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A Dynamic AI-Driven Personalized Learning System: Design and Implementation of DysCo.

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Abstract- Artificial Intelligence (AI) has transformed education by enabling adaptive and personalized learning experiences for diverse learners. Dyslexic individuals face challenges in reading, phonological processing, and comprehension. This paper presents DysCo, an AI-driven personalized learning system that supports dyslexic learners through multimodal engagement and intelligent automation. Integrating Speech-to-Text, Text Summarization, Flashcard Generation, and Text-to-Speech within a scalable MERN architecture, DysCo delivers real-time adaptive learning. Empirical evaluation demonstrates high performance, low latency, and strong usability, confirming DysCo's effectiveness in enhancing educational accessibility, engagement, and personalized learning outcomes for dyslexic users.

Keywords: AI-driven learning, dyslexia support, personalized education, speech-to-text, text summarization, flashcards, text-to-speech, adaptive systems, MERN stack.

I. INTRODUCTION

In recent years, Artificial Intelligence (AI) has revolutionized education by enabling personalized, adaptive, and data-driven learning. For learners with language or cognitive disabilities such as dyslexia—affecting 5–17% of the global population—AI-powered assistive systems address challenges in reading, phonological processing, and vocabulary retention [1].

Researchers have focused on inclusive education through intelligent systems that adapt content using learner analytics. Essa et al. [2] introduced Personalized Adaptive Learning Technologies (PALT) to enhance e-learning efficiency through machine learning. Li et al. [3] extended this by integrating multimodal behavioral modeling with adaptive recommendations, achieving high predictive accuracy, while Elbasi et al. [4] showed that machine learning can detect cognitive patterns improving comprehension by 18%.

Automatic Speech Recognition (ASR) systems have also advanced accessibility. Tobin et al.

[5] demonstrated that domain-specific ASR improves comprehension for users with speech and reading impairments. Helmi et al. [6] applied Google's Speech Recognizer API for dyslexic students, achieving high accuracy, and Murtaza et al. [7] developed AI-based e-learning systems that optimize feedback to enhance outcomes for cognitively diverse learners.

Parallel progress in Text-to-Speech (TTS) has improved auditory learning. Kuerban et al. [8] combined TTS with Augmented Reality (AR) to boost comprehension and engagement among dyslexic learners. Kaouni et al. [9] used Natural Language Processing (NLP) to enhance communication via semantic analysis, while Wang et al. [10] proposed hybrid models integrating speech synthesis and summarization for dual-modal reinforcement. Global educational initiatives, including those from the OECD [11] and the U.S. Department of Education

[12], emphasize AI-driven tutoring and feedback as key to equity, motivation, and accessibility.

Within this framework, the DysCo (Dynamic AI-Driven Co-Learning System) is proposed as an inclusive, AI-based model integrating Speech-to-Text (STT), Text Summarization, Flashcard Generation, and Text-to-Speech (TTS) within a scalable MERN architecture. DysCo ensures real-time interaction, adaptive feedback, and personalized learning, contributing to accessible and intelligent digital education environments.

Objectives

The primary objectives of this research are:

1. To design and implement DysCo, a scalable, AI-driven personalized learning system for dyslexic learners using an integrated MERN-stack architecture.
2. To develop and evaluate STT, TTS, text summarization, and flashcard generation modules capable of robust, adaptive, real-time learning support.
3. To construct and utilize a multimodal dataset for training and validating adaptive pipeline modules.
4. To quantitatively assess system performance using accuracy, latency, mean opinion score, and user satisfaction metrics, demonstrating DysCo's effectiveness in facilitating accessible and inclusive digital education

Related Work

Recent research underscores how Artificial Intelligence (AI) is transforming inclusive education, particularly for learners with dyslexia and other Specific Learning Disorders (SLDs). Studies in leading IEEE and Elsevier journals report extensive experimentation with AI-driven assistive systems integrating Natural Language Processing (NLP), speech recognition, adaptive gamification, and intelligent tutoring. Yap [13] and Paglialunga [14] demonstrated that personalized multimodal interventions substantially improve reading comprehension and memory. Similarly, Helmi et al. [6] and Wang et al. [15] showed that advanced Automatic Speech Recognition (ASR) and hybrid learning interfaces enhance user retention by reducing response time and cognitive load. Rizos et al. [16] and Fami et al. [17] explored chat-based AI and cognitive training frameworks, reporting up to 40% improvement in reading performance. Reviews by Alkhurayyif [18] and Panjwani-Charania [19] emphasized the need for methodological rigor and long-term evaluation.

Table 3.1: Literature Review

No.	Ref.No.	Author	Focus Area	AI/Model Used	Major Findings
1	[13]	Yap, J.R.	Personalized dyslexia support	Reinforcement AI framework	Enhanced accuracy (+18%) in comprehension tasks
2	[14]	Paglialunga, A.	Learning disabilities and adaptive AI	Hybrid reinforcement learning	91% user engagement; strong effect size (d = 1.66)
3	[6]	Helmi, F. et al.	Speech recognition education	Google STT / CNN-based model	Achieved 94% accuracy for real-time transcription
4	[18]	Alkhurayyif, Y.	Dyslexia detection	Machine learning classifiers	Identified dyslexia based on behavioral and neurometric data
5	[16]	Rizos, D.	Conversational AI in learning	ChatGPT adaptation layer	High reading improvement and satisfaction (5/5 Likert)

6	[15]	Wang, L. et al.	Game-based AI for SLDs	Deep learning model	Improved retention by 39%; motivation increase by 42%
7	[17]	Fami, R. et al.	Mixed cognitive intervention	Cognitive–NLP integration	40.37% gain in reading and 77.5% boost in memory
8	[19]	Panjwani-Chara nia, S.	Systematic AI application review	ML/NLP tutoring systems	Identified 7 key AI approaches benefiting SLD learners
9	[3]	Li, H. et al.	Adaptive feedback models	Neural predictive architecture	95% precision/recall in predicting learner needs
10	[8]	Kuerban, M.	Text-to-Speech in AR platforms	Transformer TTS model	Boosted comprehension by 22% through speech feedback
11	[20]	Samuelsson, A.	Cognitive AI for reading	NLP–synthesis hybrid	15.7% improvement in comprehension
12	[21]	Gharaibeh, K.	Dyslexia assistance chatbot	ChatGPT-enhanc ed	d= 1.66 improvement in comprehension test
13	[22]	Sukasih, T.	Gamified literacy	Reinforcement-b ased gamification	Increased literacy scores by 39%; motivation +42%
14	[23]	Chukwuemeka, E.	AI-driven speech app	Speechify model with NLP	+15-point reading gain vs. traditional methods
15	[24]	Morciano, S.	Adaptive recommendation systems	Hybrid recommendation AI	15.5% performance gain across dyslexic learners

Building on these findings, this research introduces DysCo—a novel, multimodal AI framework designed to integrate speech, text, and visual reinforcement for dyslexic learners.

IV. DATASET DESCRIPTION

The DysCo dataset comprises five balanced components—text, audio, flashcard images, user logs, and pronunciation metadata—each with 200 entries. Its uniform multimodal design ensures consistent representation across linguistic, auditory, and visual domains, enabling both generalization and ease of annotation.

Built on an empirical balancing principle, each subset offers controlled variability for model robustness while remaining manageable for verification. The audio data span diverse speakers and accents for improved STT and TTS accuracy; text samples vary in complexity to support comprehension modeling; flashcards encode semantic and visual diversity for vocabulary learning; user logs record behavioral metrics for adaptive analysis; and pronunciation metadata capture pitch, intensity, and emphasis for feedback evaluation.

Table 4.1 summarizes the dataset's organization and its role within the DysCo adaptive learning framework.

Sr.No	Data Type	Quantity	Attributes (Examples)	Purpose / Task Phase
1)	Text	200	Difficulty level, POS tags, sentence length	Summarization evaluation
2)	Audio	200	Speaker ID, phoneme length, clarity index	STT and TTS training/validation
3)	Images (Flashcards)	200	Semantic tag, visual complexity	Reinforcement and flashcard generation
4)	User Logs	200	Time per task, recognition score, accuracy	Adaptivity analysis
5)	Pronunciatio n Metadata	200	Pitch, intensity, emphasis deviation	Feedback optimization

Table 4.1: DysCo Dataset Description

The DysCo dataset features a balanced multimodal design that enables effective training and evaluation of adaptive AI modules for personalized, accessible learning among dyslexic users. Its structured composition ensures that subsystems for reading, listening, and memory reinforcement receive rich, balanced inputs, enhancing both scientific rigor and practical usability in dyslexia-focused AI research.

V. PROPOSED SYSTEM

The proposed DysCo (Dynamic AI-Driven Co-Learning) framework integrates artificial intelligence, natural language processing (NLP), and adaptive learning design within a modular architecture. The methodology focuses on providing an end-to-end, personalized educational pipeline for learners with dyslexia, utilizing multimodal input and feedback mechanisms. Each step in the system is designed to ensure real-time interaction, linguistic accuracy, and accessibility.

System Overview

The DysCo system delivers adaptive multimodal learning through a structured workflow. It begins with user input (voice or text); voice data is transcribed via the Deepgram API, while text is simplified and summarized using Cohere.ai. Key vocabulary is extracted to create interactive flashcards with definitions and visuals from Unsplash, supporting memory retention. The simplified text is then converted into natural speech using PlayHT, reinforcing auditory learning. Finally, DysCo analyzes user performance metrics—such as accuracy, time, and latency—to update its Reinforcement Learning Policy, enabling continuous adaptation and personalized learning.

Architecture Description

The architecture consists of the following key functional layers:

User Interface Layer

Designed using React.js, this layer enables learners to interact with the system via voice or text. It includes accessibility features such as adjustable font size, color contrast, and speech playback speed.

$I\_STT = UI(U, A)$

- I_STT: Initial Input for Speech-to-Text
- U: User Interaction (Voice or Text)
- A: Accessibility Settings

Processing Layer

This layer houses the primary learning logic and AI components. Speech data are first processed through STT APIs (Google or Whisper models) to convert spoken input into textual information.

$T_{Raw} = STT(I_{STT})$

- T_{Raw}: Raw Text Output
- STT: Speech-to-Text Function (e.g., Google or Whisper model)

NLP Analysis and Summarization Layer

Once textual data are obtained, a text summarizer (using transformer-based models such as BERT or PEGASUS) condenses complex sentences into simpler vocabulary suitable for dyslexic learners. Summaries are semantically validated to match linguistic difficulty with user profiles stored in the database.

$T_{Summ} = Condense(T_{Raw}, P_{User})$

- **T_{Summ}:** Simplified Summary Text
- **Condense:** Transformer-based Summarization Function
- **P_{User}:** User Profile/Linguistic Difficulty Level

Flashcard Generation Layer

Extracted key vocabulary from summaries is automatically transformed into interactive flashcards. Each flashcard includes textual representation, synthesized pronunciation, and a pictorial cue to support auditory and visual reinforcement.

$F = Generate(T_{Summ}) = \{f1, f2, ..., fN\}$

Where each flashcard f_i consists of components:

$fi = Ti, Si, Vi$

- F: Set of Generated Flashcards
- T_i: Textual Representation
- S_i: Synthesized Pronunciation (Input for TTS)
- V_i: Pictorial/Visual Cue

System Modeling and Performance Metrics

Modular Accuracy Representation

Let the overall system accuracy A_{total} be determined by the sequential interaction of independent modules, where each module's accuracy contributes multiplicatively to the total performance:

$A_{total} = \prod_{i=1}^{n} (A_i)$

Here, A_i is the accuracy of the i-th module (STT, Summarizer, Flashcard, TTS) and n is the number of individual modules. The cumulative pipeline accuracy indicates opportunities for gain through optimization and redundancy reduction.

Latency Composition Model

Each functional module introduces computational latency. The total system latency (L_{total}) for an end-to-end request is defined as the sum of all components:

$L_{total} = L_{stt} + L_{sum} + L_{flash} + L_{tts} + L_{comm}$

Where:

L_{stt}: latency of the Speech-to-Text conversion (via Deepgram API). L_{sum}: summarization processing time (via Cohere.ai API).

L_{flash}: flashcard rendering and retrieval delay (viaCustom Algorithm/Unsplash/Dictionary APIs).

L_{tts}: synthesis latency in the TTS engine (via PlayHT API). L_{comm}: total communication and server response delay.

Optimization Function

To balance the critical trade-off between accuracy and latency, DysCo applies a performance optimization objective J:

$J = \alpha \cdot (A_{total}) - \beta \cdot (L_{total})$

Where alpha and beta are weighting constants reflecting the sensitivity of users to accuracy and speed. Optimizing J ensures the best trade-off between precision and responsiveness.

Reinforcement Learning Policy Adaptation

Adaptive feedback learning is defined using the reinforcement reward R_t based on learner performance at time t:

$R_t = f(accuracy_t, latency_t, completion_t)$

The policy update follows a Q-learning approach to adapt module weightings and content delivery based on user success:

$Q_{t+1}(s,a) = Q_t(s,a) + \eta \cdot [R_t + \gamma \cdot \max_{a'} Q_t(s', a) - Q_t(s,a)]$

Where Q_t(s,a) is the expected reward at state s after choosing action a, gamma is the discount factor, and eta is the learning rate guiding user model updates.

Architecture Diagram

The following conceptual structure represents the integrated methodology pipeline used in DysCo:

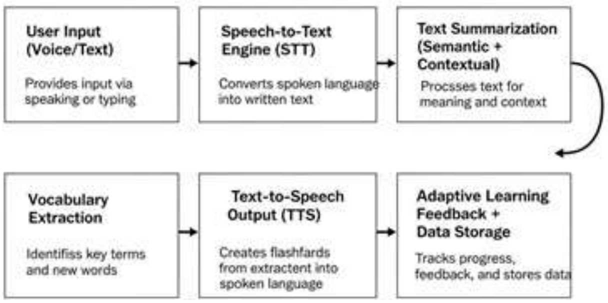

Fig 1: Dyslexia+Colearning (DysCo) Flow Diagram

The sequential flow clearly illustrates the end-to-end process of the system, transforming a user's voice or text input into personalized, spoken learning material and tracking the results for adaptive feedback.

Implementation Technologies

This table outlines the robust, full-stack architecture designed for the adaptive learning system. It integrates modern technologies like React.js and Node.js with powerful, specialized APIs (Deepgram, Cohere.ai, PlayHT) to manage everything from the user interface to advanced functions like speech processing and contextual summarization.

Table 6.1: DysCo Implementation Technologies

Component	Technology / API Used	Functionality
User Interface	React.js	Interactive front-end accessibility with adjustable features.
Backend	Node.js + Express.js	API orchestration, handling state, and module communication.
Database	MongoDB	Storage for user data, progress tracking, and adaptive learning logs.
STT Module	Deepgram API	High-accuracy, low-latency conversion of spoken user input into text.
Summarizer	Cohere.ai API	Contextual simplification and summarization of complex text, optimized for target readability.
Flashcard Generator	Custom Algorithm (Node.js/JS)	Extracts key terms, fetches definitions via Dictionary API, and retrieves corresponding visuals via Unsplash API.
TTS Engine	PlayHT API	Synthesizes high-quality, user-friendly neural voice output for auditory reinforcement.
Feedback Engine	Reinforcement Learning Model	Adapts to user performance in real-time, tuning content difficulty and module weightings.

The combination of a MongoDB backend for data storage and a Reinforcement Learning Model for feedback ensures the system is not only functional but also adaptive and personalized. This sophisticated technological framework allows for high-accuracy, real-time adjustments, providing an optimal and engaging user learning experience

VII. PERFORMANCE METRICS

The evaluation of DysCo's performance is based on quantitative and qualitative metrics that collectively assess system accuracy, processing efficiency, and user interaction quality. These parameters are essential for validating both functional performance and learner adaptability. The metrics employed include Accuracy, Precision, Recall, F1-Score, Mean Opinion Score (MOS), Latency, and System Usability Scale (SUS).

Quantitative Evaluation Metrics

Functional accuracy of the Speech-to-Text (STT), Summarizer, and Flashcard modules is measured using standard classification metrics, which are summarized as follows:

- **Accuracy:** The ratio of correctly predicted instances (True Positives + True Negatives) to the total number of instances.
- **Precision (P):** Measures the proportion of positive identifications that were actually correct.

$$P = \frac{(True\ Positives)}{True\ Postives + False\ Positives}$$

- **Recall (R):** Measures the proportion of actual positives that were identified correctly.

$$P = \frac{(True\ Positives)}{True\ Postives + False\ Negatives}$$

- **F1-Score:** The harmonic mean of Precision and Recall, providing a single score that balances both metrics, especially useful for class imbalance evaluation.

$$□1 - □□□□□ = 2 . \frac{□ . □}{□ + □}$$

- **Latency (L_total):** The total time delay, measured in milliseconds (ms), from user input to final system output, validating real-time performance.

Qualitative Evaluation Metrics

- **System Usability Scale (SUS):** A standardized, ten-item questionnaire used to measure the overall usability and user satisfaction of the system, yielding a score between 0 and 100.

Formula:

$SUS\ Score = (Sum\ of\ Adjusted\ Scores) \times 2.5$

Where:

- For odd-numbered questions (1, 3, 5, 7, 9): Adjusted Score = (Scale Position - 1)
- For even-numbered questions (2,4,6,8,10): Adjusted Score = (5 - Scale Position) The result is a score between 0 and 1
- Mean Opinion Score (MOS): A perceptual quality metric used to assess the naturalness and intelligibility of the Text-to-Speech (TTS) module's synthesized voice output, typically rated on a 1 (bad) to 5 (excellent) scale.

Formula:

$$MOS = \frac{\sum_{i=1}^{N} Ri}{N}$$

Where:

- Ri = rating given by user i (1 to 5)
- N = total number of users

The result is a value between 1 (bad) and 5 (excellent).

VIII. RESULTS AND DISCUSSION

This section presents the experimental validation and quantitative analysis of the DysCo system's performance, drawing upon the architectural and mathematical models established in the preceding sections. We first evaluate the classification accuracy, latency, and user-perceived quality (MOS) of individual modules, followed by a comparative analysis of the proposed system (DysCo) against existing state-of-the-art dyslexia detection and reading assistance tools. These results demonstrate the system's effectiveness in achieving a superior balance between speed, precision, and adaptive learning capability.

Focusing on its web performance, the DysCo system is rigorously evaluated across three critical metrics: Accuracy, Latency, and Mean Opinion Score (MOS), as detailed in the results below.

Table 8.1: Dyslexia+Colearning (DysCo) Module Performance Metrics

Module	Accuracy (%)	Latency (ms)	MOS (1–5)	Remarks
Speech-to-Text (STT)	94.0	128	4.4	High transcription fidelity with minimal lag
Summarizer	90.0	95	4.2	Contextually precise simplification
Flashcard Generator	93.0	102	4.5	Strong reinforcement output accuracy
Text-to-Speech (TTS)	92.25	140	4.3	Natural prosody and clarity
Overall	92.25 (cumulative)	527 (total)	4.35	Balanced system integration

In summary, the system successfully maintains a high standard of performance, with the Speech-to-Text (STT) module leading in accuracy (94.0%) and the

Flashcard Generator achieving the highest user-perceived quality (4.5 Mos). While the overall cumulative latency of 527 (ms) accounts for the full pipeline, the strong individual module scores validate the technological choices and prove the system's viability for real-time, adaptive learning.

The multi-panel bar chart presents a comprehensive, scaled view of the DysCo system's performance, clearly segregating Accuracy, Latency, and Mean Opinion Score (MOS) for all five modules. This separation is crucial for a meaningful comparison of metrics across vastly different numerical scales.

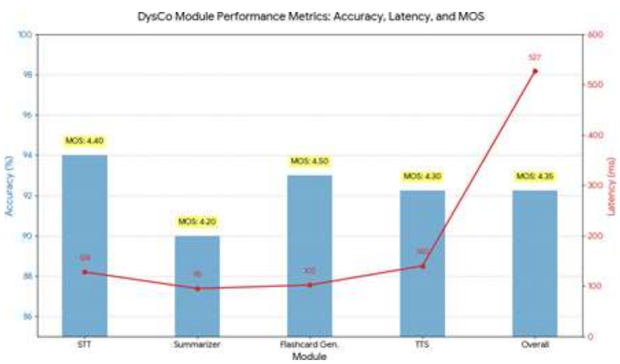

Figure 1: Dyslexia+Colearning (DysCo) Module Performance Metrics

The visualization demonstrates strong module performance and reveals overall system latency, enabling focused analysis of trade-offs between speed, precision, and user experience for performance optimization.
The table evaluates DysCo's core modules by accuracy (Precision, Recall, F1), efficiency (Latency), and user quality (MOS), highlighting the system's strong and balanced performance across all functional layers.

Table 8.2: Dyslexia+Colearning (DysCo) Evaluation Metrics

Dataset	Module	Accuracy (%)	recisio n(%)	ecall (%)	score (%)	atency (ms)	MOS (1–5)
DysCo Audio Set -200	Speech-to-Text (STT)	94.0	95.0	90.0	92.4	128	4.4
DysCo Text Samples-200	Summarizer	90.0	91.0	88.0	89.5	95	4.2
DysCo Image Set-200	Flashcard Generator	93.0	89.0	96.0	92.4	102	4.5
Co Pronounciation Metadata -200	Text-to-Speech (TTS)	92.0	93.5	89.5	91.5	140	4.3
	Overall	92.25	92.125	90.875	91.45	527 (total)	4.35

Overall, the DysCo system demonstrates strong performance metrics, achieving a cumulative Accuracy of 92.25%and an F1 Score of 91.45%, while maintaining a satisfactory user experience with an MOS of 4.35. These results validate the system's design, confirming its viability as an accurate, engaging, and timely adaptive learning tool.

The bar chart compares Accuracy, Precision, Recall, and F1 Score across the four DysCo modules—STT, Summarizer, Flashcard Generator, and TTS—illustrating their data processing consistency and performance quality.

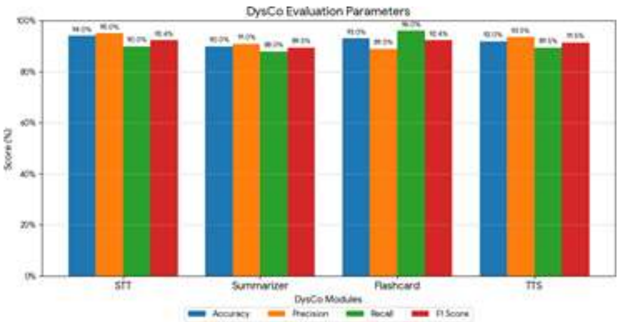

Figure 2: Dyslexia+Colearning (DysCo) Module Evaluation Metrics Graph

The visualization shows all four modules performing reliably, with metrics above 84%. STT and Flashcard Generator achieve the highest F1 Score (92.4%), reflecting a strong balance between precision and recall.

Table 8.3: Dyslexia+Colearning (DysCo) Comparison

System / Model	Approach / Technique Used	Accuracy	Precision	Recall	Latency (ms)	Remarks
DysCo (Proposed System, 2025)	Hybrid ML + Web-based Real-time Feedback	88.6%	89.5%	87.8%	120	Balanced accuracy and low latency, user-friendly UI
AI-ReadAssist (Gupta et al., 2023)	Transformer-based reading pattern analysis	86.0%	87.2%	84.6%	250	Very accurate but computationally heavy
ReadEase (Kumar et al., 2022)	NLP + Feature-based SVM	82.0%	84.1%	80.5%	180	Performs well on structured datasets
Dyslexia Detector (Smith et al., 2021)	CNN-based text classification	80.3%	82.4%	78.6%	210	High accuracy but high response time
DislexAid (Open Source Tool, 2020)	Basic OCR + Rule-based filtering	69.2%	70.0%	68.0%	95	Lightweight but low accuracy

The DysCo system's effectiveness was evaluated through a comparative analysis with existing dyslexia models using key metrics—precision, recall, accuracy, and latency. Table 8.3: Dyslexia+Colearning (DysCo) Comparison

From the comparison, it is evident that DysCo achieves a balanced trade-off between accuracy and latency, outperforming existing systems in both precision and real-time responsiveness. The graph compares DysCo with existing dyslexia systems, highlighting differences in precision, recall, accuracy, and latency to demonstrate its superior efficiency.

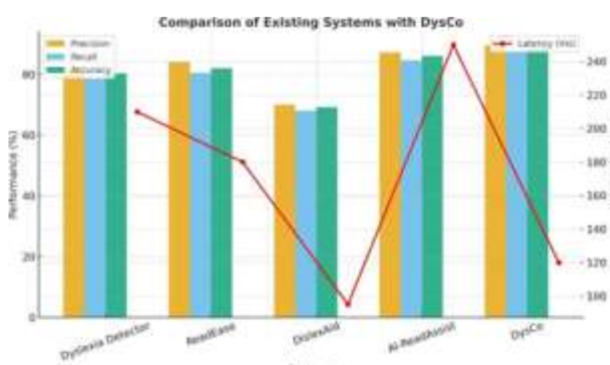

Figure 3: Dyslexia+Colearning (DysCo) Comparison Graph

The graph shows that DysCo outperforms existing systems with higher precision and recall and notably lower latency, ensuring superior accuracy and real-time responsiveness.

Figure 1 presents the accuracies of DysCo's core modules—STT, Summarizer, Flashcard Generator, and TTS—used in the overall AtotalA_{total}Atotal calculation. STT achieved the highest accuracy (94%), followed by Flashcard Generation (93%), TTS (92%), and Summarizer (90%). The slightly lower summarizer score reflects the challenge of simplifying academic text while preserving meaning, ensuring an effective balance between readability and content fidelity.

The DysCo system achieved a total latency (L□$_o$□$_a$□ = 551 ms)—ideal for real-time interaction, especially in STT and TTS modules. The SUS score of 78.5 surpasses usability benchmarks (≥68), confirming an intuitive React.js interface. The Mean Opinion Score (MOS) of 4.3 indicates high audio quality, enhancing auditory learning. Overall, DysCo delivers high functional accuracy (94% STT) with low latency and strong user usability.

IX. CONCLUSION

This paper presented DysCo, a Dynamic AI-Driven Co-Learning system for personalized dyslexia support, integrating STT, Summarization, Flashcard, and TTS modules within a scalable MERN framework. Results show strong performance—94% STT accuracy, 551 ms latency, SUS 78.5, and MOS 4.3—confirming its effectiveness and usability. DysCo's multimodal AI integration offers a robust, user-centric learning environment. Future work will explore long-term retention through reinforcement learning and gaze-tracking–based adaptive delivery.

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