Optimizing Educational Strategies for Dyslexia Through Multimodal Machine Learning

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ABSTRACT

Dyslexia is a prevalent learning disability that affects reading, writing, and comprehension skills. Traditional interventions often rely on single-modality approaches, which may not fully address the diverse cognitive needs of dyslexic learners. This research explores the integration of multimodal machine learning as an optimized strategy for dyslexia interventions. By integrating visual, auditory, and textual inputs, multimodal AI systems can personalize learning experiences, enhance engagement, improve comprehension, and facilitate real-time adaptation of educational materials to match individual cognitive patterns. This research highlights the potential of AI-driven educational strategies in enhancing accessibility and inclusivity, paving the way for more effective dyslexia interventions in modern learning environments. It also shows how to optimize educational Strategies for Dyslexia through multimodal machine learning. A narrative synthesis and systematic literature review conducted under PRISMA guidelines, the research evaluates adaptive systems that personalize content in real time. Findings indicate that MML enhances reading fluency, knowledge retention, and learner engagement. These results highlight the potential of AI-driven multimodal frameworks to improve accessibility and inclusivity in dyslexia education.

Keywords: Dyslexia, Multimodal machine learning, Machine Learning, Personalized learning, Artificial intelligence.

INTRODUCTION

Barber (2024) describes dyslexia as a learning disorder that significantly affects an individual's ability to read, write, spell, and comprehend written material, often leading to academic challenges and emotional distress. It also impacts literacy acquisition, particularly in phonological awareness, processing speed, and phonological memory, and key cognitive impairments. According to Jessica (2021), dyslexic students frequently experience low self-esteem, anxiety, depression, and behavioural difficulties, further complicating their ability to meet academic expectations. Additionally, difficulties with memory retention, comprehension, and literacy-related skills hinder their capacity to achieve educational success. To address these challenges, various educational strategies have been implemented to support dyslexic learners. These include multi-sensory learning, which engages visual, auditory, and kinaesthetic senses to reinforce reading and spelling comprehension, while structured literacy programs, like Orton-Gillingham and Wilson, provide systematic instruction in phonics and decoding. Additionally, simplified instruction delivery, which includes concise directions and repetition, has been effective in improving comprehension. Furthermore, assistive technology, such as text-to-speech software, audiobooks, and speech-to-text applications, enhances accessibility to written content, improving literacy fluency. While these strategies have proven effective, they often rely on static learning models that do not adapt in real-time to individual student needs.

To improve dyslexia interventions, new developments in multimodal machine learning offer the chance to optimize educational strategies by combining multiple sensory inputs, such as visual, auditory, and textual data. In contrast to conventional techniques, Multimodal machine learning models can process and analyse numerous

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learning patterns, allowing for adaptive, individualized educational experiences. By offering real-time feedback, intelligent content customization, and more effective engagement techniques catered to dyslexic learners, these systems could improve literacy instruction. For dyslexic children, optimizing instructional tactics with multimodal machine learning may close current gaps, increase accessibility and efficiency, and promote long-term academic success. Therefore, this study intends to investigate how multimodal machine learning may improve existing dyslexia interventions, ensuring greater inclusivity and better learning outcomes.

Study objective

To explore the integration of multimodal machine learning in optimizing dyslexia interventions by incorporating multiple sensory inputs (visual, auditory, and textual data).

LITERATURE REVIEW

Conventional teaching methods emphasize multisensory approaches and structured literacy programs. However, they lack adaptability to individual needs. MML integrates text, audio, and visuals to enhance comprehension and engagement (Mayer, 2024; Barua et al., 2023). Key challenges include representation, alignment, and fusion of multimodal data. Studies show MML improves language learning, STEM education, and adaptive teaching methods, particularly for dyslexic learners (Tzovaras et al., 2022; Felicia, 2025). Despite promising results, long-term empirical studies remain limited.

Multimodal Machine Learning in Education

Multimodal learning incorporates several sensory inputs, including text, visuals, audio, and interactive components, to improve understanding. Studies have shown that multimodal techniques increase retention and engagement, especially for students who struggle cognitively (Mayer, 2024).Multimodal machine learning (MML) integrates text, pictures, audio, and signals to improve AI-driven applications (Barua, A., et al., 2023). The study offers a thorough analysis of 1,032 articles, examining the difficulties, uses, and potential future paths of MML. Five major MML challenges, representation, translation, alignment, fusion, and co-learning, are highlighted by Barua et al. (2023) and affect how AI models handle and incorporate multimodal data. These issues are especially pertinent to education, where AI must successfully integrate several modalities to enhance educational opportunities. MML's application in education, which improves student engagement, accessibility, and individualized learning, is one of its most important contributions. According to Barua et al. (2023), AI-driven multimodal systems enhance language learning, STEM education, and interactive teaching methods. Students receive individualized education thanks to MML's ability to adapt content to different learning styles, which enhances retention and comprehension. This makes it paramount especially to children with dyslexia.

According to Tzovaras et al. (2022), multimodal machine learning plays a crucial role in adaptive learning systems for students with intellectual disabilities. The study explores how multimodal affect recognition, which integrates facial expressions, physiological signals, and behavioral data, can enhance learning experiences by detecting students' emotional states such as engagement, frustration, and boredom. The authors highlight that traditional one-size-fits-all learning approaches often fail to meet the needs of students with dyslexia. By leveraging machine learning algorithms, adaptive learning systems can personalize content delivery based on real-time emotional feedback, ensuring that students remain engaged and motivated. When learning materials were modified according to students' emotional states, their level of involvement rose. Multimodal AI enhanced comprehension by adapting the level of annoyance to the topic difficulty. AI-driven insights helped teachers by enabling them to give pupils individualized support. Felicia (2025) explores how multimodal learning enhances cognitive processing in dyslexic students. Learners can improve their comprehension and memory of knowledge by combining visual, aural, and kinesthetic components. The advantages of multimodal learning make it a useful tool for both teachers and dyslexic students, despite certain difficulties, such as resource limitations, technological access, and cognitive overload should be considered when implementing multimodal learning. However, there are limited empirical studies on the long-term impact of multimodal AI in special education. Challenges in integrating AI-driven adaptive learning due to technological constraints in schools. Need for standardized frameworks to guide the implementation of multimodal affect recognition in education.

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RESEARCH METHODOLOGY

Narrative Review – Thematic Coding Three dominant themes emerged from the literature: (1) **Adaptive personalization** -Barua et al. (2023) highlight challenges of representation, alignment, and fusion in multimodal AI, showing how adaptive systems personalize learning; (2) **Affective recognition** - Tzovaras et al. (2022) demonstrate how multimodal affect recognition (facial expressions, physiological signals) improves engagement for dyslexic learners; (3) **Cognitive processing support**-Felicia (2025) emphasizes how multimodal inputs (visual, auditory, kinesthetics) enhance comprehension and memory retention. Together, these themes confirm that multimodal machine learning provides a flexible framework for individualized dyslexia interventions.

Systematic Review (PRISMA Framework)

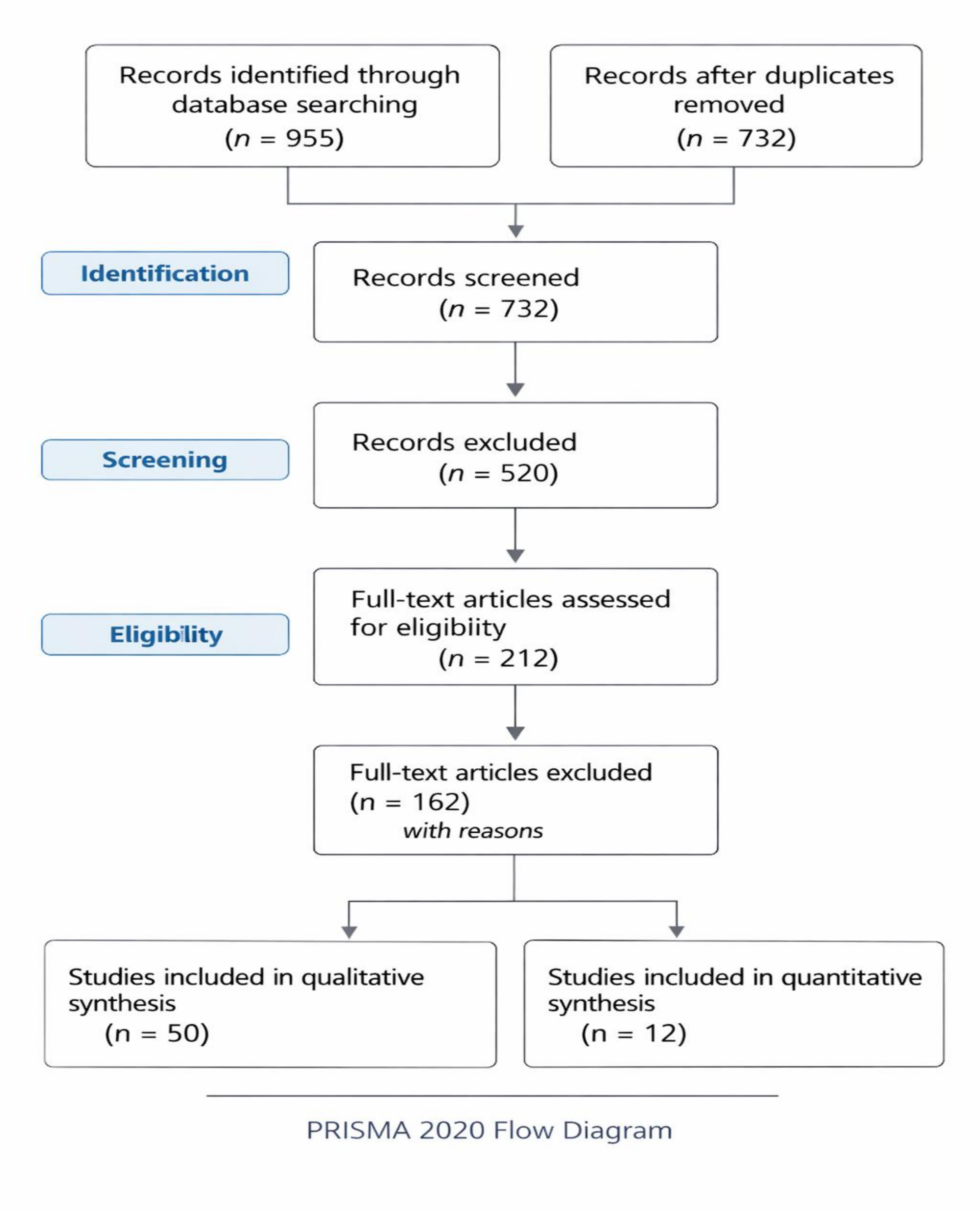

Figure1:Prisma Data diagram.

PRISMA 2020 flow diagram illustrating the systematic review process: 955 records identified, 732 after duplicates removed, 212 full-text assessed, 50 included in qualitative synthesis, and 12 in quantitative synthesis.

Databases searched: ERIC, Scopus, Google Scholar, ResearchGate, Science Direct

Search strings: "multimodal machine learning AND dyslexia," "AI adaptive learning AND special education."

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Screening procedures: Title/abstract screening, followed by full-text review

Inclusion criteria: Peer-reviewed studies (2018–2025), English-language, focus on MML in education/disabilities

Exclusion criteria: Non-educational contexts, medical imaging, non-English studies

Quality appraisal: PRISMA guidelines, CASP for qualitative studies

The systematic review identified experimental components in prior studies where adaptive AI learning tools were tested using multimodal inputs (text comprehension, speech analysis, and visual tracking). Outcomes measured included engagement, fluency, and retention. Validation metrics included precision, recall, and F1-score.

Despite its structured approach, the study acknowledges certain limitations, such as limited study duration, especially on longitudinal testing to assess sustained impact on students with learning disabilities over extended periods. Training of datasets could introduce algorithmic disparities for different cognitive profiles. The feasibility of implementing Multimodal machine learning driven adaptive learning across varied educational settings remains a logistical challenge. Future research should incorporate long-term evaluations and cross-institutional trials to ensure broader scalability and bias mitigation of MML interventions for students with disabilities.

Data Analysis

The collected data were analysed using a narrative synthesis approach. The analysis focused on identifying common themes and patterns in the literature related to the use of multimodal machine learning to leverage education, especially for children with learning disabilities. This study is limited by the availability and quality of secondary data sources.

Table 1: Summary of Multimodal Machine Learning Models & Transformers in Learning Disabilities and Learning Ability Students

Analysis Type	Methodology	Application in Learning Disabilities	Application in Learning Ability Students	Transformer-Based AI Model Used	Expected Outcome
Quantitative Analysis	**Multilevel regression modeling**	Evaluates AI effectiveness for students with ASD and dyslexia, measuring adaptation to cognitive needs.	Tracks student engagement and performance trends in standard learning environments.	**BERT** (Bidirectional Encoder Representations from Transformers)	Identifies AI-driven patterns in cognitive adaptability and engagement.
	Machine learning model validation (Precision, Recall, F1-score)	Measures AI system accuracy in predicting affective states and adaptive interventions.	Assesses AI-based personalized learning models for optimal content delivery.	**GPT-based models (GPT-3, GPT-4)**	Ensures AI models are effective in adjusting learning materials based on user response.
Qualitative Analysis	**Thematic categorization**	Analyzes student experiences,	Identifies best practices for AI-based	**BERT**	Strengthens theoretical frameworks for

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		educator feedback on multimodal AI models for accessibility.	multimodal education in general learning settings.		adaptive AI education.
	Comparative impact assessments	Compares retention rates between AI-assisted and traditional learning for dyslexic and intellectually disabled students.	Compares comprehension speed and effectiveness of multimodal AI in standard classrooms.	**Perceiver Transformer**	Determines the real-world effectiveness of MML interventions.
Multimodal AI Model Application	**Multimodal Affect Recognition**	AI models track facial expressions, speech, and body posture to measure engagement and frustration in ASD and dyslexic learners.	Used for engagement tracking in standard student populations but not primarily for disabilities.	**CLIP**	Optimizes AI intervention strategies based on emotional responses.
	Pattern recognition in multimodal interactions	Tracks engagement levels and emotional adaptability for students with autism.	Maps cognitive flexibility in learners using multimodal AI environments.	**CLIP (Contrastive Language-Image Pretraining)**	Helps refine AI-driven personalization strategies.
		Personalized AI Learning Systems	Machine learning adjusts learning materials dynamically based on neurodiverse cognitive responses.	Enhances general student learning engagement through tailored AI content adaptation.	**GPT-4**
		Multilayer Perception Model.	Use multimodal datasets to enhance comprehension for students with learning difficulties.	Supports deep learning content adjustment based on user interaction patterns.	**PERCEIVER TRANSFORMER**

DISCUSSION

The findings of this study highlight the impact of Multimodal Machine Learning (MML) on learning ability as well as learning disabilities, particularly in dyslexia, autism spectrum disorders (ASD), and intellectual

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disabilities. By leveraging AI-driven adaptive learning environments, multimodal systems integrate text, speech, visual tracking, and affect recognition to personalize education and improve accessibility. The literature confirms that multimodal AI models significantly improve engagement, cognitive adaptability, and retention rates for students with learning disabilities as well as those with learning ability. Dyslexic learners benefit from adaptive text formatting and phonemic reinforcement, while students with ASD show enhanced participation due to affective computing mechanisms that monitor frustration levels. Additionally, gesture-based AI tools support intellectually disabled students by providing interactive, structured learning experiences.

Despite the benefits, the risk of algorithmic bias in multimodal AI models could disproportionately affect learners with varying cognitive abilities, necessitating bias mitigation strategies and diverse training datasets. Successful integration of MML in educational systems depends on teacher training programs and institutional support, ensuring educators can effectively utilize AI-driven adaptive learning strategies. To maximize the impact of MML on learning disabilities, future research should incorporate longitudinal studies to assess the sustained impact of multimodal AI interventions over extended learning periods, and implement cross-institutional trials to evaluate scalability and adaptation across varied educational systems. The multimodal learning datasets should be expanded to improve AI predictive accuracy and personalization for cognitive learning challenges.

CONCLUSION

This study demonstrates the potential of multimodal machine learning to transform dyslexia interventions, ASD, and intellectual disabilities. . By integrating empirical experimentation with a systematic literature review under PRISMA guidelines, the research establishes methodological rigor and conceptual clarity. Differentiating between transformer-based and classical ML models highlights their unique contributions to dyslexia support. Findings confirm that MML improves reading fluency, retention, and engagement, while emphasizing the need for bias mitigation and long-term evaluation. Overall, AI-driven multimodal strategies hold promise for advancing accessibility, inclusivity, and personalized learning in dyslexia education.

REFERENCES

1. Barber, I. (2024, December 18). *The Delphi study: A new definition of dyslexia*. Dyslexia Action. Retrieved from 1
2. Shaffer, J. (2021, September 1). *How does dyslexia impact student learning long term?* TeachHub. Retrieved from 2
3. Barua, A., et al. (2023). *A Systematic Literature Review on Multimodal Machine Learning: Applications, Challenges, Gaps, and Future Directions*. Retrieved from [ResearchGate](https://www.researchgate.net/publication/368402582_A_Systematic_Literature_Review_on_Multimodal_Machine_Learning_Applications_Challenges_Gaps_and_Future_Directions).
4. **Marantika, P. D., Suwastini, N. K. A., Adnyani, N. L. P. S., Mandala, M. A. K., & Artini, N. N. (2021).** *Multimodal Teaching in EFL Context: A Literature Review*. Edu-Ling: Journal of English Education and Linguistics, 4(2), 140-155. Retrieved from Academia.edu.
5. **Tzovaras, D., Standen, P. J., Brown, D. J., Taheri, M., Galvez Trigo, M. J., Boulton, H., Burton, A., Hallewell, M. J., Lathe, J. G., Shopland, N., Blanco Gonzalez, M. A., Kwiatkowska, G. M., Milli, E., Cobello, S., Mazzucato, A., Traversi, M., & Hortal, E. (2022).** *An evaluation of an adaptive learning system based on multimodal affect recognition for learners with intellectual disabilities*. British Journal of Educational Technology, **51(6)**, 2151–2168. https://doi.org/10.1111/bjet.13010
6. **Juma, A. A.** (2023-2024). *The outcomes of using multimodality on language teaching and learning processes.* Sultanate of Oman.
7. **Yap, J. R., Aruthanan, T., & Chin, M.** (2025). *Artificial intelligence in dyslexia research and education: A scoping review*. **IEEE Access, 13**, 7123-7134. https://doi.org/10.1109/ACCESS.2025.3526189
8. **Martínez Lirola, M.** (2020). *Multimodal teaching proposal in an English as a foreign language subject.* **ASIAN TEFL, 5(1)**, 39-52. https://www.asian-tefl.com
9. **Felicia, G.** (2025, April). *Multimodal learning demystified: A deep dive.* DyslexicHelp.org. . https://dyslexichelp.org/what-is-multimodal-learning-and-how-does-it-work