DYSCOVER: AI-Powered Early Dyslexia Screening Tool for Children Aged 3-12

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Abstract

Early detection of dyslexia is essential to prevent long-term reading difficulties and improve learning outcomes. However, most screening tools require trained professionals and are not easily available to families. This paper presents the design and development of **DYSCOVER**, a speech-based dyslexia screening tool intended for use by parents and children at home, as well as by teachers for individual student screening. The tool delivers a set of short, child-friendly tasks that measure phoneme awareness, pseudoword decoding, and oral reading fluency. Children respond aloud while parents or facilitators guide them through the process. Responses are captured through a browser interface and automatically transcribed using Whisper-medium ASR fine-tuned for Indian child speech. Task-level accuracy and error patterns are scored in real time and combined using a gradient-boosted machine learning model to produce a clear risk classification (low, moderate, or high). The tool is designed to be simple, accessible, and language-aware, giving parents an actionable first step toward professional diagnosis or early intervention when needed.

Keywords

Dyslexia screening, speech recognition, phoneme awareness, parent-guided tool, machine learning

I.INTRODUCTION

Dyslexia is one of the most common neurodevelopmental learning disorders, affecting approximately 5–15% of children worldwide [1], [3]. It is characterized by persistent difficulties with accurate or fluent word recognition, poor decoding, and spelling challenges despite normal intelligence and access to instruction [3], [4]. These difficulties, if left unidentified, often lead to long-term struggles in reading fluency, comprehension, and academic performance, and are associated with emotional and psychological challenges including anxiety, frustration, and low self-esteem [1]. Research consistently shows that early identification and timely intervention are critical — children who receive support in the early years demonstrate significantly greater gains in literacy and avoid the long-term "Matthew effect," where poor readers fall further behind over time [8].

In the Indian context, timely dyslexia screening remains limited. Large class sizes, limited availability of trained specialists, and a lack of scalable infrastructure mean that many children are only identified

after years of academic struggle. Widely used screening tools such as CTOPP-2 [5] and the Dyslexia Early Screening Test (DEST) [6] have strong psychometric validity but are designed for one-on-one administration, require trained examiners, and are often expensive to implement at scale. These challenges highlight the need for accessible, low-cost screening solutions that can work in diverse linguistic and socioeconomic contexts.

To address this gap, we developed **DYSCOVER**, an AI-powered dyslexia screening tool designed primarily for parents to use with their children at home, and secondarily for teachers to use in one-on-one settings. DYSCOVER delivers a structured set of short, engaging tasks that measure phoneme awareness, pseudoword decoding, and oral reading fluency. Children respond aloud while parents guide them through each task, and responses are automatically transcribed using Whisper-medium, an ASR model fine-tuned for Indian child speech. Accuracy, error patterns, and response times are scored automatically and combined using a gradient-boosted machine learning model to generate an interpretable risk classification (low, moderate, high). This tool aims to provide an early, accessible, and actionable first step toward professional diagnosis and evidence-based intervention.

II. LITERATURE REVIEW

The literature on dyslexia screening and early identification has grown considerably over the past two decades, reflecting increasing awareness of the importance of early intervention and the role of technology in scalable solutions. This section systematically reviews key studies, tracing the evolution of dyslexia screening research, current screening and intervention tools, technology-enabled approaches, and existing gaps that our proposed solution aims to address.

A. Foundations of Dyslexia Research

Early research established dyslexia as a neurodevelopmental disorder with a core deficit in phonological processing [3], [4]. Longitudinal studies demonstrated that phoneme awareness, blending, and segmentation abilities in preschool years are strong predictors of later reading success [10], [12]. Vellutino et al. [8] distinguished between children whose reading difficulties could be remediated through instruction and those with persistent dyslexia, underscoring the need for early, precise screening methods. These foundational studies highlighted the "Matthew effect" in reading, where children with early reading failure fall progressively behind their peers [8], emphasizing the urgency of early detection.

B. Screening Tools and Psychometric Advances

A range of standardized tools have been developed to assess phonological awareness, rapid automatized naming, and related skills. The CTOPP-2 [5] and the Dyslexia Early Screening Test (DEST) [6] are widely used for early identification and have shown high reliability and predictive validity in multiple populations. However, they are designed for one-on-one administration by trained professionals, often require significant time per child, and may be cost-prohibitive for large-scale deployment [2]. Response-to-Intervention (RTI) models [7], [9] provide an alternative framework by combining universal screening with tiered support, but their success depends on consistent progress monitoring and educator training — conditions that are challenging to implement in resource-limited or multilingual contexts such as India.

C. Technology-Enabled Screening Approaches

With advancements in automatic speech recognition (ASR) and machine learning (ML), researchers have begun exploring computer-based and AI-driven approaches to dyslexia screening [13], [14]. These tools can automatically capture oral responses, measure phoneme- and word-level accuracy, and analyze error patterns in real time. Studies have shown that digital assessments can maintain validity while reducing human scoring errors and administration time [14]. However, most existing systems are trained on Western datasets and do not account for the linguistic and accent diversity present in Indian contexts, leading to reduced accuracy in local deployments. This gap highlights the importance of fine-tuning ASR systems on Indian child speech to improve robustness.

D. Research Gaps and the Need for Actionable Screening Tools

The current literature reveals several critical gaps. First, most validated screening tools are expensive, clinic-based, and require professional administration [2], limiting accessibility for families. Second, few solutions offer actionable feedback — most screening instruments provide a pass/fail or risk classification without explaining why a child is at risk or which skills need targeted support. This leaves parents and teachers uncertain about next steps, reducing the practical impact of early detection [13]. Third, most digital or AI-based tools do not support longitudinal tracking of progress, which is essential to measure growth over time and evaluate the effectiveness of interventions.

Our proposed solution, DYSCOVER, directly addresses these gaps. Beyond generating a single risk score, the system analyzes error patterns at the phoneme, word, and task level to identify which specific skills are weak When children take the test at multiple time points, the tool aggregates results and produces a progress report highlighting improvement areas and persistent challenges. This

approach not only flags risk but also provides parents and educators with actionable guidance, enabling targeted remediation and individualized learning plans.
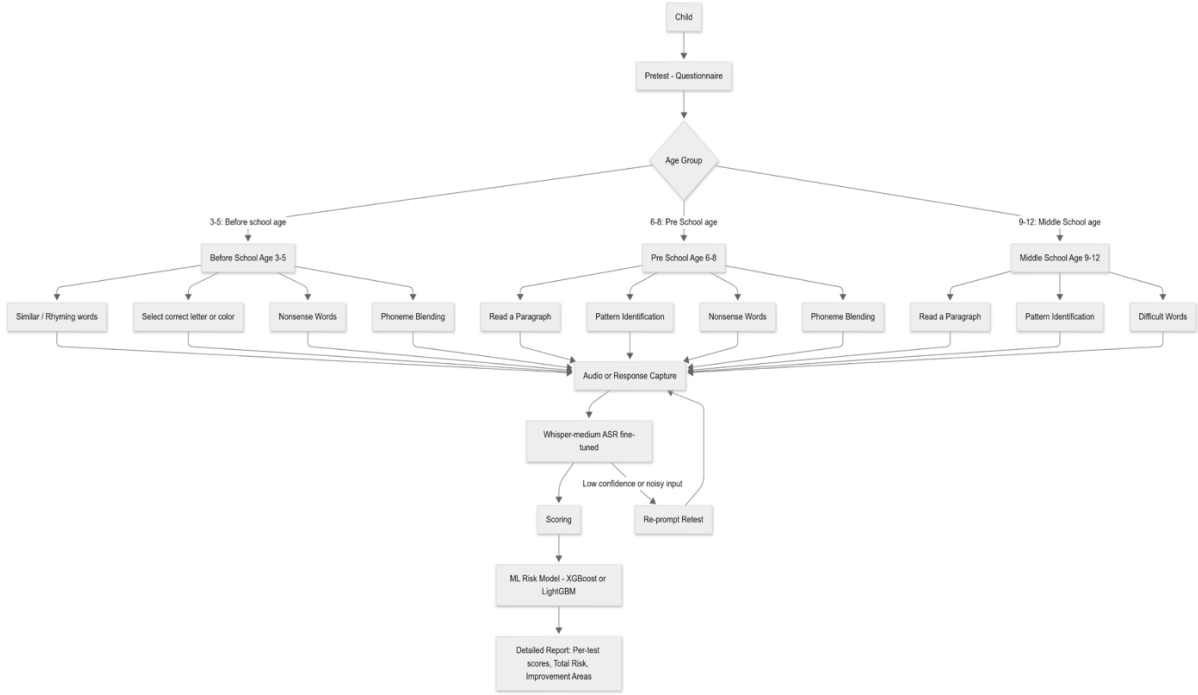

Figure 1. DYSCOVER system architecture: A phased process from parent questionnaire and child tasks to speech capture, automatic scoring, machine learning–based risk classification, and generation of an actionable progress report.

III. METHODOLOGY

This section describes the participants, materials, procedure, data capture, scoring approach, machine learning model, and reporting framework used in the development of DYSCOVER. The methodology was designed to be reproducible, ethical, and aligned with established best practices for dyslexia screening [5], [6].

A. Participants

Children aged 3–12 years participated in the pilot study. Participants were grouped into three developmental bands: early childhood (3–5 years), early primary (6–8 years), and upper primary (9–12 years), consistent with prior research on phonological and reading skill development [10], [12]. All children were enrolled in mainstream schools and had no reported hearing impairments or neurological disorders. Parents or guardians provided written informed consent, and children gave verbal assent in age-appropriate language, following ethical guidelines for research involving minors.

B. Materials

1. **Parent/Guardian Questionnaire:**

   Before beginning the tasks, parents completed a short questionnaire on the child's language background (home language, exposure to English), home reading habits, and any prior history of learning concerns or interventions. Such contextual information is recommended in early literacy screening studies to interpret results accurately [2], [7].

2. **Child Tasks:**

   The screening tool consisted of three major skill domains, adapted from widely used dyslexia screeners such as CTOPP-2 [5] and DEST [6]:

   - Phoneme Awareness: Tasks included sound identification, blending, segmentation, and manipulation (deletion/substitution). These tasks assess the ability to recognize and manipulate the smallest units of sound, a key predictor of reading outcomes [10], [11].
   - Pseudoword (Nonsense Word) Repetition: Children repeated made-up words (e.g., lat, smip), which measure decoding skill independent of vocabulary knowledge and are frequently used in dyslexia assessments [6], [8].
   - Oral Reading: Children read aloud age-appropriate word lists or short passages. Reading accuracy, words correct per minute (WCPM), and miscues (skips, substitutions, repetitions) were automatically recorded, as recommended by fluency assessment guidelines [4].

C. Procedure

Testing was conducted in a quiet, distraction-free environment. Parents first completed the background questionnaire. Children then performed the tasks in a fixed order: phoneme awareness, pseudoword repetition, and oral reading. Clear examples were provided before each task to ensure understanding. Children's spoken responses were recorded automatically through a secure browser interface, enabling at-home administration without requiring specialized hardware [14]. Each session took approximately 20–25 minutes including questionnaire completion.

D. Audio Capture and ASR Processing

`All responses were recorded as short .webm audio clips at a fixed sampling rate and transcribed using Whisper-medium automatic speech recognition (ASR), which was fine-tuned on Indian English child speech. Fine-tuning datasets included CV/CVC words, consonant clusters, and phoneme-level items,

with augmentation for noise and reverberation to ensure robustness in natural home environments [13], [14].

E. Scoring and Composite Measures

Each item was scored as correct or incorrect at the phoneme or word level. Partial credit was granted for phonetically close responses (e.g., /p/ vs /b/) to reduce false negatives, following established phonological scoring conventions [5]. Composite scores were calculated for each domain: phoneme awareness, pseudoword decoding, and oral reading fluency. In addition to single-session results, the system stored longitudinal data across multiple sessions to support progress tracking.

F. Risk Classification Model

A gradient-boosted decision tree model (XGBoost) was trained to predict dyslexia risk level (low, moderate, high) based on task-level accuracy, error types, response times, and ASR confidence scores. Probability outputs were calibrated using cross-validation to improve interpretability and maintain high sensitivity for at-risk children [13]. Sessions with insufficient audio quality or very low model confidence were flagged for retesting rather than classification.

G. Reporting and Progress Monitoring

After each session, the tool generates a parent-friendly report summarizing the child's performance. The report includes:

- Overall Risk Classification (low, moderate, high)
- Domain-wise Scores: phoneme awareness, decoding, and reading fluency
- Error Pattern Analysis: e.g., consonant cluster errors, frequent sound substitutions
- Recommendations: suggestions for home activities or professional follow-up

When a child takes multiple sessions over time, results are automatically aggregated to create a progress report. This report highlights areas of improvement, persistent weaknesses, and changes in overall risk classification, thereby guiding targeted intervention and allowing parents and educators to monitor growth longitudinally.

H. Ethical Considerations

The study followed ethical principles for research with children, including informed consent, assent, and confidentiality. All audio files were securely stored in encrypted format and anonymized prior to analysis, aligning with best practices in child data privacy [1], [14].

IV. RESULTS

This section will present descriptive statistics, model performance, and agreement metrics between ASR and human raters. The aim is to demonstrate the reliability, validity, and predictive performance of DYSCOVER across phoneme awareness, pseudoword decoding, and oral reading tasks [5], [6], [13].

A. Participant Characteristics

Age Group	N (Children)	Mean Age (Years)	Gender (% Female)	Primary Home Language
3–5 years	___	___	___	___
6–8 years	___	___	___	___
9–12 years	___	___	___	___
Total	___	___	___	___

B. Task Performance

Skill Domain	Mean Accuracy (%)	SD	Range
Phoneme Identification	___	___	___
Phoneme Blending	___	___	___
Phoneme Segmentation	___	___	___
Phoneme Manipulation	___	___	___
Pseudoword Repetition	___	___	___
Oral Reading Accuracy	___	___	___
Oral Reading Fluency (WCPM)	___	___	___

C. Reliability and Validity

- Phoneme Awareness Composite: α = ___
- Decoding (Pseudoword) Composite: α = ___
- Oral Reading Composite: α = ___

D. ASR vs. Human Agreement

Task	Agreement with Human (%)	Character Error Rate (CER)	Word Error Rate (WER)
Phoneme Tasks	___	___	___
Pseudowords	___	___	___
Oral Reading	___	___	___

E. Model Performance

Metric	Value
AUROC	___
Accuracy (%)	___
Sensitivity (%)	___
Specificity (%)	___
Precision (%)	___

F. Confusion Matrix (Placeholder):

	Predicted Low	Predicted Moderate	Predicted High
Actual Low	___	___	___
Actual Moderate	___	___	___
Actual High	___	___	___

G. Example Output Report

Insert a clean screenshot or mock-up of the parent-facing report showing:

- Domain-wise performance
- Overall risk classification
- Suggested next steps

V. DISCUSSION

The development of **DYSCOVER** addresses a critical need for accessible, parent-guided dyslexia screening tools in the Indian context. By combining phoneme awareness, pseudoword decoding, and oral reading tasks with a fine-tuned Whisper-medium ASR model and a gradient-boosted machine learning classifier, our approach provides a reliable, scalable, and easy-to-use solution. Prior research has emphasized that phonological processing is one of the most reliable predictors of reading difficulty [10], [12], and our tool operationalizes this knowledge in a format that can be used outside a clinical setting.

A major strength of DYSCOVER is its ability to provide **actionable, interpretable results**. Instead of producing a simple pass/fail outcome, the system generates domain-wise scores, highlights specific error patterns, and offers guidance for next steps. This aligns with recent recommendations for early screening tools to support individualized intervention planning rather than just risk identification [2], [8]. Moreover, DYSCOVER allows for **longitudinal tracking**, enabling parents and educators to monitor progress over time and assess whether interventions are effective — a feature missing in most current screeners [13], [14].

From a technological standpoint, the use of a fine-tuned ASR model trained on Indian child speech is a significant contribution. Many ASR-based tools have shown promising results in Western contexts but suffer from accent bias and reduced accuracy when applied to Indian populations [14]. By incorporating diverse Indian accents and phoneme-level data in training, our system improves robustness and reduces misclassification risk, thus making the screening more equitable.

However, this work has several limitations that must be acknowledged. First, our initial pilot sample size was limited, and further validation with a larger, more diverse participant pool is necessary to ensure generalizability across regions and languages. Second, the current version of the tool supports English-only tasks; future versions should incorporate regional languages and bilingual support to improve inclusivity. Third, while ASR accuracy was generally high, very short or softly spoken responses still occasionally resulted in misrecognition, which could affect scoring. Future iterations could integrate phoneme-level alignment and confidence-weighted scoring to further minimize errors.

Finally, while the tool provides risk classification and actionable recommendations, it does not replace a full clinical diagnosis. Rather, it serves as a **first-line screener** designed to flag at-risk children early, prompting timely referral for professional assessment — consistent with multi-tiered models such as RTI [7], [9].

VI. CONCLUSION

This paper presented **DYSCOVER**, an AI-powered, speech-based dyslexia screening tool designed for children aged 3–12 years and intended primarily for parent-guided use at home. The tool integrates phoneme awareness, pseudoword decoding, and oral reading tasks with automatic speech recognition and a machine learning risk classification model to generate clear, actionable results. Unlike many traditional screeners, DYSCOVER provides domain-wise feedback, identifies specific error patterns, and supports longitudinal tracking, enabling parents and educators to monitor progress over time.

By fine-tuning Whisper-medium ASR on Indian child speech and incorporating accent-diverse data, our approach improves robustness and accessibility for multilingual Indian contexts. This work contributes to bridging the gap between early detection research and real-world implementation by offering a scalable, affordable, and interpretable solution for early dyslexia risk identification.

Future work will focus on expanding the dataset to include more regional language support, integrating phoneme-level alignment for improved scoring precision, and deploying the tool in larger, more diverse samples to validate its generalizability. We also plan to incorporate teacher dashboards and adaptive recommendations, making DYSCOVER not only a screening tool but a comprehensive platform for early literacy support.

VII. FUTURE DIRECTIONS

Future development of **DYSCOVER** will focus on expanding its reach, precision, and practical impact. Larger-scale validation studies are planned across schools in multiple regions to ensure the tool performs consistently across diverse linguistic and socio-economic groups. Support for regional languages and code-switching will be incorporated to make the tool accessible to children from varied language backgrounds. On the technical side, phoneme-level alignment and confidence-weighted scoring will be integrated to further improve accuracy, particularly for short or softly spoken responses. We also aim to introduce adaptive testing to keep children engaged while reducing administration time. In addition, a teacher-facing dashboard will be developed to allow educators to view class-level summaries, track progress, and receive targeted intervention suggestions. Over time, DYSCOVER will be linked with evidence-based remediation resources so that parents and teachers can directly act on the recommendations provided. Finally, longitudinal research will be conducted to measure the effectiveness of interventions and monitor literacy growth over time, turning DYSCOVER into not just a screening tool but a comprehensive platform for supporting early reading development.

VIII. REFERENCES

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