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Leveraging Artificial Intelligence to Identify Students with Learning Challenges

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Abstract. Globally, over 79.2 million individuals are affected by learning disabilities, with a rising prevalence that challenges educational systems, especially in resource-limited settings. This study explored the effectiveness of artificial intelligence (AI)-based tools in identifying students with learning difficulties (SWLD) in Jordanian schools and investigated educators' perceptions toward these tools. Guided by the universal design for learning (UDL) and information processing theory (IPT), a mixed-methods research design was adopted. Data were collected between September and November 2024 through an online survey administered to 150 educational professionals, including teachers, school administrators, and policymakers. After excluding pilot respondents, 130 valid responses were analyzed, yielding an 87% response rate. Quantitative data were evaluated using descriptive and inferential statistics (multiple linear regression via SPSS), while qualitative responses underwent thematic analysis. Findings revealed that AI tools—particularly machine learning and natural language processing—were perceived as highly effective in the early identification of learning challenges. Additionally, educators' positive perceptions significantly

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predicted AI integration in schools, although concerns about ethical use and data security were noted. The study underscores the necessity of training and equitable access to AI technologies to support inclusive education. These results offer practical and policy-level implications for integrating AI into special education frameworks in Jordan.

Keywords: artificial intelligence; early identification; educational technology; learning difficulties; students

1. Introduction

Globally, over 79.2 million individuals live with learning impairments, with this number continuing to rise rapidly (UNICEF, 2021). Students with learning difficulties or disabilities (SWLD) often struggle across multiple domains, including auditory processing, reasoning, reading, writing, mathematics, and science, affecting their overall academic performance and school experience. These challenges are particularly pronounced in countries with limited educational resources. For instance, in the United States, approximately 2.3 million students, constituting over 15% of the student population, receive special education services for learning disabilities (LDs) (National Center for Education Statistics, 2024).

Beyond academic setbacks, SWLD often experience emotional distress in the form of despair, loneliness, and social isolation (Ouherrou et al., 2019). In this study, the acronym SWLD refers inclusively to students with either learning difficulties (such as dyslexia and dysgraphia) or diagnosed LDs, recognizing that while these terms are sometimes used interchangeably, they may differ slightly, depending on the context or diagnostic framework. Supporting these students effectively requires not only academic assistance but also emotional and psychological interventions (Panjwani-Charani & Zhai, 2023). In response to these challenges, educators have made continuous efforts to support SWLD. However, one of the most pressing issues remains the difficulty in identifying the specific needs of each individual student, particularly in large or under-resourced classrooms. Traditional diagnostic methods are often time-consuming, subjective, or inconsistent. Artificial intelligence (AI) offers significant potential to fill this gap.

AI technologies have long been recognized for their diagnostic, therapeutic, and adaptive learning capabilities. Tools powered by AI can assist in automatically grading essays, detecting reading and writing struggles, and even personalizing learning content (Drigas & Ioannidou, 2013). These capabilities are especially useful in STEM education, where foundational skills are essential (Asghar et al., 2017). However, most existing research focuses on Western contexts, with limited studies exploring how AI supports SWLD in Middle Eastern or developing countries, including Jordan. This study aimed to examine the role of AI in identifying SWLD in Jordan, while also exploring the perceptions of educators on its practical implementation. It further contributed to the literature by developing a tailored AI framework to support early identification and holistic support for SWLDs—not just for screening but also for ongoing academic and emotional support.

Thus, this study was guided by the following research questions:

1. How effective are AI-based tools in accurately identifying students with learning difficulties in Jordanian schools?
2. What are the perceptions of educators in Jordan regarding the role of AI in identifying students with learning difficulties?

2. Theoretical Framework

2.1 Universal Design for Learning

The universal design for learning (UDL) framework was developed in the early 1990s by David Rose and colleagues at the Center for Applied Special Technology (CAST). Rooted in cognitive neuroscience and educational psychology, UDL emerged from the broader concept of universal design in architecture, which promotes accessibility for individuals with disabilities. In applying these principles to education, UDL aims to eliminate barriers in the learning environment by designing curricula that accommodate all learners from the outset rather than retrofitting accommodations after difficulties arise (Rose & Meyer, 2002).

At its core, UDL is based on three primary principles: multiple means of engagement, multiple means of representation, and multiple means of action and expression (CAST, 2018). These principles align with how the brain processes information—affective, recognition, and strategic networks, respectively—and guide educators to present information in varied ways, offer diverse options for student interaction, and create multiple pathways for demonstrating learning. This neurocognitive foundation supports the understanding that learning variability is the norm, not the exception.

The relevance of UDL to the present study lies in its compatibility with AI-driven educational tools designed to support SWLD. For instance, adaptive learning platforms and intelligent tutoring systems operationalize the UDL principle of multiple means of representation by presenting instructional content in textual, audio, visual, or gamified formats tailored to the student's needs. Likewise, AI-powered communication assistants and writing support tools embody multiple means of expression, allowing SWLD to engage in learning through speech, text prediction, or symbol-based systems. Finally, the use of chatbots and interactive robots to personalize engagement reflects the call by UDL for multiple means of engagement, particularly for learners who may lack motivation or confidence due to previous academic struggles.

Contemporary scholarship continues to emphasize the integration of UDL with digital technology and AI. For example, Kumar and Wideman (2021) demonstrated that AI-infused UDL interventions significantly improved both access and outcomes for students with dyslexia and dysgraphia. These findings support the premise that AI tools, when developed in alignment with UDL, can bridge equity gaps by accommodating individual learning differences. Additionally, UDL has informed machine learning models that track learning progression and adapt instructional strategies, ensuring that interventions are both inclusive and evidence-based.

2.2 Information Processing Theory
Information processing theory (IPT) emerged in the mid-20th century as a foundational model in cognitive psychology, providing insight into how humans perceive, process, store, and retrieve information. The theory was primarily advanced by American psychologists George Miller, Donald Broadbent, Richard Atkinson, and Richard Shiffrin. In 1956, Miller's seminal work on the limitations of human short-term memory, often referenced as *The magical number seven, plus or minus two*, laid the groundwork for understanding memory capacity. This was later expanded by Atkinson and Shiffrin (1968) through their multi-store memory model, which conceptualized memory as comprising three distinct stages: sensory memory, short-term (working) memory, and long-term memory.

IPT likens the human mind to a computer system: information enters through input (sensory registers), is temporarily held and manipulated in working memory, and, if rehearsed or meaningfully encoded, is stored in long-term memory for later retrieval. Learning difficulties are often linked to breakdowns in one or more of these stages, such as inefficient encoding, limited working memory capacity, or challenges in information retrieval. These cognitive bottlenecks particularly affect SWLD, who may struggle with attention, processing speed, or organizing information meaningfully (Swanson & Jerman, 2007).

This theory is highly relevant to the present study, which explored how AI tools can support SWLD. AI-based interventions such as intelligent tutoring systems, adaptive learning platforms, and facial expression recognition tools can be understood through the lens of IPT (Mubin et al., 2017; Zhou, Wu, & Yang, 2022). These technologies aim to assist students in managing cognitive load, sustaining attention, and scaffolding memory processes. For instance, intelligent tutoring systems use real-time data to track how information is processed by students and adjust content delivery accordingly, thereby reinforcing encoding and storage in long-term memory (Holmes et al., 2019; Swanson & Jerman, 2007).

Furthermore, AI tools that offer multi-modal representations—such as combining text with audio or visual cues—help learners bypass limitations in one sensory channel, aiding in effective dual coding and retention (Barua et al., 2022). AI writing support tools, such as text predictors and grammar correctors, function as external cognitive aids that reduce processing demands in working memory, allowing learners to focus on higher-order skills such as idea generation and organization. These align with the emphasis of IPT on efficient information flow and cognitive strategy use (Drigas & Ioannidou, 2013).

Recent research continues to affirm the applicability of IPT in the AI and learning domain. For example, Zhou, Ziu, and Xu (2022) examined how machine learning algorithms can be used to detect real-time cognitive overload in students with dyslexia, providing timely interventions to support information encoding. Similarly, adaptive AI systems such as BE SPECIAL and the Intelligent Assistive Dyslexia System (IADS) are designed to optimize memory processes and reduce mental effort, particularly for learners with deficits in executive functioning and attention regulation.

3. Literature Review

3.1 Overview of Learning Disabilities

LDs encompass a range of neurological conditions that interfere with the acquisition, retention, organization, understanding, or application of verbal and nonverbal information (Al-Mahrezi et al., 2016). These conditions occur despite average or above-average intelligence and are not caused by emotional disorders, cultural differences, or socio-economic disadvantage (Dominguez & Carugno, 2023). LDs are diagnosed based on a marked discrepancy between a student's actual academic performance and the level expected given their cognitive capabilities. Research indicates that genetic and environmental influences are widely recognized contributors to LDs. Unlike sensorimotor impairments such as hearing or vision loss, LDs originate from neurological and cognitive processing challenges (Al-Mahrezi et al., 2016). For example, children with chronic health conditions show almost twice the incidence of LDs compared to their healthy peers. In the United States, the lifetime prevalence is estimated at 10% (Dominguez & Carugno, 2023).

Various LDs exist that affect students' ability to learn. *Dyslexia* is the most prevalent LD, comprising approximately 80% of all diagnosed cases. It stems primarily from deficits in phonological processing, affecting decoding, auditory processing, and reading fluency. Children often begin with decoding challenges and progress to poor comprehension, leading to avoidance of reading tasks (Kohli et al., 2018). *Dyscalculia* involves difficulties with numerical concepts, such as executing multi-step calculations, understanding symbols, or solving word problems. These skills depend on a combination of number sense, language processing, and visual-spatial reasoning (Dominguez & Carugno, 2023). *Dysgraphia* is characterized by illegible handwriting, poor spelling, and difficulty with written expression, even when basic motor skills are intact. Individuals may struggle with syntax, grammar, and clarity of thought in written language (McCloskey & Rapp, 2017). *Nonverbal learning disabilities (NVLDs)* affect abilities related to visual-spatial skills, problem-solving, and interpreting nonverbal social cues. These conditions often emerge in later elementary years and can resemble traits of autism spectrum disorder, though NVLDs are not recognized in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) (Kohli et al., 2018).

LDs often co-occur with other neurodevelopmental or psychiatric disorders such as ADHD, anxiety, obsessive-compulsive disorder, and oppositional defiant disorder. Studies show that between 20% and 70% of children with mental health diagnoses also have an LD (Dominguez & Carugno, 2023). Both intrinsic (neurological, genetic) and extrinsic (school, family) factors influence the expression and severity of LDs. Recent neuroscientific studies offer insights into these disorders. For example, individuals with dyslexia often exhibit decreased activity in the brain's left hemisphere during reading tasks. Other hypotheses suggest that learning difficulties may be linked to irregularities in corticostriatal networks, which influence communication and language development (Moreau & Waldie, 2015).

Emerging technologies, particularly AI, are beginning to influence how LDs are identified and addressed. Studies by Zhai and Nehm (2023) and Panjwani-

Charani and Zhai (2023) highlight the potential of AI in early diagnosis, adaptive learning, and emotional support for SWLDs. AI applications can now screen for dyslexia using natural language processing (NLP), track student performance, and personalize interventions based on cognitive profiles—offering new tools grounded in UDL and IPT. Despite these advancements, existing literature lacks comprehensive studies on the effectiveness of AI tools in non-Western educational systems, especially in low-resource settings such as Jordan. This study seeks to fill this gap by exploring the intersection of AI, educational practice, and LD identification within Jordanian schools.

3.2 Students with Learning Disabilities Processes (SWLDP)

LDs are neurodevelopmental disorders that interfere with the acquisition and use of language, reading, writing, reasoning, or mathematical abilities. These disorders are not the result of visual, auditory, or motor impairments, emotional disturbances, or external environmental factors such as cultural or socio-economic conditions (Rai et al., 2023). The Individuals with Disabilities Education Act (IDEA) defines LDs as disorders in one or more of the basic psychological processes involved in understanding or using spoken or written language (U.S. Department of Education, 2004). These may manifest as difficulties in listening, thinking, speaking, reading, writing, spelling, or mathematical problem-solving. The Learning Disabilities Association of America (LDA, 2022) classifies LDs into several domains. These include dyslexia, dysgraphia, dyscalculia, and NVLDs and have been explained in the previous section.

Processing difficulties associated with LDs impact both foundational skills (e.g., reading, writing, arithmetic) and higher-order cognitive functions such as organization, attention, memory, and scientific reasoning (LDA, 2022). SWLD often experience low self-esteem, increased behavioral challenges, and social difficulties, all of which may compound academic struggles. Though attention-deficit/hyperactivity disorder (ADHD) and attention-deficit disorder (ADD) are not classified as LDs, students diagnosed with these conditions frequently exhibit co-occurring learning challenges. However, LDs are neurologically based and not influenced by external conduct or behavioral issues (Buttner & Hasselhorn, as cited in Rai et al., 2023).

Recent research underscores the growing importance of AI in identifying and supporting SWLD. AI systems now leverage NLP, pattern recognition, and machine learning to detect signs of dyslexia or arithmetic difficulties through automated writing analysis, performance tracking, and diagnostic algorithms (Panjwani-Charani & Zhai, 2023; Zhai & Nehm, 2023). These technologies align with UDL principles, offering scalable and adaptive interventions personalized to each student’s learning profile. Despite this potential, many schools—especially in developing regions—lack the capacity or awareness to implement AI tools effectively. This gap highlights the importance of examining the application of AI within diverse educational systems such as those in Jordan, where educators require both training and tools to integrate these innovations.

3.3 AI Tools for Identifying Students with Learning Disabilities

Over the years, no clear definition of AI has been formulated. Nonetheless, experts have concluded that AI involves both the hardware and software produced by humans to function in both the virtual and real worlds by sensing the environment through data gathering and processing and choosing the best action to accomplish the goal (Samoili et al., 2021). This progress has enabled robots, just like humans, to learn by experience and use that knowledge to address societal issues (Zhai et al., 2020). The ability of machines to learn in both business and academia has contributed immensely to the popularity of AI. Adaptive learning technologies, interactive robots, chatbots, communication assistants, and many more are part of AI applications in education to identify and help with the problems faced by SWLDs.

In recent years, there has been an increase in research to address the problem faced by children with dyslexia. In their review of 24 studies, Poornappriya and Gopinath (2020) found that 6 investigations considered external connection based on AI to enhance learning. Of these, four focused on personalized instruction, one examined the effects of online education, and one addressed machine learning treatments generally. The primary emphasis of the bulk of the examined studies (n = 13) was the screening, prediction, or diagnosis of learning difficulties or disorders. A significant focus of studies on AI for SWLD, according to Poornappriya and Gopinath (2020), is the identification, evaluation, and forecasting of potential LDs. Improving learning outcomes for children with learning difficulties has received very little attention despite being the most crucial and challenging subject of study. By excluding studies that attempt to anticipate, screen, or diagnose learning problems, this literature review departs from Poornappriya and Gopinath's (2020) efforts to aid children with these conditions in other contexts. Also different is the level of AI integration or intensity. Table 1 presents a summary of the studies reviewed in this paper examining how AI has been applied to identify and support SWLD.

Table 1: AI applications in identifying and supporting students with learning disabilities

Studies	AI application	AI technologies	Type(s) of learning disability detected	How the AI supported SWLDs
Papakostas et al. (2021)	Interactive robot	Multimodal machine learning	Learning disabilities in general	This type of AI technology involves a physical robot that can interact with a user
Sharif and Elmedany (2022)	Intelligent tutor	Machine learning	Learning disabilities in general	This AI technology identifies a user's learning style or needs and recommends learning strategies
Wang et al. (2021) **Wu et al. (2019)**	Communicat-ion assistant	Neural machine translation; NLP; computer vision	Dyslexia	This type of AI technology supports users in written and oral communication

Abdul Hamid et al. (2018a, 2018b) **Ouherrou et al. (2019)**	Chat robot	Machine learning	Dyslexia and learning disabilities in general	AI technology uses an intelligent robot via a chat feature to support users
Latif et al. (2015) **Ndombo et al. (2013)**	Mastery learning	Machine learning	Dyslexia	This type of AI technology supports the user in mastering a learning concept through repetition or relearning until they have achieved mastery
Abdul Hamid et al. (2018a, 2018b) **Ouherrou et al. (2019)**	Facial expression	Bag of features (BOG) image classification; speed-up robust features (SURF); support vector machines (SVM)	Dyslexia and learning disabilities in general	AI technology utilizes facial expression data to provide information on student engagement
Alsobhi and Alyoubi (2019) **Flogie et al. (2020)** **Käser et al. (2013)**	Adaptive learning	Naive Bayes classifier; machine learning; Bayesian network	Dyslexia, dyscalculia, and learning disabilities in general	AI technology adapts the material to meet the user's learning style or needs
Gupta (2019) **Gupta and Chen (2022)**	Adaptive learning	Digital tool	Dyslexia	Improving instruction by having students practice words, numerals, and alphabets while considering their choice of digital resources
Zingoni et al. (2021)	BE SPECIAL	Virtual reality	Dyslexia	Effective support strategies included clear material layout, use of images, and taking pauses during lessons, emphasizing human interaction over machine-based solutions
Panjwani-Charani and Zhai (2023)	Dyslexia adaptive learning model	Advanced machine learning	Dyslexia	High accuracy rates range from 97% to 97.8%.

The review of the studies presented in Table 1 highlighted various AI applications that are used in supporting SWLD, including adaptive learning, facial expression recognition, chatbots, communication assistants, mastery learning systems, intelligent tutors, and interactive robots.

Adaptive learning – Adaptive learning platforms personalize educational content to meet each student's needs. These systems, grounded in UDL, support diverse cognitive and sensory profiles. AI-based tools such as intelligent tutoring systems, e-learning platforms, and serious educational games respond to students' real-time performance (Flogie et al., 2020; Käser et al., 2013; Yaqoub & Hamed, 2019). The BE SPECIAL platform provides personalized learning paths for students with dyslexia by analyzing their dyslexia reports and psychometric test results (Panjwani-Charani & Zhai, 2023; Zingoni et al., 2021). These tools assist teachers in selecting appropriate strategies for individual learners.

Facial expression – Facial analysis is another AI tool used to assess student engagement. Researchers have used machine learning techniques such as support vector machines (SVM), convolutional neural networks (CNN), bag of features (BOF), and speeded-up robust features (SURF) to detect facial expressions indicative of student attention or confusion (Abdul Hamid et al., 2018a, 2018b; Ouherrou et al., 2019). These applications enable instructors to adjust content delivery in real time to maintain student focus, especially among SWLD.

Chat robot – Chatbots offer accessible, real-time interaction for SWLD by answering questions, providing guidance, and giving feedback. Leveraging conversational AI, these systems mimic human dialogue to enhance accessibility and personalized support. Gupta and Chen (2022) demonstrated how chatbots offer flexible resources to meet diverse student needs, while Rajapakse et al. (2018) showcased smartphone assistants that read aloud for dyslexic users.

Communication assistant – Students with dyslexia or expressive language difficulties often struggle with verbal and written communication. AI-powered augmentative and alternative communication (AAC) tools help bridge these gaps. The additional writing help (AWH) system, based on neural machine translation (NMT), provides real-time writing assistance tailored for users with LDs (Wang et al., 2021; Wu et al., 2019). These tools improve students' confidence and expressive capacity.

Mastery learning – Mastery learning is used to help pupils with reading impairments (Latif et al., 2015). The Intelligent Assistive Dyslexia System (IADS) model by Ndombo et al. (2013) also pushed for machine learning. Developing IADS aimed to help children with dyslexia improve their reading and writing skills while simultaneously monitoring their development as learners. Through iterative practice and continuous evaluation, machine learning improves specific SWLD skills.

Intelligent tutor – Intelligent tutoring technology uses adaptive machine learning models to determine a person's strengths and weaknesses in learning. It then suggests a personalized approach to help them overcome those obstacles. To provide students with feedback on their progress and personalized solutions to help them, Sharif and Elmedany (2022) proposed using machine learning to identify patterns in students' reading, writing, and typing abilities, among other areas. While the initiative is still in its early stages and technology solutions are still under development, it has the potential to significantly benefit teachers and provide individualized assistance to students with learning impairments.

Interactive robot – Focusing on evaluating student engagement with a robot, Papakostas et al. (2021) used an interactive robot as an AI tool to support students with specific learning impairments. Unlike the chatbot, the social robot interacted with SWLDs and predicted their participation in class using multimodal machine learning (Papakostas et al., 2021).

4. Research Methodology

This study employed a mixed-methods survey approach to obtain a comprehensive understanding of the research problem. The design facilitated the collection of both quantitative data (numerical responses via structured questions) and qualitative data (open-ended responses for in-depth insights) (Ponto, 2015; Taherdoost, 2021). This approach was particularly appropriate for evaluating the perceived accuracy, usability, and effectiveness of AI-based tools in detecting learning difficulties among students. The study was conducted over a three-month period (September to November 2024) to allow adequate time for data collection and respondent engagement. The population included primary and secondary school teachers, school administrators, and educational policymakers in Jordan who are directly involved in the use or implementation of AI-based diagnostic tools for learning difficulties. Respondents were selected from educational institutions that had piloted or integrated AI-based tools in their instructional or diagnostic processes.

To ensure representative sampling across demographics and school types, a stratified random sampling method was used. This stratification accounted for variables such as school type (public, private, rural), region, and professional role. The final sample included 150 respondents: 120 teachers, 20 school administrators, and 10 policymakers. Notably, respondents from the pilot phase were excluded from the final survey sample to preserve data integrity. Data were collected using a structured online survey instrument, developed based on previous studies on the educational applications of AI (Fletcher et al., 2019; Holmes et al., 2019). The instrument consisted of two sections. Section One collected demographic information (age, gender, job title, years of experience), while Section Two addressed the effectiveness, accuracy, and ease of use of AI tools in identifying learning difficulties, as well as their impact on student outcomes. This section employed a 3-point Likert scale ranging from "*High*" to "*Low*" and also included open-ended questions to allow respondents to elaborate on their experiences and perceptions.

The survey was administered via Google Forms and distributed through email and WhatsApp, allowing broad digital access. Respondents were given two weeks to complete the survey, with two reminder notices sent. Out of the 150 distributed surveys, 130 valid responses were received, yielding an 87% response rate. A pilot study involving 10 separate respondents from outside the main sample was conducted to assess instrument reliability and clarity. Internal consistency was measured using Cronbach's alpha, yielding a value of 0.83, indicating high reliability. Content validity was reviewed by two educational technology experts to ensure alignment with the study objectives. Quantitative data were analyzed using SPSS software, employing descriptive statistics (means, standard deviations, frequency distributions) and inferential statistics (multiple linear regression) to evaluate hypotheses at a 0.05 significance level. Qualitative responses from the open-ended questions were thematically analyzed to enrich the findings with illustrative narratives and contextual interpretation.

The study also considered ethical guidelines. Respondents provided informed consent, their participation was voluntary, and data were anonymized to ensure confidentiality and protect their identity. Ethical approval was obtained from the Jordanian Ministry of Education Research Ethics Committee.

5. Results and Discussion

The analysis employed a Likert scale to evaluate respondents' responses to six items related to each research question. Each item was rated as "*High*", "*Medium*", or "*Low*" based on respondents' responses, with frequencies, percentages, means, and standard deviations provided for each response category. Descriptive statistics were used for the quantitative analysis, while thematic analysis was employed to interpret qualitative responses.

5.1 Research Questions

5.1.1 Research Question 1

- How effective are AI-based tools in accurately identifying students with learning difficulties in Jordanian schools?

Table 2 presents the descriptive statistics based on an analysis of respondents' perceptions of the effectiveness of various AI-based tools in detecting learning difficulties. Figure 1 presents a waterfall chart for these statistics.

Table 2: Effectiveness of AI-based tools in detecting learning difficulties

Item	Statement	High	Medium	Low	X	SD
1	Machine learning algorithms identify specific learning patterns accurately	88 (67.7%)	32 (24.6%)	10 (7.7%)	4.2	0.73
2	Natural language processing (NLP) tools assist in detecting reading difficulties	85 (65.4%)	35 (26.9%)	10 (7.7%)	4.1	0.72
3	Computer vision-based tools effectively assess attention-related difficulties	90 (69.2%)	30 (23.1%)	10 (7.7%)	4.2	0.74
4	Speech recognition tools accurately identify language and speech disorders	82 (63.1%)	38 (29.2%)	10 (7.7%)	4.1	0.71
5	Predictive analytics provide early warnings of potential learning difficulties	87 (66.9%)	33 (25.4%)	10 (7.7%)	4.2	0.72
6	Recommendation engines suggest effective personalized interventions	78 (60.0%)	42 (32.3%)	10 (7.7%)	4.0	0.75
Aggregate (proportional ratio)		**510 (65.4%)**	**210 (26.9%)**	**60 (7.7%)**	**4.13**	**0.72**

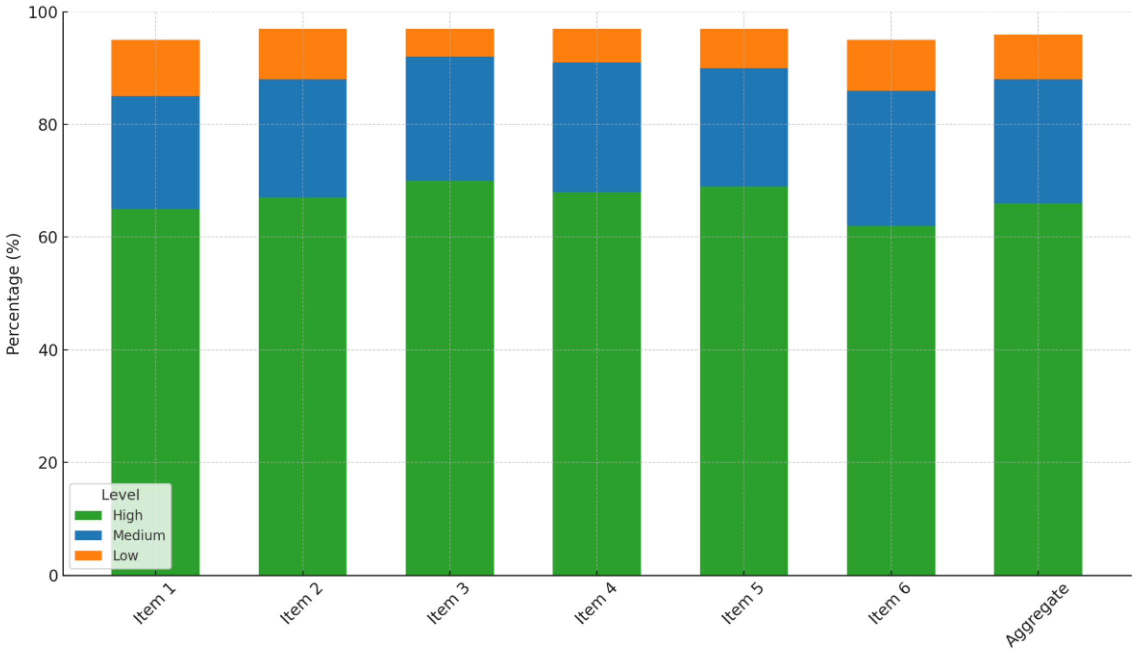

Figure 1: Waterfall chart on the effectiveness of AI-based tools in detecting learning difficulties

The results strongly support the ability of AI tools to detect learning difficulties among students, with 65.4% of respondents rating their effectiveness as high. With a high agreement rate of 67.7%, machine learning algorithms were seen as particularly effective in identifying specific learning patterns indicative of learning challenges. Similarly, NLP tools were deemed highly beneficial for detecting reading difficulties, with 65.4% rating their effectiveness as high. Computer vision-based tools, used for assessing attention-related issues, were also rated positively, with a high rating by 69.2% of respondents. Analysis yielded a predictive analytics value of 66.9%, revealing a high level of agreement on early alerts about potential learning difficulties using predictive analytics. Recommendation engines, which suggest personalized learning interventions, had the lowest high rating (60.0%), suggesting that while effective, educators may find other AI tools more precise or user-friendly. The overall mean score of 4.13 and standard deviation of 0.72 indicate a strong consensus among respondents on the usefulness of these AI-based tools in enhancing the accuracy and timeliness of learning difficulty detection.

5.1.2 *Research Question 2*

- What are the perceptions of educators and stakeholders in Jordan regarding the role of AI in identifying students with learning difficulties?

Table 3 presents the descriptive statistics based on an analysis of educators and stakeholders' perceptions of AI in education. Figure 2 presents a waterfall chart for these statistics.

Table 3: Educators and stakeholders' perceptions of AI in education

Item	Statement	High	Medium	Low	X	SD
1	AI tools are a valuable resource in supporting students	95 (73.1%)	25 (19.2%)	10 (7.7%)	4.3	0.71
2	The integration of AI in education improves learning outcomes	85 (65.4%)	35 (26.9%)	10 (7.7%)	4.2	0.74
3	AI can complement, rather than replace, traditional teaching	100 (76.9%)	20 (15.4%)	10 (7.7%)	4.3	0.70
4	Educators are open to adopting AI-based diagnostic tools	80 (61.5%)	35 (26.9%)	15 (11.5%)	4.1	0.75
5	Training in AI tools is necessary for effective implementation	105 (80.8%)	20 (15.4%)	5 (3.8%)	4.5	0.66
6	AI use should be monitored to address ethical concerns	90 (69.2%)	30 (23.1%)	10 (7.7%)	4.2	0.73
	Aggregate (proportional ratio)	**555 (71.3%)**	**165 (21.2%)**	**60 (7.5%)**	**4.27**	**0.71**

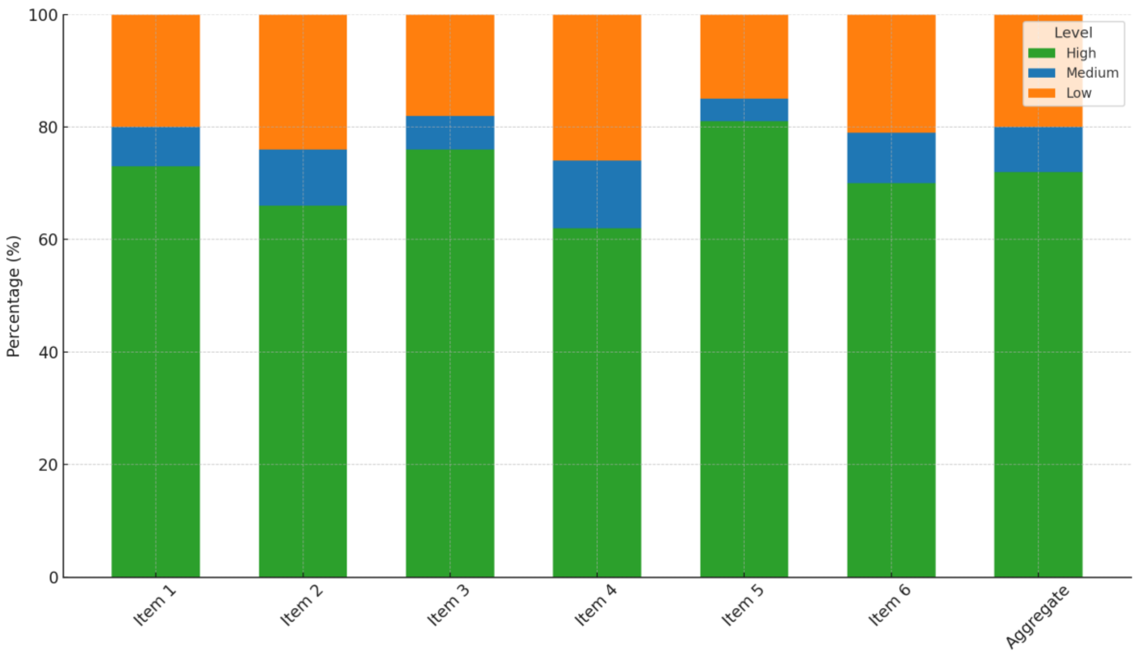

Figure 2: Waterfall chart on educators and stakeholders' perceptions of AI in identifying students with learning difficulties

Overall, respondents had a positive perspective of AI in educational diagnostics (M = 71.3%). A significant proportion of the respondents (80.8%) agreed regarding the need for training to implement AI tools effectively. This shows the importance of training educators with essential skills to use AI tools. In addition, 76.9% of respondents agreed with the statement that AI contributes to traditional teaching methods; this shows a balanced perspective for educators. However, 69.2% admitted to monitoring AI use to avoid potential ethical issues. The results confirm the reliability of AI and the support of AI in education, also indicating an understanding of the place of ethical and professional training in AI to maximize benefits.

5.2 Hypotheses Testing

5.2.1 *Hypothesis 1*

- H_0: AI-based tools do not significantly predict the accurate identification of students with learning difficulties.
- H_1: AI-based tools significantly predict the accurate identification of students with learning difficulties.

- H_0: AI-based tools do not significantly predict the accurate identification of students with learning difficulties.
- H_1: AI-based tools significantly predict the accurate identification of students with learning difficulties.

This study explored whether the effectiveness of AI-based tools could significantly predict the accurate identification of SWLD in Jordanian schools. Tables 4a to 4c present the inferential statistics yielded through the regression analysis.

Table 4a: Effectiveness of AI-based tools in detecting learning difficulties

Model	*R*	*R* square	Adjusted *R* square	Std. error of the estimate
1	0.906	0.822	0.821	0.30

Table 4b: Analysis of variance results

Model	Sum of squares	Df	Mean square	*F*	Sig.
Regression	53.48	1	53.48	591.1	0.001
Residual	11.58	128	0.090		
Total	65.06	129			

Table 4c: Coefficients

Model	Unstandardized coefficient		Standardized coefficient	*t*-cal.	Sig.
	B	Std. error	Beta		
1. (Constant)	0.228	0.162	0.906	1.41	**0.162**
AI effectiveness (x_1)	**0.950**	**0.039**		**24.31**	**0.001**

*Significant at $p < 0.05$

The regression analysis revealed a strong positive relationship between the perceived effectiveness of AI tools and their role in detecting learning challenges, with an *R*-value of 0.906 and R^2 of 0.822, indicating that approximately 82.2% of the variance in detection accuracy can be explained by the effectiveness of AI tools. The model was statistically significant ($F = 591.1$, $p < 0.001$), and the predictor variable (effectiveness) had a high unstandardized coefficient ($B = 0.950$, $p < 0.001$), showing that as perceptions of effectiveness increased, so did confidence in the diagnostic accuracy of AI. These findings led to the rejection of the null hypothesis (H_{01}), confirming that AI-based tools are not only perceived as effective but also significantly influence the accurate identification of learning difficulties. This supports the argument for integrating such tools into early diagnostic strategies in educational settings.

5.2.2 *Hypothesis 2*

- H_0: Educators' perceptions do not significantly predict the role of AI in learning difficulty identification.
- H_2: Educators' perceptions significantly predict the role of AI in learning difficulty identification.

Hypothesis 2 examined whether educators and stakeholders' perceptions significantly predict the role of AI in identifying SWLD. Tables 5a to 5c present the inferential statistics yielded through the regression analysis.

Table 5a: Effectiveness of AI-based tools in detecting learning difficulties

Model	*R*	*R* square	Adjusted *R* square	Std. error of the estimate
1	0.895	0.802	0.800	0.31

Table 5b: Analysis of variance results

Model	Sum of squares	Df	Mean square	*F*	Sig.
Regression	52.46	1	52.46	518.4	0.001
Residual	12.94	128	0.097		
Total	65.40	129			

Table 5c: Coefficients

Model	Unstandardized coefficient		Standardized coefficient	t-cal.	Sig.
	B	Std. error	Beta		
1. (Constant)	0.152	0.184	0.895	0.83	**0.409**
Perception Index (x_2)	**0.962**	**0.042**		**22.77**	**0.001**

*Significant at $p < 0.05$

The regression model yielded a high *R*-value of 0.895 and R^2 of 0.802, indicating that 80.2% of the variation in the perceived role of AI in education is explained by stakeholders' attitudes and beliefs. The regression was statistically significant ($F = 518.4$, $p < 0.001$), with a notable unstandardized coefficient ($B = 0.962$, $p < 0.001$). These results indicate that positive perceptions among educators and stakeholders significantly enhance the acceptance and integration of AI technologies in educational diagnostics. The null hypothesis (H_{02}) was therefore rejected, demonstrating that perception is a critical predictor of AI adoption in the context of special education. The findings underscore the need for professional development, awareness, and ethical framing to optimize the impact of AI in supporting students with learning challenges.

5.3 Discussion of Findings

5.3.1 *Effectiveness of AI-based tools in detecting learning difficulties*

The analysis of respondents' responses on the effectiveness of AI tools in detecting learning difficulties is summarized in Table 2. The tools assessed included machine learning algorithms, NLP, computer vision, speech recognition, predictive analytics, and recommendation engines. Overall, 65.4% of responses indicated *high* effectiveness, with a mean score of 4.13 (SD = 0.72), suggesting broad agreement on the positive role of AI in detection accuracy. Among the tools, machine learning (67.7%) and computer vision (69.2%) received the highest ratings, indicating their strong capacity to identify learning patterns and attention-related difficulties. NLP tools were also viewed favorably (65.4%) for identifying reading issues, consistent with findings from Tang and Wong (2018). Recommendation engines received the lowest high rating (60.0%), pointing to educators' preference for diagnostic tools over intervention suggestions.

To statistically test this perceived effectiveness, a simple regression analysis was conducted. The results (Table 4) show a strong positive relationship ($R = 0.906$, $R^2 = 0.822$) between AI tool effectiveness and accurate detection. The regression was significant ($F = 591.1$, $p < 0.001$), with a high unstandardized coefficient ($B = 0.950$, $p < 0.001$), indicating that increased perceptions of AI tool effectiveness significantly predicted higher confidence in detection accuracy. Consequently, Hypothesis 1 was supported, confirming the critical role AI plays in the early identification of learning challenges. These findings are consistent with studies by Holmes et al. (2019), Gligorea et al. (2024), and Barua et al. (2022), which highlighted the capacity of AI to analyze large-scale student data for rapid diagnosis. The results also align with Mubin et al. (2017) and Yates and Gikandi (2018), who emphasized the time-efficiency benefits of AI over traditional methods. Despite the overwhelmingly positive results, a minority (7.7%) rated AI effectiveness as low. This aligns with the observation of Kerr (2021) and Rai et al. (2023) that a lack of educator training may hinder tool usage. This underlines the need for strategic capacity-building initiatives.

5.3.2 *Educators' perceptions of the role of AI in learning difficulty identification*

Results from the analysis regarding educators and stakeholders' perceptions are summarized in Table 3. Overall, 71.3% of respondents rated their perception of the role of AI as *high*, with a mean of 4.27 (SD = 0.71). Most respondents (80.8%) agreed that training is crucial for effective AI integration, highlighting a key area for policy focus. Additionally, 76.9% supported the view that AI should complement, not replace, traditional teaching, echoing findings by Holmes et al. (2019) and Brynjolfsson and McAfee (2017). A significant proportion (69.2%) expressed ethical concerns around AI use, including data privacy, bias, and transparency, consistent with concerns raised by Binns (2018) and Seitz (2020). Hypothesis testing revealed that educators and stakeholders' perceptions significantly predicted the role of AI in learning difficulty identification ($R = 0.895$, $R^2 = 0.802$, $F = 518.4$, $p < 0.001$). The unstandardized coefficient ($B = 0.962$, $p < 0.001$) shows that positive perceptions drive greater integration and acceptance of AI tools. Thus, Hypothesis 2 was supported, reinforcing the idea that effective AI deployment in schools depends heavily on stakeholder buy-in. These results echo findings by Schmid et al. (2020) and Zhao et al. (2023), who observed that teacher preparedness is pivotal to successful AI integration. Educators' openness to adoption (61.5%) and agreement on the need for ethical monitoring (69.2%) reflect a mature, cautious optimism toward AI in special education.

6. Conclusion

This study examined the role of AI in identifying SWLD in Jordanian schools, integrating insights from IPT and UDL. Findings confirm that AI-based tools—particularly machine learning, NLP, and computer vision—significantly enhance early identification accuracy, supporting the emphasis of IPT on cognitive load management and the UDL principle of inclusive learning. Educator perceptions also emerged as a significant predictor of AI adoption, highlighting the need for targeted training and ethical safeguards. Theoretically, this research reinforces IPT by demonstrating how AI aligns with human cognitive processes in supporting information encoding, storage, and retrieval. Practically, it offers a data-driven framework for educational stakeholders to implement AI tools that address both academic and emotional challenges faced by SWLD. However, the study is limited by its regional focus on Jordan and reliance on self-reported perceptions, suggesting caution in generalizing findings globally. Future research should explore the longitudinal impacts of AI interventions, examine cross-cultural variations, and assess student outcomes directly. Broader inclusion of underserved contexts and diverse educational systems will further strengthen the relevance and applicability of AI in global special education. These directions are vital for advancing equitable, technology-enhanced learning.

7. Implication of Findings

The outcome of these findings presents many implications for education policy and practice in Jordan. First, it portrays the importance of incorporating AI tools in classrooms to help with the early identification of SWLD and intervene in a timely manner. The conception of most educators suggests the support of AI tools to play a transformative part in enhancing educational performance for SWLD. The results further highlight the necessity for professional development in using AI tools. The training should involve the technical characteristics of AI, ethical considerations, and individual data security in education. Lastly, policymakers should address the problems faced by schools in rural areas and underfunded schools in accessing the availability of AI tools, ensuring that schools have the facilities to incorporate AI-based diagnostic tools.

8. Limitations, Validity, and Credibility

This study is limited by its focus on Jordanian schools, which may affect the generalizability of the findings to other contexts. The use of self-reported data introduces the potential for bias, and the cross-sectional design limits insight into long-term outcomes. Validity was addressed through expert-reviewed instruments and alignment with already existing literature. Credibility was ensured via statistical testing, peer review of qualitative themes, and consistency across data sources.

9. Funding

The research had no external means of funding.

10. Conflicts of Interest

The research is not biased.

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