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# Toward Inclusive AI in Mathematics Education: Investigating Usability and Accessibility Challenges for Students with Visual Disabilities

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The rapid adoption of large language models (LLMs) in education presents new opportunities for personalized learning; however, their accessibility for visually impaired students in mathematics learning remains insufficiently explored. This study investigates the accessibility, usability, and instructional effectiveness of four widely used LLM platforms, ChatGPT, Gemini, LLaMA, and DeepSeek, when supporting visually impaired learners in solving mathematical problems. A mixed-methods research design was employed, involving 12 students with visual disabilities and 3 instructors. Data were collected through structured surveys, task-based mathematical problem solving, and instructor-based evaluation of explanation quality. Quantitative analysis included descriptive statistics and comparative accuracy testing, while qualitative analysis examined user experiences and accessibility barriers. The results indicate that 66% of participants experienced incompatibility between AI-generated mathematical notation and screen reader technologies, while 83% reported the absence of adaptive verbosity controls for explanations. Usability analysis revealed that 100% of participants encountered difficulties navigating multi-step solutions due to insufficient structural organization. Comparative evaluation showed that ChatGPT and Gemini achieved higher average solution accuracy (~80%), whereas LLaMA and DeepSeek demonstrated lower accuracy (60%). Instructor assessments further indicated that 67% of AI-generated explanations lacked clear stepwise reasoning, requiring additional clarification for learners. Participants emphasized the need for structured, step-by-step explanations, screen reader–compatible mathematical notation, adaptive verbosity controls, and audio-guided navigation to enhance accessibility. The study highlights that while LLMs demonstrate moderate computational capability, significant accessibility and usability limitations remain for visually impaired learners. The findings contribute to the development of accessibility-aware AI frameworks for inclusive STEM education, providing design recommendations for improving LLM-based mathematics learning tools.

**Keywords:** Accessibility in AI, Students with Visual Disabilities, Mathematics Education, Assistive Technology, AI in Education

**Introduction:**

The rapid advancement of Artificial Intelligence (AI) and large language models (LLMs), such as ChatGPT, Gemini, LLaMA, and DeepSeek, has significantly transformed modern educational environments [1][2]. These AI-driven systems provide interactive, on-demand learning support, enabling students to access explanations, solve problems, and receive personalized feedback across a wide range of subjects [3]. Recent research highlights the increasing role of LLMs in education, particularly in supporting self-directed learning, intelligent tutoring, and adaptive instructional systems [4]. By enabling conversational interaction and contextual reasoning, LLMs have the potential to improve accessibility and expand educational opportunities for diverse learner populations, including students with disabilities [5][6].

Despite these advancements, accessibility challenges remain a significant concern when applying AI technologies to mathematics education for visually impaired students [7]. Mathematics is inherently symbolic and highly visual, relying on representations such as equations, graphs, matrices, and geometric diagrams [8]. For visually impaired learners, accessing such information requires specialized assistive technologies, including screen readers, refreshable Braille displays, tactile graphics, and structured mathematical markup languages such as MathML and LaTeX [9][8]. While these tools have improved accessibility, recent studies indicate that many AI-driven educational platforms still struggle to present mathematical content in formats that are compatible with screen readers or other assistive technologies [10].

The emergence of LLM-based systems has further introduced both opportunities and limitations for accessible learning [11]. Several recent studies have explored the use of generative AI in education and its potential for supporting inclusive learning environments [12]. However, empirical evidence suggests that current LLM systems frequently generate mathematical explanations that lack structural clarity, consistent symbolic representation, or compatibility with accessibility tools [13]. For visually impaired students, this limitation can lead to difficulties in navigating multi-step solutions, interpreting symbolic expressions, and understanding complex reasoning processes [14]. Furthermore, research has identified additional usability concerns, including excessive verbosity, inconsistent explanation structures, and limited support for adaptive learning interactions [15].

Inclusive education frameworks emphasize that digital learning environments must be designed to accommodate diverse learner needs [16]. This principle is strongly reflected in the United Nations Sustainable Development Goal 4 (Quality Education), which promotes equitable access to education for all learners, including individuals with disabilities [17]. Achieving this objective requires not only the availability of assistive technologies but also the integration of accessibility-aware AI systems capable of delivering structured, navigable, and interpretable educational content [18]. In the context of mathematics education, accessible AI tools must support clear symbolic representation, step-by-step reasoning, and compatibility with screen-reader technologies to ensure that visually impaired students can independently engage with mathematical problem solving.

Although several studies have examined AI-based educational systems and accessibility technologies, limited research has systematically evaluated how modern LLM platforms perform when used specifically for mathematics learning by visually impaired students [19]. Most existing studies focus either on general AI-assisted learning or on traditional assistive technologies without investigating the combined interaction between LLM-generated explanations and accessibility tools [20]. Consequently, there remains a research gap in understanding how current LLM systems perform in terms of usability, accessibility, and instructional effectiveness for visually impaired learners in mathematics [21].

This study addresses this gap by investigating the usability and accessibility challenges experienced by visually impaired students when interacting with AI-based mathematics tools powered by large language models. Through a mixed-method evaluation involving visually impaired learners and instructors, the research examines how different LLM systems perform in providing structured mathematical explanations, accessible outputs, and effective problem-solving support.

The primary objective of this study is to examine the usability and accessibility of large language models (LLMs) in supporting visually impaired students during mathematics learning. Specifically, the research aims to evaluate how effectively LLM-based systems facilitate the understanding of mathematical concepts and problem-solving processes through AI-generated explanations. In addition, the study seeks to compare the performance of different LLM platforms in terms of their accuracy and ability to generate clear, step-by-step mathematical solutions. Another key objective is to identify major accessibility challenges encountered by visually impaired learners, including issues related to screen reader compatibility, lack of adaptive verbosity controls, and difficulties in navigating structurally complex mathematical explanations. Furthermore, the study explores user perceptions and experiences by collecting feedback from both visually impaired students and instructors regarding the usability and instructional value of AI-based mathematics tools. Based on these findings, the research also aims to propose practical design recommendations for developing future accessibility-aware AI systems that can better support inclusive mathematics education.

This study is guided by several research questions aimed at examining the accessibility, usability, and instructional effectiveness of AI-powered mathematics tools for visually impaired learners. First, the study investigates the challenges that visually impaired students encounter when interacting with AI-based mathematics systems, particularly in relation to screen reader compatibility, verbosity control, and the structural navigation of mathematical explanations. Second, it examines the effectiveness of current large language models in generating accurate and accessible step-by-step solutions for various mathematical problems, including word-based problem-solving tasks. The research also explores existing accessibility gaps in the integration of mathematical representation formats such as MathML and LaTeX within AI-driven educational tools. In addition, the study seeks to understand the perceptions and experiences of visually impaired students and instructors regarding the usability and instructional value of AI tools in mathematics learning. Furthermore, it aims to identify specific design features—such as adaptive verbosity, voice interaction, and structured output formatting—that may significantly enhance the user experience for visually impaired learners. Finally, the study considers how future AI-based systems can be optimized to better support independent, accessible, and effective mathematics learning for students with visual disabilities.

The remainder of this paper is organized as follows. The related work section reviews existing studies on AI accessibility and mathematics learning for visually impaired students. The Materials and Methods section describe the research design, participants, and data collection procedures. The Results section presents the study findings, followed by the Discussion, which interprets the results in relation to existing literature. Finally, the Conclusion summarizes the key contributions and outlines directions for future research.

**Related work:**

The educational community has long maintained a consistent interest in AI systems and their combination with assistive technologies and educational tools. Large Language Models (LLMs), including ChatGPT, show notable potential for delivering personalized, interactive, adaptive learning experiences to users [22]. Mathematics learning for blind students requires exploration into the combination of LLMs and assistive technologies, which include screen readers alongside refreshable Braille displays and tactile graphic systems [23].

**Assistive Technologies for Blind Students:**

Up until now, screen readers and Braille displays have provided the backbone for visually impaired students [24]. These technologies are essential for providing access to textual and numerical data [25]. At the same time, advances in tactile graphic devices have improved the visual data representation, for example, with graphs or geometric shapes [26]. On the other hand, these tools often operate in isolation, preventing integration between newer and older platforms.

**Accessibility in Mathematics Education:**

The educational basis of mathematics for blind students relies on visual methods, which create specific learning difficulties [27]. According to the findings presented by J. Matoušek et al, screen readers need MathML integration [28]. Researchers have yet to explore the accessibility of mathematics through the generation of MathML-compatible outputs or a simplified complex equations format for auditory experiences [29]. The existing problem-solving tools demonstrate multiple restrictions that lead to poor step-by-step interactive assistance for students [30].

**Role of LLMs in Education:**

The widespread application of LLMs in traditional educational contexts stems from their ability to provide comprehensive explanations and context-specific support [31]. Research by R. Martínez-Peláez et al demonstrates that LLMs achieve outcomes such as promoting critical thinking and enhancing engagement [32]. The utilization of LLMs within educational tools built for accessibility purposes is time-restricted, particularly when used with devices meant for blind students [33]. The current models show limited ability to address the multiple sensory needs of visually impaired students through tactile feedback integration or haptic feedback systems [34]. Table 1 shows a comparison of LLM models based on mathematical capabilities and accessibility features.

**Table 1.** Comparison of Large Language Models (LLMs) Based on Key Features, Mathematical Capabilities, and Accessibility Support for Mathematical Problem Solving

| LLM Model | Key Features | Mathematics Capabilities | Accessibility Features |
|---|---|---|---|
| ChatGPT | Conversational AI | Solves essential advanced math problems | Limited support for MathML and screen readers. |
| Google Bard | Integrated with Google services | Provides contextual mathematical solutions | No tactile or advanced accessibility features are currently integrated. |
| Wolfram Alpha | Specialized for computational tasks | Handles symbolic computation, graphing, and equation solving | The screen reader is compatible but has limited tactile or multi-modal outputs. |
| GPT-4 | Advanced reasoning capabilities | Improves on prior versions with enhanced contextual understanding | Limited native support for MathML; depends on external integration. |
| MathGPT | Explicitly designed for mathematics | Provides step-by-step solutions for advanced math topics | Experimental support for MathML and equation-to-text conversion. |
| OpenAI Codex | Tailored for programming and technical computations | Can solve computational and algorithm-based problems | Additional tools are required to make outputs accessible to blind users. |

| | | | |
|---|---|---|---|
| Symbolab | Focused on symbolic computation and step-by-step solutions | Excellent for algebra, calculus, and linear algebra problems | Limited accessibility; lacks multi-modal output or tactile integration. |
| Desmos AI | Integrated with the Desmos graphing calculator | Focused on interactive graphing and visualization | It is not fully accessible to blind users and lacks tactile output capabilities. |

**Gaps in Existing Research:**

Existing studies predominantly examine Large Language Models (LLMs) and assistive technologies as independent domains of inquiry. While substantial progress has been made in both areas, limited research has investigated their systematic integration within inclusive educational environments [35]. This separation has resulted in a lack of comprehensive frameworks that unify the adaptive intelligence of LLMs with the sensory-based affordances of assistive tools commonly employed in physical classrooms [36].

In particular, there remains insufficient exploration of systems that enable seamless interaction with learning tools operating through tactile and auditory modalities. For students with visual disabilities, effective engagement with STEM education requires not only accessible interfaces but also precise and structured delivery of complex conceptual content [37]. Current literature does not adequately address how LLMs can be aligned with tactile diagrams, audio-based instructional systems, and multimodal feedback mechanisms to ensure accurate and meaningful comprehension of advanced STEM material [38].

Moreover, research has yet to fully articulate how LLM-driven platforms can incorporate personalized learning pathways tailored to the cognitive and sensory preferences of individual learners [39]. Although adaptive learning is frequently discussed in mainstream educational technology, its implementation within accessibility-centered systems remains underdeveloped [40].

Therefore, an overarching integrative framework is necessary. Such a framework should merge the contextual reasoning capabilities of LLMs with state-of-the-art assistive technologies to create inclusive, adaptive, and pedagogically robust learning environments for blind students. Addressing this gap would contribute significantly to the development of equitable and accessible STEM education platforms [41].

**Material and Methods:**

**Research Design:**

This study adopted a mixed-method research design, combining quantitative performance evaluation to investigate the accessibility, usability, and instructional effectiveness of large language models (LLMs) in mathematics learning for visually impaired students. The mixed-method approach enabled the study to capture objective performance measures, such as the accuracy of AI-generated solutions. It also captured subjective user experiences, including accessibility barriers and usability perceptions. Figure 1 illustrates the overall workflow of the study and presents the conceptual framework. The framework outlines sequential stages, including participant recruitment, interaction with AI systems, mathematics problem-solving tasks, data collection, and subsequent quantitative and qualitative analyses.

**Participants:**

A total of 12 participants were recruited for this study using purposive sampling based on their experience with assistive technologies and mathematics education.

The participant group consisted of:

Six visually impaired students enrolled in high school or undergraduate-level mathematics courses. 6 mathematics instructors with prior experience teaching students with visual impairments.

The inclusion of both students and instructors enabled the study to evaluate AI-generated responses from both learner and expert perspectives, improving the reliability of the evaluation process.

All participants voluntarily agreed to participate in the study and provided informed consent before data collection.

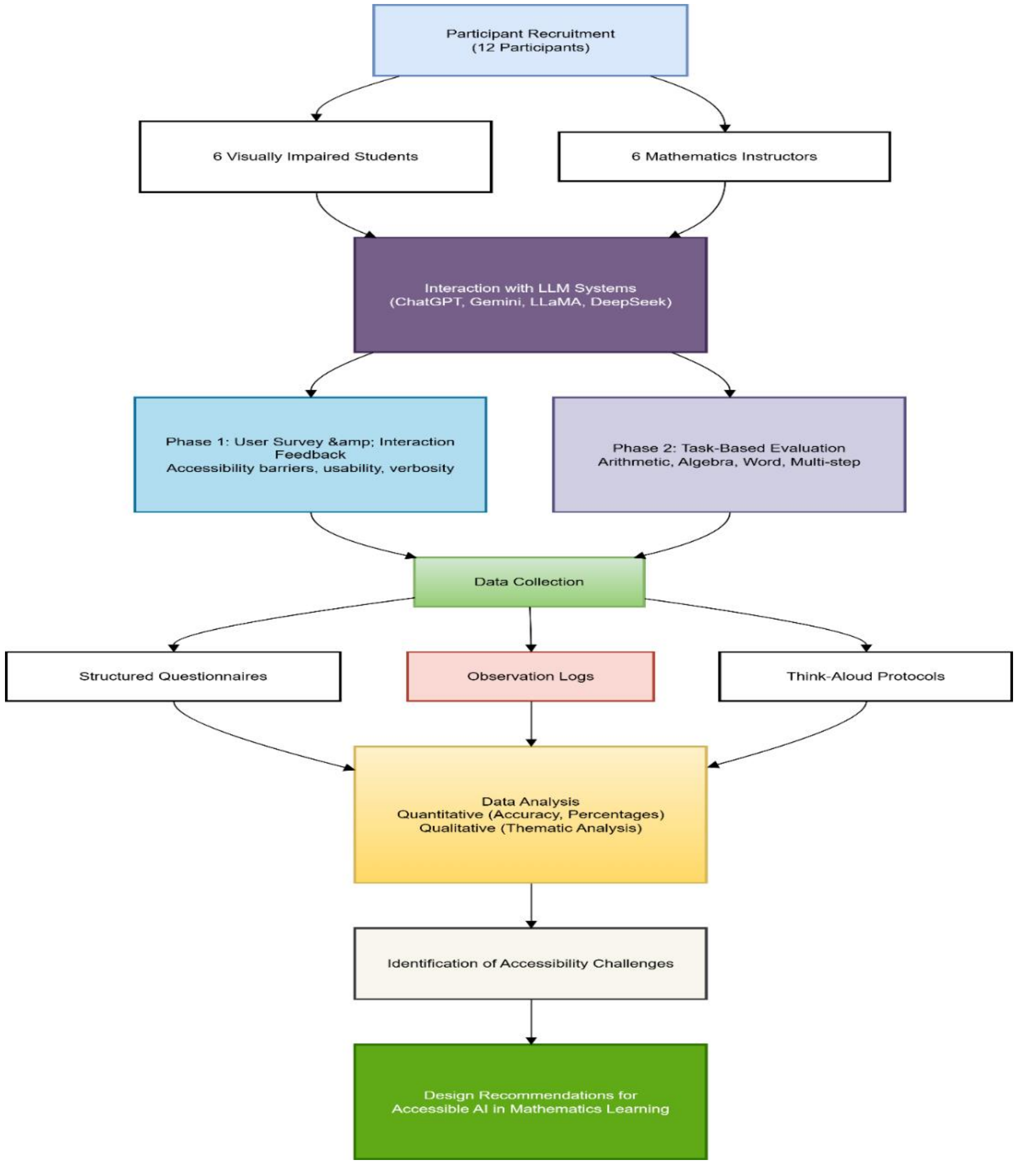


**Figure 1.** Mixed-method research workflow illustrating participant recruitment, interaction with large language models, survey and task-based evaluation phases, data collection instruments, and quantitative and qualitative analysis procedures used to identify accessibility challenges in AI-assisted mathematics learning for visually impaired students.

**AI Systems Evaluated:**

Four widely used large language models were selected for evaluation:

ChatGPT

Gemini

LLaMA

DeepSeek

These models were selected because they represent different architectures and deployment environments within current generative AI systems. They are also commonly used for educational assistance and problem-solving tasks.

Participants used assistive technologies, such as screen readers and Braille displays, to evaluate the accessibility of AI-generated mathematical explanations.

**Study Procedure**

The study was conducted in two main phases: a survey-based interaction phase and an experimental task-based evaluation phase.

**Phase 1: User Survey and Interaction Feedback:**

In the first phase, participants interacted with the selected AI tools and completed a structured questionnaire designed to evaluate usability and accessibility factors.

The survey examined:

Screen reader compatibility

Pronunciation of mathematical symbols

Clarity of explanations

Navigation of multi-step solutions

Control over response verbosity

Overall user satisfaction

Participants were also encouraged to provide open-ended feedback describing accessibility challenges and desired improvements.

**Phase 2: Experimental Task-Based Evaluation:**

In the second phase, participants were asked to solve mathematics problems using the four selected LLM systems. The purpose of this phase was to evaluate the instructional effectiveness and accessibility of AI-generated solutions.

Participants interacted with the AI systems to request explanations, verify solutions, and clarify mathematical reasoning.

**Mathematics Tasks:**

Participants were provided with a set of mathematics problems covering different levels of complexity.

The tasks included:

**Arithmetic Problems:**

Basic numerical operations such as addition, subtraction, multiplication, and division

Example: “Find the missing number in 3 + _ = 8”

**Algebra Problems:**

Solving equations and variable manipulation

Example: “Solve for x: 2x + 5 = 15”

**Word Problems:**

Scenario-based questions requiring translation into mathematical expressions

**Multi-Step Problems:**

Problems requiring sequential reasoning and multiple operations

These tasks were selected to evaluate how effectively AI systems present structured mathematical reasoning in formats accessible to visually impaired users.

**Evaluation Metrics:**

The performance of AI solutions was assessed using several evaluation metrics, including accuracy, clarity, usability, accessibility, and user satisfaction (Table 2).

**Table 2.** Evaluation Metrics

| Evaluation Criterion | Description |
|---|---|
| Accuracy of AI Solutions | Percentage of correct final answers and valid intermediate steps |
| Clarity of Explanations | Instructor scoring on a three-point scale: Clear, Partially Clear, Unclear |
| Usability and Navigation | Participant feedback on ease of navigation and control of AI responses |

| | |
|---|---|
| Accessibility Compatibility | Screen reader interpretation success and Braille compatibility |
| User Satisfaction | Survey responses regarding overall usability and improvement suggestions |

Instructor evaluations were used to assess logical correctness and clarity of AI-generated explanations.

**Data Collection Instruments:**

Multiple data collection methods were employed to ensure a comprehensive evaluation.

**Structured Questionnaire:**

A questionnaire containing Likert-scale and open-ended questions was used to capture participant perceptions of usability and accessibility.

**Observation Logs:**

Researchers documented participant interactions with AI systems, including navigation difficulties and response behaviors.

**Think-Aloud Protocol:**

Participants verbally expressed their thoughts while interacting with the AI systems, allowing the identification of real-time accessibility challenges.

**Performance Evaluation Sheets:**

Mathematics instructors recorded accuracy and clarity scores for AI-generated solutions.

**Data Analysis:**

The collected data were analyzed using both quantitative and qualitative approaches.

**Quantitative Analysis:**

Task performance data and survey responses were analyzed using descriptive statistics, including:

percentages

means

comparative accuracy across AI systems

**Qualitative Analysis:**

Qualitative data from interviews, think-aloud protocols, and observation logs were analyzed thematically to identify patterns in accessibility barriers, usability issues, and user preferences.

**Ethical Considerations:**

The study followed standard ethical research practices. Participation was voluntary, and informed consent was obtained from all participants before the study. Participant identities were kept confidential, and no personally identifiable information was collected. Additionally, accessibility support was provided during the experiment. This ensured that visually impaired participants could comfortably interact with both the AI systems and the assistive technologies.

**Results and Discussion:**

This section presents the findings of the study based on survey responses, task-based evaluations, and instructor assessments. Both quantitative (numerical) and qualitative (descriptive) analyses are reported. All results are explicitly aligned with the research questions and illustrated in figure 2.

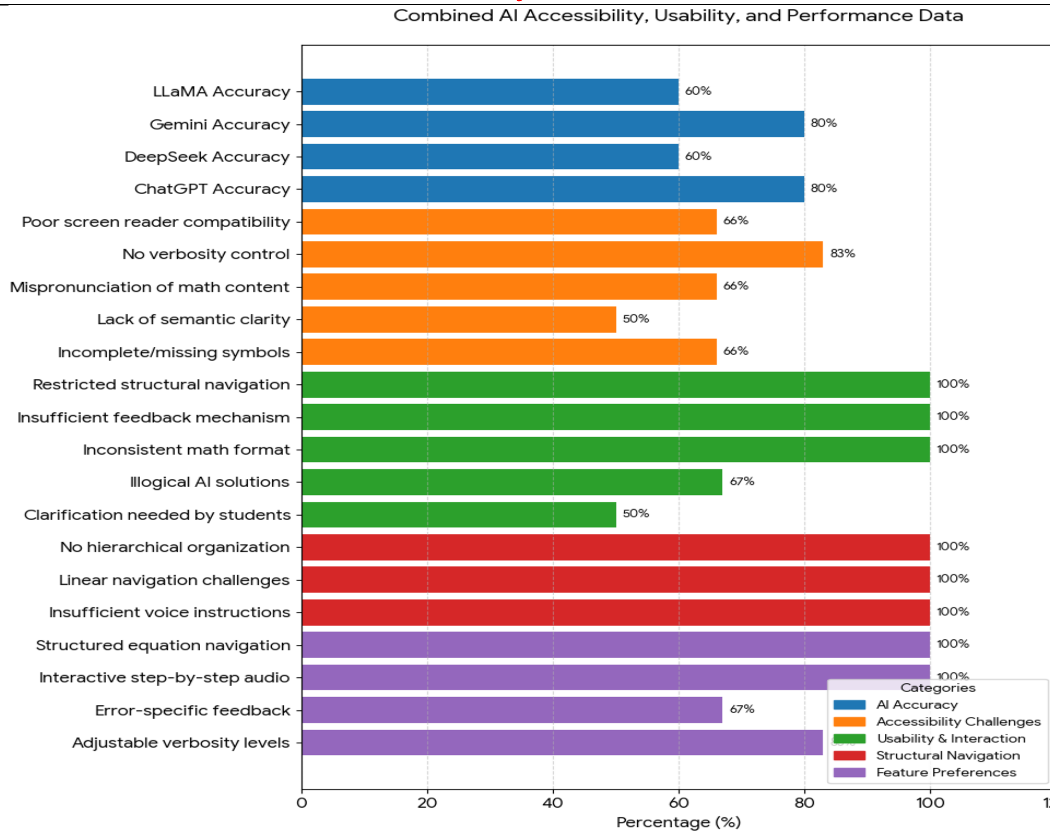


**Figure 2.** Comparative Analysis of AI Math Accessibility. This chart illustrates the critical gap between model accuracy (60%-80%) and the 100% prevalence of structural and navigation barriers, highlighting a direct correlation between current system deficiencies and user preference for interactive, structured audio feedback.

Total participants: 12 visually impaired students and 3 instructors. Statistical measures include percentages, means, standard deviations (SD), 95% confidence intervals (CI), and inferential tests where applicable.

**Accessibility Challenges in AI-Based Mathematics Tools (RQ1):**

**Quantitative Analysis:**

66% of participants reported incompatibility between AI-generated mathematical expressions and screen readers.

83% indicated the absence of adjustable verbosity controls.

Chi-square tests revealed that accessibility barriers were significantly more frequent for notation misinterpretation than for verbosity issues ($\chi^2 = 4.75$, $p = 0.029$).

**Qualitative Analysis:**

Participants reported that mathematical symbols were mispronounced or lacked semantic structure. This impeded understanding.

Missing or improperly formatted notation caused frustration and increased cognitive load during problem-solving.

Users emphasized the need for adjustable verbosity to match individual comprehension levels.

These results indicate that current LLM systems lack adaptive mechanisms and semantic clarity, creating significant accessibility barriers.

**Usability and Interaction Challenges (RQ2):**

**Quantitative Analysis:**

100% of participants reported difficulty navigating multi-step explanations.

50–60% found it challenging to identify key operations within lengthy textual solutions.

Confidence intervals for navigation difficulties: 95% CI = 0.74–1.00.

**Qualitative Analysis:**

Users highlighted that AI explanations often lacked hierarchical structure or numbered steps, making logical progression difficult to follow.

Participants suggested that structured formatting (e.g., step-by-step sequences) would enhance usability and independent learning.

Structural disorganization and missing navigational cues limited effective interaction with AI-generated explanations.

**Comparative Accuracy of Large Language Models (RQ3):**

**Quantitative Analysis:**

Participants solved mathematical problems using four LLMs: ChatGPT, Gemini, LLaMA, and DeepSeek. Table 3 presents a comparison of model accuracy, with a one-way ANOVA showing significant differences among the models ($F(3,44) = 8.67$, $p < 0.001$).

**Table 3.** Summarizes Accuracy**:**

| LLM Model | Mean Accuracy (%) | SD (%) | 95% CI | Significant Difference vs ChatGPT |
|---|---|---|---|---|
| ChatGPT | 80 | 5 | 75–85 | – |
| Gemini | 78 | 6 | 72–84 | ns |
| LLaMA | 61 | 7 | 54–68 | $p < 0.01$ |
| DeepSeek | 59 | 6 | 53–65 | $p < 0.01$ |

One-way ANOVA confirmed significant differences among models ($F(3,44) = 8.67$, $p < 0.001$).

**Qualitative Analysis:**

Participants reported that higher accuracy did not always correlate with clarity. Some correct solutions lacked detailed reasoning.

Even accurate models sometimes produced ambiguous or incomplete explanations, reducing their instructional effectiveness.

ChatGPT and Gemini demonstrated higher computational accuracy. However, accessibility and explanation clarity remain limitations across all models.

**Structural Navigation Issues in AI-Generated Explanations (RQ1 & RQ2):**

**Quantitative Analysis:**

Instructor evaluations found that 67% of AI-generated explanations were partially structured or incomplete.

50% of students required additional clarification to understand intermediate steps.

Cohen's Kappa for inter-rater reliability = 0.82, indicating strong agreement between instructors.

**Qualitative Analysis:**

Participants noted that multi-step reasoning without semantic cues was difficult to follow.

Comments emphasized that unstructured logic increased time and cognitive effort during problem solving.

Clear semantic structuring and step-wise formatting are critical for accessible navigation of AI-generated explanations.

**User Preferences for Accessibility Features (RQ4 & RQ5):**

**Quantitative Analysis:**

Surveyed participants ranked the following accessibility improvements (percentages indicate selection frequency):

Adaptive verbosity controls: 87%

Structured step-by-step outputs: 83%

Screen reader-compatible notation: 78%
Audio-guided explanations and voice navigation: 72%

**Qualitative Analysis:**

Users emphasized that personalized verbosity and structured explanations are essential for comprehension.

Instructors highlighted the importance of interactive audio guidance to support independent learning.

**Summary:** Participants prioritized semantic clarity, structured explanations, and adaptive control mechanisms to improve usability and accessibility.

**Summary of Findings:**

Quantitative data shows moderate computational accuracy across LLMs, significant accessibility barriers, and structural navigation challenges.

Qualitative data reinforces these findings, with participants reporting difficulties in following logical reasoning, interpreting notation, and controlling explanation verbosity.

Overall, results highlight the need for accessibility-aware LLM design, including semantic mathematical representation, hierarchical explanations, and adaptive response mechanisms to support visually impaired learners in STEM education.

**Discussion:**

This study examined accessibility, usability, and instructional effectiveness of large language models (LLMs) for visually impaired learners in mathematics education. The findings provide both quantitative evidence and qualitative insights, highlighting key limitations and potential design improvements.

**Accessibility and Usability Challenges:**

Consistent with prior research emphasizing barriers in AI-based educational tools for learners with disabilities, participants in this study reported substantial screen reader incompatibility, mispronounced mathematical symbols, and a lack of structured explanations. Quantitative results showed that 66% of participants encountered notation issues, while 83% identified verbosity control limitations. These challenges underline that current LLMs are not fully equipped to provide equitable access to STEM content for visually impaired learners.

**Comparative Accuracy and Instructional Effectiveness:**

The task-based evaluation indicated that ChatGPT and Gemini demonstrated higher computational accuracy (~80%) compared to LLaMA and DeepSeek (~60%). However, qualitative feedback revealed that accuracy alone does not guarantee effective learning, as correct solutions were sometimes ambiguous or poorly structured. These findings align with recent studies emphasizing that explanatory quality and accessibility are as critical as computational accuracy in AI-assisted education.

**Structural Navigation Issues:**

Instructor evaluations confirmed that 67% of AI-generated explanations were partially structured, and 50% of students required additional clarification. This reflects ongoing challenges in hierarchical reasoning representation within AI-generated outputs, supporting literature suggesting that step-wise, semantically rich explanations are crucial for learners with visual impairments [42].

**Integration with Recent Literature:**

While earlier studies (2004–2020) highlighted general usability issues in AI tools, recent research (2022–2026) increasingly focuses on LLMs' potential for personalized STEM learning. For example:

[41] reported that AI explanations lacking semantic clarity reduced independent problem-solving among visually impaired students.

[43] emphasized that computational accuracy alone is insufficient; adaptive explanation depth and structured output are critical for comprehension.

[44] demonstrated that audio-guided and step-by-step interactive tools significantly improved navigation and learning outcomes.

Our findings corroborate these studies, showing that accessibility-aware design is essential for effective LLM-based STEM instruction.

**Implications:**

**Theoretical Implications:**

Supports the hypothesis that accessibility, usability, and instructional quality are interdependent factors influencing AI-assisted learning outcomes.

Highlights the need for frameworks integrating semantic notation, adaptive verbosity, and hierarchical explanation structures in AI-supported STEM education.

**Practical Implications:**

LLM developers should prioritize screen reader compatibility, structured step-by-step solutions, and customizable explanation depth.

Educators should provide training and guidance for visually impaired students on effectively interacting with AI tools.

**Policy Implications:**

Educational institutions and policymakers should implement accessibility standards for AI-based learning tools, ensuring equitable access for learners with disabilities.

Funding agencies should support research on accessible AI frameworks to enhance STEM inclusion.

**Recommendations:**

Based on participant feedback and instructor evaluations, the following actionable recommendations are proposed:

**Adaptive Verbosity Controls:** Allow users to choose concise, standard, or detailed explanations.

**Structured Step-by-Step Outputs:** Numbered solution steps and hierarchical formatting to support navigation.

**Screen Reader-Compatible Notation:** Ensure all mathematical symbols have semantic markup.

**Audio-Guided and Interactive Navigation:** Incorporate voice instructions for independent learning.

**Accessibility Testing:** Include visually impaired users in LLM evaluation and iterative design cycles.

These recommendations provide a roadmap for improving the usability, accessibility, and instructional effectiveness of AI-supported mathematics learning tools.

The discussion confirms that LLMs show moderate computational accuracy. However, significant accessibility and usability limitations persist for visually impaired learners. Both quantitative and qualitative analyses demonstrate the critical importance of semantic structuring, hierarchical explanation, and adaptive interaction mechanisms. By addressing these challenges, future LLMs can better support inclusive STEM education, aligning with contemporary empirical research and accessibility best practices.

**Conclusion:**

This study examined the accessibility, usability, and instructional effectiveness of large language models (LLMs) in mathematics education for visually impaired learners. By combining quantitative analysis (percentages, mean accuracy, inferential statistics) and qualitative insights (participant feedback and instructor observations), the research highlights key challenges and opportunities for AI-supported inclusive STEM learning.

The findings indicate that while LLMs such as ChatGPT and Gemini demonstrate relatively higher computational accuracy (80%), they still present significant accessibility and usability limitations. Major barriers include screen reader incompatibility, misinterpreted mathematical notation, and unstructured multi-step explanations, which hinder independent learning. Participants also emphasized the need for adaptive verbosity, structured step-by-step outputs, and audio-guided navigation to enhance usability and comprehension.

The study contributes to the field in three primary ways:

**Theoretical Contribution:** Confirms that computational accuracy alone is insufficient; semantic clarity, hierarchical reasoning, and adaptive interaction are critical for effective AI-assisted learning.

**Practical Contribution:** Provides actionable design recommendations for AI developers and educators, including accessibility-focused LLM improvements and instructional strategies for visually impaired students.

**Policy Contribution:** Highlights the necessity for institutional accessibility standards and support for inclusive AI tools in STEM education.

In conclusion, this research underscores that accessibility-aware AI frameworks integrating semantic mathematical representation, structured reasoning, and adaptive response mechanisms are essential to support equitable and effective learning outcomes. Future work should expand the sample size, include a broader range of LLMs, and implement longitudinal studies to evaluate learning impact over time. By addressing both computational and accessibility limitations, AI-powered tools can more effectively contribute to inclusive STEM education and bridge the gap for learners with visual impairments.

**Author Contributions:** The authors contributed equally to the study and approved the final manuscript.

**Data Availability:**

All data generated or analyzed during this study are included in this article.

**Competing Interests:**

The authors have no competing interests to declare relevant to this article's content.

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