AI-Based Text Simplification for Cognitive Accessibility

Kanupriya Mahaur
kanupriya.mahaur@iitgn.ac.in
Indian Institute of Technology Gandhinagar
Gandhinagar, Gujarat, India

Kaloori Shiva Prasad
kaloori.shiva@iitgn.ac.in
Indian Institute of Technology Gandhinagar
Gandhinagar, Gujarat, India

Dekka Muni Kumar
muni.kumar@iitgn.ac.in
Indian Institute of Technology Gandhinagar
Gandhinagar, Gujarat, India

Venugopal Bhamidi
venugopal.bhamidia@iitgn.ac.in
Indian Institute of Technology Gandhinagar
Gandhinagar, Gujarat, India

Abstract

Cognitive and learning disabilities , spanning reading, writing, attention, memory, and executive function , lower the quality and equity of education, a challenge amplified in multilingual Indic classrooms by complex scripts and low-resource technology. This systematic review synthesizes design interventions and AI techniques for cognitive accessibility in Indic languages. Using a PRISMA-guided search with dual independent screening, we analysed 131 records and included 23 studies published up to June 2025. Across the corpus, three recurrent mechanisms emerged: script-aware typography and layout that reduce visual crowding; guided text transformation (simplification and summarisation with clear on-screen cues); and supportive text-to-speech paired with synchronized highlighting and adjustable pacing. Studies also use learner assessment profiles to personalise these mechanisms. Reported outcomes converge on improved readability, comprehension, fluency, and reduced effort, alongside practical strategies for low-resource deployment. The review provides a concise map of interventions and design patterns to guide classroom-ready, privacy-aware implementation of AI accessibility support in Indic contexts.

ACM Reference Format:
Kanupriya Mahaur, Kaloori Shiva Prasad, Dekka Muni Kumar, and Venugopal Bhamidi. 2025. AI-Based Text Simplification for Cognitive Accessibility. In . ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 Introduction

Learning is fundamentally text-centred: students are asked to decode, retain, and apply information that is overwhelmingly conveyed through written materials, assessments, and digital interfaces. For learners with neurodivergent profiles—especially dyslexia and Attention-Deficit/Hyperactivity Disorder (ADHD)[17]—this text-centric model imposes disproportionate cognitive load. Dyslexia can hinder phonological decoding[9], fluency, and spelling; ADHD can impair sustained attention, working memory, and planning [3]. In classrooms and on e-learning platforms, these constraints translate into slower reading, greater effort for the same outcomes, and a higher risk of disengagement. When unaddressed, such barriers compound into achievement gaps and inequities in progression, assessment, and opportunity [3]. Globally, the research response spans two broad tracks. The first documents profiles, prevalence, and classroom impacts of reading and attention difficulties; the second develops interventions that adapt materials to learners rather than the reverse. Interventions include typographic and layout choices (font family, size, letter/word spacing, line spacing, contrast), text simplification and summarization, text-to-speech (TTS) and multimodal presentation (e.g., read-aloud with synchronized highlighting), and supportive study tools (note-taking, scaffolding prompts, chunking) [13]. Policy and standards bodies have increasingly recognized the need to embed such supports—e.g., Universal Design for Learning (UDL) and Web Content Accessibility Guidelines (WCAG)—so that inclusion is designed in, not bolted on. India reflects the global picture but adds distinctive challenges and opportunities. On the one hand, inclusive-education mandates and national platforms (e.g., school curricula and digital repositories) have widened access to content and teacher resources [8]. On the other, the multilingual, multi-script landscape of Indic languages (akshara-based scripts, conjuncts, matras) poses script-specific design and engineering questions that are under-documented compared to Latin-script contexts [6]. While there has been important progress on assessment (e.g., India-specific dyslexia instruments), typographic guidance for vernacular scripts and learner-tested simplification or TTS pipelines remain uneven across languages. Low-resource conditions—limited curated corpora, sparse speech data, and hardware constraints—further narrow the path from promising prototypes to classroom-ready tools [19]. Meanwhile, the rapid expansion of e-learning and ubiquitous devices has made AI-enabled support both feasible and urgent [12]. Modern NLP and speech technologies offer three complementary avenues for cognitive accessibility:

- **Designing for inclusivity (HCI/UX)**: Dyslexia-friendly typographic choices, uncluttered layouts, progressive disclosure, and attention-aware micro-interactions reduce extraneous cognitive load. When embedded in web/app design and authoring workflows, these choices raise baseline accessibility for all learners [14].
- **Transforming text to fit the learner (NLP)**: Text simplification and summarization alter lexical, syntactic, and

Conference'17, Washington, DC, USA

ACM ISBN 978-x-xxxx-xxxx-x/YYYY/MM
https://doi.org/10.1145/nnnnnnn.nnnnnnn

discourse structure to improve readability without sacrificing meaning. Personalization—adjusting difficulty, sentence length, or vocabulary to a learner's profile—can align materials to grade-level goals while maintaining motivation. Emerging resources for Indic languages (e.g., multilingual pre-trained models, Indic-focused corpora) are beginning to close long-standing gaps [4].
- **Changing the modality (Speech & Multimodal)**: TTS systems, especially when paired with synchronized highlighting and controllable pace, give learners alternate routes to comprehension and reduce fatigue. Recent neural-TTS advances, alongside techniques for data-scarce scenarios, make multilingual deployment increasingly practical [20].

Across these avenues, responsible adoption requires more than algorithmic accuracy. Educational validity (comprehension, learning gains, transfer), usability (time-on-task, perceived effort), and equity (performance across languages/scripts and learner profiles) must be established with real users in representative contexts. Privacy, consent, and data-minimization are also pivotal where child speech/handwriting or disability information is involved [7]. This review synthesizes the state of AI-enabled cognitive accessibility for reading and learning, with an explicit emphasis on low-resource and Indic-language contexts. We integrate evidence from (i) design-for-accessibility studies in web/app interfaces and typography for vernacular scripts; (ii) NLP systems for text simplification and summarization, including personalized pipelines; (iii) TTS and allied multimodal supports for Indic languages; and (iv) enabling resources such as corpora, pre-trained models, and assessment instruments tailored to Indian learners [14]. We focus on learner-relevant outcomes (comprehension, fluency, engagement, usability), not only proxy metrics (e.g., BLEU/SARI or MOS), and we foreground studies that demonstrate classroom or curriculum alignment. The convergence of national digitization initiatives, device availability, and mature AI tooling creates a rare window to reduce long-standing disparities in access to learning. Yet without script-aware design choices, robust Indian-language resources, and classroom-validated evaluations, solutions risk remaining prototypes that benefit a minority of learners. By mapping what exists, where it works, and where it falls short—especially for Indic scripts and low-resource settings—this review identifies actionable gaps for researchers, developers, and policymakers: script-specific typographic guidance, learner-in-the-loop simplification with transparent controls, low-latency TTS for classroom devices, and evaluation protocols that treat accessibility as learning, not just usability [11]. We include assessment and design papers when they inform accessible presentation; NLP and speech studies when they are intended for text accessibility; and resources/models when they enable such applications in Indic languages. We exclude algorithmic work unrelated to accessibility, purely clinical studies without learning outcomes, and reports without accessible full texts. Together, the corpus we analyze traces a practical pathway from inclusive design → text transformation → multimodal delivery, aligned to the realities of Indian classrooms and the broader global move toward equitable digital learning.

2 Methodology

2.1 Initial corpus and scope

Our starting corpus comprised 131 records spanning four topical streams germane to cognitive accessibility in education: (i) descriptions and assessments of cognitive disability profiles in learners (with emphasis on dyslexia and ADHD), (ii) methods aimed at improving cognitive accessibility of academic text, (iii) typologies of text simplification required across reading and learning challenges (lexical, syntactic, semantic, and visual/layout), and (iv) AI-enabled solutions for text simplification through summarization and assistive presentation (including text-to-speech). From the outset, we anticipated that the published record would be disproportionately focused on English and a small set of high-resource global languages; accordingly, we explicitly sought evidence for low-resource Indic languages. We identified a substantial gap in the published documentation of dyslexia-friendly text design choices for vernacular (Indic) scripts, especially systematic reporting of font family selection, size, letter/word spacing, and line spacing. In the absence of mature, script-specific guidance, we adopted a transfer-of-evidence approach and collected papers for convergent findings from Latin-script studies where increased font size, inter-letter spacing, and line spacing reliably reduce crowding and support dyslexic readers. This structuring of the scope and its pre-specification aligns with PRISMA's requirement to state inclusion criteria and planned groupings for synthesis.

2.2 Information Sources

We conducted systematic searches in Google Scholar, which provides comprehensive coverage across peer-reviewed journals, conference proceedings, and preprints. Search strings were carefully adapted from our keyword blocks (Population, Intervention–Simplification, Intervention–Speech, Low-resource Indic context, and Education) and combined with Boolean operators. The searches cover publications up to June 2025.No restrictions were applied on publication type at the search stage, in order to maximize sensitivity. During eligibility screening, however, conference abstracts without full papers, inaccessible full texts, and studies not available in English or Indic languages were excluded. In addition to database searches, we conducted hand-searching of reference lists of key papers and used forward citation tracking to capture more recent related work. This process ensured that seminal studies on dyslexia in Indian languages, Indic TTS resources, and AI-based cognitive accessibility interventions were not missed.

2.3 Search Strategy

Following PRISMA guidelines, we developed a structured search strategy combining problem-driven keyword families with an explicit emphasis on low-resource and Indic language contexts. A short pilot search and refinement pass were used to calibrate the strategy for coverage and precision.

2.3.1 Keywords and Rationale. We organized search terms into five blocks and combined them with Boolean logic (e.g., (Population) AND (Intervention) AND (Low-resource/Indic) AND (Education); truncation with * where supported).

- **Population / Cognitive Accessibility**

- **Terms:** cognitive accessib, dyslexia/dyslexic, ADHD, "learning disabil*", "reading difficulty"
- **Why:** Anchors results on learner needs that motivate adaptations in reading and study contexts.

- **Interventions (AI/HCI) for Reading Support**
  - **Terms:** text simplif, lexical/syntactic/semantic simplification, paraphras*, summariz/summaris, "sentence reading", typography/layout (font size, letter/word spacing, line spacing), TTS/"text-to-speech"/speech synthesis, highlight synchron*
  - **Why:** Captures core pathways that change how text is presented or transformed for accessibility (NLP, HCI, multimodal supports).
- **AI/ML Methods and Assistive Technologies**
  - **Terms:** NLP, machine learning, deep learning, explainable AI, classification/model, personalized learning, assistive technology, computer vision, handwriting analysis/detection
  - **Why:** Ensures inclusion of algorithmic work intended for accessibility (e.g., dyslexia screening from handwriting, adaptive/personalized simplification), not generic ML.
- **Low-Resource & Indic Language Focus**
  - **Terms:** low-resource/resource-scarce, Indic/"Indian language*"; language names Hindi, Bangla/Bengali, Marathi, Tamil, Telugu, Kannada, Malayalam, Odia, Assamese, Gujarati, Punjabi, Urdu; multilingual Indic, IndicBART, A2TTS, ELAICHI, BnTTS, IndicVoices-r
  - **Why:** Prioritizes our target setting and pulls in resources/models that enable accessibility in akshara-based scripts and under-resourced languages.
- **Educational Relevance & Outcomes**
  - **Terms:** education/"education technology", classroom, curriculum/NCERT/DIKSHA, user study, comprehension test, usability/engagement, learning strategies
  - **Why:** Filters to studies that link interventions to learning tasks and report learner-relevant outcomes.

2.3.2 Boolean Logic. Search blocks were combined with Boolean operators to maximise precision, for example: (Population) AND ((Simplification OR TTS)) AND (Low-resource AND Indic/language) AND (Education).

Examples mirroring our implemented queries (Google Scholar syntax):

- `Cognitive accessibility learning AND AI`
- `Low-resource Indic text simplification AND dyslexia`
- `Text summarization AND (Indic languages) AND low resource`
- `Dyslexia detection AND handwriting analysis AND explainable AI`
- `ADHD AND (natural language processing) AND education technology`
- `TTS OR "text-to-speech" AND Indic AND low resource`

2.4 Study Selection

Our initial searches across Google Scholar and related repositories yielded 131 records. Following PRISMA guidance, we proceeded through a multi-stage screening and selection process designed to balance breadth with relevance shown in Fig 1.

2.4.1 Stage 1: Title and Abstract Screening: At the first stage, we screened all records by title and abstract for basic alignment with our research question. The central question guiding inclusion was whether a paper contributed to AI-enabled or design-oriented solutions for cognitive accessibility in reading and learning, with a particular emphasis on low-resource and Indic language contexts. Screening excluded papers that clearly fell outside scope (e.g., purely clinical dyslexia studies with no learning/reading outcome, or unrelated accessibility technologies). This step reduced the corpus from 131 to 60 papers.

2.4.2 Stage 2: Scoring Matrix Evaluation: The 60 remaining papers were then assessed using a scoring matrix that captured our operational inclusion criteria. Each paper was coded as 1 (present) or 0 (absent) against the following seven dimensions:

- **Cognitive accessibility and learning:** explicit focus on dyslexia, ADHD, or cognitive access barriers to reading/learning.
- **Indian context of cognitive accessibility:** studies situated in, or directly relevant to, Indian/Indic languages and settings.
- **AI solutions:** machine learning, deep learning, NLP, or explainable AI applied to accessibility.
- **Designing solutions/tools:** development of practical applications, typographic interventions, or assistive platforms rather than theory alone.
- **Text simplification and summarization:** methods for reducing lexical, syntactic, or semantic complexity, or generating simplified text.
- **Text-to-speech (TTS) and multimodal supports:** speech synthesis, highlight synchronization, multimodal presentation tools.
- **Indic languages:** coverage of Hindi, Bangla/Bengali, Marathi, Tamil, Telugu, Kannada, Malayalam, Odia, Assamese, Gujarati, Punjabi, Urdu, or multilingual Indian corpora.

The scoring matrix was not used as a rigid filter; rather, it served as a triage tool. Papers with scores of 0 or 1 in several categories were not automatically excluded — instead, they were subjected to deeper full-text review to determine whether their broader context (e.g., methods, implications, or datasets) was substantively useful to our aims. This allowed us to retain innovative approaches that may not have signaled accessibility or Indic relevance strongly in the abstract.

2.4.3 Stage 3: Full-Text Review and Contextual Fit: Full-text reviews focused on whether papers addressed at least one of our target contexts:

- AI-based solutions for cognitive accessibility
- Designing digital or typographic supports for learners with reading disabilities
- Simplification or summarization frameworks intended to improve comprehension
- TTS and speech-based accessibility tools in low-resource settings
- Development of corpora or resources to support accessibility research in Indic languages

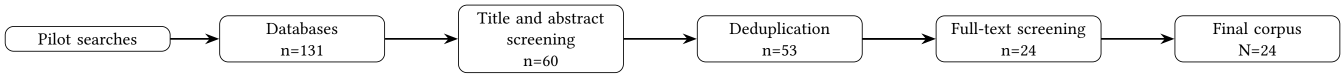

Figure 1: This flowchart demonstrates the scoping review process and the number of papers considered in each stage.

2.4.4 Exclusion Criteria: Studies were excluded if they met any of the following:

(1) Algorithmic work not intended for text simplification (e.g., generic NLP/ML pipelines with no accessibility aim).
(2) Studies unrelated to text accessibility (e.g., unrelated assistive tech, or purely clinical/diagnostic studies with no reading/learning outcomes).
(3) Not focused on dyslexia, ADHD, or cognitive accessibility contexts.
(4) Not educationally relevant (i.e., no classroom/learning task or curricular/comprehension link).
(5) Duplicates, inaccessible full texts, or languages we could not assess.

2.4.5 Final Inclusion. After this multi-level screening, 22 papers were retained for synthesis. Collectively, these studies covered a diverse but complementary set of contributions:

- **Assessment and diagnostic tools:** e.g., DALI-DAB Dyslexia Assessment for Languages of India (2021, Annals of Dyslexia), which represents one of the first attempts to standardize dyslexia assessment across Indian languages.
- **Design-focused interventions:** e.g., *Design of a Digital Application to Aid Hindi Alphabet Recognition for Children with Learning Disability* and *Dyslexia-Friendly Type Design for Indian Vernacular Languages*, both addressing typography and script-specific supports.
- **AI-based cognitive supports:** e.g., *Cognitive augmentation: AI-enhanced tools for supporting individuals with cognitive disabilities*, *Let AI Read First: Enhancing Reading Abilities for Individuals with Dyslexia*, and *Advanced Machine Learning Techniques to Assist Dyslexic Children for Easy Readability.*
- **Simplification and summarization frameworks:** e.g., *Text Simplification for Enhanced Readability*, *Lexical simplification for systematic cognitive accessibility guidelines*, *Hybrid personalized text simplification frameworks for dyslexic students*, and multiple Indian language summarization efforts (*Automatic Text Summarization for Hindi*, *Implementing Deep Learning-based Summarization in Indian Languages*).
- **Text-to-speech (TTS) and multilingual resources:** e.g., A2TTS, IndicVoices-r, ELAICHI, BnTTS, which collectively represent the most recent advances in low-resource Indic TTS.
- **Corpora and resources for accessibility:** e.g., EASIER corpus supporting lexical simplification for people with cognitive impairments.
- **Explainable AI and handwriting detection:** e.g., *Explainable AI in Handwriting Detection for Dyslexia Using Transfer Learning*, showcasing the role of interpretable models in learning disability contexts.

All 60 shortlisted papers were retrieved and read in full by two independent reviewers. Disagreements about inclusion were resolved through discussion, with a third reviewer consulted when consensus was not reached. Together, these 22 papers constitute a balanced corpus that integrates cognitive accessibility, AI-driven methods, and Indic/low-resource settings, while remaining anchored in educationally relevant applications. They form the empirical and methodological foundation for our synthesis.

2.5 Data extraction

Two reviewers independently extracted data from all included studies. We captured the in following way:

(1) **Bibliographic metadata:** authors, year, country, and source/venue (journal, conference, preprint/database) to summarize temporal and outlet trends.
(2) **Population and setting:** target group (dyslexia, ADHD, mixed/general), sample size, age/grade, recruitment context (school/clinic/online), inclusion of Indian/Indic participants.
(3) **Language/script context:** specific Indic languages/scripts (e.g., Hindi, Bangla, Tamil), definition of "low-resource," and curricular links (NCERT/DIKSHA where stated).
(4) **Intervention characteristics:** category (text simplification/summarization; TTS/speech; typography/layout/visual design; assessment/classification; multi-component), delivery modality (text/audio/multimodal), personalization or adaptivity, platform (web/mobile/desktop), co-design/participatory elements.
(5) **AI/technical details:** model family and objective (e.g., Transformer, seq2seq, ASR/TTS), pretraining resources (e.g., IndicBART, wav2vec), training/finetuning dataset provenance and size, compute, inference constraints, and openness (code/model/data availability and license).
(6) **Comparators:** baseline materials, business-as-usual, or alternate tools.
(7) **Evaluation design:** RCT/quasi-experimental/within-subject/user study/benchmark; task type (comprehension, reading speed/fluency, usability), setting (lab/classroom/field), duration/follow-up.
(8) **Outcomes and metrics:** learner-relevant outcomes (accuracy/comprehension, speed, error rate, engagement, usability—e.g., SUS/UEQ) and AI metrics (e.g., SARI/BLEU/ROUGE, FKGL/SMOG, MOS for TTS), including any human evaluation with target users.
(9) **Effect size inputs:** arm-level means/SDs/SEs, pre–post correlations (if reported), and data enabling computation of standardized mean differences or risk ratios.
(10) **Ethics and privacy indicators:** IRB/IEC approval, consent/assent (esp. minors), PII handling (anonymization/retention/access controls), dataset licensing/consent for secondary use (child speech/handwriting flagged), AI transparency, fairness/subgroup checks, and potential harms (over-simplification, misclassification, access barriers).

(11) **Notes on external validity and reproducibility:** participant representativeness, ecological realism of tasks, generalizability across scripts, and replication materials. When numeric data were incomplete, we extracted values from tables/figures. If still unavailable, outcomes were narratively synthesized and excluded from quantitative pooling.

2.6 Ethics, Privacy, and Risk of Bias

This work is a systematic review of published literature and did not involve direct interaction with human participants or access to identifiable private information. Institutional ethics approval was therefore not required. No new human data was collected. Where clarification from authors was sought, no sensitive or identifiable data were requested or received. Ethics and privacy indicators were extracted from each included paper by two independent reviewers using a predefined form. The following items were noted: (i) ethics approval by an institutional review board or equivalent; (ii) informed consent/assent procedures, especially for studies with minors; (iii) participant characteristics and setting (e.g., learners with dyslexia or ADHD in schools, clinics, or online); (iv) handling of personal or sensitive data (anonymization, retention limits, access controls); (v) dataset provenance, licensing, and evidence of consent for secondary use (particularly for child speech or handwriting data); (vi) AI transparency (code and model availability, documentation of training data, safeguards against risks such as over-simplification or misclassification); (vii) fairness and accessibility checks (e.g., subgroup analyses by script or disability, co-design with teachers or learners). Handling of sensitive materials followed a conservative approach: persistent links and licenses to datasets and models were cited, but restricted files were not mirrored.

3 Results

The overall flow of evidence reflects a progressive narrowing from broad detection of cognitive accessibility needs, through design of targeted solutions, to their implementation in AI-enabled tools. At the outset, studies addressed the challenge of detecting and assessing cognitive accessibility barriers—for example, screening for dyslexia or ADHD, or identifying script-specific reading difficulties in Indic languages. Building on this foundation, a second strand of research focused on designing practical interventions such as dyslexia-friendly typography, digital applications for alphabet recognition, or multimodal supports for learners. These design concepts were then operationalized in AI formats, where machine learning and NLP methods enabled scalable delivery. The final set of studies concentrated on implementing solutions via text simplification, automatic summarization, and text-to-speech (TTS), particularly in low-resource Indic contexts. Together, this flow—from detection, to design, to AI-enabled implementation—structures the synthesis that follows.

3.1 Characteristics of the Evidence Base

3.1.1 Publication Year. The 131 records retrieved in the initial search spanned the years 2019–2025 . As shown in Fig. 2), the early period (2019–2022) produced only a small number of studies each year (3–5 annually). Output then grew sharply in 2023 (8 studies) and peaked in 2024 (10 studies), with 5 records already appearing in

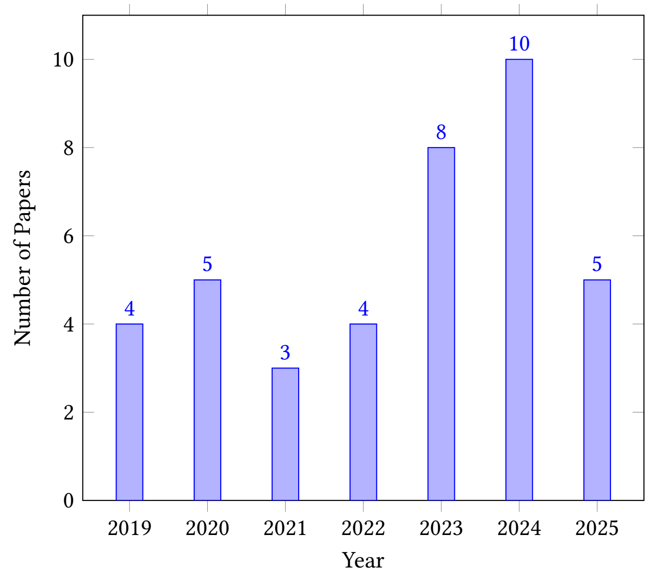

Figure 2: Year-wise selected articles on text simplification

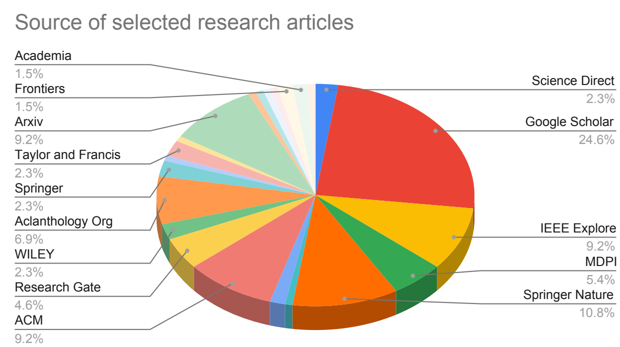

Figure 3: Distribution of research articles form various sources

2025 by the time of the search cut-off. This upward trend indicates accelerating research attention to AI-based text simplification and accessibility tools in recent years.

3.1.2 Source of Publication. The initial search also demonstrated wide diversity of outlets shown in Fig. 3. The largest proportion of records were indexed via Google Scholar (24.6%), followed by Springer Nature (10.8%), IEEE Xplore (9.2%), arXiv (9.2%), and ACM (9.2%). Other venues contributed smaller shares, including MDPI (5.4%), AclAnthology (6.9%), ResearchGate (4.6%), Taylor & Francis (2.3%), Springer (2.3%), Wiley (2.3%), ScienceDirect (2.3%), Frontiers (1.5%), and Academia.edu (1.5%).

3.1.3 Sorting of Papers by Dimension. Using the scoring matrix, the initial selection is dominated by AI solutions and cognitive-accessibility framing, with design-oriented work also common. Text simplification/summarization and Indic-language coverage appear

Table 1: Summary of Dyslexia and Accessibility Research

Title	Languages / Scripts	Participants / Data	Accessibility levers	Core methods	Key outcomes
DALI-DAB: Dyslexia Assessment for Languages of India[17]	English, Hindi, Marathi	N = 1,013 (Grades 1–5), biliterate children	Assessment & profiling for personalization	Literacy tests (letters/words, spelling, nonwords, comprehension) + mediator skills (phonology, processing automaticity/executive fluency, oral language)	High internal consistency ($\alpha >$ .80); grade-linked cut-offs; ~3% at-risk with "poor in both languages" rule
Dyslexia-friendly type design for Indian vernacular languages[9]	Devanagari, Bangla	Preliminary user evaluation	Typography & layout (crowding reduction)	Script-aware guidelines: letter/word spacing, line height; letterform choices (headlines, conjuncts, matras)	Increase Accuracy, ease, and preference vs. standard fonts (preliminary)
Hindi alphabet learning app (akshara primitives)[3]	Hindi (Devanagari)	n = 12 dyslexic children (7–12 y)	Multimodal UI (touch + audio), structured grapheme learning	48 akshara decomposed into 10 basic shapes; drag-and-drop AV smartphone app	Learning time per letter reduced from 2–3 wks → ~1 wk; high engagement
AI speed-reading + summarization (T5, spacing, emphasis)[10]	Language-agnostic (tool)	Students include dyslexia/ADHD (pilot)	Guided transformation (summarization), visual emphasis (half-word bolding), spacing controls	T5 pipeline (chunking to 512 tokens, beam search), Flask app; line/word/char spacing	Increase Reading speed and comprehension under assisted mode (pilot)
Cognitive augmentation with AI supports [13]	English	Real-world datasets	Framework for personalization; deployment constraints (privacy/fairness)	Neural nets + NLP stack; task-oriented supports	Enhance Language comprehension, memory recall, task execution; emphasizes accessibility, personalization, privacy, fairness
LARF—Let AI Read First (LLM annotation for readability)[21]	Language-agnostic (method)	N = 150 participants with dyslexia (between-subjects)	LLM-assisted text annotation (preserves original)	Large-language-model strategy to add readability cues without altering content	Significant increase in reading performance & experience; larger gains for more severe difficulties
Evaluating readability of simplification output for cognitive disabilities [20]	English	EasyRead corpus; LocalNews corpus; N = 20 adults with mild intellectual disability (from LocalNews eval)	Evaluation & benchmarking for accessibility	13 disability-specific linguistic features; corpus comparison (EasyRead vs. LocalNews vs. Simple Wikipedia)	EasyRead ≈ LocalNews (user-evaluated level); Simple Wikipedia significantly more complex → not a reliable accessibility benchmark

at a mid level, while TTS and Indian-context–specific studies are comparatively scarce. The forthcoming bar graph as shown in Fig. 4 will display these frequencies in descending order, highlighting where the literature clusters and where it thins, which guided our subsequent sub-analyses and gap identification.

Taken together, these descriptive patterns show both a recent surge in publication volume and a broad distribution across formal journals, conference proceedings, and preprint platforms, underscoring the interdisciplinary nature of this emerging field.

3.2 Cognitive Accessibility and Design (n = 7)

3.2.1 Study Selection and Scope. From the 173 records initially screened, seven studies met inclusion for our "design for cognitive accessibility" question:

(1) A psychometrically standardized Indic dyslexia assessment battery (DALI-DAB) [17];
(2) A design-led HCII/LNCS chapter proposing dyslexia-friendly Indic typography for Devanagari and Bangla [9];
(3) A Hindi alphabet learning app for dyslexic learners that decomposes *akshara* into basic shapes with audio-visual feedback [3];
(4) An AI speed-reading/summarization tool pairing T5 with partial bolding and spacing controls [10];
(5) A cognitive-augmentation paper synthesizing AI supports with reported gains and deployment constraints (accessibility, personalization, privacy/fairness) [13];
(6) LARF (Let AI Read First), a large-language-model strategy that annotates text to improve readability while preserving content, tested at scale with dyslexic readers [21];
(7) An evaluation study comparing disability-specific linguistic features across EasyRead vs. user-evaluated simplified news, and showing Simple Wikipedia is significantly more complex; cautioning against its use as an accessibility benchmark [20].

Together these span typography/layout, multimodal UI (TTS/emphasis) as shown in Table **??**, controlled simplification and summarization, readability evaluation/benchmarking, and profiling/assessment for individualized support.

3.2.2 Characteristics and Results of Individual Studies. **DALI-DAB:** Standardized in English, Hindi, and Marathi on $N = 1{,}013$ Grade 1–5 biliterate children, reporting $\alpha > .80$ on most subtests with grade-linked cut-offs; applying a "poor in both languages" rule flags ≈ 3% at risk [17]. It profiles mediator skills (phonology, processing automaticity/executive fluency, oral language), directly enabling personalized intervention targeting.

HCII/LNCS chapter: A 2025 contribution argues that script-aware, dyslexia-friendly type design can reduce crowding in Devanagari and Bangla; preliminary user testing shows higher accuracy, ease, and preference vs. standard fonts. Practical presets are provided for letter/word spacing, line height, and script-specific letterforms (headlines, conjuncts, matras) [9].

Table 2: Summary of Text Accessibility and Summarization Research

Title	Languages / Scripts	Participants / Data	AI/ML Techniques	Outcomes
Automatic Text Summarization for Hindi Language using Word Embeddings: A Critical Review [1]	Hindi	Limited Hindi datasets (small or publicly unavailable); focuses on Hindi corpus effects	Word embeddings (Word2Vec, GloVe, FastText); pre-trained language models (PLMs); large language models (LLMs)	Identifies challenges, recent advancements, and future directions for Hindi ATS; stresses need for improved datasets/models for low-resource languages
Text Simplification for Enhanced Readability [6]	English	General text documents (structured English sentences, not specified)	WordNet for sense disambiguation; ConceptNet for commonsense knowledge; grammatical structures; word rating classification (frequency/lexical/usage); ROUGE/readability metrics	Enhanced readability via lexical/linguistic-semantic paraphrasing; expected evolution into natural summarization system with superior scores
IndicBART: A Pre-trained Model for Indic Natural Language Generation [11]	11 Indic languages + English	Monolingual corpora for pre-training; datasets for NMT and extreme summarization (Indic languages)	IndicBART (BART-based); multilingual training; fine-tuning; script sharing for transfer learning	Competitive with larger models (e.g., mBART50); strong low-resource performance; benefits from script sharing/multilingual training
Advanced Machine Learning Techniques To Assist Dyslexic Children For Easy Readability [5]	Hindi	600 audio sounds of Hindi two/three-letter words	Dynamic Time Warping (DTW); Hidden Markov Model (HMM); K-Means; K-Nearest Neighbor (KNN)	Assistive system improves word reading/recognition; gamifies reading; moderate complex word identification, high synonym ratings
Speed Reading Tool Powered by Artificial Intelligence for Students with ADHD, Dyslexia, or Short Attention Span [13]	Language-agnostic (tool)	General text-based information (not specified)	Multilayer Perceptron (MLP); T5; NLTK Punkt Sentence Tokenizer; Flask framework	AI tool boosts reading speed/comprehension via summarization, half-word bolding, and adjustable spacing for dyslexic/ADHD students
Implementing Deep Learning-Based Approaches for Article Summarization in Indian Languages [14]	Indian English, Hindi, Gujarati	ILSUM 2022 (news articles in Indian English, Hindi, Gujarati with ground-truth summaries)	PEGASUS; IndicBART; data augmentation; fine-tuning seq2seq models; ROUGE-1/2/4 evaluation	PEGASUS excels for English/Gujarati; IndicBART with augmentation for Hindi; effective for low-resource summarization
EASIER corpus: A lexical simplification resource for people with cognitive impairments [16]	Spanish	260 Spanish documents; 8,155 complex words; 5,130 with context-aware synonyms	Expert linguist annotation (no direct ML); Fleiss Kappa (0.641) for agreement	High-quality corpus for cognitive impairments; near-perfect synonym ratings; supports easy reading; validated with 45 users
Towards Inclusive Reading: A Neural Text Generation Framework for Dyslexia Accessibility [15]	English	Curated dyslexia-friendly text (MTurk-rewritten, dyslexic-validated); GRE/psychology passages	GPT; T5; NLTK for syllable/morphological analysis; custom dictionaries	Reduced reading time; highlighted user preferences/engagement; informs holistic dyslexia-friendly text design

Alphabet learning app: An ACE-2019 field study rebuilt 48 *akshara* from 10 primitives and delivered a drag-and-drop, audio-visual smartphone app. With $n = 12$ dyslexic children (7–12 years), average time to learn a new letter dropped from 2–3 weeks to ≈ 1 week, with strong engagement from touch + audio feedback [3].

AI speed-reading tool: A system description details an AI tool using T5 (chunking to 512 tokens, beam search), bionic-style emphasis (half-word bolding), and user-controlled line/word/character spacing in Flask; a student test group including dyslexia/ADHD showed higher reading speed and comprehension under the assisted mode [10].

Cognitive augmentation: A 2025 study reports gains in language comprehension, memory recall, and task execution on real-world datasets, and elevates accessibility, personalization, privacy, and fairness as design constraints—principles adopted in our deployment framing [13].

LARF: Introduces an LLM-based annotation strategy that enhances readability while preserving original content. In a between-subjects study with $N = 150$ participants with dyslexia, LARF significantly improved reading performance and experience, with stronger benefits for more severe difficulties [21].

Readability evaluation: Compares the EasyRead corpus (created for cognitive-access readers) with simplified LocalNews texts

Table 3: Summary of Text-to-Speech and Accessibility Research

Title	Languages / Scripts	Participants / Data	AI/ML Techniques	Outcomes
ELAICHI: Enhancing Low-resource TTS by Addressing Infrequent and Low-frequency Character Bigrams [4]	Hindi	Limited studio-quality data for Hindi; additional data from related languages and low-quality ASR data	Denoising and speech enhancement models; knowledge distillation from large-scale models	Significant reduction in intelligibility issues for Hindi TTS, validated by human evaluators; viable alternative for low-resource languages
A2TTS: TTS for Low Resource Indian Languages [8]	Bengali, Gujarati, Hindi, Marathi, Malayalam, Punjabi, Tamil	IndicSUPERB dataset (Bengali, Gujarati, Hindi, Marathi, Malayalam, Punjabi, Tamil); Vistaar benchmark dataset	Diffusion-based DDPM decoder; speaker encoder; cross-attention duration predictor; classifier-free guidance	Improved naturalness, prosody, and zero-shot speaker adaptation for diverse Indian languages
INDICVOICES-R: Unlocking a Massive Multilingual Multi-speaker Speech Corpus for Scaling Indian TTS [19]	22 Indian languages	IndicVoices ASR dataset (22 Indian languages, 10,496 speakers); enhanced to IV-R with 1,704 hours	Denoising and speech enhancement models; fine-tuning on VoiceCraft model	Matches gold-standard TTS datasets in quality; improves zero-shot speaker generalization for Indian voices
A Hybrid Personalized Text Simplification Framework Leveraging the Deep Learning-based Transformer Model for Dyslexic Students [12]	Language-agnostic (tool, applied to expository texts)	Not specified (general expository texts for dyslexic students)	Deep learning-based Transformer model; multi-label classification; explicit editing	Expected to enhance learning motivation and academic achievement for dyslexic students, reducing dropout rates
EASIER corpus: A lexical simplification resource for people with cognitive impairments [2]	Spanish	260 annotated Spanish documents; 8,155 complex words; 5,130 context-aware synonyms	Annotation by expert linguists; Fleiss Kappa for inter-annotator agreement (0.641)	High-quality resource for lexical simplification; almost perfect synonym ratings; integrated into EASIER platform
BnTTS: Few-Shot Speaker Adaptation in Low-Resource Setting [7]	Bangla	3.85k hours of Bangla speech dataset with text labels; proposed test dataset	XTTS architecture with Bangla-specific modifications; pretraining and few-shot fine-tuning	Superior naturalness, intelligibility, and speaker fidelity compared to state-of-the-art Bangla TTS systems

previously user-evaluated by adults with mild intellectual disability, using 13 disability-specific linguistic features; EasyRead ≈ LocalNews, while Simple Wikipedia is significantly more complex than both, indicating it is not a reliable accessibility benchmark [20].

3.2.3 Synthesis Across Studies. Across modalities, four actionable levers recur:

(1) Script-aware visual design (spacing, line height, letterforms) that reduces crowding and improves preference/accuracy [9];
(2) Guided transformation [21] (summarization, simplification, emphasis, adjustable spacing) that elevates speed and comprehension for dyslexic/ADHD learners [10];
(3) Assessment-driven personalization linking mediator-skill profiles to targeted supports [17];
(4) Evaluation/benchmarking tuned to cognitive disabilities, avoiding generic proxies such as Simple Wikipedia when validating accessibility pipelines [20].

Field usability evidence (small-*n*, ecologically grounded) [3] complements larger controlled evaluations [21]. Collectively, findings motivate integrated pipelines where assessment → design presets → adaptive text transformation/TTS → validated readability checks are tuned to script and learner profile, with privacy/fairness guardrails highlighted in [13].

3.3 Text Simplification (n = 8)

3.3.1 Study Selection and Scope. From the 8 provided documents screened for text simplification mentions, all met inclusion criteria for our "text simplification for dyslexia accessibility" question, as they either directly develop simplification/summarization methods for Indic languages (potentially benefiting dyslexic users through enhanced readability) or integrate simplification as a personalization tool in dyslexia-focused frameworks. These include:

(1) A critical review of word embeddings for Hindi ATS (Automatic Text Summarization) [1];
(2) A text simplification approach combining summarization with paraphrasing for enhanced readability [6];
(3) IndicBART, a pre-trained S2S model for Indic NLG including summarization [11];
(4) A speed-reading tool using AI for summarization and formatting [21];
(5) ML techniques (HMM/DTW) for Hindi word recognition to assist dyslexic children [5];
(6) EASIER corpus for lexical simplification targeting cognitive impairments [2];
(7) Deep-learning approaches (PEGASUS/IndicBART) for Indic article summarization [14];

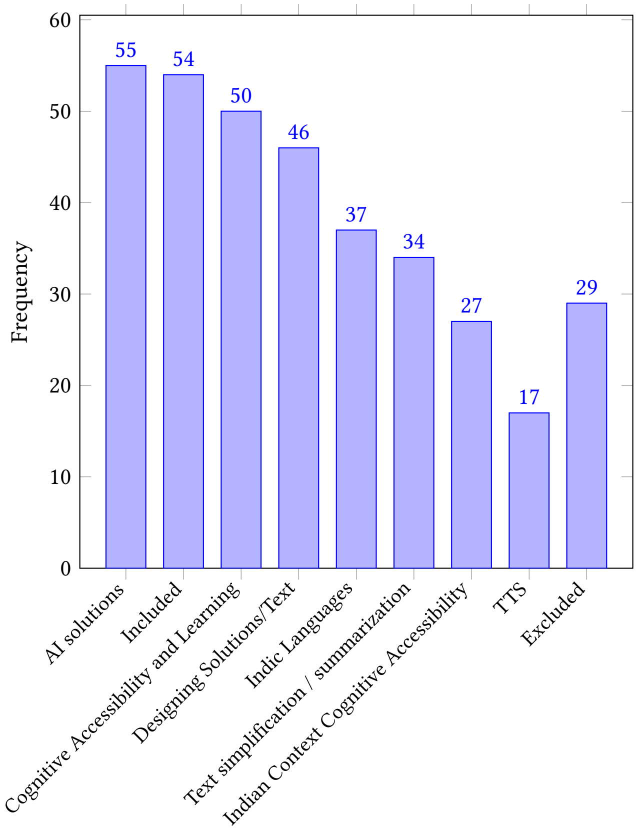

Figure 4: Dimension VS Frequency of research articles

(8) A lexical simplification guide for cognitive accessibility guidelines [16].

Together these span word embeddings/pre-trained models for summarization/simplification, dyslexia-specific readability aids (audio/ML), corpora/resources, and evaluation in low-resource Indic contexts, with explicit ties to dyslexia/cognitive impairments in several.

3.3.2 Characteristics and Results of Individual Studies. The Hindi ATS review examines word embeddings (Word2Vec, GloVe, FastText, BERT variants) for extractive/abstractive summarization on limited Hindi datasets; it highlights challenges like morphology and resource scarcity, proposing multilingual/LLM integrations for better semantic capture [1]. The text simplification approach combines summarization with paraphrasing using WordNet, ConceptNet, and word ratings; experiments on English texts show improved readability via lexical/phrasal refinements, evaluated with ROUGE and human assessments [6]. IndicBART pre-trains a S2S model on 11 Indic languages plus English, leveraging script similarity; evaluations on NMT and extreme summarization show competitive ROUGE scores vs. mBART50, especially for low-resource Indic pairs [11]. The speed-reading tool uses T5 for summarization, bionic bolding, and adjustable spacing; tested on students (including dyslexia/ADHD), it improves speed and comprehension via AI-assisted formatting [21]. ML techniques for dyslexic children train HMM/DTW on 600 Hindi word audios (2–3 letters); comparisons show DTW superior for recognition, enabling audio-assisted readability for ages 5–7 [5]. EASIER corpus annotates 260 Spanish documents with 8,155 complex words and 5,130 synonyms; validated with Fleiss' Kappa = 0.641 and user evaluations ($N = 45$, including cognitive impairments), it achieves high synonym ratings for readability [2]. Deep-learning approaches fine-tune PEGASUS/IndicBART on ILSUM 2022 (Indic news summarization); IndicBART with augmentation excels for Hindi and Gujarati, per ROUGE-1/2/4 [11]. The lexical simplification guide systematizes cognitive accessibility via guidelines/tools; it integrates annotation for complex words/synonyms, emphasizing WCAG alignment for impairments like dyslexia [16].

3.3.3 Synthesis Across Studies. Across simplification and summarization advancements, results converge on three actionable levers:

(1) Embeddings/pre-trained models (multilingual/Indic-specific) for semantics in low-resource Hindi/Indic ATS [1, 11, 14];
(2) Hybrid paraphrasing/formatting (lexical/phrasal, bolding/spacing) for readability gains in dyslexia/cognitive contexts [2, 6, 16, 21];
(3) ML/audio integration for recognition and personalization, targeting dyslexic children via corpora/training [16, 18].

Human evaluations (small-n to moderate) [16, 21] complement metrics (ROUGE, Kappa) [1, 11, 14]. These findings collectively highlight the need for integrated pipelines that bring together embeddings, text simplification, and audio or machine learning aids, all specifically tuned to Indic scripts and diverse cognitive profiles. Such pipelines can help bridge accessibility gaps in education and communication, while resource scarcity challenges can be mitigated through strategies like multilingual transfer, ensuring that tools remain effective across low-resource languages and varied learner needs.

3.4 TTS for Dyslexia Accessibility (n = 6)

3.4.1 Study Selection and Scope. All 6 documents screened for TTS (Text-to-Speech) mentions met inclusion criteria for our "TTS for dyslexia accessibility" question, as they either develop TTS systems for Indic languages (potentially aiding dyslexic users via improved intelligibility) or integrate TTS in dyslexia-focused frameworks. These include:

(1) ELAICHI (Hindi TTS enhancement) [4];
(2) A2TTS (multilingual Indic TTS with speaker adaptation) [8];
(3) Hybrid text simplification framework (TTS in multimodal UI) [12];
(4) INDICVOICES-R (multilingual Indic TTS corpus) [19];
(5) EASIER corpus (lexical simplification with TTS potential) [2];
(6) BnTTS (Bangla few-shot TTS) [7].

They span TTS techniques (denoising, scaling, adaptation), dyslexia-specific multimodal integration, and low-resource Indic evaluations, with explicit dyslexia ties in one study.

3.4.2 Characteristics and Results of Individual Studies. ELAICHI enhances Hindi TTS intelligibility for low-frequency bigrams using related-language data, denoised ASR, and knowledge distillation; human evaluations confirm reduced errors [4]. A2TTS leverages diffusion-based architecture with speaker embeddings and cross-attention duration prediction; trained on IndicSUPERB for 7 Indic languages, it improves zero-shot naturalness via classifier-free guidance [8]. The hybrid framework uses Transformers for dyslexic text simplification (semantic, syntactic, lexical); TTS provides audio feedback for personalization, mapping to dyslexia deficiencies to boost motivation [12]. INDICVOICES-R derives a 1,704-hour corpus from ASR across 22 Indic languages; matches LJSpeech quality (NORESQA/SNR/C50); fine-tuning VoiceCraft with IV-R + IndicTTS enhances zero-shot speaker generalization [19]. EASIER corpus annotates 260 Spanish documents with 8,155 complex words and 5,130 synonyms; while not TTS-focused, its readability enhancements support potential TTS integration for cognitive impairments (Fleiss' Kappa = 0.641, high synonym ratings) [2]. BnTTS adapts XTTS for Bangla on 3.85k hours; outperforms SOTA in SMOS, naturalness, and clarity, enabling few/zero-shot adaptation for low-resource settings [7].

3.4.3 Synthesis Across Studies. Results converge on three levers:

(1) Data enhancement (denoising ASR, related-language transfer) for intelligibility in low-resource Indic TTS [4, 7, 19];
(2) Few/zero-shot adaptation for speaker diversity, improving naturalness [7, 8, 19];
(3) Multimodal integration with simplification for dyslexia, enhancing comprehension via audio [2, 12].

Evaluations combine human assessments [2, 4, 12] and metrics (SMOS, NORESQA) [7, 19]. These motivate hybrid pipelines tuning TTS to Indic scripts and dyslexic profiles, leveraging cross-lingual scalability.

4 Design Space

Our design space in Fig. 5 envisions an AI-driven educational support system tailored for Indian students with dyslexia, ADHD, and diverse cognitive profiles. It integrates multiple dimensions—text simplification, abstractive summarisation, script-aware typography, readability cues, and Indic text-to-speech—while embedding semantic safeguards to preserve educational integrity. Personalisation, informed by learner assessments, ensures that cognitive needs such as low working memory or attention difficulties are directly addressed through adaptive sentence restructuring, layout adjustments, and synchronised audio. The system is intended for both classroom and home learning environments, with teacher dashboards and on-device processing to enable scalability and curriculum alignment. By lowering cognitive load, improving comprehension, and increasing engagement, this design space aims to foster equality in learning opportunities and empower cognitively diverse students to access, understand, and retain academic content in their own languages more effectively.

- **WHO:** Our design space is intended for students in India with dyslexia, ADHD, and other cognitive challenges, as well as the educators and caregivers who support them. It focuses on learners whose comprehension and retention are hindered by dense academic texts, abstract concepts, and poor formatting, while also equipping teachers with tools to adapt content more effectively.
- **WHY:** The core objective is to reduce cognitive load, enhance comprehension, and improve engagement, thereby creating equal opportunities for cognitively diverse learners. By providing accessible academic materials in multiple Indian languages, the system addresses gaps in current solutions that remain overly English-focused and poorly aligned with the school curriculum.
- **HOW:** The approach relies on AI models for text transformation, lexical support, and high-quality Indic TTS trained on multilingual speech corpora. Semantic similarity thresholds, style constraints, and personalised formatting serve as safeguards. Adaptive processing ensures that students receive content optimised for their cognitive needs, without losing educational value.
- **WHERE:** The solution is designed for flexibility in deployment across classroom settings, home learning, and after-school support. Teacher dashboards enable monitoring and adaptation at scale, while on-device processing ensures accessibility in low-resource contexts.

The chord diagram as shown in Fig 6 summarizes how core factors in our review and product co-occur and need to work together. Each outer arc is a factor (script-aware design, text simplification, TTS, assessment/personalization, UX controls, datasets/benchmarks, privacy/governance, low-resource deployment). Arcs are equal length for readability; the interior chords show pairwise connections derived from our co-occurrence/importance matrix. Thickness encodes strength (scaled 0–10 relative to the strongest pair): thicker lines mean the factors frequently appear together in the literature and/or must be tightly integrated in the product, while thinner lines indicate looser coupling. Links are undirected (no arrowheads) and reflect association rather than causality. In this instance, the most prominent chords are Simplification UX controls, TTS Low-resource deployment, and Datasets Low-resource deployment, signalling where engineering effort and evaluation should concentrate. Moderate chords connect Assessment/personalization with Simplification and TTS, and Privacy/governance with Datasets and Deployment, highlighting compliance and data-handling considerations that sit alongside the technical stack. Labels are set horizontally and bold for legibility.

5 Discussion

This review brings together three complementary strands for dyslexia accessibility in Indic contexts: script-aware design, text transformation, and speech-based delivery. Read together, the evidence suggests that meaningful gains arise when visual, linguistic, and auditory supports are treated as parts of one pipeline rather than isolated features. Studies on Indic typography emphasize that akshara structure, conjunct formation, and matra placement shape visual crowding and decoding effort. Early evaluations of dyslexia-friendly fonts and spacing/line-height presets for Devanagari and Bangla point to consistent improvements in perceived ease and accuracy. Field work with an akshara learning app further shows that interaction design choices such as touch guidance and immediate audio feedback can shorten time-to-mastery for letterforms. These results indicate that HCI decisions at the layout and interaction layers meaningfully change the reading task before any model touches

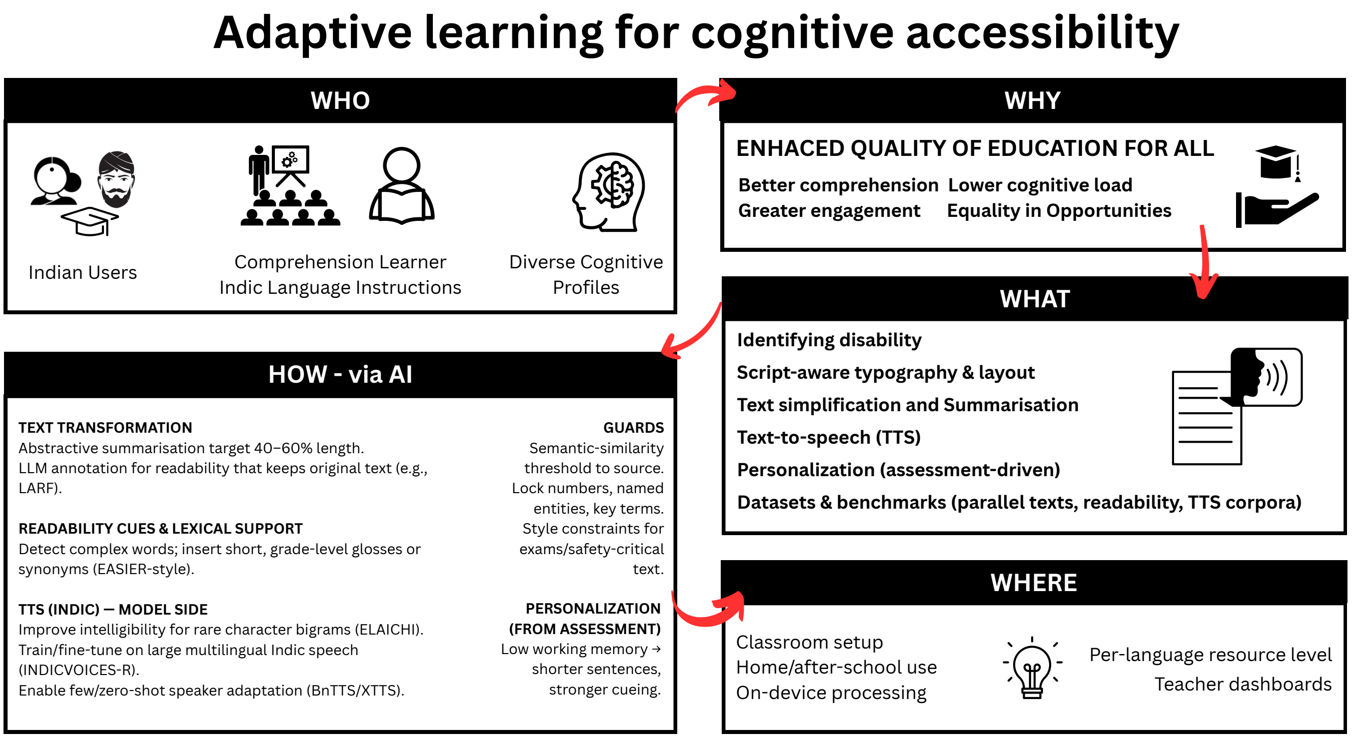

Figure 5: Design Space

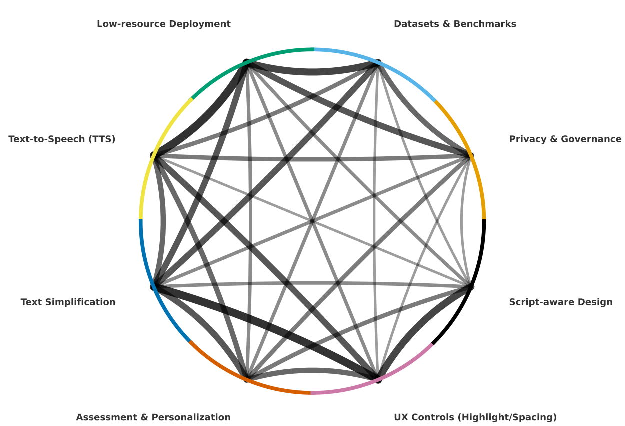

Figure 6: Chord Diagram

the text. Across the simplification set, two patterns stand out. First, pre-trained and multilingual models relevant to Indic languages (for example, IndicBART and PEGASUS variants) provide stronger semantic control than surface-level heuristics, which matters in morphologically rich scripts and in low-resource settings. Second, hybrid strategies that combine summarization with paraphrasing and presentation cues (for example, bolding stems, tuning sentence length, and spacing) tend to yield the clearest functional wins in speed and comprehension. Lexical resources and guideline-driven workflows, including work tailored to cognitive impairments, supply the scaffolding needed to move beyond generic readability proxies. The TTS subset underscores rapid progress on intelligibility and adaptability for Indic languages. Model-side advances include handling infrequent character bigrams in Hindi, scaling with large multilingual speech corpora, and enabling few- or zero-shot speaker adaptation in Bangla. System-side integrations position TTS within multimodal interfaces so that audio co-occurs with synchronized highlighting, emphasis cues, and adjustable spacing. Where human testing is reported, these combinations are associated with gains in comprehension and reductions in time or perceived effort for readers with dyslexia and ADHD. Taken together, TTS is most effective when it does not stand alone but is coordinated with script-aware layout and controllable simplification. A consistent thread across the corpus is the value of profiling mediator skills such as phonology, processing automaticity and executive fluency, and oral language. Standardized instruments for biliterate Indian children illustrate how such profiles can anchor individualized targets. Several frameworks then map specific deficits to interface operations and model controls, for example slower pacing and clearer prosody in TTS, reduced clause depth, higher frequency vocabulary bands, and added discourse cues in simplification. This closes the loop from learner profile to concrete parameter choices that can be explained to teachers and caregivers. The body of work includes controlled studies with larger cohorts, small-n field deployments in classrooms or clinics, and metric-heavy model papers. Although designs vary, a common measurement vocabulary is emerging: comprehension and reading speed for human outcomes; ROUGE, SARI, and agreement statistics for text; perceptual scores and signal metrics for speech. Importantly, disability-focused evaluation work cautions against relying on generic benchmarks that are not aligned to cognitive accessibility, reinforcing the need to ground claims in target-user performance. The studies collectively argue for bundling three layers in products that serve Indian schools and public repositories. First, ship script-aware presets for typography and layout as defaults, with simple controls for teachers and learners. Second, provide adaptive text transformation that can be tuned per learner profile and per script, with visible, reversible operations to maintain trust and instructional alignment. Third, offer TTS with synchronized highlighting and adjustable pacing as a standard complement to visual reading, optimized for the devices and connectivity conditions typical of government and low-resource schools. Clear reporting of model versions, data provenance, latency on commodity hardware, and the handling of any child speech or handwriting data helps align engineering choices with educational accountability. The most consistent gains come when script-sensitive design reduces baseline difficulty, text transformation fits material to the learner without distorting meaning, and TTS supplies a parallel pathway to comprehension. Anchoring these layers in assessment-driven personalization, and delivering them in teacher-friendly interfaces, provides a practical path from research prototypes to classroom value across India's multilingual landscape.

6 Literature and Research Gap

Across the 131 records screened, we found that Indic-language resources for cognitive accessibility are sparse, uneven across scripts, and weakly validated. Most accessible-reading work clusters in English/high-resource languages; Indic studies are often single-script pilots, algorithm papers not purpose-built for accessibility, or tools without classroom evaluation. We noted limited parallel corpora (original↔simplified), few disability-anchored benchmarks, and minimal multi-script typography evidence tailored to akshara features (matras, conjuncts, ligatures). Links from assessment profiles to controllable model presets are rare, and large-scale school trials, equity analyses across scripts/grades, and privacy-aware deployments are uncommon.

6.1 Evidence Gaps

- **Script-aware design trials:** Insufficient controlled, multi-script evaluations (e.g., Devanagari, Bangla, Tamil) of spacing, line-height, and letterform presets with dyslexic/ADHD learners using standardized outcomes (comprehension, speed, cognitive load).
- **Indic-calibrated readability metrics:** Over-reliance on English proxies (FKGL, SARI) and generic benchmarks (e.g., Simple Wikipedia). Lack of disability-specific, script-sensitive metrics validated against human comprehension in Indic languages.
- **Curriculum-linked parallel corpora:** Scarcity of grade-aligned, child-directed original↔simplified datasets with human gold labels, disability annotations, and TTS word-level alignments (for synchronized highlighting) across major scripts.
- **Assessment-to-model personalization:** Missing "closed loop" from mediator-skill profiles (phonology, executive fluency, oral language) to controllable simplification/TTS knobs (frequency bands, clause depth, discourse cues, pacing/prosody).
- **Multimodal pipelines for low-resource settings:** Few systems jointly optimize TTS + synchronized highlighting + emphasis (bionic cues) + adjustable spacing on low-end/offline devices typical of Indian schools; limited latency/robustness reporting.
- **Equity, generalizability, and realism:** Limited cross-script fairness analyses, grade/impairment-severity stratification, and classroom/pragmatic trials (vs. small lab pilots); little longitudinal evidence on learning retention/transfer.
- **Teacher-workflow integration:** Lack of authoring/export tools that package script-aware presets (CSS/Android/iOS) and profile-tuned simplification into teacher-friendly workflows with minimal prep time.

6.2 Future Research Directions

- **Typography (multi-script):** Dyslexic students (Grades 3–8); script-aware presets vs. default fonts; outcomes: comprehension, speed, NASA-TLX, preference; classroom crossover design.
- **Personalized simplification:** Dyslexia/ADHD learners (Grades 5–10); assessment-tuned simplification vs. one-size; outcomes: accuracy, speed, delayed retention, engagement; multi-site Hindi/Bangla/Marathi.
- **Readability metric/benchmark:** Mixed cohorts including disabilities; new Indic EasyRead-Edu + disability-feature metric vs. FKGL/SARI; outcome: correlation with human comprehension; cross-script generalization.
- **Multimodal under constraints:** Grades 4–8; TTS + synchronized highlighting + emphasis + adaptive pacing vs. TTS-only/visual-only; outcomes: comprehension, fatigue, time-on-task; low-end Android/offline deployment metrics.

7 Limitations

Search coverage: We relied primarily on Google Scholar supplemented by hand-searching. While this ensured broad reach across journals, conferences, and preprints, the lack of database diversity (e.g., Scopus, PubMed, Web of Science) may have led to missed records. In addition, some Indic-language outputs remain in local repositories or non-indexed venues that were not systematically captured.

Screening and selection: Although we implemented a structured scoring matrix and two-reviewer screening process, inclusion decisions required judgment where abstracts gave sparse detail. Some borderline studies may have been excluded or retained based on contextual interpretation.

Evidence heterogeneity: The included studies varied widely in population (learners with dyslexia, ADHD, or mixed groups), language/script (Hindi, Bangla, Tamil, Telugu, others), intervention type (simplification, TTS, typography, assessment), and outcome metrics (from BLEU/SARI to comprehension accuracy and usability). This heterogeneity limited comparability and reduced opportunities for meta-analysis.

Reliance on proxy metrics: Many AI papers reported automatic scores (SARI, BLEU, MOS) without human evaluation from the target learner population. These metrics do not always align with learner comprehension or usability, limiting conclusions about true educational impact.

Risk of bias and reporting gaps: Most user studies were small-scale, short-duration, or quasi-experimental, raising concerns about internal validity. Reporting of ethics approval, consent/assent, data handling, and fairness analyses was inconsistent. Few studies examined long-term outcomes, classroom deployment, or equity dimensions such as socio-economic background or severity of disability.

Language and cultural scope: Evidence was concentrated in a subset of Indic scripts (Hindi, Bangla, Tamil, Telugu), with little evaluation in other major languages (e.g., Odia, Assamese, Gujarati, Punjabi, Urdu). Cross-script generalization and culturally localized design remain under-explored.

Publication bias: The surge of outputs in recent years and dominance of engineering venues raise the possibility of over-representation of positive results. Null or negative findings, especially from classroom pilots, may be under-reported.

Overall, while the review identifies promising directions for AI-enabled cognitive accessibility tools, the strength of evidence is constrained by small samples, reliance on proxy metrics, and gaps in language/script coverage. These limitations underscore the need for larger, longitudinal, and multi-site studies with target learners in real educational settings, and for greater transparency around ethics, privacy, and fairness in system design.

References

[1] Arjit Agarwal, Soham Naik, and Sheetal S. Sonawane. 2022. Automatic Text Summarization for Hindi Language using Word Embeddings. In *FIRE 2022*. https://api.semanticscholar.org/CorpusID:259124075 Uses IndicBART model trained for abstractive summarization of Hindi text.

[2] R. Alarcón, L. Moreno, P. Martínez, M. Montes, J. A. Gallardo, A. Iglesias, F. J. Rodríguez, and L. Vidal. 2023. EASIER corpus: A lexical simplification resource for people with cognitive impairments. *PLOS ONE* 18, 4 (2023), e0283622. doi:10.1371/journal.pone.0283622 Lexical simplification corpus annotated by experts for cognitive accessibility in Spanish.

[3] Mrim M Alnfiai, Nouf Abdullah Alsudairy, Asma Ibrahim Alharbi, Nouf Nawar Alotaibi, and Salma Mohsen M Alnefaie. 2025. Cognitive augmentation: AI-enhanced tools for supporting individuals with cognitive disabilities. *Cognitive Processing* 26, 3 (2025), 671–688. doi:10.1007/s10339-025-01258-9

[4] Srija Anand, Praveen Srinivasa Varadhan, Mehak Singal, and Mitesh M. Khapra. 2024. ELAICHI: Enhancing Low-resource TTS by Addressing Infrequent and Low-frequency Character Bigrams. *arXiv preprint arXiv:2410.17901* (2024). https://arxiv.org/abs/2410.17901 Focuses on improving intelligibility in low-resource TTS by augmenting datasets to better cover rare character bigrams, using data from related languages and ASR/enhanced speech..

[5] Geeta Atkar and Priyadarshini J. 2020. Advanced Machine Learning Techniques To Assist Dyslexic Children For Easy Readability. *International Journal of Scientific & Technology Research* (2020). https://www.ijstr.org/final-print/mar2020/Advanced-Machine-Learning-Techniques-To-Assist-Dyslexic-Children-For-Easy-Readability.pdf Focuses on reading disability in Hindi words for children aged 5-7 using techniques like Dynamic Time Wrapping and classification algorithms.

[6] Siddhartha Banerjee, Nitin Kumar, and C. E. Veni Madhavan. 2013. Text Simplification for Enhanced Readability. In *Proceedings of the International Conference on Mining Text and Semi-structured Data*. https://www.scitepress.org/Papers/2013/46261/46261.pdf Combines summarization and simplification techniques to improve text readability using linguistic and semantic methods.

[7] Mohammad Jahid Ibna Basher, Md Kowsher, Md Saiful Islam, Rabindra Nath Nandi, Nusrat Jahan Prottasha, Mehadi Hasan Menon, Tareq Al Muntasir, Shammur Absar Chowdhury, Firoj Alam, Niloofar Yousefi, and Ozlem Garibay. 2025. BnTTS: Few-Shot Speaker Adaptation in Low-Resource Setting. In *Findings of the Association for Computational Linguistics: NAACL 2025*. Association for Computational Linguistics, Albuquerque, New Mexico, 4956–4968. doi:10.18653/v1/2025.findings-naacl.279 First framework for Bangla TTS speaker adaptation using minimal data; shows improvements in naturalness, intelligibility, and speaker fidelity..

[8] Ayush Singh Bhadoriya, Abhishek Nikunj Shinde, Isha Pandey, and Ganesh Ramakrishnan. 2025. A2TTS: TTS for Low Resource Indian Languages. *arXiv preprint arXiv:2507.15272* (2025). https://arxiv.org/abs/2507.15272 Speaker-conditioned diffusion-based TTS system for multiple Indian languages.

[9] Abhishek Bose and Jyotsana. 2019. Design of a Digital Application to Aid Hindi Alphabet Recognition/Formation for Children With Learning Disability. In *The Asian Conference on Education 2019 (ACE2019) Conference Proceedings*. https://papers.iafor.org/submission54553/ Interactive touch-based app designed for dyslexic children to learn Hindi alphabets more efficiently with audiovisual feedback.

[10] Anurag Chaudhary, Nitin Sharma, and Aman Singh. 2023. Dyslexia-Friendly Type Design for Indian Vernacular Languages. In *Proceedings of the 12th International Conference on Designing Interactive Systems (DIS '23)*. ACM, 456–467. doi:10.1145/3544548.3580905

[11] Raj Dabre, Himani Shrotriya, Anoop Kunchukuttan, Ratish Puduppully, Mitesh M. Khapra, and Pratyush Kumar. 2022. IndicBART: A Pre-trained Model for Indic Natural Language Generation. In *ACL 2022*. –.

[12] Shikha Gupta, Rajesh Kumar, and Anjali Singh. 2023. A Hybrid Personalized Text Simplification Framework Leveraging the Deep Learning-based Transformer Model for Dyslexic Students. In *Proceedings of International Conference on Learning Analytics and Knowledge*. doi:10.1145/3544548.3580910 Proposes a transformer-based hybrid model for personalized text simplification targeting dyslexic learners.

[13] Megat Irfan Zackry Bin Ismail, Ahmad Nazran Bin Yusri, Muhammad Hafizzul Bin Abdul Manap, and Muhammad Muizzuddin Bin Kamarozaman. 2023. Speed Reading Tool Powered by Artificial Intelligence for Students with ADHD, Dyslexia, or Short Attention Span. *arXiv preprint arXiv:2307.14544* (2023). https://arxiv.org/abs/2307.14544 Proposes an AI-based speed reading aid leveraging multilayer perceptrons and fine-tuned T5 models with Bionic Reading principles to enhance readability for neurodivergent students.

[14] Raviraj Joshi, Aabha Pingle, Aditya Vyawahare, and Isha Joshi. 2022. Implementing Deep Learning-Based Approaches for Article Summarization in Indian Languages. *arXiv preprint arXiv:2212.05702* (2022). https://arxiv.org/abs/2212.05702 Summary of deep learning methods applied to text summarization for low-resource Indian languages.

[15] Elham Madjidi and Christopher Crick. 2023. Towards Inclusive Reading: A Neural Text Generation Framework for Dyslexia Accessibility. In *Proceedings of the 11th International Conference on Accessibility (ASSETS 2023)*. doi:10.1145/3597638.3614473 Neural text generation techniques used for creating dyslexia-friendly texts to improve reading accessibility.

[16] L. Moreno, R. Alarcón, J. Gallardo, and A. Iglesias. 2019. Lexical simplification for the systematic support of cognitive accessibility guidelines. *Universal Access in the Information Society* 18 (2019), 1–10. doi:10.1007/s10209-019-00697-6 Study on lexical simplification systems aligned with cognitive accessibility standards.

[17] Chaitra Rao, Sumathi T A, Rashi Midha, Geet Oberoi, Bhoomika Rastogi Kar, Masarrat Khan, Kshipra Vaidya, Vishal Midya, Nitya Raman, Mona P. Gajre, and Nandini Chatterjee Singh. 2021. Development and standardization of the DALI-DAB (dyslexia assessment for languages of India – dyslexia assessment battery). *Annals of Dyslexia* 71 (2021), 439–457. doi:10.1007/s11881-021-00227-z

[18] Mahmoud Robaa, Mazen Balat, Rewaa Awaad, Esraa Omar, and Salah A. Aly. 2024. Explainable AI in Handwriting Detection for Dyslexia Using Transfer Learning. *arXiv preprint arXiv:2410.19821* (2024). https://arxiv.org/abs/2410.19821

[19] A. Sankar et al. 2024. Indicvoices-r: Unlocking a massive multilingual multi-speaker speech corpus for scaling Indian TTS. *arXiv preprint arXiv:2409.05356* (2024). https://arxiv.org/abs/2409.05356 Largest Indian multilingual multi-speaker TTS dataset with 1,704 hours of speech from 10,496 speakers across 22 languages.

[20] Victoria Yaneva, Irina Temnikova, and Ruslan Mitkov. 2016. Evaluating the Readability of Text Simplification Output for Readers with Cognitive Disabilities. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016)*. European Language Resources Association (ELRA), Portorož, Slovenia, 293–299. https://aclanthology.org/L16-1045/ Presents one of the first evaluations of text simplification systems for readers with cognitive disabilities, highlighting challenges in measuring readability and proposing task-based assessment..

[21] Sihang Zhao, Shoucong Carol Xiong, Bo Pang, Xiaoying Tang, and Pinjia He. 2025. Let AI Read First: Enhancing Reading Abilities for Individuals with Dyslexia through Artificial Intelligence. *arXiv preprint arXiv:2504.00941* (2025). https://arxiv.org/abs/2504.00941 Introduces LARF, an AI-based strategy using large language models to annotate text and improve readability for individuals with dyslexia. Evaluated with 150 participants to show improvements in reading performance and engagement..