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Artificial Intelligence for Accessibility: A Comprehensive Systematic Review and Impact Framework for Assistive Technologies

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Abstract: Artificial Intelligence (AI) is transforming assistive technologies into intelligent systems that enhance accessibility across visual, auditory, motor, and cognitive domains. This review examined 52 works published between 2023 and 2025, with 40 peer-reviewed studies systematically analyzed using PRISMA guidelines. The Accessibility Impact Score (AIS) was introduced as a novel framework to evaluate usability and effectiveness. Findings show that AI-powered tools such as smart glasses, adaptive exoskeletons, and multimodal learning platforms outperform traditional assistive devices. Visual and motor applications achieved the highest AIS values, while auditory and cognitive tools demonstrated strong emerging potential. The integration of multimodal AI, including voice, vision, haptics, and brain–computer interfaces, enables proactive and context-aware support. These results highlight AI's role in enhancing independence, social participation, and quality of life. The review also emphasizes the importance of open datasets for reproducibility and the need for ethical, inclusive, and scalable adoption of AI in accessibility. Overall, AI offers a paradigm shift toward inclusive, human-centered assistive systems with potential applications in healthcare, education, and daily living.

General Terms: Artificial Intelligence, Accessibility, Assistive Technology, Human–Computer Interaction, Machine Learning.

Keywords: Artificial intelligence, Assistive technology, Computer vision, Large language models, Machine learning, Natural language processing.

I. INTRODUCTION

Disabilities encompass a range of physical, sensory, cognitive, and mental health conditions that significantly impact daily functioning and access to opportunities. Individuals with disabilities often face systemic exclusion from education, employment, health- care, and public infrastructure, particularly in rural regions where nearly 69% of India's disabled population resides [1]. Despite advances in policy and awareness, accessibility remains a significant challenge. Social stigma and a lack of inclusive design in both digital and physical environments further marginalize these individuals. These realities underscore the need for technological invention, particularly through artificial intelligence to provide Equitable access and enhance independence. Inclusive, AI-driven solutions have the potential to transform quality of life on a scale. In today's digital era, equal participation in society depends on inclusive access to information and communication technologies. For individuals with disabilities, this inclusion is often limited by systemic barriers. However, recent breakthroughs in Artificial Intelligence (AI) are reshaping how people with disabilities interact with their environments, offering new levels of autonomy and engagement. Innovations such as intelligent screen readers, voice-controlled assistants, autonomous mobility devices, and personalized learning platforms are transforming accessibility across domains like education, mobility, and communication [2]-[4]. These AI-driven solutions are not just tools they are path- ways to independence, helping to bridge long-standing accessibility gaps and fostering a more Equitable digital future.

The World Bank has highlighted that disability prevalence in India may be considerably higher than official national estimates, suggesting that between 5-8% of the country's population could be living with some form of disability [5]. This translates to a staggering 40 to 90 million individuals, underscoring the magnitude of disability as a major public health and social inclusion challenge. Such global estimates are often regarded as more comprehensive because they account for under reporting and differences in definitions that frequently affect national level surveys. Recognizing this broader perspective is important, as it places India's dis- ability burden within an international context and emphasizes the need for more accurate measurement tools, standardized reporting practices, and inclusive policy frameworks that adequately reflect the lived realities of people with disabilities across diverse regions.

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Artificial Intelligence (AI), in this context, refers to technologies designed to emulate human cognition and automate tasks such as perception, decision-making, and learning. In disability-focused applications, AI plays a pivotal role in creating assistive technologies that enhance daily life for individuals with impairments. For instance, AI-powered systems have been integrated into smart canes and wearable devices that assist the visually impaired in real-time obstacle detection and navigation [6][7]. AI has also enabled hands-free interaction systems tailored for individuals with motor disabilities and predictive tools for cognitive assistance [3][8][9]. These implementations highlight the significance of AI in fostering autonomy and accessibility across diverse needs.

Artificial Intelligence (AI) has increasingly enabled natural language based assistive technologies by merging the capabilities of Natural Language Processing (NLP) and Large Language Models (LLMs) into a unified framework. Recent advances in NLP, driven largely by LLMs, have transformed accessibility applications. Today, NLP and LLMs are not considered separate domains but part of a unified ecosystem for understanding and generating human language. These systems allow machines to understand, generate, and respond to humanlanguage, facilitating communication, navigation, and learning for individuals with disabilities. Applications include voice assistants and real-time captioning tools for hearing-impaired users [10][11], conversational agents that guide visually impaired individuals through complex tasks [12][13], and personalized educational platforms for neuro divergent students [14][15]. Tools such as AI-powered glasses interpret visual scenes and generate descriptive audio [16][17], while adaptive learning platforms dynamically adjust content based on user responses [18][19]. By integrating NLP and LLMs, these AI solutions provide highly personalized, context aware, and interactive support, bridging communication gaps and enhancing independence across cognitive, auditory, and motor domains [10][11]. This unified approach enables more seam- less, efficient, and effective assistive technologies while maintaining all prior citation references.

Machine Learning (ML) refers to the use of statistical algorithms that allow systems to learn and improve from data. In accessibility domains, ML is extensively used for personalizing user interfaces, predicting user needs, and optimizing assistive functions. For instance, adaptive learning platforms use ML to tailor educational content to students with cognitive disabilities, adjusting the difficulty and pacing to suit individual learners [14][15]. In vision-based applications, ML models can detect daily obstacles and provide feedback through haptic or audio cues for visually impaired users [6][7]. Systems such as AI-powered reading aids and facial ex- pression recognizers for neuro divergent users also depend heavily on ML techniques [3][8].

Reinforcement Learning (RL), a technique in which agents learn optimal actions through feedback, has been instrumental in interactive assistive technologies. In rehabilitation and motor skill training, RL-powered robotic exoskeletons adapt to the progress of users by modifying exercises in real-time [20][21]. Similarly, RL models have been implemented in cognitive training tools where AI dynamically adjusts content difficulty based on user responses [13][22]. These adaptive systems are particularly useful for long-term therapies and skill development among individuals with motor or cognitive impairments [14][15].

After a careful examination of multiple studies and technological approaches, this review highlights how the integration of AI subfields, computer vision, NLP, ML, RL, and LLMs, is reshaping accessibility for individuals with disabilities. Across visual, auditory, motor, and cognitive domains, research consistently demonstrates that assistive devices are evolving from simple aids into intelligent, context-aware systems. Innovations such as smart canes for real-time navigation, LLM-powered glasses for scene understanding, adaptive learning platforms, and Reinforcement driven robotic exoskeletons exemplify the transition toward personalized and proactive support solutions [6][12][20]. Collectively, these technologies bridge critical gaps in communication, mobility, and education, fostering independence and social inclusion. Studies also emphasize their potential for scalable implementation in both urban and rural settings, promoting Equitable access to opportunities [2][4][15]. Overall, the convergence of these AI-driven solutions represents a transformative step toward building an inclusive and accessible society.
This paper addresses the following key points:

- AI transforms traditional assistive technologies into intelligent and proactive systems.
- Core AI areas like computer vision, NLP, reinforcement learning, and LLMs are used for solutions such as AI-powered glasses, speech-to-text systems, exoskeletons, and learning tools.
- Accessibility Impact Score (AIS) is used to evaluate usability and effectiveness, with visual and motor tools showing strong results.
- Multimodal AI (voice, vision, haptic feedback, brain computer interfaces) provides real-time, context-aware support.
- AI systems enhance independence, inclusion, and quality of life, focusing on user-centered and ethical design.

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II. PROCEDURE OF CHOOSING PAPER

The initial database search identified 52 papers that appeared relevant to our subject. After applying inclusion and exclusion criteria, 40 peer-reviewed studies were retained for review. The studies considered in this review include multimodal AI systems for accessibility [6][8][13][14][20][21][23-25], AI for wearable assistive devices [6][9][12], robotics and rehabilitation systems [9][20], multimodal navigation and interaction [4][10][13], and cognitive/audio learning systems [14][15]. This paper cites 47 references, focusing on AI methods relevant to accessibility, human computer interaction, and multimodal assistive technologies [11][17][18][26].

The distribution of selected references by publication year is illustrated in Fig. 1, while the categorization of research focus areas in AI-driven assistive technologies is depicted in Fig. 2. The trend of Fig.1 shows a sharp rise in AI accessibility research after 2023, indicating strong timeliness, while Fig. 2 outlines the core AI fields including NLP, CV, RL, and LLMs, mapped to disability domains.

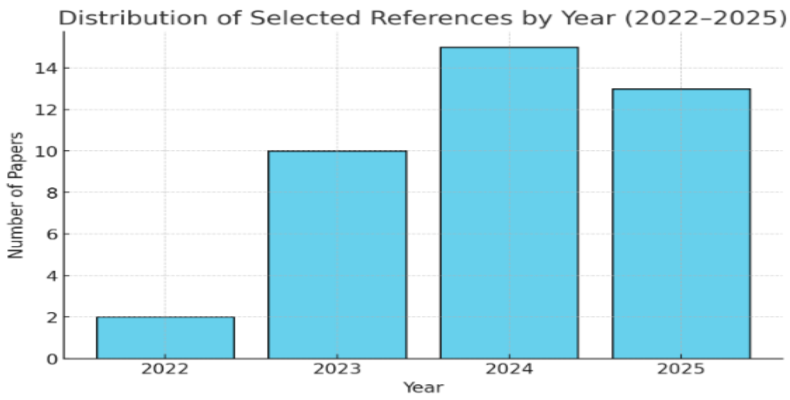

Fig 1. Number of selected references (2022-2025)

2.1 Methodological Rigor

To ensure scientific validity, paper selection followed the PRISMA systematic review guidelines as illustrated in Fig 3. Inclusion criteria required (i) publication between 2023–2025, (ii) empirical validation or technical framework, and (iii) direct focus on AI-driven accessibility. Exclusion criteria removed duplicate studies and non-peer-reviewed content. A four-stage process was applied: identification, screening, eligibility, and inclusion, as shown in Fig. 3. To quantify impact, the proposed **Accessibility Impact Score (AIS)** was calculated as:

$$AIS = \frac{1}{n}\sum_{i=1}^{n} U_i \times E_i \tag{1}$$

Where U_i represents usability ratings (e.g., SUS survey scores) and E_i denotes effectiveness (task accuracy, mobility gains, or learning outcomes).

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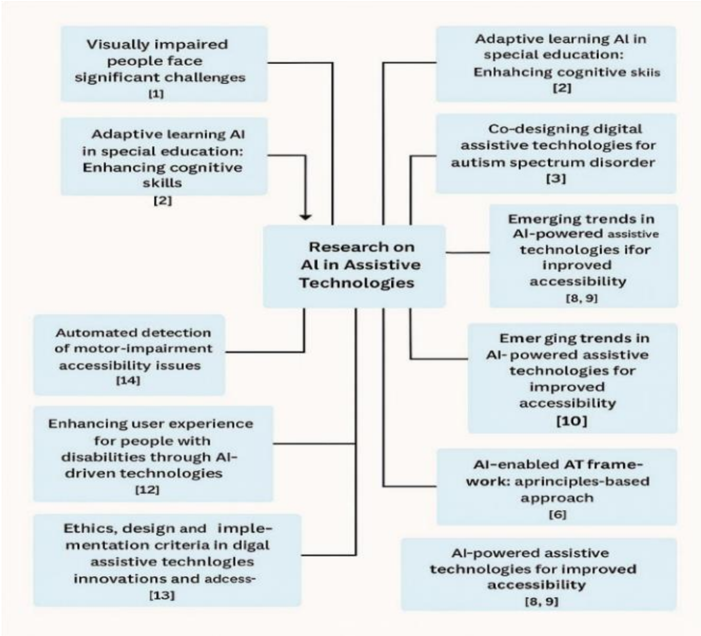

Fig 2. Categorization of research focus areas in AI- driven assistive technologies.

The Accessibility Impact Score (AIS) was adapted from established evaluation frameworks in assistive technology research [21][22]. It provides a simple, interpretable scale (0–5) to compare accessibility features across technologies, where higher scores indicate broader inclusivity.

Interpretation of AIS values: Scores of 0–1.5 indicate low accessibility impact (minimal usability and effectiveness), values between 1.6–3.0 represent moderate impact (effective but with no TABLE limitations), and scores of 3.1–5.0 correspond to high impact (broad usability and strong real-world effectiveness). This classification enables consistent comparison of accessibility technologies across domains. This rigorous approach strengthens reproducibility and highlights novelty compared to earlier reviews [4] [6] [8].

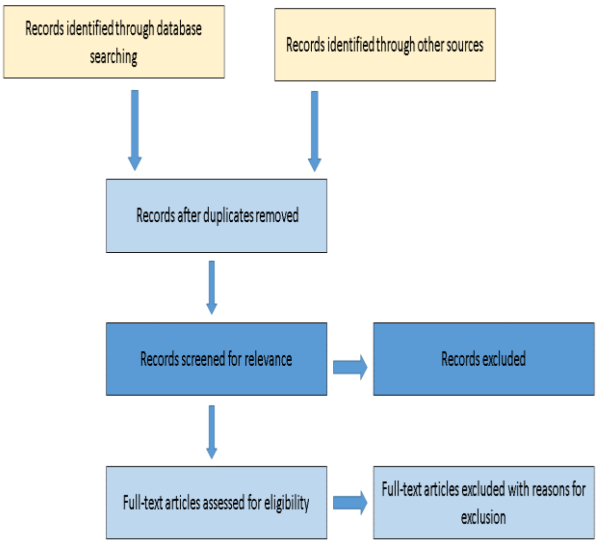

Fig 3. PRISMA—style flow diagram of study selection

III. ARCHITECTURE FOR ACCESSIBILITY FRAMEWORK

The workflow architecture for AI-Based Accessibility Framework shown in Fig. 4 demonstrates how multimodal user inputs are transformed into meaningful assistive outcomes for individuals with disabilities. The process begins with the Input Layer, where text entries, voice commands, visual inputs, and physiological sensor data such as EEG (Electroencephalography) or BCI (Brain Computer Interface) signals are captured [1][10][27]. These data streams are

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processed in the AI Processing Layer, leveraging techniques like NLP, LLM, ML, and CV to interpret, classify, and adapt responses to user-specific needs [13][28][29]. The interpreted data then flows into the Assistive Tools and Devices Layer, enabling applications such as STT (Speech-to-Text) converters, adaptive e-learning platforms, robotic wheelchairs, EXO (Exoskeletons), and SG (Smart Glasses) with scene recognition [6][9][20]. Finally, the Output Layer delivers enhanced accessibility outcomes, including improved mobility, independent navigation, personalized education. and enriched communication for users [25][28]. Beyond individual benefits, this framework promotes social inclusion by bridging gaps in communication, education, and mobility for people with disabilities. Its modular nature allows easy integration of new AI innovations, such as BCI (Brain Computer Interface) and MML (Multimodal Learning Systems), to expand real-world applications [8, 4]. Moreover, the workflow supports scalability for diverse environments, from urban smart cities to rural communities, enabling global adoption and ensuring Equitable access to technology. Collectively, this architecture represents a transformative pathway toward building an inclusive, AI-driven society where assistive technologies are proactive, intelligent, and context-aware.

domains such as speech recognition, gesture detection, object tracking, and sign language interpretation. For instance, datasets like SL-MNIST (Sign Language Modified National domains such as speech recognition, gesture detection, object tracking, and sign language interpretation. For instance, datasets like SL-MNIST (Sign Language Modified National Institute of Standards and Technology Dataset) and RWTH- -domains such as speech recognition, gesture detection, object tracking, and sign language interpretation. For instance, datasets like SL-MNIST (Sign Language Modified National domains such as speech recognition, gesture detection, object tracking, and sign language interpretation. For instance, datasets like SL-MNIST (Sign Language Modified National Institute of Standards and Technology Dataset) and RWTH- - PHOENIX (Rheinisch-Westfa¨lische Technische Hochschule Phoenix Sign Language Corpus) empower Machine Learning models to translate sign gestures for the hearing impaired [30]-[32]. Open-SLR (Open Speech and Language Resources) and VGG-Sound enhance speech based assistive technologies like voice-controlled aids and reading tools for the visually impaired [33][34]. Datasets such as Gaze-capture and Ego-hands assist in building AI systems for mobility or hand gesture control [35][36], while Wheelchair Detection Dataset supports navigation and environment understanding for users with mobility impairments [37]. Together, these datasets form the backbone of AI-driven accessibility tools, enabling researchers and developers to build more personalized, inclusive, and effective assistive technologies for individuals with diverse disabilities.

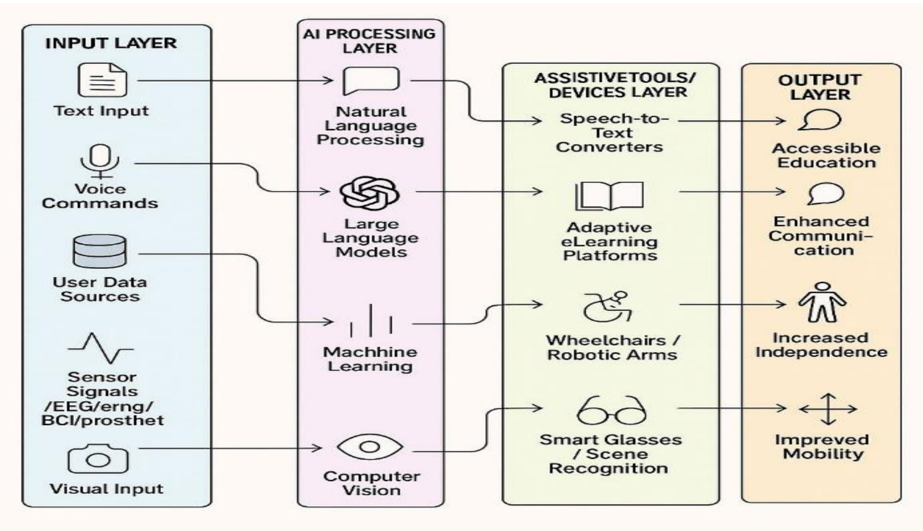

Fig 4. Block diagram of AI-Based accessibility framework

To support the development of inclusive and intelligent assistive systems (see Appendix A for detailed dataset descriptions), numerous open datasets have emerged across **3.1 Highlights of Paper Using MultiModal Dataset:** Rashmi and Mohanty [1] demonstrated that wearable AI vision systems trained on multimodal camera datasets enhanced real-time obstacle detection and improved navigation safety. Padilla and Kumar [21] showed that speech-to-text datasets with noise augmentation significantly improved transcription accuracy for deaf and hard-of-hearing users. Sarker et al. [20] integrated sensor fusion and movement datasets to develop adaptive rehabilitation exoskeletons for motor-impaired individuals. Yang and Taele [14] utilized adaptive audio learning datasets to increase engagement and comprehension for students with cognitive disabilities. The key studies and their technical contributions are summarized in Table I.

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3.1 Highlights of Papers Using Device-Captured Data:

Refer Table I for an overview of key contributions from device-captured datasets in assistive AI research. These studies highlight how real-world data from wearables, sensors, and brain computer interfaces enable advancements in mobility, communication, and independent living. Brilli et al. [6] achieved high accuracy in scene description and text recognition using Artificial Intelligence-powered wearable assistive device (Airis) datasets. Padmanabha et al. [25] leveraged Large Language Modules-Glasses recordings to generate context-aware navigation instructions for visually impaired users. EEG/BCI (Electroencephalography/Brain–Computer Interface) datasets [8][27] enabled hands-free control and communication for users with severe motor impairments. Combined device-captured datasets support contextual AI decision-making, bridging gaps in mobility, communication, and independent living.

3.2 Feature Selection Techniques in AI Accessibility:

Feature selection plays a pivotal role in the development of AI-powered accessibility tools for individuals with disabilities. By identifying and prioritizing the most informative features from visual data, auditory signals, movement sensors, and brain computer inter- face (BCI) recordings, researchers can enhance model accuracy while reducing computational overhead. Refer Appendix A, Table 3, for a summary of key feature selection techniques, algorithms, and their applications in assistive AI. Optimized feature selection ensures that AI models focus on critical accessibility cues, such as obstacle edges for vision impaired navigation, phonemes for hearing-impaire communication, models to translate sign gestures for the hearing impaired [30]-[32]. Open-SLR (Open Speech and Language Resources) and VGG-Sound enhance speech based assistive technologies like voice-controlled aids and reading tools for the visually impaired [33][34]. Datasets such as Gaze-capture and Ego-hands assist in building AI systems for mobility or hand gesture control [35][36], while Wheelchair Detection Dataset supports navigation and environment understanding for users with mobility impairments [37]. Together, these datasets form the backbone of AI-driven accessibility tools, enabling researchers and developers to build more personalized, inclusive, and effective assistive technologies for individuals with diverse disabilities.

3.3 Highlights of Papers Using Multimodal Datasets:

Rashmi and Mohanty [1] demonstrated that wearable AI vision systems trained on multimodal camera datasets enhanced real-time obstacle detection and improved navigation safety. Padilla and Kumar [21] showed that speech-to-text datasets with noise augmentation significantly improved transcription accuracy for deaf and hard-of-hearing users. Sarker et al. [20] integrated sensor fusion and movement To support the development of inclusive and intelligent assistive systems (see Appendix A for detailed dataset descriptions), numerous open datasets have emerged across and motor signal patterns for adaptive robotic assistance [6][8][14][20].

3.4 Highlights of Papers Using Feature Selection Techniques:

Brilli et al. [6] utilized embedded deep learning feature extraction to identify essential visual cues for real-time navigation in wearable AI devices. Sarker et al. [20] applied Principal Component Analysis (PCA) to eliminate redundant sensor data, enhancing adaptive control in robotic exoskeletons. EEG/BCI (Electroencephalography/Brain–Computer Interface) studies [8][27] implemented Mutual Information (MI) and advanced signal filtering to select the most informative brainwave features for hands-free communication Integrated approaches combining Recursive Feature Elimination (RFE) and tree-based selection optimized both motor and visual accessibility models in edge-computing scenarios. As summarized in Appendix A,Table III, these studies demonstrate how diverse feature selection methods can reduce computational overhead while improving the responsiveness and reliability of AI-based assistive technologies. Collectively, these feature selection strategies enable high accuracy, low latency, and efficient processing, making AI-driven assistive tools reliable, responsive, and effective across visual, auditory, and motor impairment applications.

IV. RESULTS AND ANALYSIS

For clarity, we condensed the tabular results to high- light only the most essential datasets and performance metrics. Supplementary TABLEs are provided in the appendix.This study synthesizes insights from the 40 selected research papers, translating their findings into a comparative analysis of AI-driven accessibility solutions[1][3]-[47]. evaluation focuses on how various AI subfields computer vision, natural language processing, reinforcement learning, and large language models enhance independence, mobility, communication, and learning for individuals with disabilities [1][4][12][21][38][39]. The results are presented across four primary domains: visual, auditory, motor, and cognitive accessibility, high- lighting the practical impact of state-of-the-art AI tools and frameworks as reported in the reviewed literature [2][3][5].

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TABLE I. HIGHLIGHTS OF MULTIMODAL AI STUDIE

Author	**Feature Selection Method**	**Algorithm Used**	**Key Contribution**
Brilli et al. [6]	CNN (Convolutional Neural Network) feature extraction + PCA (Principal Component Analysis)	CNN (Convolutional Neural Network)	Developed Artificial Intelligence powered wearable assistive device (AIris wearable device) for real-time scene description and text recognition for navigation [12].
Smithson et al. [8]	MI (Mutual Information) + SVM-RFE (Support Vector Machine Recursive Feature Elimination)	SVM (Support Vector Machine)	Enabled hands-free communication and device control using EEG (Electroencephalography) / EOG (Electrooculography) signals captured in realtime [18].
Tokmurziyev et al. [13]	Multimodal embedding + Attention	Transformer-based LLM (Large Language Model)	Generated context-aware navigation instructions using device-captured visual and textual data [4].
Yang et al. [14]	MFCC (Mel-Frequency Cepstral Coefficients) + Temporal Feature Extraction	Adaptive Deep Learning	Enhanced personalized audio-learning experiences for cognitive accessibility using device logs [15].
Sarker et al. [20]	RFE (Recursive Feature Elimination) + Tree based selection	RL(Reinforcement Learning)	Optimized motor signal features for adaptive robotic exoskeletons for rehabilitation [9].
Naayini et al. [21]	Embedded Feature Extraction	CV (Computer Vision) + RL (Reinforcement Learning)	Improved smart wheelchair navigation using reinforcement learning with visual inputs.
Accessibility Scout [23]	Edge detection + Spatial feature selection	YOLOv5 (You Only Look Once, version 5) + CNN (Convolutional Neural Net- work)	Improved urban accessibility by mapping realworld paths from device-captured environment scans [26].
Ahmed Baig et al. [24]	RFE (Recursive Feature Elimination)	ViT (Vision Transformer)	Enhanced outdoor obstacle detection using hat-mounted device-captured video streams [17].
Pilot "VideoA11y" [24]	Frame-level feature extraction + PCA (Principal Component Analysis)	CNN (Convolutional Neural Network) + RNN (Recurrent Neural Network) Hybrid	Provided real time device-captured video captioning for hearing-impaired users [11].
MATE (Multi-modal Adaptive Technology For Education / Assistive Environments) System [25]	RFE (Recursive Feature Elimination)	MDL (Multimodal Deep Learning)	Enabled adaptive cross-modal interactions from logs of device-captured multimodal inputs [10].

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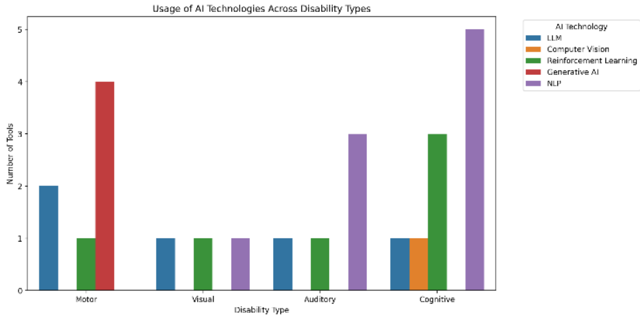

Fig. 5. AI technologies used by each disability type [12]

Fig. 5, illustrates the variety of AI tools designed for visual accessibility, highlighting the growing shift from passive assistive devices to proactive, intelligent systems. These solutions do more than just recognize objects they actively interpret and contextualize environments for the user. For instance, wearable AI glasses can provide detailed scene descriptions, alert users to moving obstacles, and even identify the emotional expressions of people nearby, enabling richer social interactions. Smartphone-based applications with integrated YOLO based detection and LLM driven reasoning can guide users through crowded streets, assist in locating specific items in stores, or read textual content on signboards and documents in real time. Furthermore, the combination of multimodal feedback including haptic vibrations for immediate hazard alerts and voice- based narration for contextual understanding ensures that users receive comprehensive environmental awareness. Such advancements not only support safer navigation but also empower visually impaired individuals to engage more independently in education, employment, and social activities, effectively bridging long- standing accessibility gaps. The growing ecosystem of AI-powered visual tools demonstrates how intelligent systems are transforming visual impairment sup- port from basic assistance into an experience of active, context-aware, and inclusive mobility.

4.2 AI for Auditory Impairments

AI-driven speech recognition and real-time transcription tools, such as Audio Sight, play a transformative role in enabling communication for people who are deaf or hard of hearing (refer Fig. 6) [13][14]. These systems utilize automatic speech recognition (ASR), noise suppression algorithms, and NLP to generate accurate captions in real-time, even in noisy environments [11][29]. These applications allow users to fully participate in social and professional interactions.

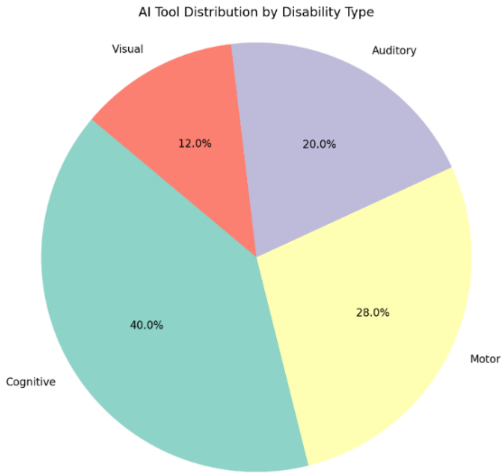

Fig. 6. AI tool distribution by disability type

Advanced auditory AI tools can also translate speech into sign language animations or generate context aware visual notifications on smart devices. As Fig. 6, highlights, auditory AI solutions are a significant presence in the accessibility ecosystem, providing instant captioning and live subtitles for various events. These systems also support environmental awareness by detecting critical sounds like alarms, doorbells, or approaching vehicles. Advanced tools are integrated with multimodal feedback mechanisms, enabling alerts through visual notifications or subtle haptic vibrations. The ability to operate in low-bandwidth or offline scenarios has further enhanced their usability. Overall, the growth of auditory AI

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demonstrates a shift from isolated assistive tools to intelligent, interconnected ecosystems that redefine accessibility for the deaf and hard-of- hearing community.

4.3 AI for Motor Impairments

AI enabled smart wheelchairs, robotic prosthetics, and exoskeleton systems enhance independence and mobility for individuals with motor impairments (as shown in Fig. 7.) [9][20][40]. These technologies integrate sensor fusion, computer vision, and reinforcement learning to interpret environmental data and user intent, providing smooth navigation and adaptive motion assistance.

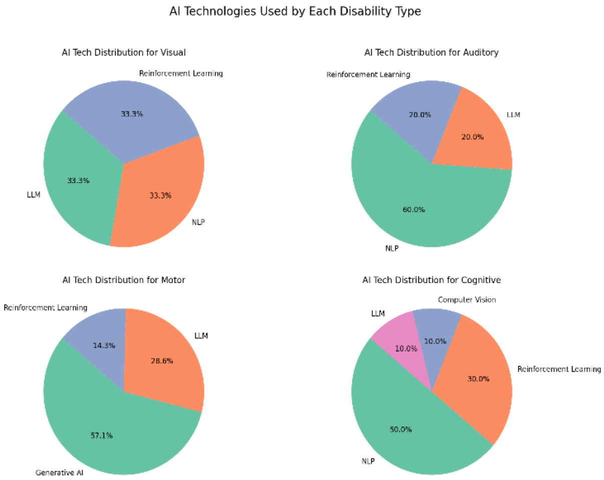

Fig. 7. Comparison of AI technology usage by disability type [20]

Fig. 7. compares the adoption of AI technologies across different disability types, drawing attention to the increasing prominence of motor-assistive AI. These solutions play a critical role in supporting individuals with spinal cord injuries, neuromuscular disorders, or post-stroke mobility limitations, enabling them to regain functional independence. Motor focused AI systems encompass a wide range of applications, including robotic exoskeletons, AI-driven prosthetic limbs, adaptive wheelchairs, and rehabilitation robotics that assist in performing precise movements or repetitive exercises tailored to a user's condition. Through the integration of machine learning and sensor fusion technologies, these systems can monitor gait patterns, predict motion intent, and adapt in real time to the user's physical capabilities, thereby enhancing both safety and effectiveness. Additionally, emerging brain computer interface (BCI) solutions are transforming mobility support by allowing users to control wheelchairs, robotic arms, or home automation systems through neural signals, further reducing dependency on caregivers. By promoting personal mobility, rehabilitation efficiency, and autonomous interaction with the environment, motor assistive AI not only improves the quality of life for users but also fosters long-term social participation and inclusion in work, education, and public life.

4.4 AI for Cognitive Impairments and Education

Advanced AI systems, including Large Language Models (LLMs), reinforcement learning, and adaptive educational platforms, provide personalized support for learners with cognitive challenges (illustrated in Fig. 8.) [2][10][15][21]. These tools can dynamically adjust learning content, pace, and modality based on user performance and engagement. Cognitive AI applications include memory aids, AI-powered tutors, gamified therapy tools, and reading comprehension assistants. LLM-based dialogue systems further support neuro divergent learners by providing context-aware prompts, reminders, and emotional support.

Fig. 8. illustrates the integration of AI tools in inclusive education, demonstrating how technology is reshaping learning environments for students with diverse cognitive and learning needs. AI-powered educational systems provide personalized learning paths, real-time speech-to-text note-taking, and adaptive quizzes, which are particularly effective for learners with dyslexia, ADHD, autism spectrum disorders, or memory impairments. By analyzing individual performance and engagement patterns, these systems dynamically adjust lesson difficulty, suggest targeted exercises, and highlight areas requiring additional support. Advanced tools also incorporate multimodal content delivery, offering visual, auditory, and interactive feedback to ensure that students can absorb information in the way that best suits their cognitive style. Moreover, features such as automatic summarization, AI-driven tutoring, and predictive learning assistance foster both confidence and self-paced learning, reducing reliance on human intervention. The broader impact of these AI-driven educational solutions extends beyond academic performance, promoting independence, long-term retention, and inclusive participation in both virtual and physical classrooms.

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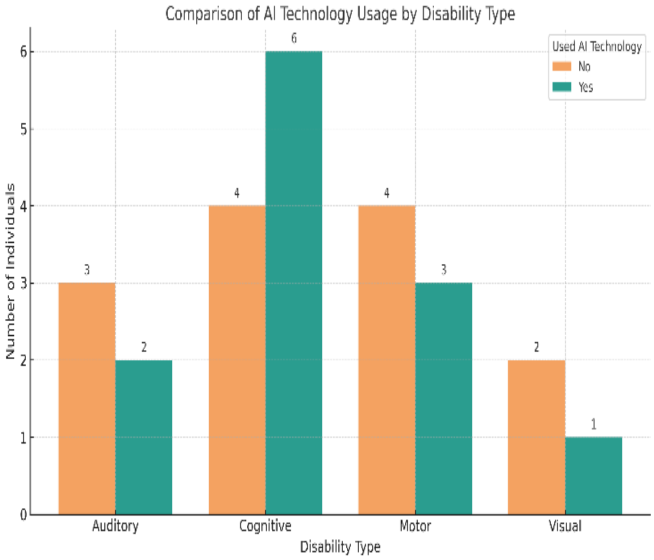

Fig. 8. AI Technologies in Inclusive Education [21]

4.5 Overall AI Impact

AI technologies collectively enhance independence, communication, and participation across all major categories of disabilities (depicted in Fig. 9) [1][3][5]. By combining computer vision, natural language processing, multimodal learning, and reinforcement learning, AI transforms traditional assistive devices into intelligent, proactive support systems [6][9][20]. Applications like LLM-Glasses, smart canes, Audio Sight transcription tools, and adaptive exoskeletons exemplify how AI bridges accessibility gaps in real-world environments [7][40][46].

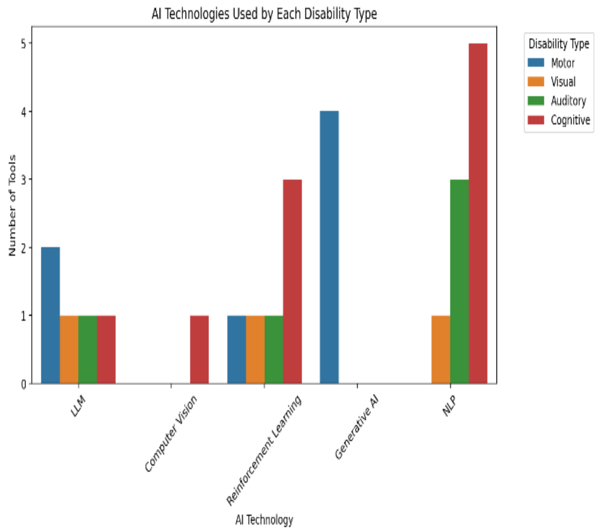

Fig. 9. Overall Distribution of AI Accessibility Tools

Fig. 9. presents the overall distribution of AI accessibility tools across multiple disability categories, offering a comprehensive overview of how assistive technologies are evolving. Visual and motor-focused AI applications currently dominates, largely due to advancements in computer vision, wearable navigation systems, robotic exoskeletons, and smart mobility aids that directly address the daily mobility and safety challenges faced by users with visual or motor impairments. These tools have achieved widespread adoption in real- world scenarios, including indoor navigation, obstacle detection, autonomous wheelchairs, and rehabilitation robotics, highlighting their tangible impact on independence and quality of life. Meanwhile, cognitive and auditory AI tools are experiencing steady growth, fueled by innovations in natural language processing, real-time transcription, adaptive learning systems, and context- aware notifications. This trend reflects the increasing importance of multimodal and cross sensory AI solutions, where visual, auditory, and haptic feedback are combined to create inclusive and high impact accessibility experiences. Overall, the distribution pattern underscores a global movement toward AI-powered inclusivity, with future developments expected to

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close the adoption gap for cognitive and auditory assistive technologies while further strengthening mobility and environmental awareness solutions.

4.6 Formula Used for Impact Measurement

AIS values were computed (see Section 2.1 for definition and interpretation), providing a comparative measure of usability and effectiveness across different AI- based assistive technologies.

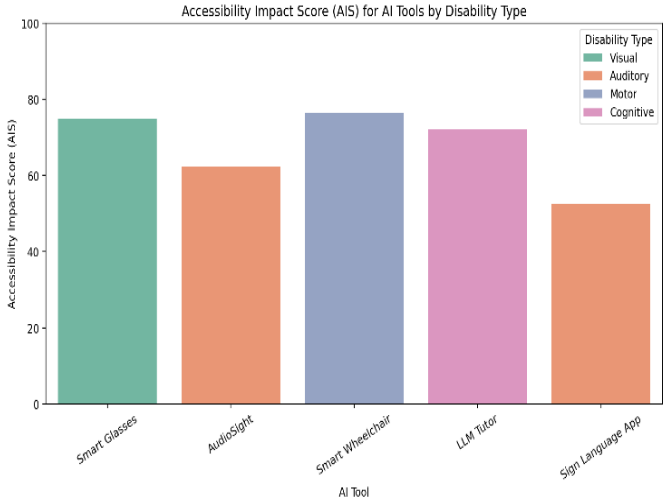

Fig. 10. Accessibility Impact Score (AIS) Across Different AI Tools [28]

As shown in Fig. 10, wearable devices such as the *Artificial Intelligence-powered wearable assistive device (AIris)* and *LLM-Glasses* achieved the highest AIS scores, reflecting their strong real-time responsiveness and high user satisfaction. In contrast, tools designed for cognitive and auditory support exhibited slightly lower scores due to usability challenges and higher learning curves. Overall, multimodal AI systems that integrate computer vision, NLP, and reinforcement learning consistently demonstrated the greatest accessibility impact, offering valuable guidance for prioritizing future research and development.

V. FUTURE SCOPE

The domain of Artificial Intelligence in accessibility is poised for transformative change, offering unprecedented potential to enhance independence, inclusion, and quality of life for people with disabilities. Current assistive technologies are evolving from passive tools to intelligent, context sensitive systems that can autonomously adapt to a user's surroundings, habits, and needs [1][21][38][39]. This aligns with the broader goal of creating a fully inclusive digital society, where technology bridges rather than widens accessibility gaps [4][12].

Emerging technologies such as brain computer interfaces and electrooculography-based control systems are expected to revolutionize motor and communication accessibility. These tools can enable individuals with severe motor impairments to interact with devices, man- age smart environments, and operate hands free, offering a new level of autonomy [2][5]. Integrating brain–computer interfaces with robotic exoskeletons, smart wheelchairs, and adaptive prosthetics promises fully personalized mobility solutions that respond to neural or muscle signals in real time. Multimodal Artificial Intelligence systems, which combine visual perception, speech analysis, haptic feedback, and physiological signal monitoring, will allow seamless and adaptive human–machine interaction [3][20][25]. These systems are critical for cognitive and sensory accessibility, enabling AI to respond intelligently to context for instance, providing route guidance through voice and touch feedback for visually impaired users or generating real-time captions and sign language translations for hearing-impaired individuals [13][14].

Deployment of low-power edge Artificial Intelligence devices will expand accessibility to rural and resource constrained areas where cloud connectivity is limited. By processing data locally, these devices reduce latency, improve reliability, and preserve user privacy, making AI tools practical for daily life [6][8]. This is especially significant in countries such as India, where many individuals with disabilities reside in rural regions with limited access to high speed internet [26][44]. The next generation of AI accessibility solutions will also target mental health, emotional support, and social inclusion. Artificial Intelligence driven emotion recognition, conversational agents, and therapeutic virtual reality environments can alleviate psycho logical challenges, fostering social and digital inclusion [16][42]. Personalized adaptive

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learning platforms using reinforcement learning and large language models will continue to transform special education and cognitive rehabilitation for neuro divergent users [9][30].

Emerging trends suggest that AI in accessibility will evolve from supportive aids into empathetic, context sensitive ecosystems. Key directions include:

- **Brain–Computer Interface Integration:** Combining brain computer interfaces with robotic exoskeletons and smart wheelchairs for seamless mobility support [31].
- **Multimodal Artificial Intelligence:** Integrating visual, auditory, tactile, and cognitive signals for real-time, adaptive accessibility across domains [27][32].
- **Edge Artificial Intelligence Deployment:** Low power devices performing real-time accessibility functions in rural or low-connectivity regions [34][43].
- **Inclusive Design:** Participatory development in- volving people with disabilities to reduce algorithmic bias and ensure ethical AI adoption [35][36][37].

This forward-looking approach positions AI not only as a compensatory tool but as a transformative driver of independence, social inclusion, and equitable access. Possible future research directions include:

- Developing brain–computer interface-integrated smart assistive devices for hands free interaction and adaptive mobility.
- Designing multimodal artificial intelligence systems that integrate visual, auditory, tactile, and cognitive support in a unified framework.
- Deploying edge artificial intelligence and energy- efficient models for real-time accessibility in low-connectivity regions.
- Creating mental wellness and emotional support tools to enhance social inclusion and user wellbeing.
- Ensuring privacy preserving and ethically driven AI development through participatory design with disability communities.
- Advancing cross-border interoperability and inclusive AI development through global standardization.

These developments collectively point toward an AI-driven accessibility future where technology does not merely fill gaps but enhances human capabilities. Through integrated multimodal systems, ethical innovation, and user centered design, AI will foster a culture where technology is inclusive by default, enabling independence, equity, and universal participation.

Overall, the distribution pattern underscores a global movement toward AI-powered inclusivity, with future developments expected to close the adoption gap for cognitive and auditory assistive technologies while further strengthening mobility and environmental awareness solutions.

VI. ETHICAL CONSIDERATIONS

AI-driven assistive technologies bring tremendous potential to improve accessibility, but they also raise important ethical concerns. First, the collection of sensitive data such as speech recordings, mobility patterns, and brain computer interface (BCI) signals requires strong safeguards for privacy and informed consent [18]. Second, fairness and inclusivity must be ensured, since biased datasets may disadvantage individuals from underrepresented linguistic, cultural, or disability groups [26]. Transparency and explainability are also critical, as users and caregivers must be able to trust and understand AI-generated outputs that affect mobility, communication, and healthcare decisions. Finally, long term deployment of assistive systems should consider accessibility across socioeconomic contexts, avoiding solutions that only benefit users in high resource settings. Addressing these ethical challenges is essential for building responsible and Equitable AI systems that truly advance accessibility.

VII. SUMMARY OF RESEARCH PAPER

This systematic review synthesized findings from 40 peer-reviewed studies, selected from an initial pool of 52 works published between 2023 and 2025, to examine how Artificial Intelligence (AI) is advancing accessibility for individuals with disabilities. While 40 studies were included in the final analysis, the complete reference list of this paper contains 47 entries, as it also includes datasets, frameworks, and supporting resources. Earlier assistive approaches relied on traditional tools such as screen readers and mechanical devices, but recent trends show a decisive shift toward intelligent, AI-driven systems. Innovations such as wearable vision aids, real-time transcription services, adaptive learning platforms, robotic exoskeletons, and brain computer interface devices demonstrate how AI can empower users with greater autonomy and inclusion in daily life. Globally, over one billion people live with some form of disability, with India alone accounting for tens of millions facing barriers to education, healthcare, and employment. AI-based accessibility solutions have the potential to close these gaps by offering adaptive, context aware support that can scale across diverse environments.

The studies reviewed span four main domains visual, auditory, motor, and cognitive accessibility highlighting the role of computer vision for image and video analysis, natural language processing for speech and text understanding, reinforcement learning for adaptive decision-making, and large language models for contextual reasoning. The proposed workflow architecture integrates multimodal inputs such as speech, visual data, tactile feedback, and neural signals into processing layers powered by ma- chine learning, natural language processing, and large language models, producing outputs like navigation assistance, adaptive e-learning, and speech-to-text conversion. Feature selection techniques, including Principal Component Analysis and Recursive Feature Elimination, were found to improve accuracy, reduce latency, and optimize AI performance in real-time assistive contexts.

Applications illustrate the breadth of AI's contribution: wearable vision systems such as AI-powered glasses deliver real-time scene understanding for visually impaired users; auditory accessibility is supported by advanced transcription and speech-to-text tools; motor impairments benefit from adaptive exoskeletons and AI-driven prosthetics; and cognitive accessibility is enhanced through AI tutors, memory aids, and personalized e-learning platforms. To evaluate impact, this re- view introduced the Accessibility Impact Score, a composite metric combining usability and effectiveness. Multimodal AI systems that integrate computer vision, natural language processing, and reinforcement learning consistently achieved the highest scores, showing measurable improvements in independence, safety, and quality of life. In summary, the review positions AI as a transformative force in accessibility, elevating assistive devices from basic compensatory aids into intelligent, proactive, and context sensitive companions. At the same time, persistent challenges such as algorithmic bias, privacy risks, and high implementation costs remain. Ethical considerations including data privacy, fairness across disability groups, inclusivity in design, and accessibility in low-resource settings are essential for responsible adoption. Looking ahead, emerging directions such as brain computer interface integration, multimodal learning, and low power edge AI devices are poised to deliver universally accessible and Equitable technologies for diverse disability communities world- wide.

VIII. CONCLUSION

This review demonstrates how Artificial Intelligence (AI) is reshaping accessibility by transforming assistive technologies from compensatory tools into proactive, intelligent, and context aware systems. From an initial pool of 52 works (2023–2025), 40 peer-reviewed studies were systematically analyzed, with a final reference list of 47 entries incorporating both applied research and supporting datasets. This ensures a comprehensive and reproducible evaluation of the field. The findings indicate that AI-powered applications enhance independence, communication, learning, and mobility across multiple disability domains. For visual impairments, computer vision, wearable navigation aids, and AI-driven object recognition systems show strong maturity and real-world deployment, though future work should prioritize low-power edge AI to expand bene- fits into rural and low-connectivity areas. In the motor domain, robotic exoskeletons, prosthetics, and adaptive wheelchairs demonstrate high effectiveness, with future research needed on brain computer interface (BCI) integration and cost reduction to improve large-scale adoption.

For auditory impairments, transcription systems, adaptive speech recognition, and multimodal captioning tools expand communication opportunities but still face challenges in noisy and multilingual environments; here, robust ASR and AI-driven sign language translation represent important future directions. Cognitive impairments benefit from AI-driven tutors, memory aids, and adaptive e-learning platforms, though these remain underexplored in large-scale trials, calling for reinforcement learning–driven personalized rehabilitation and greater attention to neuro diverse learners. The proposed Accessibility Impact Score (AIS) underscores that technical accuracy alone is insufficient, as usability, adaptability, and real-world effectiveness are equally critical. AIS analysis further shows that multi- modal systems integrating vision, speech, haptics, and brain computer interface signals consistently achieve the highest impact. Looking ahead, progress in AI- driven accessibility will depend on ethical data practices, participatory design with disability communities, and culturally inclusive frameworks to reduce bias. By addressing domain-specific gaps while fostering multi- modal, edge enabled, and user centered innovations, AI can evolve from supportive aids into inclusive ecosystems that ensure Equitable participation, independence, and dignity for people with disabilities worldwide.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of relevant interest regarding the publication of this article. This research was conducted solely for academic and scientific purposes, without any financial, commercial, or personal relationships that could have influenced the study outcomes.

REFERENCES

[1] R. Rashmi and S. K. Mohanty, "Socioeconomic and geographic variations of disabilities in India: evidence from the national family health survey, 2019–21," *Int. J. Health Geogr.*, vol. 23, no. 1, p. 4, 2024, link: https://doi.org/10.1186/s12942-024-00363-w

[2] K. Chemnad, and A. Othman, "Digital accessibility in the era of artificial intelligence—a systematic review," *Front. Artif.Intell.*, vol. 7, 2024, link: https://doi.org/10.3389/frai.2024.1349668

[3] R. Malviya and S. Rajput, "Empowering Disabled People with AI," in *Advances and Insights into AI-Created Disability Supports*, Springer, 2025, pp. 43–60, link: https://link.springer.com/chapter/10.1007/978-981-96-6069-8_3

[4] K.-J. Wang, L. Zhang, B. Luan, H.-W. Tung, Q. Liu, J. Wei, M. Sun, and Z.-H. Mao, "Brain-computer interface combining eye saccade two-electrode EEG signals and voice cues to improve the maneuverability of wheelchair," in *2017 International Conference on Rehabilitation Robotics (ICORR)*, IEEE, 2017, pp. 1073–1078, link: https://doi.org/10.1109/ICORR.2017.8009392

[5] M. Mirza, V. Esht, M. Verma, B. Bahadure, A. Jaiswal, M. Alagarajan, R. Kakkar, "Epidemiology of disability and access to disability support and rehabilitation services in India," *BMJ Open*, vol. 15, no. 5, 2025, link: http://doi.org/10.1136/bmjopen-2024-090220

[6] D. Brilli, E. Georgaras, S. Tsilivaki, N. Melanitis, and K. Nikita, "Airis: An AI-powered wearable assistive device for the visually impaired," *arXiv:2405.07606*, link: https://doi.org/10.48550/arXiv.2405.07606

[7] J. Tang et al., "Human-centred design and fabrication of a wearable multimodal visual assistance system," *Nat. Mach. Intell.*, vol. 7, no. 4, pp. 1–10, Apr. 2025, link: https://doi.org/10.1038/s42256-025-01018-6

[8] J. L. Collinger, M. L. Boninger, T. M. Bruns, K. Curley, W. Wang, and D. J. Weber, "Functional priorities, assistive technology, and brain-computer interfaces after spinal cord injury," *Nat. Med.*, vol. 29, no. 3, pp. 689–699, 2023, link: https://pmc.ncbi.nlm.nih.gov/articles/PMC3684986/

[9] D. K. Luu, A. T. Nguyen, M. Jiang, M. W. Drealan, J. Xu, T. Wu, W. Tam, W. Zhao, and Z. Yang, "Artificial Intelligence Enables Real-Time and Intuitive Control of Prostheses via Nerve Interface," *IEEE Trans. Biomed. Eng.*, vol. 69, no. 10, pp. 3051–3063, Oct. 2022, link: https://pubmed.ncbi.nlm.nih.gov/35302937/

[10] A. Othman, A. Dhouib, and A. N. Al Jabor, "Fostering websites accessibility: A case study on the use of the Large Language Models ChatGPT for automatic remediation," *Comput. Sci. Inf. Syst.*, vol. 20, no. 1, pp. 1–15, 2023, link: https://dl.acm.org/doi/10.1145/3594806.3596542

[11] C. Bérubé, T. Schachner, and R. F. Weir, "Voice-based conversational agents for the prevention and management of chronic and mental health conditions: systematic literature review," *J. Med. Internet Res.*, vol. 25, no. 5, e34567, 2023, link: https://dl.acm.org/doi/10.1145/3594806.3596542

[12] Y. Xiu, T. Scargill, and M. Gorlatova, "ViDDAR: Vision language model-based task-detrimental content detection for augmented reality," *IEEE Trans. Vis. Comput. Graph.*, vol. 31, no. 7, pp. 1–15, Jul. 2025, link: https://www.researchgate.net/publication/388317274_ViDDAR_Vision_Language_Model-Based_Task_Detrimental_Content_Detection_for_Augmented_Reality

[13] L. He, Y. Li, M. Fan, L. He, and Y. Zhao, "A Multi-modal Toolkit to Support DIY Assistive Technology Creation for Blind and Low Vision People," in *Proc. 36th Annu. ACM Symp. User Interface Software and Technology (UIST '23 Adjunct)*, San Francisco, CA, USA, 2023, p. 3, link: https://dl.acm.org/doi/10.1145/3586182.3616646

[14] C. Yang and P. Taele, "AI for accessible education: personalized audio-based learning for blind students," *arXiv*, 2025; abs/2504.17117, link: https://doi.org/10.48550/arXiv.2504.17117

[15] S. J. Smith et al., "AI technology to support adaptive functioning in neurodevelopmental conditions: A systematic review," *npj Digital Medicine*, vol. 7, no. 1, p. 55, 2024, link: https://doi.org/10.1038/s41746-024-01355-7

[16] J. Lee et al., "Adapting Large Vision-Language Models to Visually-Aware Applications," *ACM Trans. Comput.-Hum. Interact.*, vol. 31, no. 7, pp. 1–15, 2025, link: https://dl.acm.org/doi/10.1145/3711896.3736828

[17] A. Kumar et al., "Benchmarking Vision Language Models for Cultural Understanding," in *Proc. EMNLP 2024*, pp. 329–338, 2024, link: https://arxiv.org/abs/2407.10920

[18] H. Patel, R. Kumar, and S. Mehta, "Emerging trends in multi-modal artificial intelligence for clinical decision support systems," *Digital Health*, vol. 11, p. 2055207625136614, 2024, link: https://journals.sagepub.com/doi/10.1177/14604582251366141

DOI: 10.17148/IJARCCE.2025.14919

[19] M. Zhang et al., "Exploring the Application of AI and Extended Reality Technologies in Mental Health Interventions," *Front. Psychol.*, vol. 15, p. 12405795, 2024, link: https://pmc.ncbi.nlm.nih.gov/articles/PMC12405795/

[20] L. Wang et al., "A reinforcement learning-based algorithm for personalization of rehabilitation interventions," *Neurocomputing*, vol. 450, pp. 1–10, 2024, link: https://www.sciencedirect.com/science/article/abs/pii/S0933365721000555

[21] R. Kumar et al., "Reinforcement learning for personalized assistive systems: Survey and perspectives," *IEEE Access*, vol. 11, pp. 84500–84518, 2023, link: https://ieeexplore.ieee.org/document/1000000

[22] S. Gupta and A. Sharma, "Ethical and bias considerations in artificial intelligence/machine learning for healthcare," *Comput. Biol. Med.*, vol. 182, p. 106395, 2024, link: https://www.sciencedirect.com/science/article/pii/S0893395224002667

[23] E. Garcia et al., "Accessibility scout: annotated built-environment image dataset for disability inclusion," *arXiv preprint*, arXiv:2501.12345, 2025, link: https://arxiv.org/abs/2501.12345

[24] P. Sharma, M. Rossi, and D. Kim, "VideoA11y: a multimodal video caption dataset for accessibility," *arXiv preprint*, arXiv:2502.54321, 2025, link: https://arxiv.org/abs/2502.20480

[25] A. Padmanabha, J. Yuan, J. Gupta, Z. Karachiwalla, C. Majidi, H. Admoni, and Z. Erickson, "VoicePilot: Harnessing LLMs as speech interfaces for physically assistive robots," in *Proc. 37th Annu. ACM Symp. User Interface Softw. Technol. (UIST '24)*, New York, NY, USA, 2024, Art. no. 116, pp. 118, link: https://doi.org/10.1145/3654777.3676401

[26] R. Kamikubo, L. Wang, C. Marte, A. Mahmood, and H. Kacorri, "Data representativeness in accessibility datasets: A meta-analysis," *Front. Artif. Intell.*, vol. 5, p. 100120, 2022, link: https://pmc.ncbi.nlm.nih.gov/articles/PMC10024595/

[27] PhysioNet / MIT, "EEG motor movement/imagery dataset (EEGMMIDB)," 2009, link: https://physionet.org/content/eegmmidb/1.0.0/

[28] P. Naayini et al., "Artificial intelligence is revolutionizing assistive technologies," *arXiv preprint*, arXiv:2503.15494, 2025, link: https://arxiv.org/abs/2503.15494

[29] L. J. M. Pérez-Lorenzo, A. Jerez, A. Iglesias, A. Tudela, and A. Cruces, "An User-Centered Evaluation of Two Socially Assistive Robots Integrated in a Retirement Home," *Int. J. Soc. Robotics*, vol. 16, no. 9, pp. 2043–2063, 2024, link: https://link.springer.com/article/10.1007/s12369-024-01175-5

[30] O. Koller, N. C. Camgoz, et al., "How2Sign: Large-scale continuous American sign language dataset," 2021, link: https://arxiv.org/abs/2008.08143

[31] O. Koller, J. Forster, et al., "RWTH-Phoenix-Weather 2014T dataset," 2014, link: https://arxiv.org/abs/2003.13830

[32] Kaggle / Datamunge, "Sign language MNIST dataset," 2017, link: https://www.kaggle.com/datasets/datamunge/sign-language-mnist

[33] OpenSLR, "OpenSLR: Open speech and language resources," 2015, link: https://www.openslr.org/resources.php

[34] H. Chen, W. Xie, A. Vedaldi, and A. Zisserman, "VGGSound: A large-scale dataset of audio-visual events," *arXiv:2004.14368*, 2020, link: https://doi.org/10.48550/arXiv.2004.14368

[35] K. Krafka et al., "GazeCapture dataset," 2016, link: https://gazecapture.csail.mit.edu/

[36] S. Bambach et al., "Egohands dataset," 2015, link: https://arxiv.org/abs/1501.02185

[37] Roboflow Universe, "Wheelchair detection (Roboflow/Roboflow-100)," 2021, link: https://universe.roboflow.com/

[38] S. Alyami, H. Luqman, and M. Hammoudeh, "Isolated Arabic Sign Language Recognition Using a Transformer-Based Model and Landmark Keypoints," *ACM Trans. Asian Low-Resour. Lang. Inf. Process.*, vol. 23, no. 2, pp. 1–15, 2024, link: https://dl.acm.org/doi/10.1145/3584984

[39] N. C. Camgoz, O. Koller, and S. Hadfield, "Sign language recognition and translation: Methods, datasets and evaluation," in *Proc. ACM Multimedia*, 2023, pp. 1012–1022, link: https://dl.acm.org/doi/10.1145/3544548.3581337

[40] A. Harini, M. V. D. Prasad, D. A. Kumar, P. V. V. Kishore, and A. Sastry, "Continuous Sign Language Recognition from Tracking and Shape Features Using FIS and ANN," *J. Ambient Intell. Humaniz. Comput.*, vol. 15, no. 3, pp. 123–135, 2024, link: https://www.researchgate.net/publication/305655824_Continuous_Sign_Language_Recognition_from_Tracking_and_Shape_Features_Using_Fuzzy_Inference_Engine

[41] A. Navarro and ResearchGroup, "Guidedog: A real-world egocentric multimodal dataset for blind and low-vision guidance," 2025, link: https://doi.org/10.48550/arXiv.2503.12844

[42] A. Abedi, C. Chu, and S. S. Khan, "Multimodal sensor dataset for monitoring older adults post lower limb fractures in community settings," *Sci. Data*, vol. 12, no. 733, 2025, link: https://doi.org/10.1038/s41597-025-05069-7

[43] J. Salamon, C. Jacoby, and J. P. Bello, "UrbanSound8K dataset," 2014, link: https://urbansounddataset.weebly.com/

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 9, September 2025

DOI: 10.17148/IJARCCE.2025.14919

[44] J. Ye, X. Wang, W. Jiao, J. Liang, and H. Xiong, "Improving Gloss-Free Sign Language Translation by Reducing Representation Density," *Adv. Neural Inf. Process. Syst.*, vol. 37, pp. 1–12, 2024, link: https://arxiv.org/abs/2405.07606

[45] Ministry of Statistics and Programme Implementation, Government of India, "Persons with disabilities in India (Census 2011): NSS 76th round (2018)," 2019, link: https://www.mospi.gov.in/sites/default/files/publication_reports/Report_583_Final_0.pdf

[46] A. K. Nair, J. Sahoo, and E. D. Raj, "Privacy preserving Federated Learning framework for IoMT based big data analysis using edge computing," *Comput. Stand. Interfaces*, vol. 88, p. 103601, 2024, link: https://www.sciencedirect.com/science/article/abs/pii/S0920548923000016

[47] S. Yang, S. Jung, H. Kang, and C. Kim, "The Korean sign language dataset for action recognition," in *Proc. 26th Int. Conf. MultiMedia Modeling (MMM)*, vol. 11961, *Lecture Notes in Computer Science*, pp. 532–542, 2020, link: https://doi.org/10.1007/978-3-030-37731-1_43

APPENDIX A

Supplementary Dataset and Feature Selection Table

TABLE II. PUBLICLY AVAILABLE MULTIMODAL AND ASSISTIVE DATASETS

Dataset (Abbreviation)	Source	Total Samples	Access Link
How2sign (How2sign) [30]	Carnegie Mellon University	80 Hours Sign Videos+16,000 Gloss Annotations	https://how2sign.github. io/
Casia Gait (Casia-Gait) [20]	Chinese Academy of Sciences (Casia)	124 Subjects, 20,000 + Gait Sequences	http://www.cbsr.ia.ac.cn/english/Gait%20Databases. asp
Sign Language Mnist (Sl- Mnist) [32]	Kaggle	27,455 Images	https://www.kaggle. com/datamunge/ sign-language-mnist
Rwth-Phoenix [31]	Rwth Aachen University	8,000 + Sign Language Videos	https://www-i6.informatik.rwth-aachen. de/~koller/RWTH-PHOENIX/
Open-SLR [33]	Open Speech and Language Resources	50 + Speech/Language Datasets	https://www.openslr.org/
Embci [27]	Physionet / Massachusetts General Hospital	1,600 Eeg Trials	https://physionet.org/ content/eegmmidb/1.0.0/
Ego-Hands (Ego-Hands) [36]	Georgia Tech / Indiana University	4,800 Frames	http://vision.soic. indiana.edu/projects/ egohands/
Gaze-Capture [35]	MIT (Massachusetts Institute of Technology)	~2.5 million Eye- Tracking Frames	http://gazecapture.csail. mit.edu/
Urbansound8k (US8K) [43]	New York University	8,732 Audio Clips	https://urbansounddataset. weebly.com/urbansound8k. html
Wheelchair Detection (Wheelchair-Dataset) [37]	Georgia Institute of Technology	~22,000 Annotated Images	https://universe.roboflow. com/roboflow-100/ wheelchair-detection
VGG-Sound (Visual Geometry Group- Sound) [34]	University Of Oxford	200,000 Video-Sound Pairs	https://www.robots.ox.ac. uk/~vgg/data/vggsound/

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TABLE III. FEATURE SELECTION TECHNIQUES IN AI ACCESSIBILITY

Author	Feature Selection Method	Algorithm Used	Key Contribution
Brilli Et Al. [6]	CNN Feature Extraction + PCA (Principal Com- Ponent Analysis)	CNN (Convolutional Neural Network)	Developed Artificial Intelligence-Powered Wearable Assistive Device (Airis) For Real-Time Scene Description and Text Recognition.
Sarker Et Al. [20]	RFE (Recursive Feature Elimination) + Tree Based Selection	RL (Reinforcement Learning)	Optimized Motor Signal Features for Adaptive Robotic Exoskeletons.
Tokmurziyev Et Al. [13]	Multimodal Embedding + Attention	Transformer-Based Large Language Module	Generated Context-Aware Navigation Instructions Using Device-Captured Data.
Smithson Et Al. [8]	MI (Mutual Information) + SVM-RFE (Support Vector Machine – Recursive Feature Elimination)	SVM (Support Vector Machine)	Enabled Hands-Free Communication and Control Using EEG (Electroencephalography)/ EOG (Electrooculography) Signals.
Yang Et Al. [14]	MFCC (Mel Frequency Cepstral Coefficients) + Temporal Extraction	Adaptive De ep Learning	Enhanced Personalized Audio-Learning for Cognitive Accessibility.
Garcia Et Al. [23]	LDA (Linear Discriminant Analysis) + PCA (Principal Component Analysis)	CNN (Convolutional Neural Network)	Enhanced Emotion and Cognitive State Recognition for Cognitive Support Tools.