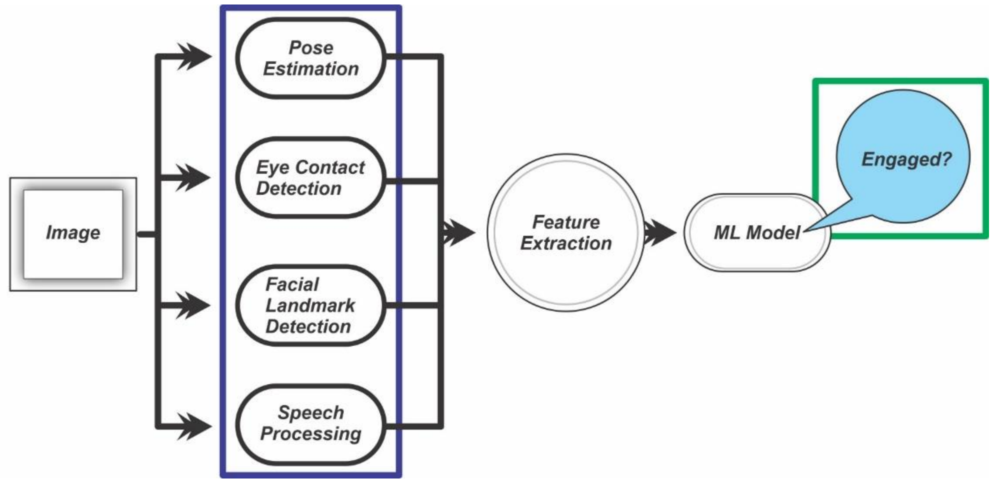


Figure 2. Diagram illustrating the Methodology with inputs highlighted in blue and outputs highlighted in green

Adapted from "Estimating children's engagement interacting with robots in special education using machine learning," by Papakostas et al. (2021), published in Mathematical Problems in Engineering. Copyright 2021 by George A. Papakostas et al.

Augmentation, conversely, entails substituting existing learning activities with human assistance but with functional enhancements. Six studies in this review were classified at the augmentation level, focusing on utilizing AI to improve the support provided to individuals with learning disabilities by educators or other adults. For instance, Rajapakse et al. (2018) observed that while numerous applications existed to aid individuals with dyslexia, these applications primarily focused on identifying dyslexia and offering long-term solutions rather than immediate day-to-day support. Consequently, they developed ALEXZA, an application employing AI to tailor learning content to the preferences of dyslexic individuals using the app. ALEXZA utilized an image pre-processing algorithm to enhance the quality of captured text and images, allowing users to manipulate and enhance the text through various features. These features included a) segmenting or chunking the captured text, b) altering text format (e.g., color, font), c) text-to-speech functionality, d) text highlighting, e) dictionary integration, f) word replacement using machine learning, and g) a Smart AI Assistant. Figure 3 below illustrates screenshots of the prototype application, demonstrating how scanned text can be manipulated within the app. While altering text, such as changing its format or having it read aloud, may appear to merely substitute printed text, for students with learning disabilities, particularly those with language-based issues like dyslexia, these features facilitate their learning (thus falling within the augmentation level of the SAMR-LD model). For a student grappling with a reading disability, the functionalities offered by the ALEXZA application enable them to access previously challenging content.

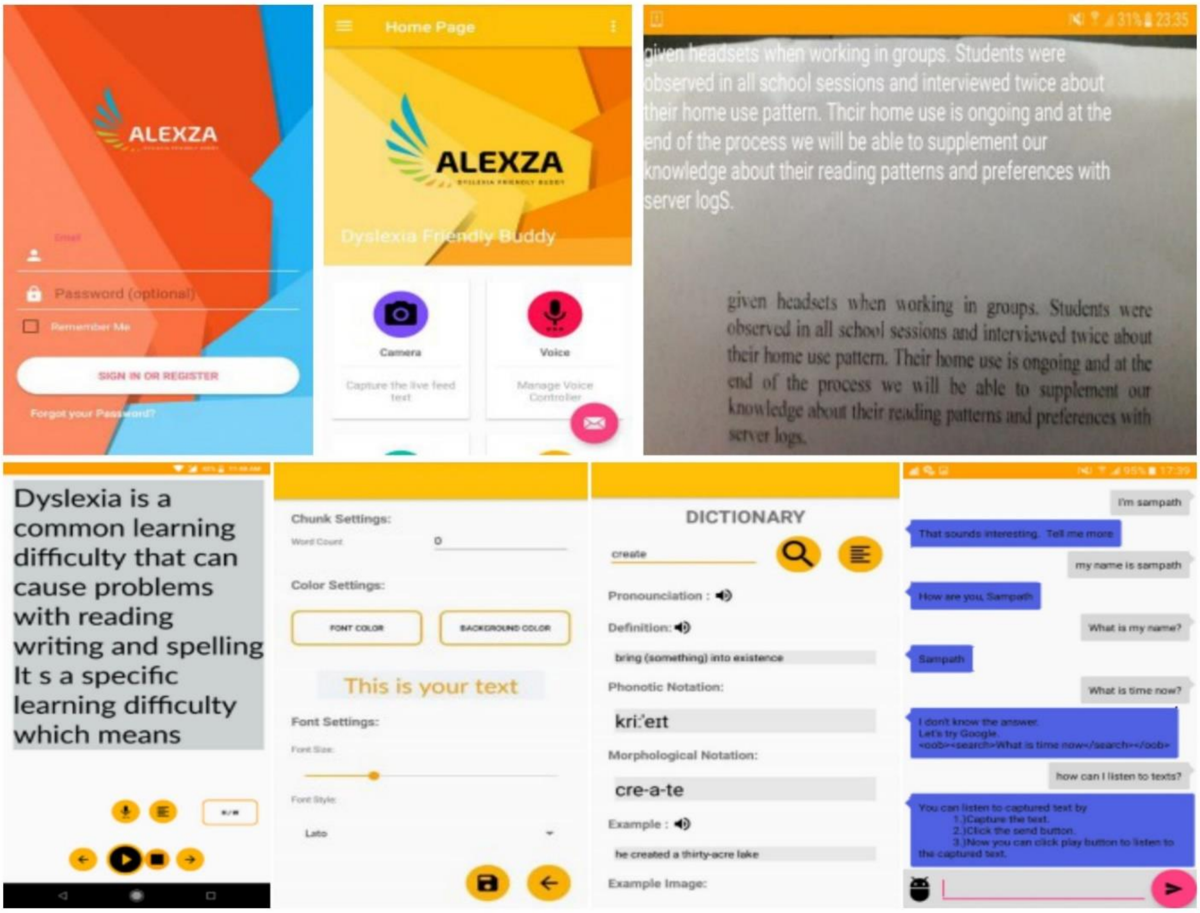


Figure 3: ALEXZA Application Prototype showcasing inputs highlighted in blue and outputs in green

Adapted from "ALEXZA: A mobile application for dyslexics utilizing artificial intelligence and machine learning Concepts" by Rajapakse et al. (2018), presented at the 2018 3rd International Conference on Information Technology Research (ICITR)

Another illustration of AI technology operating at the augmentation level of the SAMR-LD model is the Additional Writing Help (AWH), designed as a writing assistant for individuals with dyslexia. AWH proofreads text before posting on social media, focusing on common word errors made by dyslexic individuals while preserving slang, abbreviations, and other social media features (Wu et al., 2019). AWH effectively "translates" text with typical writing issues seen in dyslexia into error-free writing. This tool goes beyond the typical support provided by a classroom teacher, as it can assist a broader range of individuals with dyslexia and provide support at a faster pace and in greater depth, thereby enhancing the teacher's practice. Modification represents the third level of AI integration, involving the use of AI to redesign a learning activity with human assistance, resulting in significant functional improvements. Only two studies in this review were classified at this level. Sharif and Elmedany (2022) proposed a model that utilizes a dynamic machine learning approach to identify an individual's learning difficulties and subsequently recommend personalized learning strategies based on collected data and predictions. Their proposed model, depicted in Figure 4 below, integrates quantitative data like Electroencephalogram (EEG) data and qualitative data such as behavioral information gathered from interactions with psychologists. Moreover, Sharif and Elmedany's (2022) proposed model includes an ongoing process of identifying learning difficulties and recommending personalized strategies on a weekly or monthly basis, depending on the severity of individual needs. Their model exemplifies the modification level of AI integration, as it entails using AI to redesign teaching practices with substantial functional enhancements. An essential aspect of their model is the provision of individualized, personalized strategies tailored to each user's specific needs. This task poses significant challenges for classroom teachers, both in terms of the time required and the ability to generate such personalized strategies effectively (Figure 4).

Figure 4: Proposed model by Sharif and Elmedany (2022)

While teachers are capable of identifying individualized strategies for each student, this process is time-consuming and necessitates teachers to gather various forms of data and possess a broad range of support strategies. The highest level of AI integration, redefinition, involves redesigning a learning activity with human assistance to such an extent that it would be impossible without AI technology. Four studies in this review were categorized at the redefinition level of integration. Zingoni et al. (2021) presented an example of AI technology at the redefinition level with their software platform BESPECIAL. This software utilizes clinical reports from experts and self-evaluation questionnaires from users to assess the problems they face while studying and helpful solutions. Initially, this AI technology would be considered at the modification level of integration as it identifies the user’s learning needs and matches tools and strategies accordingly. However, what elevates it to the redefinition level is the digitization of content. The BESPECIAL software not only identifies needs and individualized strategies but also adapts the material according to the user's needs and preferred learning style (Figure 5).

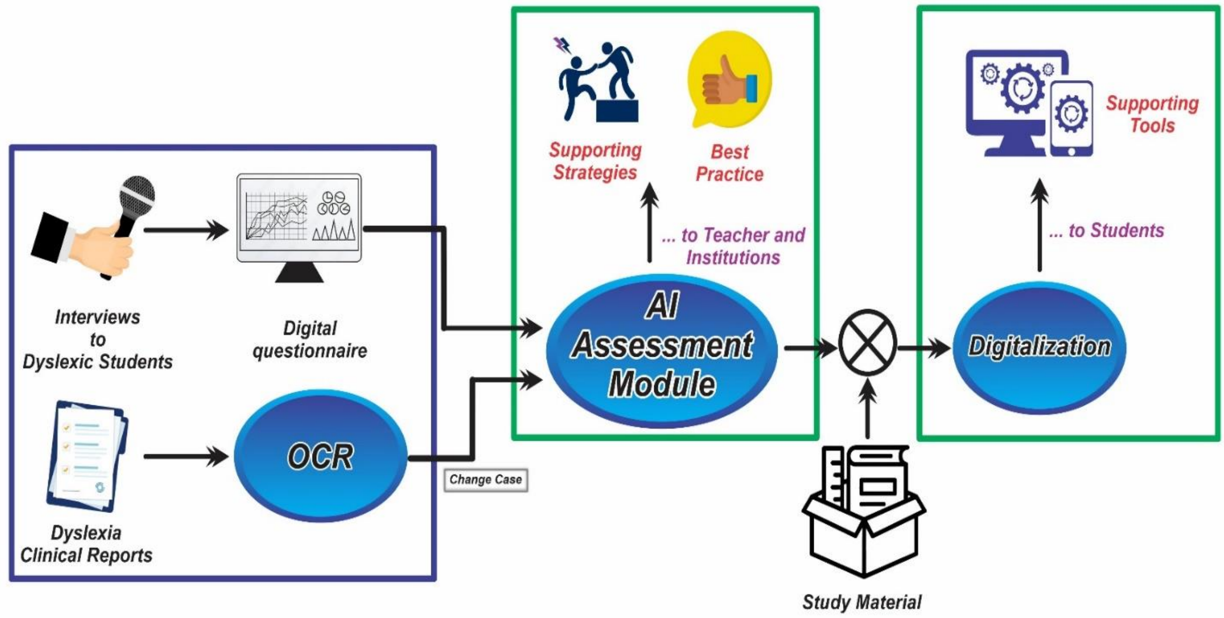


Figure 5: BESPECIAL Diagram with inputs in blue and outputs in green

Adapted from "Investigating issues and needs of dyslexic students at university: proof of concept of an artificial intelligence and virtual reality-based supporting platform and preliminary results" by Zingoni et al. (2021), in Applied Sciences, 11(10).

DISCUSSION AND CONCLUSION

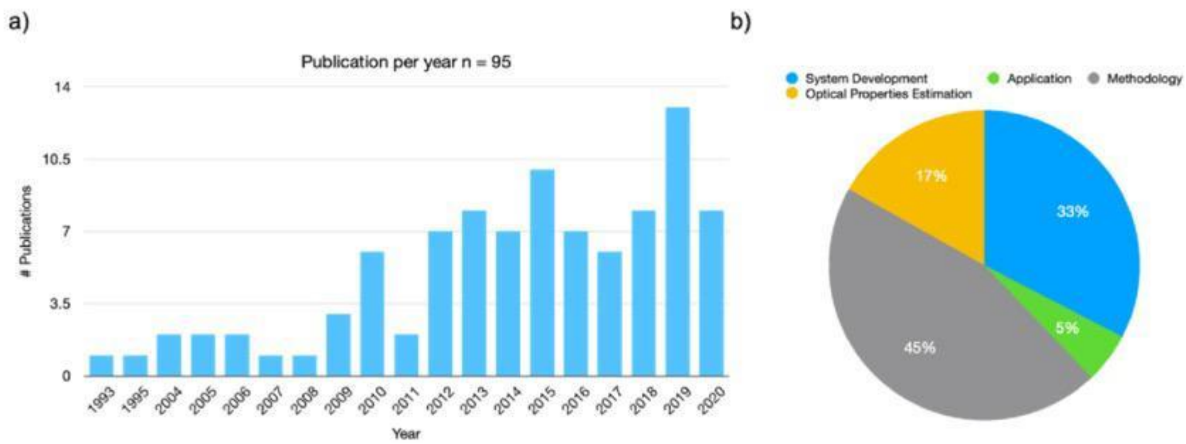
This review reveals a diverse range of AI applications employed to support the learning of students with learning disabilities (SWLDs), showcasing various ways in which these technologies are integrated into the learning process. Unlike studies focusing solely on diagnosing or identifying learning disabilities, our review specifically targets research on leveraging AI to support the learning process of SWLDs. Through this lens, our findings underscore the significant potential of AI in enhancing the learning experience for SWLD (Figure 5).

Further exploration and development in the realm of AI-driven support for SWLDs extend beyond mere identification and diagnosis of learning disabilities. There's a clear call for more research and empirical evidence to advance our understanding of how AI can effectively aid SWLDs in their learning journey. This review sheds light on the current landscape of AI applications tailored for SWLDs, with a specific focus on dyslexia. Out of the 16 studies examined, a significant portion concentrated on dyslexia, underlining a burgeoning interest in leveraging AI for supporting individuals with learning disabilities, albeit with a notable gap in research addressing dyscalculia. The review underscores the growing momentum in utilizing AI to assist learners with disabilities while highlighting the imperative for continued investigation in this domain. Moreover, the concentration of studies on school-age children, spanning from 7 to 12 years, underscores the critical need to cater to this demographic's educational needs. While this focus is promising in addressing the challenges faced by young learners, the inclusion of individuals above 18 years or unspecified age segments emphasizes the necessity for research encompassing a broader age spectrum. This broader approach is essential for comprehensively gauging AI's potential impact on the learning experiences of

SWLDs across different age groups. The delineation of seven distinct types of AI applications employed to aid students with SWLDs, encompassing adaptive learning, facial expression analysis, chat robots, communication assistants, mastery learning systems, intelligent tutors, and interactive robots, offers a comprehensive insight into the breadth of AI technologies utilized in this domain. Among these, adaptive learning emerged as the most prevalent, featured in five out of the 16 studies, underscoring the potential of AI to deliver tailored educational experiences crucial for the academic progress of SWLDs. The geographic diversity of the studies, spanning countries such as the United States, Malaysia, Pakistan, Italy, China, Greece, India, Morocco, Slovenia, Saudi Arabia, South Africa, Sri Lanka, United Kingdom, and Switzerland, signifies a burgeoning global interest in harnessing AI to support individuals with learning disabilities. Furthermore, the identification of diverse AI applications aimed at aiding SWLDs underscores the multifaceted approaches adopted to cater to this population's unique needs. Moreover, the application of the SAMR-LD framework, a modified version of Puentedura's (2006) SAMR model, to assess the integration of AI into learning activities for SWLDs furnishes a structured framework for understanding the spectrum of technology integration levels and their impact on student achievement. Analysis revealed that AI technologies were deployed in varied capacities to bolster the learning experiences of SWLDs, with studies categorized across four levels: substitution, augmentation, modification, and redefinition. This observation underscores the potential of AI to not only augment but also transform the learning trajectories of individuals with SWLDs, suggesting that higher degrees of AI integration may correlate with enhanced student outcomes (Table 3).

Table 3: AI Application Integration Levels for Supporting Students with Learning Disabilities

Integration Level	Description	Example
Substitution	Technology replaces an existing learning activity without enhancing functionality compared to human assistance for SWLDs.	AI technology provides teachers with basic insights into SWLDs, such as engagement metrics. (Papakostas et al., 2021)
Augmentation	Technology aids learning activities, surpassing human assistance for SWLDs by improving functionality.	AI technology serves as a writing assistant for dyslexic individuals, correcting word errors while preserving informal language features like slang and abbreviations common in social media. (Wu et al., 2019)
Modification	Technology redesigns learning tasks significantly improving functionality compared to human assistance for SWLDs.	AI technology generates tailored practice levels for SWLDs through adaptive tests, catering to individual needs and facilitating skill mastery. (R. Gupta, 2019)
Redefinition	The highest level of integration where technology transforms learning tasks in ways impossible in traditional environments for SWLDs.	AI technology identifies dyslexia type, discerns preferred learning styles, and adapts material accordingly for optimal learning experiences. (Yaquob & Hamed, 2019)



Graph 1: A1 Summary of literature reviewed

This review significantly enhances our understanding of the role of AI in bolstering the literacy and numeracy education of SWLDs, emphasizing the imperative for continued exploration in this field. The global representation of countries and the diverse array of AI applications employed underscore a burgeoning interest in leveraging AI technology to assist individuals with learning disabilities. Utilizing the adapted SAMR-LD model, the analysis provides a structured framework for assessing the impact of AI on student proficiency in reading, writing, and math. Moving forward, it is essential for research endeavors to delve deeper into the usability, feasibility, and efficacy of AI tools tailored for SWLDs. A comprehensive synthesis of findings in these domains will facilitate a nuanced understanding of how AI can be effectively harnessed to support the unique needs of SWLDs. Acknowledgement This content has been developed with the support of the National Science Foundation (NSF) under Grants No. 2101104 and 2138854. The opinions, findings, and conclusions expressed herein are solely those of the authors and do not necessarily reflect the views of the NSF.

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