Acta Educationis Generalis
Volume 15, 2025, Issue 1

DOI: 10.2478/atd-2025-0009

Analysis of AI Mobile Applications for Ensuring Digital Accessibility in Higher Education for People with Disabilities

Radka Nacheva*

Received: July 17, 2024; received in revised form: November 19, 2024; accepted: November 20, 2024

Abstract:
Introduction: Over 1 billion people worldwide have disabilities, necessitating their inclusion in health systems and workplaces. Artificial intelligence (AI) is revolutionizing accessibility and digital inclusion for these individuals, improving everyday tasks and enabling autonomous mobility. AI can be applied to visually impaired, reduced mobility, and cognitive disabilities, supporting their inclusion in learning and work environments, and promoting social and digital inclusion.
Methods: The study investigates mobile applications for disabled individuals in higher education, utilizing readability analysis of texts generated using Otter.ai, using qualitative methods to assess the accessibility of AI-generated samples.
Results: Results show that the auto-generated text's readability is about or below average level.
Discussion: The text, tailored for computer science students, emphasizes human-computer interaction and user interface (UI) usability, utilizing specialized terms and real-time recording for hearing impairments.
Limitations: The data of this study were collected only from Otter.ai based on the narration of part of a computer science-related lecture. No other AI tools are used for automatic text generation.
Conclusions: Based on the analysis, we made changes to the AI-generated content, cutting down lengthy paragraphs, simplifying complicated words, and utilizing straightforward language without compromising the intended message.

Key words: artificial intelligence, digital accessibility, higher education accessibility, text readability.

* Radka Nacheva, University of Economics – Varna, Faculty of Informatics, Varna, Bulgaria; r.nacheva@ue-varna.bg; ORCID: 000-0003-3946-2416

Introduction

The integration of technology in higher education is crucial for creating inclusive and accessible learning environments. Over 1 billion people worldwide have some form of disability, and the increasing number of these individuals necessitates their inclusion in health systems and workplaces. Artificial intelligence (AI) is revolutionizing accessibility and digital inclusion for these individuals. AI solutions can improve everyday tasks, and mobile applications can help them remain autonomous. AI can be applied to any disability profile, such as visually impaired people using Seeing AI to read mail or place documents, people with reduced mobility using virtual personal assistants like Amazon Alexa, and people with cognitive disabilities using text summarization applications. AI technology supports the inclusion of people with disabilities in learning and work environments, providing new opportunities for social and digital inclusion. Some authors state that education remains inaccessible to a significant part of people with disabilities (Todoranova & Penchev, 2023). In this sense, artificial intelligence has changed the educational paradigms, particularly in higher education. AI-powered applications can ensure digital accessibility, an important aspect of inclusive education. This refers to the ease of access and use of digital resources by the students and faculty, regardless of their physical abilities or disabilities (Ioannidi, 2023; Norwich, 2022; Dodd et al., 2020). Norwich (2022) states that educational research on effects has design limitations, utilizing quasi-experimental designs and multi-variate statistical analyses of longitudinal and administrative data sets, despite their focus on effects.

AI algorithms can help design mobile applications to cater to individual needs, providing personalized learning experiences (Akhtar, 2023). Features like voice recognition, text-to-speech, and predictive text can significantly improve the accessibility of digital content. Mobile applications used by disabled people in the educational process aim to address the diverse accessibility needs of students, ensuring equitable access to educational resources and opportunities (Yaseen et al., 2019; Mayordomo-Martínez et al., 2019; Silva et al., 2023). Accessibility in this context includes visual, auditory, motor, and cognitive dimensions (Hassan, 2023). In this sense, as Lu et al. (2023) state, multimodal affective computing is crucial for enhancing emotional changes in learners through intelligent systems and efficient digital interventions. Another study examines the mobile application development industry's digital accessibility awareness, adoption of accessibility practices, motivations for accessible products, and barriers preventing proper accessibility (Leite et al., 2021).

The utilization of AI in mobile applications for higher education is a multifaceted endeavour that seeks to overcome barriers to learning and foster an inclusive educational ecosystem (Pikhart, 2020). By harnessing AI, these applications provide enhanced content delivery and personalized, adaptive learning experiences that resonate with individual needs and learning styles (Peng et al., 2019). Salah et al. (2020) explore adaptive learning, adjusting content delivery based on individual learning preferences and accessibility needs. It assesses content accessibility, integrates assistive technologies, and supports real-time communication for inclusivity.

Another paper provides an overview of recent research and application development advancements aimed at improving the usability of mobile applications for people with visual impairments, highlighting the challenges they often face in interacting with these applications (Al-Razgan et al., 2021). Zong et al. (2022) identify three key design dimensions for expressive software accessibility: structure, navigation, and description. Structure refers to the organization of chart entities, navigation involves the structural, spatial, and targeted operations a user can perform, and description refers to the semantic content, composition, and verbosity of the screen reader's narration.

In this regard, the current paper aims to explore mobile applications for people with disabilities that enhance digital accessibility in higher education. It explores the benefits, challenges, and future implications of AI in ensuring digital accessibility in higher education, aiming to promote equality in educational opportunities and make higher education more inclusive and accessible. An experiment was conducted with readability analysis of texts automatically generated with Otter.ai to explore its accessibility for people with special needs.

1 Literature review

In today's educational environment, incorporating digital tools and resources into classroom learning has become more and more crucial (Ajani, 2024). Virtual co-teaching and the incorporation of digital technology have become standard practices in education (Svobodová, Kříž, & Veteška, 2024). The same source states that these developments are a reaction to digital advancements that elementary and secondary schools must adapt to, and they are important in tackling global issues. In this sense, the new way of teaching needs to be taken into account to answer to the new technological developments.

We can point out that AI mobile applications focus on creating an inclusive digital environment. These applications used to support students in higher education are developed to improve digital accessibility. They involve user needs analysis, speech recognition, language translation, adaptive learning paths, multimodal content accessibility, voice command navigation, real-time collaboration, predictive text and autocomplete, and assistive technology compatibility (Standen et al., 2020; Fonggi & Oktavianus, 2021; Ogundokun et al., 2021; Gonçalves et al., 2021; Gligorea et al., 2023; Belgacem et al., 2023). Batanero et al. (2022) conducted user research to identify the specific accessibility needs of students with disabilities, including visual, auditory, motor, and cognitive impairments.

Speech recognition and text-to-speech functionalities are implemented to assist students with difficulty typing and visual impairments (Gottardi et al., 2022). AI-driven language translation features are also implemented to accommodate students from diverse linguistic backgrounds (Kolhar & Alameen, 2021). Adaptive learning algorithms are developed to tailor content delivery based on individual student preferences and learning styles (El-Sabagh, 2021). Multimodal content accessibility is ensured through alt text and descriptions, audio descriptions for multimedia content, voice command navigation, and real-time collaboration features (Cecilia et al., 2023). Predictive text and autocomplete features are also integrated to enhance text input for users with motor disabilities or those struggling with precise typing (Kristensson et al., 2020).

AI mobile applications are increasingly being integrated into educational technology platforms to improve digital accessibility for students with diverse needs. These tools may not be standalone applications but contribute to creating more inclusive learning environments. Microsoft Office 365 Education, Google Workspace for Education, Anthology Ally, ReadSpeaker, Voice Dream Reader, Texthelp's Read&Write, KNFB Reader, and Otter.ai are some examples of AI-driven tools that enhance digital accessibility in higher education (McElaney, 2020; Student Accessibility Services, 2022; Semantix, 2023).

Microsoft Office applications often include built-in accessibility features like Immersive Reader, which provides text-to-speech and other reading assistance tools (Microsoft, 2023). Google Workspace tools like Google Docs and Slides offer accessibility features, and Google Meet may integrate AI features for real-time transcription and language translation (Kurian, 2023). Anthology Ally enhances inclusive environments by making digital content accessible for all, integrating seamlessly with any LMS and public-facing website, providing feedback, alternative formats, and comprehensive reporting (Anthology, 2023).

ReadSpeaker is a text-to-speech solution that integrates with various educational platforms, making digital content more accessible by providing a spoken version of the text (ReadSpeaker, 2023). Voice Dream Reader combines text-to-speech and other accessibility features to make digital content more accessible to individuals with visual or reading impairments (Perkins School for the Blind, 2022). Texthelp's Read&Write is a literacy support tool that offers help with everyday tasks like reading text out loud, understanding unfamiliar words, and integrating with various platforms (Texthelp, 2023), while KNFB Reader is a mobile app designed to read printed text aloud that helps blind, low-vision, dyslexic, and other print-disabled users (National Federation of the Blind, 2023). Otter.ai is a transcription service that uses AI to convert spoken words into written text in real-time, benefiting students with hearing impairments (Chen, 2021).

Other examples of mobile applications used to support disabled people include Be My Eyes, Seeing AI, Ava, Voice Access, Tecla Access, MindMeister, and mobile phones' screen readers. Be My Eyes and Seeing AI uses artificial intelligence to narrate information by using a smartphone's rear camera to identify objects, text, and people, providing audible experiences and enabling tasks for visually impaired individuals (Dürr, 2021). Auditory impairments supporting applications' examples are Ava and Live Transcribe which provide real-time captioning for in-person and virtual conversations, as well as notifying critical environmental sounds, providing feedback, and making transcripts readable from two sides for both speakers and listeners to check results (Pragt et al., 2022). Tools like mobile phones' screen readers, provide also spoken feedback to users with visual impairments. Smartphones with integrated accessibility features like screen readers often fail to meet users' needs due to the social stigma associated with disability-related devices (Sankhi & Sandnes, 2020). Voice Access and Tecla Access are targeted to support people with motor impairments, which allow users to control mobile devices using voice commands. They enable individuals with mobility impairments to control mobile devices by using adaptive switches or wheelchair-driving controls, as well as by using speaker-dependent, limited vocabulary, and offline speech recognizers (Bhargav et al., 2020).

MindMeister supports people with cognitive impairments. It is a mind-mapping tool that utilizes visual images, notes, and a learning style to maximize brain power in remembering information, as well as encourages students to explore their potential and create motivation to present and visualize ideas in learning material using shorter, regular words (Putra et al., 2022).

In summary, mobile applications in higher education have made significant strides in promoting inclusivity, equity, and accessibility. The personalized learning experiences that they offer foster independence, confidence, and self-advocacy among students with disabilities. The transformative potential of mobile applications in higher education contributes not only to academic success but also to a broader educational landscape where diversity is real. In this sense, there is a need to test the accessibility aspects of applications that support students' daily activities to verify their practical applicability.

2 Method

2.1 Data collection

A readability analysis of AI-generated texts is conducted within this research an 8-paragraph, 680-word lecture presentation voice-over English text was automatically generated using the Otter.ai tool. The text has been revised by removing meaningless words and inserting punctuation marks. According to Microsoft Word statistics, the words after the manual review are 674. The overall review shows that the most common problem with auto-generated text is not putting punctuation in the right places, even though the narration follows an intonation that marks at least the beginning and end of the sentence. Another problem noticed is that some of the specialized terms are not recognized correctly, especially longer words. This may also be due to the pronunciation of the words by the narrator.

2.2 Research procedure

Readability analysis is important for assessing the comprehension and clarity of automatically generated texts, especially for those created by AI systems. This process involves collecting samples of AI-generated texts to ensure a comprehensive and effective analysis, ensuring the intended audience can easily perceive the content. The following stages are performed (Figure 1): Define Research Parameters; Text Collection; Text Preprocessing; Readability Analysis; and Interpret Results.

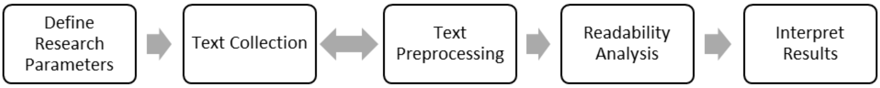

Figure 1. Research procedure stages.

Define Research Parameters: To evaluate AI-generated texts, it is first necessary to define the parameters of the study, specifically what the objectives of the study are, as well as the appropriate metrics for evaluating the readability of the texts. This ensures a comprehensive analysis of the generated texts, which may include multiple samples. The process involves determining sample lengths and selecting appropriate metrics. Choosing appropriate readability metrics depends on the target audience and the type of text. Well-known metrics for improving the difficulty classification of educational texts, as Rooein et al. (2024) state, are the Flesch Reading Ease Score, Flesch-Kincaid Grade Level, Gunning Fog Index, SMOG Index, Coleman-Liau Index, Automated Readability Index (ARI). These metrics help to evaluate the readability of the text and provide a wide range of comprehension.
Text Collection: Automatic AI text generation depends on research objectives. These can be lecturing narrations, books, conversations in online conference rooms, etc. AI tools such as ChatGPT, Microsoft Copilot, Jasper, Chatsonic, etc. can also be used. The generated texts are stored in a meta-repository, from which

the texts are retrieved for further processing. Metadata generally includes generation parameters, AI model version, and date of generation for future reference.

Text Preprocessing: Usually, the preprocessing stage involves cleaning and tokenizing text into words and sentences.

Readability Analysis: Automated readability tools like Python Libraries and online tools like WebFX, Data·Yze, and Readable can calculate readability scores. Manual evaluation can be done too and it involves content review and consistency of writing style and tone. Comparative analysis is part of this stage, as well. It compares AI-generated texts with human-written texts to benchmark performance and evaluates changes across different versions. All methods help assess the readability of content for the intended audience.

Interpret Results: At this stage, it is outlined whether the text needs to be improved for readability or not. Analysis of readability results is performed and areas for improvement are identified. The results of the text readability study will show whether the text generated by AI is more complex than the text written by humans, and which of the two types of text needs to be refined. It is usually done to simplify the sentence structure and reduce the complex words.

3 Results and discussion

A readability analysis involves evaluating the complexity and clarity of the content to ensure it is easily comprehensible. We generated text by using Otter.ai based on the narration of part of a lecture about user interface (UI) usability. A manual review was conducted to ensure that readability improvements align with the overall quality and coherence of the content. Readability testing tools WebFX, Data·Yze, and Readable were used to identify areas for improvement, revising and simplifying the text based on readability metrics. Microsoft Word’s readability statistics are also applied to compare the results of the mentioned tools.

The readability testing tools use metrics like the Flesch Reading Ease Score, Flesch-Kincaid Grade Level, and Gunning Fog Index. The Flesch Reading Ease formula measures the difficulty of understanding English text content, based on factors like word length, sentence length, word form, and syllables (Eleyan et al., 2020). The Flesch-Kincaid Grade Level formula uses similar measures but uses weighting factors like word usage per sentence and syllables per word (Eleyan et al., 2020). The Gunning Fog Index Formula measures English text readability and generates scores indicating the level of education required to understand the text (Eleyan et al., 2020). Another considered metric is the Simple Measure of Gobbledygook (SMOG) Index, renowned for its simplicity, classifies a word's difficulty based on the number of syllables (Lee & Lee, 2023). The Coleman-Liau Index (COLE) is a less-used variation among the five, but it is still used in

studies outside of computational linguistics (Lee & Lee, 2023) which is also used by the mentioned tools.
Table 1 includes the results of the automatically generated text analysis done with WebFX, Data·Yze, and Readable, as well as the available Microsoft Word readability statistics. Most metrics are offered by Readable, but only some of them are summarized in the table, looking for a match with the other tools.

Table 1

Results of the automatically generated text analysis

Metric	*WebFX*	*Data·Yze*	*Readable*	*Microsoft Word*
Flesch Reading Ease Score	42.6	42.58	42.6	41.7
Flesch-Kincaid Grade Level	12.6	12.39	12.4	12.6
Gunning Fog Index	15	14.99	14.8	-
SMOG Index	10.8	13.79	13.8	-
Coleman-Liau Index	12.7	-	11.2	-
Number of Words	678	-	673	674
Number of Sentences	32	33	33	31
Words Per Sentence	21.19	20.39	20.4	21
Characters Per Word	4.8	4.84	4.8	4.8
Percentage of Difficult Words	16.52%	17.09%	Grade D	22.5%
Average Reading Ease	42.6 of 100	-	57 of 100	-

The overall analysis of the data in Table 1 shows that the readability of the auto-generated text is about or below average, with Readable detecting 74 problems. The other tools do not show the total number of problems found in the text. The main issues found are related to sentence length and word length. The recommendations the tools come up with are to shorten sentence length and keep to no more than 6% long sentences in the entire text. Gunning Fog Index is suitable for various materials, particularly business writing and publishing, and offers grading suitable for all ages (Readable, 2019).
Scores for the Flesch Reading Ease Score and Flesch-Kincaid Grade Level metrics are similar across all four columns of Table 1. The Gunning Fog Index also scores roughly the same. For all three metrics, it is recommended: to shorten long sentences, and reduce the use of passive voice and adverbs.
The analysis done by WebFX, Data·Yze, and Readable is based mainly on the understanding that the text should be intended for a general audience that does not have specialist knowledge in a given field. We take into account that the automatically generated text is intended for the student audience, in particular computer science students in the field of human-computer interaction. The text is aimed at UI usability, which necessitates the use of specialized terms that cannot

be replaced by other words. The quality of the texts of course depends on the volume, the speaker's pronunciation, background noises, and internet connection. However, the automatic generation of texts should help students with hearing impairments who can record their lectures or conversations in real-time, which will help their learning to some extent.

Conclusions

Accessibility in higher education is crucial for inclusivity, equity, and diversity of learning opportunities. It goes beyond compliance with regulations and is a fundamental acknowledgement that education should be a universal right, accessible to every individual, regardless of their physical or cognitive abilities. Mobile applications that support disabled individuals play a transformative role in this journey, empowering students to navigate academic challenges with greater independence and confidence. They provide visual and auditory support, and adaptive learning features, and break down barriers, creating an educational landscape that accommodates diverse needs. This results in a more inclusive, learner-centric educational ecosystem that nurtures the strengths and potentials of every individual.

Revisions to the AI-generated text that we made are based on the analysis, simplifying complex sentences, breaking down large paragraphs, and using clear language without sacrificing the intended meaning. The readability analysis is done with three tools that show four main metrics - Flesch Reading Ease Score, Flesch-Kincaid Grade Level, Gunning Fog Index, and SMOG Index. Microsoft Word also supports some metrics, but overall it shows statistics for text length, number of sentences, paragraphs, and words.

Acknowledgements

This research was funded by the NPI-65/2023 project "Artificial Intelligence to Help People with Disabilities in Ensuring Digital Accessibility in the Higher Education Learning Process".

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