SSR Journal of Artificial Intelligence (SSRJAI)

OPEN ACCESS

Homepage: https://ssrpublisher.com/ssrjai/

Volume 3, Issue 8, 2026 ISSN: 3049-0413

# Enhancing Technical Education for People with Visual Impairments Using Artificial Intelligence

Fadayomi Bayonle[1], Oludele Awodele[2], Gregory O. Onwodi[3], Ibrahim A. Gangfada[4], Taiwo Oluwafeyisayo Aitalegbe[5], Ayeleso Anthony O.[6], Isah A. Lawal[7]

[1,4]African Centre of Technology Enhanced Learning, National Open University of Nigeria, Plot 91, Abuja 900108, Nigeria

[2]Department of Computer Science and Artificial Intelligence, Babcock University, Ilisan-Remo, Nigeria

[3]Department of Computer Science, Faculty of Computing National Open University of Nigeria, Plot 91, Abuja 900108, Nigeria

[5]Faculty of Computing, Nile University of Nigeria, jabi, Abuja, Nigeria, Plot 91, Abuja 900108, Nigeria

[6]Faculty of Environmental Science. NOUN

[7]Noroff University College, Kristiansand, Norway

***Received:*** *05.06.2026* | ***Accepted:*** *26.06.2026* | ***Published:*** *04.08.2026*

***Corresponding author:** Fadayomi Bayonle

**DOI:** *10.5281/zenodo.21787446*

**Abstract** **Original Research**

People with visual impairments remain critically underrepresented in technical education and science, technology, engineering, and mathematics (STEM) disciplines worldwide. Despite decades of legislative mandates and accessibility standards, fundamental barriers persist: programming environments remain largely visual, mathematical notation is predominantly conveyed through sight-dependent formats, laboratory work assumes visual observation, and digital learning platforms frequently fail to meet even basic accessibility requirements. This paper presents a comprehensive examination of how artificial intelligence (AI) technologies can systematically address these barriers and enhance technical education for learners with visual impairments. We organise our analysis around six categories of AI-enabled interventions: (i) natural language processing (NLP) and large language models (LLMs) for intelligent content transformation and description generation; (ii) computer vision systems for real-time scene understanding, object recognition, and diagram interpretation; (iii) automatic speech recognition and synthesis for hands-free interaction with technical tools; (iv) adaptive learning systems that personalise instructional content based on individual needs and modalities; (v) AI-powered code accessibility tools including intelligent code navigation and auditory programming environments; and (vi) multimodal AI assistants that integrate vision, language, and speech for comprehensive educational support. We propose the AI-Enhanced Accessible Technical Education (AI-ATE) framework that maps specific AI capabilities to identified barriers across the technical education lifecycle. The paper concludes with a research agenda identifying priority directions for the field.

**Keywords:** visual impairment, technical education, artificial intelligence, accessibility, assistive technology, STEM education, natural language processing, computer vision, adaptive learning, inclusive education.



## 1. Introduction

The World Health Organisation estimates that at least 2.2 billion people globally have a near or distance vision impairment, of whom at least 1 billion have a condition that could have been prevented or remains unaddressed (Bourne et al., 2021). Within this population, an estimated 43 million people are blind, and 295 million have moderate to severe vision impairment. For these individuals, access to education — particularly technical and scientific education — remains a persistent and largely unresolved challenge.

Technical education encompasses disciplines including computer science, engineering, information technology, mathematics, physics, chemistry, and vocational-technical trades. These fields share a common characteristic: they are profoundly visual in their pedagogy. Programming interfaces present code in visual text editors with syntax highlighting. Circuit diagrams, engineering drawings, and mathematical graphs convey essential information through spatial relationships that are fundamentally inaccessible to someone who cannot see. Laboratory work assumes the ability to make visual observations. Digital learning platforms continue to rely on visual content delivery, interactive simulations, and graphical user interfaces that frequently violate accessibility standards (Park et al., 2019; Zong et al., 2022).

Students with visual impairments are significantly underrepresented in STEM higher education programmes globally. In the United States, individuals with visual impairments earn a disproportionately small share of STEM degrees relative to their population (Slaton, 2020). In sub-Saharan Africa, the disparity is even more pronounced: many universities lack basic assistive technology infrastructure to support visually impaired students in technical programmes (Okyere et al., 2018; Dalton et al., 2019). The United Nations Convention on the Rights of Persons with Disabilities (UNCRPD), ratified by 190 countries, explicitly guarantees the right to education without discrimination (UN, 2006), yet the gap between legislative aspiration and educational reality remains vast.

Traditional assistive technologies — screen readers, refreshable Braille displays, screen magnification software, and text-to-speech engines — have been instrumental in providing basic access to digital content. However, these tools were primarily designed for accessing textual information and are fundamentally inadequate for the visual, spatial, and interactive demands of technical education. A screen reader can read the text of a programming assignment but cannot describe the spatial relationship between components in a circuit diagram. A Braille display can render characters of a mathematical equation but cannot convey the geometric properties of a function's graph.

Artificial intelligence offers transformative potential to bridge this accessibility gap. Unlike traditional assistive technologies that adapt the presentation of content, AI systems can actively interpret, transform, and generate content in modalities suited to the learner's needs. A large language model can generate natural language descriptions of complex visual content (OpenAI, 2023). A computer vision system can recognise objects, interpret diagrams, and provide real-time spatial information (He et al., 2017). An adaptive learning system can tailor instruction to the individual learner's profile (Mousavinasab et al., 2018). Speech recognition systems can enable hands-free interaction with technical tools (Radford et al., 2023).

This paper makes the following contributions. First, we present a systematic analysis of the barriers that visually impaired learners face across the technical education lifecycle. Second, we provide a comprehensive review of AI technologies applicable to addressing these barriers, organised into six functional categories. Third, we propose the AI-Enhanced Accessible Technical Education (AI-ATE) framework. Fourth, we identify critical challenges and open problems. Fifth, we articulate a research agenda for the field. The remainder of this paper is organised as follows. Section 2 reviews related work. Section 3 examines barriers. Section 4 surveys AI technologies. Section 5 presents the AI-ATE framework. Section 6 discusses challenges. Section 7 proposes future directions. Section 8 concludes.

## 2. Literature Review

### 2.1 Assistive Technology in Education

Screen readers, which convert on-screen text to speech or Braille output, remain the most widely used assistive technology for visually impaired computer users. JAWS (Job Access With Speech) and NVDA (NonVisual Desktop Access) together serve millions of users worldwide. Refreshable Braille displays provide a complementary output modality using piezoelectric pins to render tactile representations of text (Holloway et al., 2022). The effectiveness of these tools in educational contexts has been studied extensively. Hadwen-Bennett et al. (2018) conducted a literature review on making programming accessible to learners with visual impairments, finding that while basic textual access is achievable, significant barriers remain in spatial and interactive content.

Studies have consistently shown that visually impaired students spend substantially longer on tasks involving diagrams, charts, and spatial content compared to their sighted peers (Giudice et al., 2020). More recent assistive technologies have begun incorporating AI capabilities. Applications such as Seeing AI and Be My AI use computer vision and large language models to provide real-time descriptions of the visual environment, including charts and diagrams (Real and Araújo, 2019). While these tools demonstrate the potential of AI for visual interpretation, they are general-purpose applications not specifically designed for educational contexts.

### 2.2 AI in Education

The application of AI to education spans intelligent tutoring systems (Graesser et al., 2004), adaptive learning platforms (Corbett and Anderson, 1995), and, more recently, large language model-based educational tools (Kasneci et al., 2023). Intelligent tutoring systems use AI to provide individualised instruction, adapting the sequence and difficulty of learning activities. Systems such as AutoTutor (Graesser et al., 2004) and ALEKS (Harati et al., 2021) have demonstrated significant learning gains. However, these systems have not been designed with accessibility as a primary consideration.

The emergence of large language models has fundamentally altered the AI in education landscape. GPT-4 (OpenAI, 2023) and successors have demonstrated capabilities in natural language understanding, generation, and reasoning. In educational contexts, LLMs have been applied to automated assessment, personalised tutoring, and content generation (Kasneci et al., 2023). Crucially for accessibility, LLMs can serve as real-time content transformers: converting visual descriptions to natural language, generating alternative text for images, and translating between modalities.

### 2.3 Accessibility in Technical Education

In computer science education, the dominance of visual programming environments creates significant barriers (Hadwen-Bennett et al., 2018). The pedagogical shift towards visual block-based programming environments in introductory courses has paradoxically reduced accessibility for beginners (Milne and Ladner, 2018; Mountapmbeme et al., 2022). In mathematics and science education, the representation of equations, graphs, and diagrams poses fundamental challenges. Tactile graphics provide static representations but are expensive, time-consuming to produce, and cannot represent dynamic content (Holloway et al., 2022).

In engineering and vocational education, laboratory work presents perhaps the most significant accessibility challenge. Supalo et al. (2009) developed adaptive tools and techniques for teaching chemistry to blind students, including talking instruments. Watters et al. (2021) extended this with AI tools for accessible science education. In African contexts, the challenges are compounded by resource limitations. Dalton et al. (2019) examined inclusion, universal design, and universal design for learning in higher education across South Africa and the United States, finding significant gaps in both contexts.

### 2.4 AI for Accessibility

A growing body of research explores the application of AI specifically to accessibility challenges. In the visual impairment domain, this includes automatic alt-text generation, visual question answering (Gurari et al., 2018), and navigation assistance (Messaoudi et al., 2022). Gurari et al. (2018) introduced the VizWiz Grand Challenge for answering visual questions from blind people, establishing a benchmark for visual question answering in accessibility contexts. Zong et al. (2022) developed rich screen reader experiences for accessible data visualization, demonstrating that multi-level textual descriptions significantly improved visually impaired users' understanding of data visualisations.

## 3. Barriers to Technical Education for Visually Impaired Learners

This section identifies and categorises the barriers into five areas: content access, content creation and interaction, practical and laboratory work, assessment, and social and institutional.

### 3.1 Content Access Barriers

***Visual Content.*** Technical education relies heavily on visual content: circuit diagrams, engineering drawings, mathematical graphs, chemical structures, and flowcharts. This content is predominantly produced in visual formats without alternative text, tactile representations, or other non-visual modalities. Algorithm visualisations and data structure animations are entirely visual and typically inaccessible (Zong et al., 2022).

***Mathematical Notation.*** Mathematical expressions in digital content are typically rendered as images or using visual formatting that screen readers cannot reliably interpret. While LaTeX provides a textual source format, most students encounter mathematics in visually rendered formats where the underlying LaTeX is unavailable.

***Digital Textbooks and Learning Materials.*** A significant proportion of digital textbooks remain inaccessible. Born-digital materials often use visual formatting that screen readers cannot parse correctly. Scanned PDF documents require OCR processing before any assistive technology can access them (Park et al., 2019).

### 3.2 Content Creation and Interaction Barriers

***Programming Environments.*** Modern integrated development environments (IDEs) are heavily graphical, relying on visual features like syntax highlighting, inline error markers, and code completion dropdowns. While these IDEs can be used with screen readers, the experience is significantly less efficient (Hadwen-Bennett et al., 2018). Baker et al. (2019) documented the educational experiences of blind programmers, highlighting persistent barriers in modern development workflows.

***Collaborative Tools.*** Technical education increasingly involves collaborative work using tools such as Git, Jira, and visual collaboration platforms. These tools are predominantly visual and present significant accessibility barriers (Pandey, 2023).

***Content Authoring.*** Creating technical content — writing code, drawing diagrams, creating presentations — is often more challenging for visually impaired students than consuming it. Tools for drawing circuit diagrams and creating CAD models are inherently visual.

### 3.3 Practical and Laboratory Work Barriers

***Measurement and Observation.*** Laboratory work typically requires reading instruments, observing visual phenomena, and making precise measurements. These tasks assume functional vision. Alternative approaches — such as auditory output of instrument readings and tactile models — have been developed but are not universally available (Supalo et al., 2009; Watters et al., 2021).

***Safety.*** Laboratory safety protocols often rely on visual warnings: colour-coded hazard labels, indicator lights on equipment, and visual observation of dangerous conditions.

***Hands-on Assembly.*** Many technical courses involve physical construction: assembling circuits, building prototypes, soldering components. These tasks require visual alignment and spatial reasoning guided by sight.

### 3.4 Assessment Barriers

***Written Examinations.*** Technical examinations frequently include diagrams, graphs, and other visual content. Standard accommodations (extended time, a scribe, or a reader) do not fully address the fundamental modality mismatch.

***Online Assessment.*** Online examination platforms often use visual question formats (drag-and-drop, hotspot questions, interactive simulations) that are inaccessible. Timed assessments may not account for the additional time required by assistive technology users.

***Coding Assessments.*** Programming assessments on platforms such as LeetCode and HackerRank present coding challenges in visual interfaces with time pressure that creates additional barriers for visually impaired candidates.

### 3.5 Social and Institutional Barriers

***Attitudinal Barriers.*** Prevalent stereotypes about the inability of visually impaired individuals to succeed in technical fields create a discouraging environment. In many African contexts, disability is stigmatised (Naami, 2015; Shakespeare et al., 2021).

***Institutional Capacity.*** Most educational institutions lack the infrastructure, trained personnel, and institutional commitment to support visually impaired students in technical programmes (Okyere et al., 2018; Dalton et al., 2019).

***Resource Constraints.*** In low- and middle-income countries, the cost of assistive technology places it beyond the reach of most institutions and individual students. Internet connectivity, required for cloud-based AI services, is unreliable in many rural areas.

## 4. AI Technologies for Enhancing Accessibility in Technical Education

### 4.1 Natural Language Processing and Large Language Models

***Automated Alt-Text Generation.*** LLMs with multimodal capabilities can generate detailed natural language descriptions of images, including charts, diagrams, and mathematical graphs. For technical education, this capability can be applied to automatically generate alt-text for all visual content in textbooks, slides, and online materials (Smits et al., 2024).

***Content Transformation.*** LLMs can transform content between modalities: visual mathematical expressions can be converted to LaTeX or spoken descriptions, code can be explained in natural language, and diagrams can be described in structured natural language that preserves spatial relationships.

***Interactive Tutoring.*** LLM-based conversational agents can serve as accessible tutors that respond to natural language queries about technical content. A visually impaired student can ask about a circuit diagram or graph and receive a detailed natural language response (Kasneci et al., 2023).

***Real-Time Captioning and Description.*** NLP models can provide real-time transcription and description of live lectures, laboratory demonstrations, and collaborative sessions (Radford et al., 2023).

### 4.2 Computer Vision

***Object and Scene Recognition.*** Convolutional neural networks and vision transformers (Dosovitskiy et al., 2021) can recognise objects, scenes, and spatial relationships in real time. In educational contexts, this can be applied to laboratory environments and classroom settings (He et al., 2017).

***Document and Diagram Interpretation.*** Computer vision models combined with OCR can interpret scanned documents, engineering drawings, circuit diagrams, and mathematical expressions.

***Real-Time Visual Assistance.*** Camera-equipped devices running computer vision models can provide continuous real-time visual information to visually impaired users. In a laboratory setting, such a system could read instrument displays, identify colours, or locate components (H.A. et al., 2021).

### 4.3 Speech Recognition and Synthesis

***Automatic Speech Recognition (ASR).*** ASR systems such as Whisper (Radford et al., 2023) convert spoken language to text with near-human accuracy. For visually impaired students, ASR enables hands-free interaction with technical tools.

***Text-to-Speech (TTS).*** Modern neural TTS systems produce natural-sounding speech that can convey the structure and emphasis of technical material (Tan et al., 2021).

***Sonification.*** AI-driven sonification converts data and visual information into sound. Graphs can be represented as pitch changes over time and scatter plots as spatial audio. Walker and Cothran (2003) and Walker and Mauney (2010) demonstrated that auditory graphs can enable visually impaired students to understand data relationships with accuracy comparable to visual inspection.

### 4.4 Adaptive Learning and Personalisation

***Learner Modelling.*** AI systems can build detailed models of individual learners, tracking their knowledge state, learning preferences, and areas of difficulty. For visually impaired students, these models can additionally track accessibility preferences and adapt the experience accordingly (Mousavinasab et al., 2018).

***Personalised Content Delivery.*** Adaptive learning systems can automatically select and adapt content based on the learner's profile. For a visually impaired student, this might mean automatically replacing visual content with audio descriptions and adjusting complexity based on demonstrated understanding (Harati et al., 2021).

***Intelligent Scaffolding.*** AI systems can provide context-aware support. When a student struggles with a concept, the system can provide additional explanations, alternative representations, or targeted practice (Graesser et al., 2004).

### 4.5 AI-Powered Code Accessibility

***Auditory Programming Environments.*** AI can transform the programming experience from a visual to an auditory one, using different voices, tones, and spatial audio to convey code structure and semantics (Schanzer et al., 2019).

***Intelligent Code Navigation.*** LLMs can serve as intelligent code navigators. A programmer can ask natural language questions and receive contextual responses (Vaithilingam et al., 2022).

***Automated Code Review and Feedback.*** AI-powered code analysis tools can provide auditory or textual feedback on code quality and potential errors (Sarsa et al., 2022).

### 4.6 Multimodal AI Assistants

***Integrated Assistants.*** The most promising direction is the development of integrated multimodal AI assistants that combine vision, language, speech, and haptic capabilities into a single coherent system.

***Context-Aware Support.*** Unlike standalone accessibility tools, integrated assistants can maintain context across activities and modalities, tracking what the student has learned and providing proactive assistance (Bennett et al., 2018).

## 5. The AI-ATE Framework

Based on the barrier analysis and technology survey, we propose the AI-Enhanced Accessible Technical Education (AI-ATE) framework, organised into four layers.

### 5.1 Content Layer

The content layer addresses the accessibility of educational content at the point of creation and delivery:

(1) **Automatic Content Transformation Engine::** An LLM-powered pipeline that automatically converts visual content into multiple accessible formats: structured natural language descriptions, LaTeX source, Nemeth Braille, and sonified representations.

(2) **Real-Time Visual Description Service::** A vision-language model providing on-demand descriptions during live instruction, laboratory sessions, and collaborative activities.

(3) **Mathematical Content Accessibility Module::** A specialised component that converts between visual mathematical notation, LaTeX, spoken mathematics, and Nemeth Braille, and generates auditory graphs.

(4) **Document Accessibility Processor::** An OCR and document analysis pipeline that processes scanned PDFs and images, extracting text, structure, equations, and figures into accessible, structured output.

### 5.2 Interaction Layer

(1) **Accessible Programming Environment::** An AI-enhanced code editor providing auditory syntax highlighting, natural language code navigation, and intelligent code completion via speech.

(2) **Voice-Controlled Laboratory Interface::** A speech-driven interface for laboratory equipment. Students can query instrument readings and receive auditory feedback, supplemented by computer vision for visual information.

(3) **Collaborative Tool Accessibility Layer::** An intermediary layer making collaborative tools accessible through natural language interfaces.

### 5.3 Adaptation Layer

(1) **Learner Profile Manager::** Maintains a detailed profile for each student including visual acuity, preferred modalities, speech rate preferences, and description verbosity level.

(2) **Adaptive Content Selector::** Selects the most appropriate content format and presentation for each student based on their profile.

(3) **Pacing and Scaffolding Engine::** Adjusts the pace of instruction and level of scaffolding based on learner performance and interaction patterns.

### 5.4 Orchestration Layer

(1) **Context Manager::** Maintains awareness of the current educational context and activates appropriate components.

(2) **Integration Hub::** Provides APIs for integrating with learning management systems, assistive technology, and institutional systems.

(3) **Analytics and Reporting::** Tracks accessibility metrics and learning outcomes for continuous improvement.

(4) **Edge Deployment Manager::** Manages lightweight, offline-capable AI models for resource-constrained environments using model quantisation and selective cloud offloading (Han et al., 2015).

## 6. Challenges and Limitations

### 6.1 Technical Challenges

***Accuracy and Reliability.*** LLMs are known to produce incorrect or misleading outputs ("hallucinations"). In technical education, where precision is paramount, inaccurate AI outputs could create confusion or safety hazards (Huang et al., 2024).

***Latency.*** Real-time accessibility support requires low-latency processing. Current multimodal LLMs may introduce latency that disrupts instruction. In laboratory settings, high latency could compromise both learning and safety.

***Domain-Specific Performance.*** General-purpose AI models may perform poorly on domain-specific technical content such as engineering drawings or circuit diagrams.

### 6.2 Deployment Challenges

***Resource Requirements.*** State-of-the-art AI models require significant computational resources. Edge deployment using optimised smaller models is a potential solution but involves trade-offs (Han et al., 2015).

***Connectivity.*** Many AI capabilities depend on cloud-based services requiring reliable internet connectivity. In many parts of sub-Saharan Africa and South Asia, connectivity is unreliable.

***Cost.*** The cost of AI services, assistive hardware, and technical support can be prohibitive for institutions in low-income settings.

### 6.3 Ethical and Social Challenges

***Privacy.*** AI-powered accessibility tools that process camera feeds, speech, and interaction data raise significant privacy concerns. Visually impaired students should not have to sacrifice privacy for accessibility.

***Dependence and Agency.*** There is a risk that AI-powered accessibility tools could create dependence, reducing the development of independent skills. AI tools should empower learners, fostering independence rather than dependence.

***Bias and Fairness.*** AI models trained on data that underrepresents people with disabilities may produce biased outputs. Urbina et al. (2024) identified ability bias in AI systems, highlighting the need for disability-aware model training.

### 6.4 Pedagogical Challenges

***Teacher Training.*** Effective deployment of AI-powered accessibility tools requires teachers who understand both the technology and the pedagogy of inclusive technical education (Dalton et al., 2019).

***Curriculum Integration.*** AI accessibility tools must be integrated into the curriculum seamlessly. This requires curriculum redesign that embeds accessibility as a fundamental design principle.

***Assessment Validity.*** When AI tools mediate the assessment process by transforming visual content into alternative formats, ensuring that the transformed assessment measures the same construct is a significant psychometric challenge.

## 7. Future Research Directions

### 7.1 Multimodal Integration

Current research has primarily focused on individual AI capabilities in isolation. Future work should prioritise integrating multiple AI modalities into coherent systems that mirror the multimodal nature of sighted technical learning. Research questions include: How can vision, language, and speech models be jointly optimised for real-time accessibility support? How can multimodal systems gracefully degrade when some modalities are unavailable?

### 7.2 Edge Deployment for Low-Resource Settings

Research is needed on lightweight, offline-capable AI models that can run on affordable hardware without cloud connectivity. Techniques such as model quantisation (Han et al., 2015), knowledge distillation, and federated learning should be explored for accessibility applications. Evaluation should prioritise performance on low-end hardware in realistic conditions.

### 7.3 Co-Design Methodologies

AI accessibility tools are frequently designed for visually impaired users rather than with them. Future research should adopt participatory design and co-design methodologies that centre the lived experience of visually impaired learners throughout the design process (Sitbon and Farhin, 2017).

### 7.4 Standardised Evaluation Benchmarks

The field lacks standardised benchmarks for evaluating AI-powered accessibility tools in educational contexts. Future work should develop comprehensive evaluation frameworks that assess accuracy, usability, learning outcomes, latency, and equity across diverse user populations.

### 7.5 Teacher Training and Professional Development

Research is needed on effective approaches to training technical education teachers to use AI-powered accessibility tools, including developing practical training programmes and evaluating their impact on student outcomes.

### 7.6 Longitudinal Impact Studies

Most existing studies evaluate AI accessibility tools in short-term, controlled settings. Longitudinal studies are needed to assess the long-term impact on academic achievement, career progression, and self-efficacy in technical fields.

### 7.7 Ethical and Governance Frameworks

As AI becomes more deeply integrated into the education of visually impaired learners, robust ethical and governance frameworks are needed, addressing transparency, accountability, data sovereignty, and the prevention of algorithmic discrimination.

## 8. Conclusion

This paper has presented a comprehensive analysis of how artificial intelligence can enhance technical education for people with visual impairments. Our analysis reveals a landscape of significant unmet need: despite decades of legislative mandates and assistive technologies, visually impaired learners continue to face profound barriers in accessing technical education.

AI technologies offer genuinely transformative potential. Large language models can generate natural language descriptions of visual content and transform content between modalities. Computer vision systems can interpret diagrams and provide real-time visual information. Speech recognition and synthesis enable hands-free interaction with technical tools. Adaptive learning systems can personalise the educational experience. We have proposed the AI-ATE framework to organise these capabilities into a systematic, layered architecture.

However, realising this potential requires addressing significant challenges in accuracy, latency, resource requirements, ethical considerations, and pedagogical integration. We have identified seven priority research directions to advance the field. Progress in these areas, guided by the active participation of visually impaired learners and informed by the principles of universal design, can move towards the goal of truly inclusive technical education.

The stakes are high. Technical education is the gateway to employment, economic independence, and full participation in the digital economy. For the world's 2.2 billion people with vision impairments, AI-powered accessibility is not merely a technical challenge — it is a matter of equity, dignity, and human rights.

## References


Baker, C. M., Bennett, C. L., and Ladner, R. E. (2019). Educational experiences of blind programmers. In Proceedings of the 21st International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS), pp. 1–12. DOI: 10.1145/3287324.3287410.

Bennett, C. L., Brady, E., and Branham, S. (2018). Interdependence as a frame for assistive technology research and design. In Proceedings of the 20th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS), pp. 161–173. DOI: 10.1145/3234695.3236348.

Bourne, R. R. A., Steinmetz, J. D., Saylan, M., Mersha, A. M., Weldemariam, A. H., Wondmeneh, T. G., ... and Vos, T. (2021). Causes of blindness and vision impairment in 2020 and trends over 30 years, and prevalence of avoidable blindness in relation to VISION 2020: the Global Burden of Disease Study. The Lancet Global Health, 9(2), e144–e160. DOI: 10.1016/S2214-109X(20)30489-7.

Corbett, A. T. and Anderson, J. R. (1995). Knowledge tracing: modeling the acquisition of procedural knowledge. User Modeling and User-Adapted Interaction, 4(4), 253–278. DOI: 10.1007/BF01099821.

Dalton, E., Lyner-Cleophas, M., Ferguson, B. T., and McKenzie, J. (2019). Inclusion, universal design and universal design for learning in higher education: South Africa and the United States. African Journal of Disability, 8, a519. DOI: 10.4102/ajod.v8i0.519.

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... and Houlsby, N. (2021). An image is worth 16x16 words: transformers for image recognition at scale. In Proceedings of the International Conference on Learning Representations (ICLR). DOI: 10.48550/arXiv.2010.11929.

Giudice, N. A., Guenther, B. A., Jensen, N. A., and Haase, K. N. (2020). Cognitive mapping without vision: comparing wayfinding performance after learning from digital touchscreen-based maps vs. tactile maps. Frontiers in Human Neuroscience, 14, 87. DOI: 10.3389/fnhum.2020.00087.

Graesser, A. C., Lu, S., Jackson, G. T., Mitchell, H. H., Ventura, M., Olney, A., ... and Louwerse, M. M. (2004). AutoTutor: a tutor with dialogue in natural language. Behavior Research Methods, Instruments, and Computers, 36(2), 180–192. DOI: 10.3758/BF03195563.

Gurari, I., Li, Q., Stangl, A. J., Guo, A., Lin, C., Grauman, K., ... and Bigham, J. P. (2018). VizWiz Grand Challenge: answering visual questions from blind people. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3608–3617. DOI: 10.1109/CVPR.2018.00380.

H.A., S. U. Rao, Ranganath, S., and Ashwin, T. S. (2021). A Google Glass based real-time scene analysis for the visually impaired. IEEE Access, 9, 164434–164448. DOI: 10.1109/ACCESS.2021.3135024.

Hadwen-Bennett, A., Sentance, S., and Morrison, C. (2018). Making programming accessible to learners with visual impairments: a literature review. International Journal of Computer Science Education in Schools, 2(2), 25–38. DOI: 10.21585/ijcses.v2i2.25.

Han, S., Mao, H., and Dally, W. J. (2015). Deep compression: compressing deep neural networks with pruning, trained quantization and Huffman coding. arXiv preprint arXiv:1510.00149. DOI: 10.48550/arXiv.1510.00149.

Harati, H., Sujo-Montes, L., Tu, C.-H., and Armfield, S. (2021). Assessment and Learning in Knowledge Spaces (ALEKS) adaptive system impact on students' perception and self-regulation. Education Sciences, 11(10), 603. DOI: 10.3390/educsci11100603.

He, K., Gkioxari, G., Dollar, P., and Girshick, R. (2017). Mask R-CNN. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 2961–2969. DOI: 10.1109/ICCV.2017.322.

Holloway, L., Ananthanarayan, S., Butler, M., De Silva, M. T., and Marriott, K. (2022). Animations at your fingertips: using a refreshable tactile display to convey motion graphics for people who are blind or have low vision. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, pp. 1–15. DOI: 10.1145/3517428.3544797.

Huang, L., Yu, W., Ma, W., Zhong, W., Feng, Z., Wang, H., ... and Lv, N. (2024). A survey on hallucination in large language models: principles, taxonomy, challenges, and open questions. ACM Transactions on Information Systems. DOI: 10.1145/3703155.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... and Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. DOI: 10.1016/j.lindif.2023.102274.

Messaoudi, M. D., Ménélas, B.-A. J., and Mcheick, H. (2022). Review of navigation assistive tools and technologies for the visually impaired. Sensors, 22(20), 7888. DOI: 10.3390/s22207888.

Milne, L. R. and Ladner, R. E. (2018). Blocks4All: overcoming accessibility barriers for children with visual impairments in block-based programming. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, pp. 1–10. DOI: 10.1145/3173574.3173643.

Mousavinasab, E., Zarifsanaiey, N., Niakan Kalhori, S. R., Rakhshan, M., Keikha, L., and Ghazi Saeedi, M. (2018). Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods. Interactive Learning Environments, 29(1), 142–163. DOI: 10.1080/10494820.2018.1558257.

Mountapmbeme, A., Okafor, O., and Ludi, S. (2022). Accessible Blockly: an accessible block-based programming library for people with visual impairments. In Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS), pp. 1–14. DOI: 10.1145/3517428.3544806.

Naami, A. (2015). Disability, gender, and employment relationships in Africa: the case of Ghana. African Journal of Disability, 4(1), a95. DOI: 10.4102/ajod.v4i1.95.

Okyere, C., Aldersey, H. M., Lysaght, R., and Sulaiman, S. K. (2018). Implementation of inclusive education for children with intellectual and developmental disabilities in African countries. Disability and Rehabilitation, 40(16), 1870–1880. DOI: 10.1080/09638288.2018.1465132.

OpenAI (2023). GPT-4 technical report. arXiv preprint arXiv:2303.08774. DOI: 10.48550/arXiv.2303.08774.

Pandey, M. (2023). Accessibility of collaborative programming for blind and visually impaired developers. University of Michigan Deep Blue. DOI: 10.7302/22320.

Park, K., So, H.-J., and Cha, H. (2019). Digital equity and accessible MOOCs: accessibility evaluations of mobile MOOCs for learners with visual impairments. Australasian Journal of Educational Technology, 35(6), 48–63. DOI: 10.14742/ajet.5521.

Radford, A., Kim, J. W., Xu, T., Brockman, G., McLeavey, C., and Sutskever, I. (2023). Robust speech recognition via large-scale weak supervision. In Proceedings of the 40th International Conference on Machine Learning (ICML), pp. 28492–28518.

Real, S. and Araújo, Á. (2019). Navigation systems for the blind and visually impaired: past work, challenges, and open problems. Sensors, 19(15), 3404. DOI: 10.3390/s19153404.

Sarsa, S., Denny, P., Hellas, A., and Leinonen, J. (2022). Automatic generation of programming exercises and code explanations using large language models. In Proceedings of the 2022 ACM Conference on International Computing Education Research (ICER), pp. 27–43. DOI: 10.1145/3501385.3543957.

Schanzer, E., Bahram, S., and Krishnamurthi, S. (2019). Accessible AST-based programming for visually-impaired programmers. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1–14. DOI: 10.1145/3287324.3287499.

Shakespeare, T., Ndagire, F., and Seketi, Q. E. (2021). Triple jeopardy: disabled people and the COVID-19 pandemic. The Lancet, 397(10282), 1331–1333. DOI: 10.1016/S0140-6736(21)00625-5.

Sitbon, L. and Farhin, S. (2017). Co-designing interactive applications with adults with intellectual disability. In Proceedings of the 29th Australian Conference on Computer-Human Interaction (OzCHI), pp. 487–491. DOI: 10.1145/3152771.3156163.

Slaton, A. (2020). Body? What body? Considering ability and disability in STEM disciplines. In ASEE Annual Conference and Exposition. DOI: 10.18260/1-2--19261.

Smits, T. C., L'Yi, S., Mar, A., and Gehlenborg, N. (2024). AltGosling: automatic generation of text descriptions for accessible genomics data visualization. Bioinformatics, 40(3), btae670. DOI: 10.1093/bioinformatics/btae670.

Supalo, C. A., Mallouk, T. E., Amorosi, C., Lanouette, J., and Wohlers, H. D. (2009). Using adaptive tools and techniques to teach a class of students who are blind or low-vision. Journal of Chemical Education, 86(5), 587. DOI: 10.1021/ed086p587.

Tan, X., Qin, T., Soong, F. K., and Liu, T.-Y. (2021). A survey on neural speech synthesis. arXiv preprint arXiv:2106.15561. DOI: 10.48550/arXiv.2106.15561.

United Nations (UN) (2006). Convention on the Rights of Persons with Disabilities. United Nations Treaty Series, vol. 2515, p. 3. New York: United Nations.

Urbina, J. T., Vu, P. D., and Nguyen, M. V. (2024). Disability ethics and education in the age of artificial intelligence: identifying ability bias in ChatGPT and other language models. Archives of Physical Medicine and Rehabilitation. DOI: 10.1016/j.apmr.2024.08.014.

Vaithilingam, P., Zhang, T., and Glassman, E. L. (2022). Expectation vs. experience: evaluating the usability of code generation tools powered by large language models. In CHI Conference on Human Factors in Computing Systems Extended Abstracts, pp. 1–7. DOI: 10.1145/3491101.3519665.

Walker, B. N. and Cothran, J. T. (2003). Sonification sandbox: a graphical toolkit for auditory graphs. In Proceedings of the International Conference on Auditory Display (ICAD).

Walker, B. N. and Mauney, L. M. (2010). Universal design of auditory graphs: a comparison of sonification mappings for visually impaired and sighted listeners. ACM Transactions on Accessible Computing, 2(3), 1–16. DOI: 10.1145/1714458.1714459.

Watters, J. D., Hill, A., Weinrich, M., and Supalo, C. A. (2021). An artificial intelligence tool for accessible science education. Journal of Science Education for Students with Disabilities, 13(1), 10. DOI: 10.14448/jsesd.13.0010.

Zong, J., Lee, C., Lundgard, A., Jang, J. W., Hilderbrand, D. S., Satyanarayan, A., and Adar, E. (2022). Rich screen reader experiences for accessible data visualization. Computer Graphics Forum, 41(3), 15–27. DOI: 10.1111/cgf.14519.