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Hybrid RTI Models Leveraging AI for Ongoing Progress Tracking of Students with Specific Learning Disabilities: An Indian School Framework.

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Abstract

Specific Learning Disabilities (SLD) in India continue to be under-identified due to delayed screening, limited teacher training, and systemic constraints. This paper proposes a Hybrid RTI-AI Model that integrates Artificial Intelligence with the Response to Intervention framework to support early identification, continuous progress monitoring, and personalised instruction. Aligned with inclusive education goals promoted by the Ministry of Education, India under NEP 2020, the model offers a scalable, data-driven approach suited to diverse and resource-constrained Indian school contexts.

Keywords: Specific Learning Disabilities; Artificial Intelligence in Education; Response to Intervention; Inclusive Education.

1. Introduction

Specific Learning Disabilities (SLD) are common developmental disorders that affect a child's academic, emotional, and social growth. Worldwide, between 5% and 15% of school-age children have SLDs like dyslexia, dyscalculia, and dysgraphia (American Psychiatric Association, 2013). In India, although these conditions are recognized under the Rights of Persons with Disabilities (RPwD) Act, 2016, efforts to identify and address them early remain inconsistent and underdeveloped.

A leading cause of this gap is the absence of systematic assessment and monitoring. Teachers often rely on subjective referrals, with students only formally assessed when academic problems become visible. By then, secondary issues like low self-esteem, anxiety, and social withdrawal may have already emerged. This highlights the urgent need for scalable, evidence-based systems to identify SLD early and offer continuous, personalised support. Response to Intervention (RTI) and the Multi-Tiered System of Support (MTSS) are widely adopted worldwide as structured frameworks that provide tiered interventions tailored to students' needs. However, Indian schools face challenges such as large class sizes, insufficient teacher training, stigma around disabilities, and a lack of technological infrastructure, which impede RTI/MTSS implementation.

Artificial Intelligence has the potential to transform RTI/MTSS models by integrating analytics, helping educational institutions monitor student progress, reduce subjective judgments, and promote data-driven decision-making. This paper presents a Hybrid RTI-AI Model designed for Indian schools, discusses challenges from both global and Indian perspectives, and outlines a comprehensive framework for AI integration.

2.Literature Review

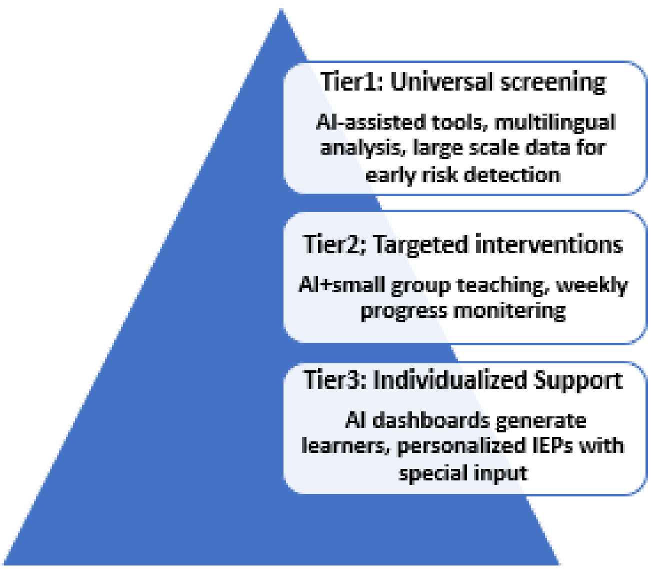
2.1 Understanding SLD in the Indian Context

Specific Learning Disabilities (SLD) are often under-recognised and not well supported across India, mainly because of structural and socio-cultural issues. Challenges such as linguistic diversity, the lack of standardised screening methods, and societal stigma hinder accurate diagnosis (Karande & Kulkarni, 2005). Children growing up in multilingual settings are frequently misclassified as simply underachieving instead of being correctly diagnosed with learning disabilities. Although laws such as the Rights of Persons with Disabilities (RPwD) Act of 2016 and the National Education Policy (NEP) 2020 exist, their implementation of inclusive education varies greatly between states (Sharma, 2019). This variation highlights the need for developing context-sensitive, scalable intervention models.

2.2 RTI/MTSS: A Global Standard in Education

Response to Intervention (RTI) is now a globally recognised, evidence-based method for early identification of students facing learning difficulties. It functions through a three-tiered system that includes:

- Tier 1 emphasises universal screening and delivering high-quality classroom instruction.
- Tier 2 provides targeted small-group interventions, and
- Tier 3 offers detailed, personalised support for students who do not respond to previous interventions (Fuchs & Fuchs, 2006).



Building on RTI, the Multi-Tiered System of Support (MTSS) is an integrated framework that encompasses behavioural, social-emotional, and academic elements (Sugai & Horner, 2009). Both models emphasise the importance of data-driven decision-making, continuous assessment, and preventive strategies, which have been linked to improved learning outcomes in the U.S. and Finland (Gersten et al., 2020). These principles underpin similar frameworks within India's education system.

2.3 Challenges to Implementing RTI/MTSS in India

Despite strong evidence, India's implementation of RTI/MTSS remains sluggish, mainly due to teacher shortages and insufficient training in evidence-based methods for students with SLD (Mukhopadhyay & Mani, 2002). Large classes, with 40 to 60 students, make it difficult to provide adequate support. The challenges are compounded by stigma and lack of awareness, as teachers and parents often confuse SLD with laziness or low intelligence (Karande & Kulkarni, 2009). Dependence on psychoeducational assessments, which are mostly conducted in urban areas, slows down intervention in rural areas (Singal & Muthukrishna, 2014). These issues emphasise the urgent need for innovative, technology-driven support solutions.

2.4 Role of AI in Education

Artificial Intelligence has become a key focus in education due to its ability to personalise, scale, and enhance efficiency. Its applications include adaptive learning, predictive analytics, speech-to-text technology, and handwriting recognition (Luckin et al., 2016). Regarding Specific Learning Disabilities (SLD), AI can analyse large datasets to identify early risks, provide tailored learning experiences, support multilingual and culturally sensitive assessments, and reduce teachers' workloads through automation (Chen et al., 2020).

3. Conceptual Framework: Hybrid RTI-AI Model

3.1 Rationale

India's educational system needs a flexible framework tailored to its socio-cultural context. The Hybrid RTI-AI Model merges RTI/MTSS and artificial intelligence to solve structural issues. By combining educator expertise, cultural insights, and AI accuracy, it aims to bridge gaps and provide timely, data-driven support for students with SLD.

3.2 Hybrid RTI-AI Model: Its Structure

The Hybrid Model incorporates the three-tier RTI framework, enhanced by AI applications.

- Level 1: Universal Screening (driven by AI). AI technologies assess early reading and math skills using eye-tracking, speech recognition, and handwriting analysis. Multilingual systems foster cultural sensitivity, while automated dashboards provide teachers with student risk profiles.
- Stage 2: Targeted Interventions (AI + Teacher-Led). Here, artificial intelligence detects common mistakes among student groups, allowing teachers to deliver targeted lessons.

Weekly AI-generated reports help educators make informed adjustments to their teaching methods, supported by interactive tools that keep students engaged.

- Level 3: Comprehensive, Personalized Support (driven by AI). AI dashboards develop detailed learner profiles that highlight strengths, weaknesses, and response patterns. These insights help educators and psychologists design tailored Individualized Education Programs (IEPs) suited to each student. Adaptive platforms then offer continuous, personalized assistance by promoting collaboration among teachers, specialists, and parents, ensuring a holistic approach to care.

4. Practical Importance for Indian Schools

4.1 Alignment with NEP 2020

India's National Education Policy (NEP, 2020) emphasises the importance of inclusive education, early identification of learning issues, and the integration of technology into teaching methods. The Hybrid RTI-AI Model embodies these principles by providing scalable and affordable solutions that turn policy goals into practical classroom practices.

4.2 Feasibility in Resource-Constrained Environments

This model's effectiveness comes from leveraging existing technology. Smartphones and tablets allow access to AI tools even in remote areas, while cloud platforms reduce hardware costs. Additionally, automating assessment and progress tracking eases the workload for educators managing large classes.

4.3 Breaking Down Cultural and Linguistic Barriers

India's multilingual education system complicates the identification of students with specific learning difficulties (SLD). AI tools tailored for multilingual settings can help solve this challenge. When AI models are trained with local data, assessments become more culturally relevant, providing students from diverse linguistic and cultural backgrounds with fair support and better opportunities.

5. Professional and Ethical Concerns

Integrating AI into the assessment and intervention of Specific Learning Disabilities (SLD) must prioritize ethical issues. Protecting student data privacy is essential, as it involves the secure handling of sensitive information. It is also important to address algorithmic bias to prevent AI from unintentionally disadvantaging students based on factors such as language, socioeconomic status, or cultural background. Supporting teacher autonomy remains critical; AI tools should assist, not replace, human judgment. Ensuring equitable access to digital resources for everyone is vital, as the digital divide could exacerbate existing educational disparities.

6. Policy and Practice Implications

Implementing the Hybrid RTI-AI Model requires systemic support. Policymakers should consider piloting AI integration within RTI frameworks, especially in government schools.

Teacher training must include AI literacy and data-driven techniques. Collaboration among educators, psychologists, technologists, and policymakers is essential for the initiative's sustainability. Funding should prioritize scalable AI solutions to improve inclusive education in both urban and rural areas.

7. Conclusion

India's education system is at a crucial stage where integrating technology and inclusive teaching strategies is essential to address long-standing challenges in identifying and supporting students with diverse learning needs. The proposed Hybrid RTI-AI Model offers an innovative and practical approach to improve early detection, intervention, and ongoing monitoring of students with Specific Learning Disabilities (SLD). By combining the Response to Intervention (RTI) or Multi-Tiered System of Supports (MTSS) framework with AI technology, Indian schools can transform both diagnostic and instructional practices (Fuchs & Fuchs, 2017; Lin et al., 2020).

In India, diagnosing SLD has often been delayed due to factors such as insufficient teacher training, limited access to specialists, and a lack of real-time data (Karanth & Rozario, 2016). The RTI-AI hybrid method addresses these issues by utilising AI-driven analytics to continuously gather and analyse data on student performance, classroom behaviour, and learning outcomes (Brynjolfsson & McAfee, 2017). This automation enables schools to detect learning difficulties much earlier than traditional assessments. Consequently, it reduces diagnostic delays and supports teachers in providing timely, personalised interventions (Gersten et al., 2020).

Furthermore, the model effectively adapts to India's diverse linguistic and cultural educational environment. Training AI algorithms on multilingual data helps address linguistic barriers that often hinder accurate diagnosis and support for children from various regions and language backgrounds (Mitra & Dangwal, 2020). Educators worldwide can utilize standardised digital platforms equipped with AI to monitor student progress, develop personalised instruction, and share evidence-based reports with parents and specialists (OECD, 2021).

The Hybrid RTI-AI Model tackles major systemic issues, such as teacher shortages and unequal resource distribution. By using AI-powered monitoring tools, schools in remote areas can perform virtual assessments, analyze learning data, and offer instructional support, reducing their reliance on highly specialized staff (UNESCO, 2023). Moreover, the system encourages data-driven decision-making, helping policymakers and administrators distribute resources more effectively and ensure aid reaches the most vulnerable populations (Papamitsiou & Economides, 2019). Aligned with the 2020 National Education Policy (NEP), which prioritizes equity, inclusion, and technological integration in education, this model supports a flexible and adaptable learning framework (Ministry of Education, 2020). The NEP emphasizes utilizing emerging technologies to deliver high-quality education for all students, including those with disabilities. The Hybrid RTI-AI Model embodies this approach by combining continuous monitoring with targeted, tiered interventions, thereby promoting the inclusion of students in mainstream classrooms (Rao & Narayan, 2021).

Future research should evaluate this model in various Indian environments—urban, rural, and tribal—to confirm its scalability and cultural appropriateness (Kumar et al., 2022). Moreover, creating ethical guidelines is essential for safeguarding data privacy, ensuring informed consent, and supporting equitable AI use in educational decision-making (Floridi & Cowls, 2019).

With ongoing policy support, collaboration among educators, psychologists, technologists, and policymakers, as well as continuous technological advancements, the Hybrid RTI-AI Model has the potential to greatly transform inclusive education in India. It aims to improve the accuracy and efficiency of identifying learning needs while fostering a more equitable, adaptable, and human-centered education system that ensures all learners are included.

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