REVIEW

Leveraging machine learning to enhance accessibility in data visualizations: a systematic literature review

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Abstract
As data visualizations become increasingly central to communication, analysis, and decision-making across a variety of fields, the need to ensure their accessibility becomes critical. Visual representations, such as charts, graphs, and infographics, are effective tools for conveying complex information; however, they often present significant barriers for individuals with various types of impairments. This paper explores the potential of Machine Learning (ML) to enhance the accessibility of data visualizations. Specifically, we present a Systematic Literature Review (SLR) that investigates how ML techniques have been applied to make visual data more inclusive. The review considers both visualization-related aspects (such as visualization types and source, target user, and evaluation) and ML-related factors (including data formats, preprocessing, and model types and evaluation). Our findings reveal that only a limited number of studies directly address the use of ML for improving visualization accessibility, and there is a lack of standardized solutions or frameworks in this area. Our contribution focused on the identification of a conceptual framework based on nine key open challenges that highlight the lack of consideration for infographics, particular types of charts, printed chart, different kind of impairments, involvement of users, accurate interpretation of complex visual data, real-time support, standard benchmarking, the potential bias and, hence, the need for continued research and development at the intersection of data visualization and machine learning, with a strong focus on accessibility and inclusivity.

Keywords Data visualization · Accessibility · Machine learning · Deep learning · Large language model

1 Introduction

As modern society becomes increasingly reliant on data-driven decision-making, the importance of visual representations of information continues to grow [1–3]. The advent of big data has led to a proliferation of complex datasets across various sectors, ranging from healthcare and finance to education and public policy [4, 5]. In this context, visual tools such as charts, infographics, and maps have become indispensable for conveying information in a clear and comprehensible manner [6–8]. These visual formats are particularly effective in helping users identify trends, draw comparisons, and gain a holistic understanding of multifaceted data structures [9, 10]. Despite their widespread utility, these visual representations can pose substantial accessibility challenges for individuals with visual impairments. Such individuals often encounter significant barriers in engaging with or

interpreting content that relies heavily on graphical or spatial encoding [11]. For users who are blind or have low vision, traditional visualizations are largely inaccessible unless they are accompanied by alternative modalities, such as textual descriptions, tactile graphics, or auditory feedback, that convey the same underlying information [12, 13]. In the absence of such alternatives, critical insights embedded in data visualizations remain out of reach for a portion of the population, effectively excluding them from data-driven discourse and decision-making processes.

Recent technological advancements in the fields of cro:mlMachine Learning (ML), cro:dlDeep Learning (DL), and, more notably, cro:llmLarge Language Models (LLMs) offer promising avenues for addressing these accessibility issues. These models possess the ability to analyze vast quantities of data, recognize patterns within visual structures, and generate coherent and contextually rich natural language descriptions. As such, ML, DL, and LLMs can be leveraged to create systems that automatically interpret and translate visual data into accessible formats, including narrative summaries or audio-based explanations [14, 15]. These capabilities not only hold potential for increasing the inclusivity of digital information but also contribute to the broader goal of creating equitable access to data [16, 17]. Nevertheless, despite the technological potential at hand, the application of ML techniques to enhance the accessibility of data visualizations remains a relatively underexplored area.

Many challenges persist in terms of model accuracy, generalizability, contextual understanding, and alignment with user needs, particularly for individuals with varying degrees and types of visual impairment. There is also a noticeable absence of standardized frameworks or widely accepted best practices that guide the development of accessible visualization tools based on ML.

While some prior literature reviews have addressed accessibility in visual communication, they are often narrow in scope (e.g., focusing only on text generation [18]) or too general to capture the specific opportunities presented by LLMs [19]. The intersection of advanced ML and DL techniques and accessibility in data visualizations remains an open and underexplored research frontier.

This paper addresses this gap through a comprehensive cro:slrSystematic Literature Review (SLR) aimed at mapping and critically analyzing the role of ML, DL, and LLMs in making data visualizations more accessible. Our review is structured around ten key dimensions: one general dimension describing study characteristics; four focused on visualization aspects (types of visualizations, data sources, target users, and evaluation methods); and five related to ML techniques (data format, data preprocessing, model types, use of ML, and evaluation strategies).

The findings of our review reveal a relatively small but growing body of work that attempts to address accessibility through the lens of ML. While some innovative approaches and prototypes have been proposed, there is still a lack of maturity in this research area, particularly in terms of real-world deployment, user-centered design, and empirical validation. Furthermore, our analysis highlights nine key open challenges that must be addressed to advance the integration of ML and accessibility in the context of data visualizations. These challenges span technical, methodological, and ethical dimensions.

The remainder of the paper goes as follows. Section 2 presents some related works. Section 3 details our approach, from the research question to the data collection process. The results are presented in Sect. 4 and discussed in Sect. 5. Finally, Sect. 6 concludes the paper, presenting some final remarks and future works.

2 Background and related work

This work is unfolding alongside a growing interest in using ML, DL, and LLM, and emerging technologies to increase the accessibility of data visualizations. This section describes some of the more relevant studies and projects that inspired our review.

2.1 Accessible data visualization

Making data visualizations accessible to individuals with visual impairments or other disabilities is a critical step toward inclusivity in the digital age. Traditional visualizations rely heavily on sight, which creates barriers for people with visual impairments. However, several strategies and tools can be employed to overcome these barriers, as the existing literature proves. Among the approaches to enhance accessibility, two notable possibilities include (1) applying *Chartability* [20], a heuristic framework designed to improve the accessibility of visualizations, systems, and interfaces for all users, or (2) integrating pre-existing accessibility modules within widely adopted data visualization tools, such as the *HighChart Accessibility Module* [21].

These options rely on providing a detailed textual description of the charts or a good color contrast between the elements of the data visualizations. Tactile graphics, which convert visual charts and diagrams into a format that can be read through touch, provide another solution, especially for individuals who read Braille [22]. However, this old-fashioned approach presents some limitations, including the high cost of refreshable tactile displays, especially for low- and middle-income users, and the persistent problem of lacking training datasets for the machine learning model [23]. Following this line of thought, researchers are exploiting sonification strategies [24], combined also with haptic feedback [25], or the physicalization of data [26] to overcome the limitations of relying solely on vision. Sonification and physicalization are promising approaches for making data accessible to individuals with visual impairments or other disabilities. However, each method comes with inherent limitations that impact its overall effectiveness. Moreover, haptic feedback also faces certain challenges, especially in the context of data representation. Sonification, as mentioned, offers an alternative to traditional visualizations by allowing users to "hear" data patterns. However, this approach faces several challenges [27]. Some key limitations are the precision of vision versus audition and the cognitive load imposed on users, especially when complex or multivariate data is sonified. The design of auditory mappings is also crucial; poorly designed sonifications can be non-intuitive, further complicating the process for users to grasp patterns and insights effectively. Moreover, there could be some differences in auditions for individuals, followed by a lack of standardized tools. At the same time, while physicalization opens up new avenues for accessibility, it also presents significant challenges [28]. Scalability is one of the main limitations: physical objects cannot easily represent large or highly detailed datasets due to space or material constraints. In addition, because physicalizations are typically static, representing dynamic or temporal data can be difficult. Furthermore, there is currently no formal design language to help users interpret data physicalizations. Haptic feedback also has limitations in terms of hardware, functionality, and user experience [29].

Another possible approach consists of the introduction of audio data narratives, which are multimodal representations combining textual descriptions and sonification (data mapped to non-speech sounds). The authors defined design principles through co-design workshops with screen reader users and then developed a dynamic programming approach to automatically generate these narratives. Evaluation with screen reader users showed that the audio narratives significantly increased user insights and improved their ability to extract and comprehend information from both the sonification and the accompanying description, proving the method's effectiveness in providing direct, accessible, and up-to-date access to data on the web.

Following these motivations, we decided to focus on the new trend of using ML, DL, and LLMs to overcome these limitations and investigated their use to create or make visualization accessible. In light of this, Singh et al., in their review, analyzed Chart Visualizations made accessible for Blind and Visually Impaired People (BVIP) through methods involving cro:aiArtificial Intelligence (AI) [30]. In particular, they just focused on a pipeline that exploits these methods in five steps: element extraction, classification, text recognition, data extraction, and summarization. In our review, we wanted to extend this to include visualization-related dimensions and target users' involvement to verify the tools' effectiveness.

2.2 ML, DL, and LLMs for accessibility

Recent years have seen a surge in the deployment of ML, DL, and LLMs to enhance digital accessibility across a broad range of applications. One compelling example is DexAssist, a dual-LLMs framework designed for voice-enabled web navigation, which splits responsibilities between a "navigator" LLMs that generates interaction commands and a support LLMs that validates these actions, demonstrating a boost in task success rates across e-commerce sites [31]. Similarly, Savant targets blind desktop users by interpreting diverse GUI layouts through LLMs-driven commands, enabling uniform navigation across heterogeneous applications and improving efficiency in user trials with 11 cro:blvBlind or Low Vision (BLV) participants [32].

On mobile platforms, ScreenAudit applies LLMs to dynamically traverse app screens, analyze accessibility metadata, and detect screen-reader violations with notably higher coverage (69.2%) than rule-based tools (31.3%) across a suite of 14 app screens [33]. This confirms the potential of LLMs to identify complex accessibility issues overlooked by existing static analyzers.

LLMs-driven restructuring and validation of HTML has also been explored. Yu et al. developed a browser plugin that leverages LLMs to optimize heading hierarchies and labels in real time, significantly enhancing screen-reader navigation without altering webpage content [34] while Delnevo et al. investigated the use of LLMs for accessibility validation [35]. In the domain of iconography, IconDesc explores LLMs fine-tuned to generate descriptive alt-text for UI icons during app development, yielding improved semantic accuracy and developer workflow efficiency compared to baseline methods [36].

Beyond interface analysis, LLMs have been integrated into assistive robotics: VoicePilot uses GPT-based speech interfaces to control feeding robots, enabling older adults to issue high-level, natural language commands in daily living activities [37].

Academic publishing has not been left behind. Xu et al. utilized ML-based heuristics to audit figures in open-access publications, identifying common accessibility violations–such as missing labels or low contrast–and underscoring the need for automated figure correction tools [38]. Meanwhile, Mehendale et al. introduced AXNav, a system that converts natural-language instructions into accessibility testing scripts, successfully replaying 70–85% of test cases among professional testers [17].

To conclude, a global trend involves the increasing application of ML approaches, including DL algorithms and specifically LLMs, to enhance accessibility across various digital domains; however, a significant research and practical gap persists concerning their comprehensive integration and effective utilization for data visualization accessibility.

3 Methods

This Section details the Research Question that drove this study, the methodology followed to collect and process data.

3.1 Research question

Following the increasing popularity of ML and LLMs, we wanted to analyze the literature to understand if these tools were previously exploited to make data visualizations accessible for people with impairments. In particular, we focused on the following research question (RQ): *How can ML and LLMs help make data visualization accessible?*

With the final goal of answering our RQ, we have identified 10 dimensions of interest. In particular, the first one is related to the study context, four of them aim to investigate the visualization aspect (D2-D5), and five are related to the ML side (D6-D10). Hence, we analyzed:

- (D1) *Context*: this dimension considers the general context of the study;
- Visualization-related dimensions:
  - (D2) *Visualization type*: this dimension analyzes the type of visualization taken into consideration in the study. We distinguished between infographics, charts, and maps;
  - (D3) *Visualization source*: this dimension identifies the source of the visualization, considering online, offline, and printed;
  - (D4) *Target users*: this dimension takes into account the target users for the visualization, namely the ones who will interact with the accessible visualization;
  - (D5) *Evaluation*: this dimension reports information about the evaluation, considering whether an evaluation was carried out and, if so, how and with or without the involvement of the target users.
- Machine learning-related dimensions:
  - (D6) *Data format*: this dimension analyzes the format used to provide the data to the model;
  - (D7) *Preprocessing of data*: this dimension identifies possible preprocessing activities to prepare the data;
  - (D8) *Model Type*: this dimension reports the specific machine learning model;
  - (D9) *Use of ML*: this dimension describes how the model facilitates data visualization accessibility;
  - (D10) *Model Evaluation*: this dimension details whether the model has been quantitatively evaluated with a dataset.

Such ten dimensions were derived through a literature-driven process, grounded in a comprehensive review of prior work on accessible data visualizations, machine learning applications in visualization, and multimodal accessibility techniques. We systematically identified recurring themes, concerns, and features across these studies, which were then organized into preliminary categories. Through an iterative refinement process, these categories were consolidated and adjusted to ensure comprehensive coverage of both visualization-specific and machine learning-related considerations. While no formal user study was conducted to validate the dimensions, they reflect prevailing insights and priorities in the literature regarding accessibility, technical feasibility, and potential user impact.

3.2 Methodology

In answering our RQ, we selected the SLR approach, and for the relevant articles selection, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement [39].

The process for paper collection was carried out on June 5 with an automatic search in three online databases, named Scopus, ACM Digital Library, and IEEE Xplore. The selection of databases was limited to Scopus, ACM Digital Library, and IEEE Xplore, as these sources provide adequate coverage of the research domain. Specifically, ACM DL and IEEE Xplore are the primary publication venues for computer science and engineering, ensuring direct access to the most relevant studies. Scopus complements them by offering broad multidisciplinary indexing, thereby reducing the risk of omitting significant contributions. In order to answer our RQ, we wanted to find *data visualization* made *accessible* through the use of *ML*, *DL*, or *LLMs*. Consequently, we searched for articles that contain in the title, abstract, or keyword the following terms:

- (“accessible data visualization” OR “accessible data visualisation” OR “accessible dataviz” OR “accessible data viz” OR “accessible visualization” OR “accessible visualisation” OR (“accessibility” AND (“data visualization” OR “data visualisation” OR “dataviz” OR “data viz” OR “chart”)))
- (“Machine Learning” OR “ML”) OR (“LLM” OR “Large Language Model”) OR (“Deep learning” OR “DL” OR “AI” OR “Artificial Intelligence”) OR (“Vision Language Model” OR “Intelligent Interface”))

Moreover, to be included in our search, we selected only articles written in English and published in conference proceedings or journals related to the computer science or engineering field.

In the end, the automatic search provided 124 results, as shown in the PRISMA flow diagram in Fig. 1. Then, we performed two rounds of paper screening. In the first one, we removed the duplicates (27), while in the second one, we excluded (i) papers from Doctoral Consortium or Ph.D. Dissertation (4), (ii) papers whose PDF was not available (1), and (iii) review papers (4). Hence, during the screening phase, we removed 9 papers; thus, we had 88 papers potentially eligible for our SLR.

In the last phase of the processing, we manually analyzed the 91 remaining papers, and we applied one last criterion for the exclusion: papers should contain technical solutions exploiting ML or LLMs to make data visualizations accessible for people with impairments. After this stage, 73 papers (out of 91) were excluded from the analysis, since they were considered out of scope; thus, leaving us with 18 papers. The screening process was conducted by two of the authors. To ensure alignment, an initial subset of 30 papers was independently reviewed by both authors to determine inclusion or exclusion. In cases of doubt or disagreement, the two reviewers discussed the decision until consensus was reached. This procedure allowed us to establish shared criteria and then apply them consistently to the remaining 61 papers. Whenever uncertainties arose during this stage, communication between the two reviewers ensured agreement and helped minimize potential bias in the selection process.

4 Results

As we expected, due to the emerging topic, the majority of the selected papers are very recent: two of them were published in 2022 ([40, 41]), four of them in 2023 ([42–45]), eight of them in 2024 ([46–53]), and one before june 2025 ([54]), as visible in Fig. 2. The remaining three are older, especially one from 2005 ([55]).

Table 1 reports information about the year, the type of publication (if conference proceedings or journal articles), and publication venues. As shown, three papers were published in a journal, and the other 15 are included in conference proceedings.

The summary of the analysis of the papers, according to the proposed dimensions, is reported in Tables 2 and 3.

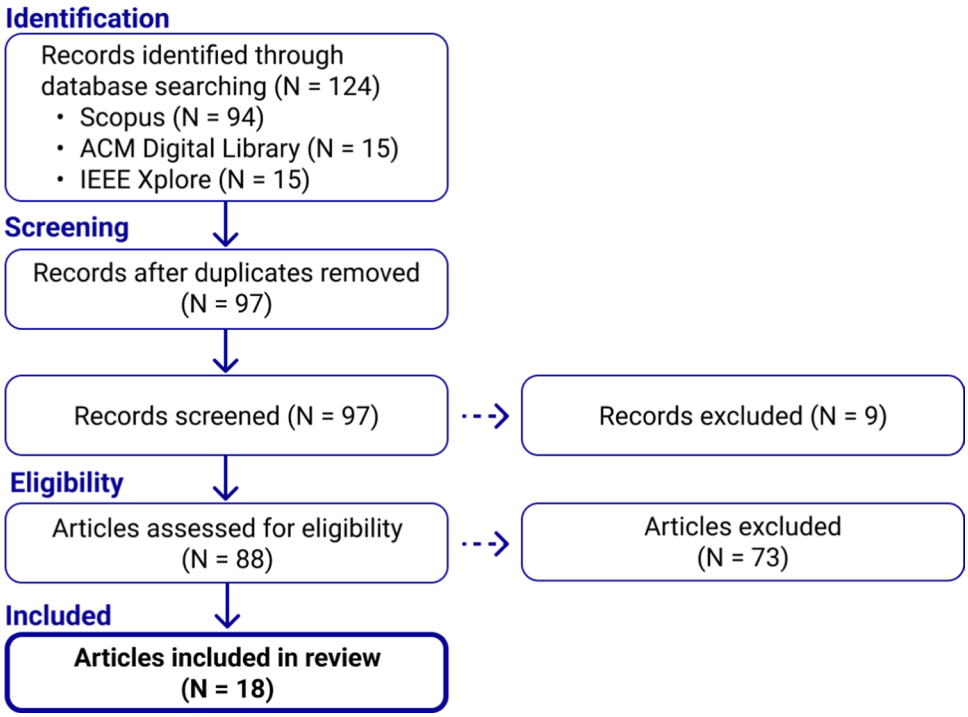

Fig. 1 PRISMA flow diagram of paper selection. The initial search across three databases (Scopus, ACM DL, and IEEE Xplore) yielded 124 records. After removing duplicates and applying the first screening, 91 papers were retained. Following a full-text eligibility assessment, only 18 papers met the inclusion criteria and were included in the final analysis. This illustrates the rigorous filtering process and the relatively limited number of studies directly addressing the research focus.

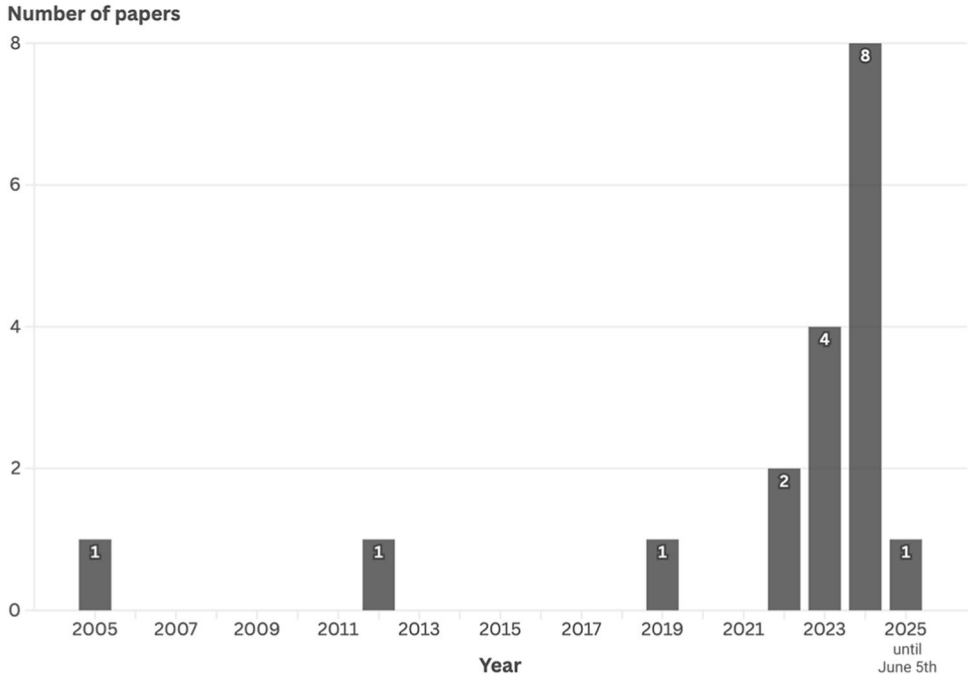

Fig. 2 Distribution of papers per year. After sporadic contributions between 2005 and 2021, the field has seen a sharp increase since 2022, peaking in 2024 with eight publications. This trend reflects a growing research interest and recognition of accessibility as a central challenge, though the earlier scarcity of work also highlights how recent and still emerging this area of inquiry is.

Table 1 Summary table for the 18 papers included in the SLR, with a focus on the year, type of paper, and publication venue

Paper	Year	Type	Venue
ID01 [55]	2005	Conference	Computers and Accessibility
ID02 [56]	2012	Conference	Image Processing
ID03 [57]	2019	Conference	Neural Networks
ID04 [40]	2022	Conference	Computational Science
ID05 [41]	2022	Conference	Computing Communication and Networking Technologies
ID06 [42]	2023	Conference	User Interface Software and Technology
ID07 [43]	2023	Conference	Scientific Document Understanding
ID08 [44]	2023	Article	IEEE Open Journal of the Computer Society
ID09 [45]	2023	Conference	Data Science, Machine Learning and Applications
ID10 [46]	2024	Article	Computer Graphics Forum
ID11 [47]	2024	Conference	Intelligent User Interfaces
ID12 [48]	2024	Conference	Conference on Computers Helping People with Special Needs
ID13 [49]	2024	Article	Journal of the Audio Engineering Society
ID14 [50]	2024	Conference	Computers Helping People with Special Needs
ID15 [51]	2024	Conference	Computers and Accessibility
ID16 [52]	2024	Conference	Pattern Recognition
ID17 [53]	2024	Conference	User Interface Software and Technology
ID18 [54]	2025	Conference	Information Retrieval

4.1 D1: context

First of all, all the selected papers were analyzed in relation to dimension D1, the context of use of the proposed solutions. Analyzing the papers, we found two contexts of use. The former is *creating accessible visualizations*. In this context, the authors aim to create accessible visualizations by providing a tool that supports those who design and develop them. Their goal is not only to make the visual content accessible but also to empower creators with an intuitive and effective tool. By focusing on the needs of developers, they ensure that the tool facilitates the creation of visualizations or alternatives that are inclusive and usable for individuals with disabilities. The latter context is *making visualization accessible*. It involves retrofitting visual content that may not have

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Table 2 Summary table for the 18 papers included in the SLR, with a focus on the context (D1) and visualization-related dimensions (D2-D5)

Paper	D1	D2	D3	D4	D5
ID01 [55]	Making visualization accessible	Bar	Printed and offline	Blind people	×
ID02 [56]	Making visualization accessible	Bar, pie, line	Offline	Not specified	×
ID03 [57]	Making visualization accessible	Bar, pie	Offline	Analysts / People with visual impairments	×
ID04 [40]	Making visualization accessible	Pie, dot, bubble, scatter	Online and Offline	Not specified	×
ID05 [41]	Making visualization accessible	Bar, line	Printed	People with visual or print impairments	×
ID06 [42]	Making visualization accessible	Bar, line, scatter, map	Offline	People with visual impairments	×
ID07 [43]	Making visualization accessible	Bar	Offline	People with visual or print impairments	×
ID08 [44]	Making visualization accessible	Bar	Offline	People with visual impairments or having difficulty understanding the visualization	×
ID09 [45]	Making visualization accessible	Not specified	Offline	Not specified	×
ID10 [46]	Creating accessible visualization	Bar, line, pie, scatter, heatmap, box plot	Online	Screen Reader Users	✓
ID11 [47]	Making visualization accessible	Line	Offline	People with visual impairments	✓
ID12 [48]	Making visualization accessible	Line, bar, scatter, error-bar	Offline	People with visual impairments	✓
ID13 [49]	Creating accessible visualization	Line (for light curves and stellar spectra)	Not applicable	Not specified	✓
ID14 [50]	Making visualization accessible	Bar, line	Offline but designed for online settings	People with visual impairments	×
ID15 [51]	Making visualization accessible	Box plot	Online	People with visual impairments	✓
ID16 [52]	Making visualization accessible	Area, map, heatmap, bar, manhattan, interval, line, pie, scatter, surface, venn	Offline	Not specified	×
ID17 [53]	Making visualization accessible	Line, bar, scatterplot, choropleth map	Online	People with visual impairments	✓
ID18 [54]	Making visualization accessible	Not specified	Offline	People with visual impairments	×

been designed with accessibility in mind. The process typically requires adapting or improving visualization to ensure that it can be used effectively by people with disabilities, particularly those with visual impairments. This might involve adding alternative text descriptions, making the chart interactive through keyboard navigation, or incorporating question-and-answer functionality.

Looking at the papers, we saw that only two papers focused on a tool to create accessible visualizations (or alternative forms of visualization), while the majority (16) focused on making visualizations accessible. The imbalance between making visualization accessible and creating accessible visualizations suggests that the

Table 3 Summary table for the 18 papers included in the SLR, with a focus on the machine learning-related dimensions (D6-D10)

ID	D6	D7	D8	D9	D10
ID01 [55]	Image	Gaussian filters	N. A	Chart Element Detection and Chart Text Detection	Custom (244 figures)
ID02 [56]	Image	Chart Element Detection and Chart Text Detection	OCR	Descriptive Data Table	Custom (300 images)
ID03 [57]	Image	No	ChartNet	Visual Question Answering	Custom (2k images)
ID04 [40]	Image	No	CRAFT	Chart Component Detection and Extraction	FigureQA
ID05 [41]	Image	Chart Element Detection and Chart Text Detection	VGG-16, CRAFT	Description generation	N. A
ID06 [42]	Vega-lite spec	Vega-lite spec	GPT 3.5 Turbo	Analytical query, Visual query, Contextual query, and Navigation query	N. A
ID07 [43]	Image	Chart Element Detection and Chart Text Detection	Azure OCR	Descriptive Data Table	Custom (12k images)
ID08 [44]	Image	Chart Element Detection and Chart Text Detection	TAPAS, TAPAS ++, Vision TAPAS	Table Question Answering	ChartQA, PlotQA, and Custom Data
ID09 [45]	Image	Noise reduction, image resizing, contrast adjustment, and linearization	Pillow and Tesseract OCR system	Text Localization and Text Extraction	Not specified
ID10 [46]	Raw Data and Chart metadata	No	GPT 3.5 Turbo	Description generation	N. A
ID11 [47]	Image	Image segmentation	Tesseract OCR system	Chart Element Detection and Chart Text Detection	N. A
ID12 [48]	Image	No	LLaVA−1.5	Tactile accessible SVG	Custom (10k images)
ID13 [49]	Spectrum	No	VAE	Sonification	MILES library
ID14 [50]	Image	Chart Detection	T5	Description generation	Chart-to-Text, VisText
ID15 [51]	Image and Maidr specification [63]	No	GPT4-Vision and Gemini Pro-Vision v1	Description generation Visual Question Answering	N. A
ID16 [52]	Image	No	Swin Transformer	Chart Classification	ICPR 2022 CHART competition
ID17 [53]	Vega-lite spec Observable Plot HighCharts	Vega-lite spec	GPT4	Analytical query, Visual query, Contextual query, and Navigation query	Dataset presented in [64]
ID18 [54]	Image and user prompt	No	GPT-4Vision	Chart Editing	ChartCraft

research community has so far prioritized remediation strategies over preventive design. Such a focus, while valuable for addressing the vast amount of inaccessible content already in circulation, may limit the long-term impact on inclusive practices, as it treats accessibility as an afterthought rather than as an integral part of the design process. Focusing on the making of accessible visualization, we identified six main strategies, as visible in Fig. 3. These include: transforming the visualization into a data table readable by screen readers (four papers), creating tactile representations (three papers), converting the visualization into an audio representation or sonification (four papers), using Q&A functionalities to extract information from the chart (six papers), generating descriptive alt-text or chart summaries (seven papers), and enabling keyboard navigation to interact with different chart components (three papers). Additionally, one paper focuses on optimizing chart classification to improve accessibility, a feature that can be integrated into the broader strategies of Q&A or alt-text generation [52]. Notably, eight papers employed multiple strategies in combination to enhance the overall accessibility output, highlighting a trend toward multimodal and integrative approaches [40–44, 46, 47, 53]. The heterogeneity of solutions raises questions about scalability and standardization: for example, sonification may be effective in certain contexts but difficult to generalize, while automated alt-text generation may improve coverage but risks oversimplification. Taken together, these findings reveal both progress and limitations: current research offers a rich set of strategies for retrofitting visualizations, but comparatively little attention has been devoted to empowering creators to design inclusively from the outset. Addressing this gap could foster more sustainable and user-centered accessibility practices, moving from remediation toward integrated accessibility by design.

4.2 D2-D5: dimensions for visualization

In this section, we will analyze the papers under the lens of the dimensions related to Data Visualization (D2-D5), as mentioned in Sect. 3.1.

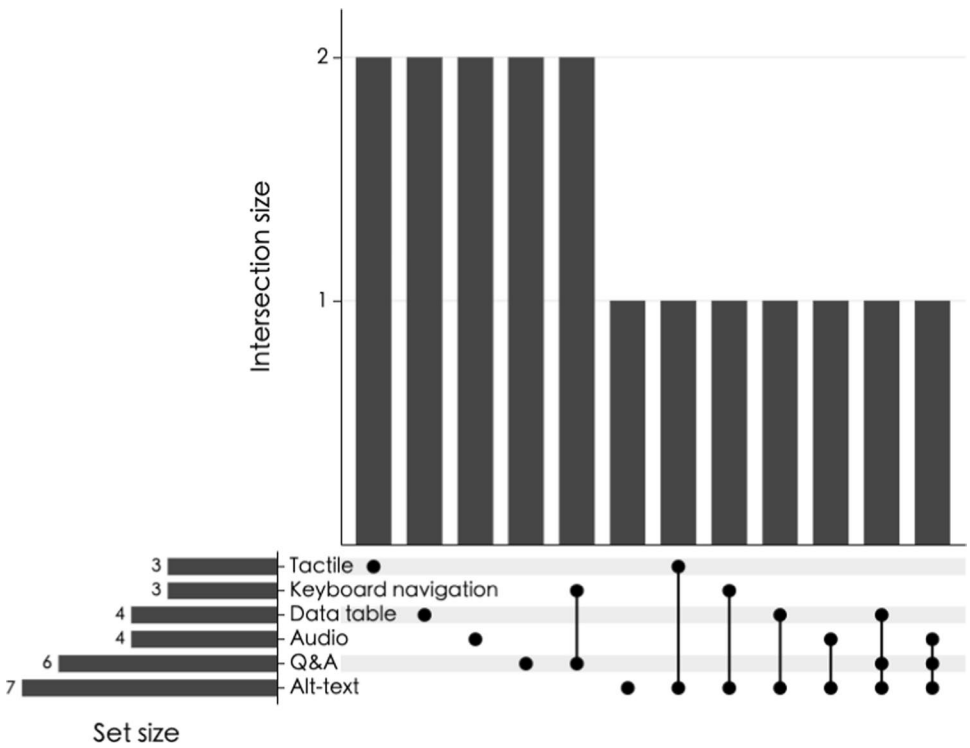

Fig. 3 An upset [58] representing the six different strategies exploited to make a visualization accessible through ML, DL techniques or LLMs. Alt-text, Q&A, and audio descriptions are the most frequently implemented supports, while tactile modalities and keyboard navigation appear less often. Importantly, most features are addressed in isolation or in pairs, with few studies combining multiple accessibility strategies. This indicates that current approaches remain fragmented and rarely provide multimodal solutions, highlighting an opportunity for future research to explore more integrated and comprehensive accessibility frameworks.

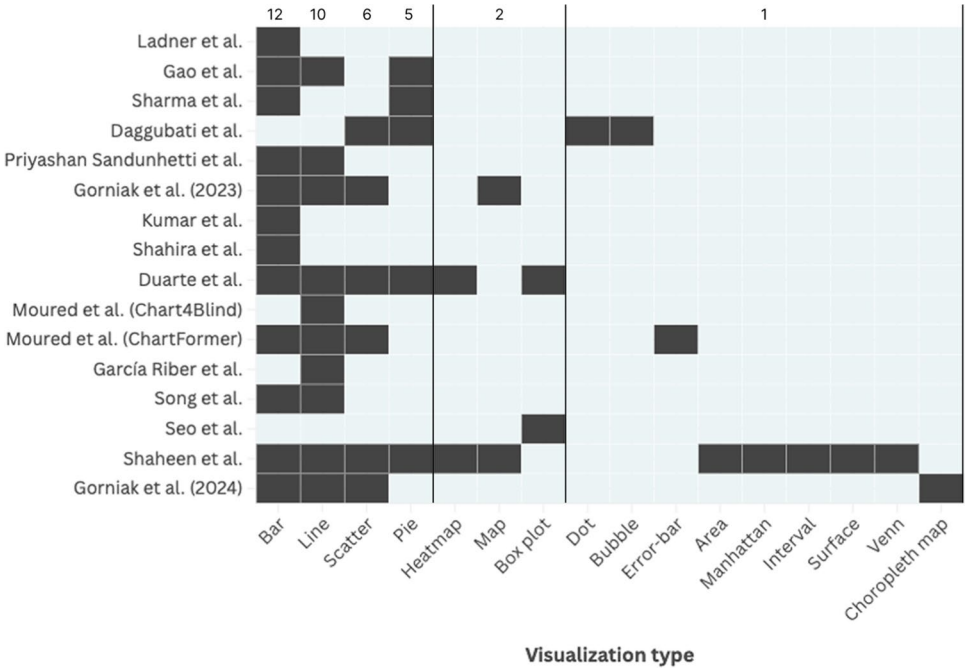

Fig. 4 Distribution of visualization types supported across different accessibility-focused works. While bar, line, and scatter plots are the most frequently addressed, receiving attention in more than ten studies, more complex or less common chart types (e.g., bubble charts, interval plots, choropleth maps) are covered only once. This highlights a clear research imbalance: the focus has been primarily on standard charts, leaving significant gaps in accessibility solutions for more advanced or domain-specific visualizations.

4.2.1 D2: visualization type

We analyzed papers based on the kind of visualization they wanted to create or make accessible. In particular, considering the broad range of visualization types, we followed the definitions made by Alberto Cairo in [59] and we distinguished between:

- *Charts*: representations made through the visual encoding of data into different symbols in terms of shapes, colors, or proportions (e.g., bar chart, area chart, pie chart);
- *Maps*: representations of geographical area, with or without data associated with that area (e.g., choropleth map, dot map).

Looking at the 18 papers, we found that 16 address charts as a visualization type [40–44, 46–53, 55–57], but only three also consider maps [42, 52, 53]. Only two studies have not specified a particular visualization type. In particular, some solutions, like the one proposed in [46], are chart-independent as they work with standard data visualizations (e.g., stacked and classical bar charts, heat maps, and box plots).

From our analysis, it emerges that the most frequently considered visualizations are those based on the Cartesian coordinate system, particularly bar charts, line charts, and scatter plots. Bar charts were referenced in 12 papers, line charts in 10, and scatter plots in 6, as illustrated in Fig. 4. This trend aligns with the widespread use of these chart types in data visualization practice, where they are favored for their simplicity, readability, and effectiveness in displaying comparisons and trends over time or categories. However, their overrepresentation raises a critical issue: research in this area tends to mirror mainstream visualization habits rather than challenge them. Consequently, less conventional yet equally relevant visualization forms (e.g., network graphs, treemaps, or more advanced spatial representations) remain underexplored, potentially limiting the scope of accessibility solutions.

When shifting the focus to maps, only a limited number of studies addressed their use. Specifically, two papers [42] and [52] discussed the use of general geographical maps, while a single study [53] considered choropleth maps, which provide a more nuanced, color-based representation of spatial data. This relatively lower representation suggests that while spatial visualizations are important, they may be less frequently prioritized in research on accessibility or visualization tools for BLV users. The marginal presence of maps suggests that spatial visualizations, despite being central in many applied domains (e.g., urban planning, epidemiology, environmental

monitoring), are not a priority in current accessibility research. This gap points to a missed opportunity: advancing accessible techniques for maps could substantially broaden the inclusivity of data visualization, given the critical role spatial reasoning plays in many real-world decision-making contexts.

4.2.2 D3: visualization source

We also took into account the visualization source. In particular, we identified three kinds of sources:

- *Online visualization*: it includes all those visualizations that are available through a web client (regardless of whether it is desktop or mobile);
- *Offline visualization*: it includes all the visualizations available through technological support (be it desktop, mobile, or smartwatch) without the need for an Internet connection to be displayed (e.g., images of charts, charts included in PDF documents);
- *Printed visualization*: it included all the visualizations printed on papers (e.g., in books, magazines, or newspapers).

Analyzing the selected papers, we observed that 11 of them focus on offline visualizations. These solutions often rely on precompiled datasets composed of chart images, annotations, and question-answer pairs–such as PlotQA [60], as seen, for example, in [42] and [44]. In contrast, only four studies explicitly address online visualizations. Among these, [40] processes digital images retrieved from the web, while [46] presents a web-based solution that integrates a React component designed to enhance accessibility by enabling direct interaction with SVG elements in online charts. A hybrid case is found in [50], where the system operates offline but is explicitly tailored for online environments, suggesting a potential for real-time web integration. Printed visualizations receive comparatively less attention, being considered in only two papers. In [55], printed charts are scanned and converted into color bitmap images for further processing. Meanwhile, [41] proposes a mobile application aimed at supporting the interpretation of printed materials, offering assistance to BLV users in physical settings. This distribution between online and offline or printed visualizations highlights a strong research bias toward offline, dataset-driven solutions. While such approaches are valuable for benchmarking and controlled experimentation, they risk overlooking the dynamic and interactive nature of real-world visualization use, which increasingly takes place in online environments. Similarly, the limited exploration of printed materials suggests that accessibility in non-digital settings, where BLV users still face significant challenges, remains under-prioritized. Addressing these imbalances could broaden the impact of accessibility research, ensuring that solutions are not confined to artificial or highly controlled scenarios but extend to the diverse contexts in which users encounter data visualizations.

4.2.3 D4: target users

From a cro:hciHuman-Computer Interaction (HCI) perspective, we also considered the target users who will benefit from the accessible visualization, and we distinguished between:

- *people with visual impairments*: people with visual impairments can suffer from a partial (low vision) or total loss (blindness) of visual perception, or color blindness;
- *analyst*: people who work with data visualization to extrapolate insights from raw data;
- *people with print impairments*: people having difficulties reading printed material due to a perceptual, physical, or visual impairment.
- *people with difficulties in reading or understanding visualizations*: people with a low level of data visualization literacy [61].

As expected, our analysis revealed that 13 of the reviewed papers explicitly identify people with visual impairments as their primary target users. For instance, the system proposed in [42] is specifically designed for blind users, while the solution in [46] targets screen reader users, encompassing both blind and low-vision individuals.

Beyond this core focus, a few studies broaden the scope of accessibility: [44] considers users who struggle with reading and interpreting charts, while [57] is oriented toward human analysts who need to extract insights from visual data. This strong emphasis on visual impairments is unsurprising, as discussions around visualization accessibility typically center on making content accessible to individuals with limited or no sight. However, two studies– [41] and [43]–also extend their attention to users with print impairments, acknowledging the need for inclusive access beyond vision loss alone. Lastly, five papers did not define a specific target user group but instead described improving visualization accessibility in general terms as the objective of their research ([40, 45, 49, 52, 56]). Analyzing these results, accessibility research on visualizations remains heavily centered on blindness and low vision, while other user groups with distinct but equally relevant needs, such as those with cognitive, learning, or motor impairments, are rarely considered. Although such a focus is understandable, given the historical prominence of visual impairment in accessibility debates, it risks narrowing the scope of proposed solutions and overlooking opportunities to design for a wider spectrum of marginalized users. Moreover, studies that refrain from specifying a user group may contribute to generalizable frameworks, but they also risk diluting their impact by not grounding design choices in the concrete needs of particular communities.

4.2.4 D5: evaluation

We also examined how each paper approached the evaluation phase, with a particular focus on whether the evaluation involved target users and adopted HCI methodologies. Unfortunately, only 6 out of 18 papers included user-based evaluations of their proposed solutions.

Among the most comprehensive is the study in [46], which conducted a dual-perspective evaluation. On one hand, the authors performed an online study involving 15 screen reader users, 13 of them blind and 2 with low vision. Participants interacted with 10 charts presented as a dashboard and were assessed based on task completion time, success rate, and interaction method (e.g., keyboard shortcuts, navigational strategies, and descriptions). Participants also provided verbal feedback and completed the System Usability Scale (SUS) [62], offering rich insights into usability from actual end users. On the other hand, the authors also included two data visualization experts in the evaluation to gather qualitative feedback from those likely to use the tool for authoring visualizations, acknowledging the importance of both creator and consumer perspectives. The SUS questionnaire was also employed in [47], where the authors surveyed 10 sighted participants to assess the usability of their visualization authoring tool. In addition, they tested the accessibility of the generated visualizations with three BLV users and involved four sighted participants during the design phase to incorporate early user feedback. Also, Gorniak et al. ([53]) evaluated their system with six BLV individuals, providing feedback on usability through SUS. Similarly, [49] conducted a survey-based evaluation of their sonification system with 46 participants, including individuals with partial or complete vision loss, as well as potential domain experts such as astronomers and musicians, and non-expert users. This diversity in participant backgrounds provided a broader understanding of the system's usability and applicability. In [48], the evaluation involved four users with blindness or visual impairments to assess the effectiveness of generated SVG charts on a tactile display, aiming to understand how well the system supports non-visual interaction. Other studies also included target users in their evaluation processes. For instance, Seo et al. ([51]) tested their approach with eight BLV participants. The study involved both structured and unstructured sessions, focusing on how BLV users interact with the system to interpret box plots.

Given the focus of our SLR, it is not surprising that only a limited number of studies included user evaluations. Most of the remaining works, such as [42–44, 50, 52, 54, 56, 57], primarily concentrated on model performance, assessing their solutions through machine learning metrics rather than through direct interaction with end users. This imbalance reveals a broader issue: while technical accuracy and efficiency are important, they cannot fully capture the lived experience of accessibility. Systems that perform well in benchmark datasets may fail in practice if they do not align with users' strategies, expectations, and constraints. Consequently, the limited integration of user-centered methodologies represents a critical weakness in the field, constraining the real-world impact of many proposed solutions.

4.3 D6-D10: machine learning related dimensions

In this section, we will analyze the papers under the lens of the dimensions related to ML (D6-D10), as mentioned in Sect. 3.1.

4.3.1 D6: data format

The format in which data is provided to ML, DL, and LLMs plays a critical role in shaping system capabilities, influencing everything from input preprocessing to final accessibility output. In this dimension, we examined the data modalities and structures used across the selected studies, with attention to modality-specific implications for accessibility-focused systems.

A large proportion of the reviewed works [41, 43–45, 47, 48, 50, 52, 55–57] adopt raw chart images as input. This approach is particularly suited for vision-based models capable of detecting graphical elements (e.g., bars, axes, legends, or labels). It also mirrors real-world conditions where end-users may encounter visualizations as static, pixel-based content.

Some studies extend image inputs with auxiliary information. For instance, [54] supplements images with user prompts, enabling multimodal interaction. Others integrate structured metadata, such as JSON representations of chart structures [51], allowing models to reason jointly over visual content and underlying data semantics.

Alternatively, several works rely exclusively on textual and structured data. For example, [46] feeds raw numerical data along with chart properties into an LLMs to generate descriptions, while [42] and [53] process specifications written in Vega-Lite, Observable Plot, or HighCharts–all declarative grammars for visualization. This design abstracts away visual encoding in favor of semantic interpretation, enabling more structured querying.

Finally, [49] stands out for its unique input format–raw stellar spectra–used for the purpose of sonification, expanding accessibility to non-visual sensory modalities. This highlights the potential for ML systems to go beyond visual parsing and include domain-specific scientific data in accessibility pipelines.

These diverse data formats reflect the richness of use cases and also indicate an opportunity for future research to establish standard input schemas that balance fidelity, interoperability, and accessibility considerations.

4.3.2 D7: preprocessing of data

Preprocessing is a fundamental yet often underreported component of ML pipelines, especially in domains like chart understanding where input complexity is high. In this dimension, we examined whether and how input data were transformed or enriched prior to model ingestion.

In many vision-based systems, preprocessing involved feature extraction and segmentation. For example, [41, 43, 44, 50, 56] employed multi-step pipelines to identify chart elements such as titles, legends, and data marks. These pipelines often combined OCR techniques with custom computer vision models. In [47], image segmentation was used to isolate visual regions of interest, forming the basis for downstream tactile or auditory rendering.

Image normalization techniques were also reported. [45], for instance, applied contrast enhancement, resizing, and noise filtering to improve input clarity for ML models, enhancing recognition of low-contrast or cluttered visualizations–a common real-world challenge.

In systems utilizing structured chart specifications, such as [42, 53], preprocessing focused on format normalization. Here, user-authored or dataset-provided charts were transformed into compliant Vega-Lite (or equivalent) structures, enabling consistent parsing and interpretation.

Interestingly, several recent works [40, 46, 48, 49, 51, 52, 54, 57] report no explicit preprocessing, often relying on the generalization capabilities of foundation models (e.g., LLMs or multimodal models) to process raw input. This may reflect a growing trend toward end-to-end learning and zero-shot inference, where preprocessing is either minimized or embedded implicitly within model internals.

Overall, while preprocessing remains highly task-dependent, its presence or absence reveals meaningful differences in system design philosophies, ranging from highly engineered pipelines to more emergent, prompt-driven architectures. Traditional pipelines based on segmentation, extraction, and normalization risk propagating errors across stages. In contrast, end-to-end systems powered by large multimodal models downplay preprocessing, shifting complexity into the model itself. While this design offers greater flexibility, it risks treating preprocessing as an afterthought, potentially obscuring issues of bias, interpretability, and data loss. Critically, few studies interrogate the trade-off between explicit preprocessing and implicit model generalization. As a result, system designers may overlook opportunities for hybrid approaches that combine the interpretability of explicit preprocessing with the adaptability of foundation models.

4.3.3 D8: model type

Understanding the types of models employed is essential to mapping the landscape of ML/DL/LLMs applications in accessibility. Here, we identify the architectures and paradigms that underlie the reviewed systems, with attention to how model choices align with accessibility goals.

Several works [40, 43, 45, 47, 56] rely primarily on pre-trained OCR systems for text extraction, often as a first step toward structural understanding. These systems are typically not re-trained but serve as off-the-shelf components.

More advanced systems incorporate DL models tailored to specific tasks. For example, [44] combines Mask R-CNN for object detection with an improved variant of TaPas [65] for table-based question answering. Other architectures include ChartNet [57], an extension of the MAC-Network for visual question answering, and a fusion of VGG-16 and CRAFT in [41]. [49] trains a Variational Autoencoder for spectrum-to-sound translation, and [52] adopts a Swin Transformer for chart classification.

The role of LLMs and multimodal models is increasingly prominent. Early LLMs-based systems like [46] and [42] use GPT−3.5 Turbo, whereas [53] upgrades to GPT-4 for richer semantic reasoning. Vision-enabled LLMs also appear: GPT-4 Vision is utilized in [54] and [51], with the latter also exploring Google Gemini Pro-Vision. [50] employs T5 for chart-to-text translation, and [48] integrates LLaVA−1.5, a large multimodal model combining CLIP-style vision encoders with Vicuna, a fine-tuned LLMs.

These results indicate that model selection is highly correlated with task complexity: lightweight models suffice for static recognition, while LLMs and transformers dominate in systems requiring context-aware interaction, multimodal reasoning, or user-guided generation. However, there is a tendency to choose models without critically examining accessibility-specific limitations. For example, OCR-based pipelines treat accessibility as a byproduct of text extraction, neglecting higher-order meaning-making. Similarly, while transformers and LLMs expand the scope to interactive reasoning, they are often evaluated primarily on task performance rather than user-centered outcomes such as cognitive load reduction. Moreover, reliance on proprietary models (e.g., GPT-4, Gemini Pro-Vision) raises concerns about reproducibility, transparency, and long-term sustainability for accessibility communities. This suggests that model choice should not be treated as a purely technical decision but as one with ethical and social ramifications.

4.3.4 D9: use of ML

This dimension examines the ways in which ML, deep learning (DL), and large language models (LLMs) specifically advance visualization accessibility, from technical capabilities to methodological innovations and conceptual shifts in assistive interaction design.

At the technical level, ML and DL models enable automatic visual parsing, the recognition and extraction of structural elements such as axes, tick marks, legends, and data points from chart images. Systems like those proposed in [40, 45, 47, 55] rely on convolutional networks or object detection pipelines to identify graphical

primitives. This low-level understanding is crucial, as it forms the foundation for generating tactile graphics or screen-reader-friendly descriptions, bridging the gap between visual content and non-visual modalities.

Methodologically, these techniques also support semantic summarization: transforming dense visual information into coherent natural language narratives. For instance, works like [41, 46, 50] train models to produce descriptive captions that highlight trends, comparisons, or outliers, rather than merely listing values. This shift from syntactic to semantic output aligns better with how users consume and interpret data, reducing cognitive load and improving comprehension.

A further methodological advance is the use of table reconstruction [43, 51, 56], where visual content is converted back into structured data. This enables downstream tasks, like querying, filtering, or auditory rendering, without relying on purely visual cues. By reintroducing machine-readable structure, these systems unlock interactivity that static alternatives cannot provide.

At a conceptual level, recent work illustrates how LLMs broaden the scope from passive description to active and adaptive interaction. For example, TaPas++ in [44] supports question answering over chart data, moving beyond one-way narration to user-driven exploration. Similarly, [57] and [52] apply models for visual question answering (VQA) and classification, supporting dynamic information retrieval based on user context.

Emerging multimodal systems demonstrate deeper integration. [54] uses GPT-4 Vision to enable editing of inaccessible charts, giving users agency to modify visualizations directly. [42, 53] combine LLM-based query classification with prompt chaining, adapting responses to analytical vs. visual questions. This modular reasoning reflects a conceptual shift toward personalization and context awareness in assistive technologies.

Finally, works like [49] and [48] push the boundaries of modality itself: translating raw spectra into auditory representations using variational autoencoders (VAEs), or generating tactile SVGs through multimodal LLMs. These approaches reimagine what "accessible visualization" can mean, moving from visual mimicry toward multimodal, user-adaptive experiences.

The reviewed works collectively demonstrate that ML enables both low-level parsing and high-level semantic interaction, yet the focus is on the technical novelty rather than accessibility impact. For example, semantic summarization and VQA represent significant methodological advances, but few studies interrogate whether these outputs truly align with user needs or preferences. Similarly, multimodal systems that offer chart editing or auditory sonification showcase conceptual innovation; however, little evidence exists about their usability in practice. A critical gap lies in the assumption that more advanced capabilities inherently translate to better accessibility. Without rigorous end-user validation, these systems risk producing technically impressive but socially misaligned tools. Moreover, the framing of accessibility as a technical challenge overlooks the importance of co-design with BLV users, who could help identify whether systems should prioritize efficiency, interpretability, or adaptability.

4.3.5 D10: model evaluation

Evaluation remains a critical bottleneck in this domain, with few standardized benchmarks and limited consensus on appropriate metrics for accessibility impact. In this dimension, we examined the methods used to assess model performance.

Several works did not conduct empirical evaluations [41, 46, 47, 51], possibly due to the exploratory nature of prototypes or lack of labeled datasets for accessibility-specific tasks.

Others developed custom datasets to assess their approaches under controlled conditions [42, 43, 45, 48, 55–57]. While effective for internal validation, this limits reproducibility and cross-study comparison.

A smaller subset leveraged publicly available benchmarks. [44] used a combination of PlotQA, ChartQA, and VegaLite-based datasets, evaluating both element extraction and question answering. [40] employed FigureQA, while [50] used Chart-to-Text and VisText. [52] evaluated performance on the ICPR 2022 CHART competition dataset. The ChartCraft dataset enabled multimodal evaluation in [54], while [53] reused a dataset from [64]. [49] used the MILES library to evaluate audio-based accessibility.

Evaluation practices across the reviewed works remain fragmented, revealing a systemic weakness in the field. Heavy reliance on custom datasets and heterogeneous benchmarks makes results difficult to compare, while the absence of standardized accessibility metrics undermines claims of progress. Importantly, evaluation rarely extends beyond technical accuracy: measures of usability, cognitive effort, or user trust are almost entirely absent. This disconnect signals a deeper issue: models are being optimized for recognition tasks rather than for accessibility outcomes. Even studies that engage with end-user testing often treat it as a secondary validation step rather than as central evidence of effectiveness. The field risks creating an evaluation culture where technical novelty is rewarded but accessibility impact is under-measured. Moving forward, there is a pressing need for community-driven benchmarks that foreground user experience, particularly for blind and low-vision populations, and for adopting participatory evaluation protocols that shift emphasis from laboratory accuracy to lived accessibility.

5 Discussion

Considering that 18 papers are too few to conduct an in-depth analysis, we cannot draw definitive conclusions or fully address our research question. However, it is worth considering the trends over time and the importance of multisensory approaches in the context of accessibility, as engaging multiple senses can enhance user experience and inclusivity, opening new possibilities for research and practical applications. As a result of our analysis, many open challenges remain, and reflections can be made on the papers that were excluded due to being off-topic, which may offer insights or suggest potential avenues for further exploration.

5.1 Trends over time

Looking at the temporal distribution of strategies, we can observe a clear shift over time. Until 2019, papers mainly relied on single approaches, reflecting early and more isolated explorations (e.g., tactile in 2005, data tables in 2012, Q&A in 2019). From 2022 onwards, however, we see the emergence of combinations of strategies, particularly those centered around alt-text and keyboard navigation, indicating a more experimental phase where different methods were tested together. In 2024, the trend shifted again towards single strategies. At the same time, 2024 also marked the year in which approaches related to the creation of accessible data visualizations, rather than only their accessible rendering, started to be explored–suggesting a broader openness to alternative directions. It is worth noting that 2024 was also the year with the highest number of papers overall, confirming its role as a turning point in this research landscape. We also noticed that in the last year and a half, there has been an increase in studies involving target users in the evaluation phase, indicating greater attention to the effectiveness of the proposed solutions.

5.2 Multisensory approach

The importance of multisensory approaches in creating multimodal visualizations and multimodal systems or tools is crucial to ensuring an inclusive and enriched user experience. Integrating information not only visually but also through audio, such as text-to-speech, sonification [66], or other sound-based modalities, and tactile experiences like data physicalization [67] provides an additional layer of accessibility that goes beyond the limitations of a single sensory channel. A key example of this integration is the use of audio data narratives, which combine textual descriptions and sonification to provide accessible, multimodal, and up-to-date access to online data visualizations, significantly increasing the insights gained by screen reader users [68]. Another notable case is the VibroVision vest [69], which uses a two-dimensional array of vibration motors to project spatial information onto the wearer's abdomen, enabling perception of object shape, position, and distance through touch. In this context, advanced LLMs can play a key role by facilitating the automatic generation of audio descriptions, sound interpretations, or even the design of customized tactile outputs. This multisensory approach not only

makes information more accessible to people with diverse abilities but also enriches the experience for all users, engaging them immersively through multiple senses and fostering a deeper, more intuitive understanding of data. In this context, the concept of data visualization may be too narrow, and adopting a broader framing, such as data representation could better capture the diversity of multisensory methods that support deeper and more intuitive understanding of information [70].

5.3 Visualization open challenges

The little we can say on the visualization side concerns five issues.

5.3.1 Lack of infographics

We observed that none of the reviewed papers addressed the accessibility of infographics, i.e., visual representations designed to convey one or more messages through a combination of textual, graphical, and spatial elements [59]. This omission is particularly significant, as infographics have become an essential medium across various domains, including journalism, marketing, education, and science communication, where they serve as powerful tools for translating complex data into accessible visual narratives and effectively engaging diverse audiences [71–73]. Their importance lies in their ability to combine text, imagery, and data visualization to enhance comprehension, retention, and recall of information. By presenting key insights in a clear and visually appealing format, infographics can reduce cognitive load, highlight relationships and trends that might be overlooked in textual data, and facilitate faster decision-making [74]. Moreover, they are highly shareable across digital platforms, increasing the visibility and impact of information among both expert and non-expert audiences. Moreover, there is an emergence of a growing research area focused on making infographics accessible to individuals with visual impairments or learning disabilities [75, 76]. Infographics differ significantly from standard charts in that they often incorporate multiple types of visualizations, narrative structures, icons, and typographic elements within a single composition. Their richness in semantic layering and visual storytelling poses unique challenges for accessibility and understanding due to their complexity [77]. At the same time, this complexity opens the door for the application of LLMss, which have shown promising results in understanding multimodal content and generating context-aware, structured answers to users' queries [78]. LLMs could be used not only to describe individual graphical components but also to convey the intentional narrative and hierarchical structure of an infographic. Moreover, they could facilitate adaptive summaries tailored to users' preferences or cognitive needs.

For these reasons, future research should explore how LLMs and related AI techniques can support the accessible translation of infographics, both for BLV users and for people with cognitive or learning disabilities. This could include developing approaches for generating alternative text that accurately conveys complex visual information, designing adaptive chart representations for users with different types of cognitive or visual impairments, or creating interactive systems that allow users to query and explore infographics in real time without sacrificing informational richness. Integrating this perspective would help bridge the current gap between visual storytelling and inclusive design in the visualization accessibility landscape.

5.3.2 Lack of particular types of charts

Most papers tend to focus primarily on common chart types such as bar charts and line charts, which are indeed widely used and generally well understood. However, this narrow focus often comes at the expense of other important visualization types, including box plots, choropleth maps, heatmaps, and word clouds, which are frequently employed in data analysis and communication of qualitative or multidimensional information.

These underrepresented visualizations play a crucial role in various analytical contexts. For example, box plots are essential for summarizing distributions and identifying outliers; heatmaps are widely used in scientific and biomedical research to reveal patterns across large matrices; choropleth maps are standard for representing

geographically distributed data; and word clouds are often used to quickly convey themes or trends in textual datasets. Their absence in many accessibility-oriented studies suggests a potential gap in support for more complex or domain-specific visual content, which may limit the applicability of proposed solutions in real-world scenarios. Future research should develop methods to make these underrepresented visualization types accessible, for instance by designing algorithms that generate descriptive summaries, adaptive tactile or auditory representations, or real-time interactive alternatives.

Addressing this gap is essential to ensure that accessibility solutions are not only effective for basic chart types but also inclusive of the diverse range of visual formats used in exploratory data analysis, social sciences, health research, and journalism.

5.3.3 Lack of printed chart

Most of the papers have largely overlooked printed visualizations, particularly in recent studies, despite the fact that a vast number of graphs and charts are routinely encountered in newspapers, textbooks, and other printed media. Printed visualizations remain a critical medium for information dissemination, especially in educational contexts and traditional media consumption, where digital alternatives may not always be accessible or available.

Neglecting this category means missing an important area where accessibility solutions could have a significant real-world impact, helping individuals with visual impairments access and interpret information from physical sources. This gap underscores the need for future research to extend beyond digital-only approaches and consider hybrid or offline scenarios, including techniques for scanning, interpreting, and conveying printed visual content in accessible formats. Future research should explore methods for making printed visual content accessible, such as developing AI-driven systems for scanning, interpreting, and converting static charts into descriptive, auditory, or tactile formats. Investigating hybrid approaches that integrate offline and digital accessibility tools could significantly expand the real-world impact of visualization accessibility, enabling individuals with visual impairments to access information across both physical and digital media.

5.3.4 Lack of consideration for different kinds of impairments [79–82]

While most existing work has focused narrowly on accessibility for individuals with visual and print impairments, other user groups also face barriers that deserve attention. For instance, older adults often encounter age-related sensory and cognitive challenges that affect their ability to process complex visual information. Recent studies have expanded the scope of consideration to include the older population [79, 80]. Similarly, people with Intellectual and Developmental Disabilities (IDD) may require simplified representations, guided navigation, or multimodal support to engage effectively with visualizations, as addressed in [81, 82]. Future research should therefore aim to broaden the scope of accessible visualization by developing techniques that address this diversity of needs. Promising directions include adaptive interfaces that dynamically adjust the level of complexity, multimodal representations that combine visual, auditory, and tactile cues, and personalized accessibility features that take into account both sensory and cognitive differences. These efforts highlight the importance of designing inclusive visualization tools that cater to a broad spectrum of abilities and promote equitable access to information across diverse communities.

5.3.5 Lack of involvement of users

Depending on the specific context of use for a tool or framework, it is crucial to consider different user categories during both the design and evaluation phases. For example, when developing a tool aimed at creating accessible visualizations, it is important to involve designers and developers throughout these stages, as they will be the primary users responsible for integrating accessibility features into their visual outputs.

At the same time, the visualizations produced by such tools must be evaluated by the end users, namely, the individuals who will ultimately interact with and benefit from the accessible visualizations. This user-centered evaluation is equally important when the primary goal is to make existing visualizations accessible, ensuring that the solution truly addresses the needs of the target audience.

It is essential to avoid focusing exclusively on machine learning metrics such as accuracy or error rates, which, while important, do not capture the full picture of usability and accessibility. Incorporating direct feedback from real users allows for a more comprehensive assessment and helps guarantee that the tool effectively supports the people it is intended to assist.

In order to close this gap in the involvement, practitioners should consider research on user-centered design and co-creation with people with visual impairments, which has consistently emphasized the importance of adapting methodologies beyond conventional visual design techniques. Successful applications have been shown through the combination of user-centered design processes with contextual methods and rapid prototyping, which enabled the development of accessible products and packaging for BLV end users [83]. Participatory design practices have also been enriched by the use of audio-tactile mock-ups, audio diaries, and accessible prototyping techniques, allowing researchers and participants to overcome the visual constraints of traditional design tools when creating cross-modal interactive systems [84]. Practical guidelines and action checklists have been further developed to ensure that participatory design sessions remain ethical and inclusive across the entire system development lifecycle [85]. At the same time, reflections on voice-based and tactile co-design have pointed to challenges in artifact creation and the establishment of shared representations, while also proposing strategies to facilitate shared meaning among participants with vision impairments [86].

5.4 ML-related open challenges

Despite recent advances, the application of ML to the accessibility of data visualizations remains constrained by several open challenges. These issues stem not only from technical limitations in current models but also from a lack of robust methodologies for evaluating and deploying such systems in ways that genuinely meet the needs of users with disabilities.

5.4.1 Lack of accurate interpretation of complex visual data

One of the most fundamental challenges lies in the accurate interpretation of complex visual data. While computer vision and multimodal models have made strides in recognizing simple chart components, most ML systems still struggle to understand more intricate visualizations such as multi-series line graphs, stacked bar charts, or infographics with layered semantics. Crucially, the transformation of visual information into accessible formats–particularly natural language descriptions–must preserve the underlying data integrity, trends, and nuances. Existing models often miss critical insights such as patterns, anomalies, or comparisons, and may overgeneralize or hallucinate content. While large multimodal models (e.g., GPT-4 Vision or LLaVA) offer promising capabilities for fusing visual recognition with language generation, their capacity for fine-grained reasoning over structured visual data remains limited and largely untested in accessibility contexts.

A key research direction is the development of hybrid systems that combine computer vision with structured reasoning. For example, coupling vision encoders with declarative visualization grammars (e.g., Vega-Lite) could enable systems to map visual content into machine-readable specifications before generating accessible outputs. Another promising approach is the creation of task-specific multimodal benchmarks where models must identify anomalies, correlations, or trends across complex charts rather than simply naming chart elements. To address hallucination, future work should also explore domain-adaptive training strategies. Models should be fine-tuned on datasets reflecting real accessibility scenarios (e.g., tactile graphics, voice queries) rather than on generic vision-language corpora.

5.4.2 Lack of real-time support

Another significant limitation is the lack of real-time support for dynamic or interactive visualizations. Many users with visual impairments encounter data in live or streaming contexts, such as dashboards, financial tickers, or scientific instruments. Current ML-based systems are typically designed for static inputs and cannot yet accommodate real-time interaction, updates, or conversational querying. This restricts their utility in practical settings where users may need to explore and manipulate visual data on the fly. Enabling temporal reasoning and interactive dialogue over evolving visual content represents a complex but vital research frontier.

Research should prioritize architectures and pipelines capable of handling streaming visual data. This might involve integrating lightweight visual parsing modules with memory-augmented LLMs that can maintain continuity over evolving data states. Concrete research directions include: (i) designing low-latency multimodal APIs for screen readers that can request incremental updates as a visualization changes; (ii) exploring predictive caching strategies so that common user queries can be answered in real time; and (iii) developing conversational agents that allow iterative exploration of dynamic dashboards.

5.4.3 Lack of standard benchmarking

Equally pressing is the absence of standardized benchmarking for this domain. Most studies to date rely on ad hoc datasets and task-specific metrics, which impedes meaningful comparison across systems and hinders cumulative progress. There is an urgent need for shared evaluation frameworks that assess not only the technical accuracy of model outputs but also their functional accessibility and user impact. Metrics should account for clarity, informativeness, cognitive load, and usability by screen reader users or those relying on alternative sensory modalities. Without such standards, it remains difficult to quantify the benefits–or harms–introduced by ML-driven accessibility solutions.

Future research should aim to build community-wide benchmarks tailored for accessibility. This requires three concrete steps: first, the creation of open datasets that include both visualizations and accessibility-oriented annotations (e.g., natural language summaries, tactile renderings, sonification mappings). Second, the design of multidimensional metrics that go beyond accuracy to measure accessibility outcomes such as cognitive load, trust, and task completion time by BLV users. Third, the establishment of shared evaluation protocols that encourage reproducibility and longitudinal testing across models. An actionable direction is to integrate benchmarking efforts into existing accessibility challenges (e.g., ACM ASSETS competitions) to ensure wide adoption and external validation. Without such collective infrastructure, individual prototypes will continue to remain incomparable and fragmented.

5.4.4 Potential bias

Finally, concerns around bias and fairness must be more systematically addressed. ML models trained on unbalanced or non-representative data may propagate biases in how visual content is interpreted or described. This is particularly problematic in accessibility contexts, where misleading descriptions can impair understanding or trust. Moreover, model transparency is often lacking, making it difficult for users or developers to assess when and how errors occur. Ensuring that accessibility-focused ML systems uphold principles of fairness, explainability, and user agency is not only an ethical imperative but also a prerequisite for real-world adoption.

To mitigate bias, future systems should embed fairness auditing and transparency mechanisms directly into their design. One practical research direction is the use of explainable AI techniques that allow users to query how specific visual elements were interpreted, thereby supporting error detection and user agency. Another direction is the intentional diversification of training corpora: visualization datasets should represent a range of cultural conventions, chart types, and accessibility scenarios to avoid overfitting to narrow visual domains. Researchers could also investigate participatory data collection, where people with disabilities co-create annotation guidelines

that reflect their interpretive needs. Finally, bias mitigation should not be treated as a one-off correction but as an iterative process: continuous monitoring pipelines should flag accessibility errors or skewed descriptions in deployed systems.

5.5 Comparative insights and state-of-the-art gaps

Across the reviewed studies, a clear evolution emerges from early rule-based or vision-only systems toward end-to-end, multimodal, and language-driven models. This progression reflects both technical maturation and a widening understanding of what accessibility entails. Earlier works (e.g., [43, 55, 56]) primarily targeted structural recognition, extracting axes, labels, or data marks through segmentation and OCR. These approaches achieved relatively high precision (often above 85–90% for well-structured charts) but were limited to static, homogeneous input types and required extensive preprocessing. Their contributions mainly addressed what was visible, not how it could be meaningfully conveyed to non-visual users.

More recent systems integrate deep learning and transformer-based architectures to move from syntactic extraction to semantic reasoning. For example, ChartNet [57] and ChartFormer [48] introduced neural models that infer relationships and trends, while multimodal and LLMs-driven approaches [46, 51, 54] enable interactive querying and description generation. These models resolve the problem of rigid visual encoding by learning context-sensitive mappings between visual and textual modalities. However, their evaluation remains fragmented: while some report BLEU or F1 scores, few assess usability or accessibility outcomes.

A parallel trend concerns multisensory and non-visual modalities. Works such as [49] explore sonification and tactile generation, expanding accessibility beyond text-to-speech toward embodied and auditory representations. Yet these systems often rely on small-scale prototypes and lack standardized performance comparisons, making it difficult to identify best practices or generalize results.

Despite these advances, two major gaps persist. First, there is no shared benchmark or unified evaluation protocol that measures accessibility effectiveness across modalities–technical accuracy dominates, while cognitive load, user satisfaction, and interpretability remain underexplored. Second, many recent systems depend on proprietary models (e.g., GPT-4, Gemini Pro-Vision), which hinders reproducibility and transparency, especially for accessibility communities with limited resources.

In summary, the current state of the art demonstrates impressive technical progress but uneven accessibility validation. Future research must bridge this gap by combining robust, open evaluation frameworks with participatory design practices that directly involve blind and low-vision users in assessing whether new methods genuinely enhance access, comprehension, and agency.

5.6 Toward a conceptual framework for open challenges

While the nine open challenges identified above provide valuable insights, taken in isolation, they risk appearing as a fragmented list. To address this, we propose a conceptual framework that organizes the challenges into four interconnected dimensions: content coverage, user inclusivity, technical robustness, and evaluation and trustworthiness.

- Content coverage concerns the breadth of visualization types supported (e.g., infographics, non-standard charts, printed media).
- User inclusivity focuses on the diversity of end users and their direct involvement in design and evaluation.
- Technical robustness highlights the capacity of ML systems to accurately and interactively process complex visualizations in real time.
- Evaluation and trustworthiness emphasizes the need for standardized benchmarks, fairness auditing, and explainable systems.

This framework not only clarifies how individual challenges relate to each other but also provides a structured research agenda. Future work should aim to advance all four dimensions in tandem: broadening coverage of visualization genres, ensuring inclusivity for diverse user groups, improving technical robustness of ML methods, and grounding progress in rigorous, trustworthy evaluation. Such an integrative perspective moves the field beyond descriptive cataloging of challenges toward a roadmap for systematic, user-centered innovation in accessible visualization.

5.7 Out of scope papers

During the eligibility phase, all 91 papers were reviewed to determine whether they were on topic or not. While many were deemed off-topic, we can still reflect on the reasons behind these exclusions, as they may offer valuable insights into the scope and focus of the research.

Accessibility Meaning

The majority of the papers were excluded because they were considered off-topic. Most of these papers presented a concept of accessibility that differed from what we intended to explore in this study. Their focus often diverged from the specific aspects of accessibility in visualizations that we aimed to address. In line with the philosophy of data democratization, [87] and [88] discussed the accessibility of data or information in their study. Their work emphasizes the importance of making data and information widely available and usable by all, thus contributing to a more inclusive approach to data access. On the same line, [89] discussed the accessibility (in terms of availability) of the information, while [90] talked about accessibility to data analysis tools, exploring accessibility as a way to effectively interact with and derive insights from the data, regardless of users' abilities or technical expertise. Following the same line of thought, [91] defines accessibility as the reduction of technical barriers in complex industrial systems. Similarly, [92] advances accessibility by offering field users immediate, hands-free access to critical geotechnical information via intuitive gesture controls and visual overlays. This approach removes the need for handling physical documents or navigating lengthy reports, enabling users to quickly grasp site conditions. Such enhanced accessibility not only improves safety but also facilitates faster, better-informed decision-making, minimizes project delays, and ultimately reduces costs by streamlining information access and risk management. Finally, others view accessibility as providing access to resources, focusing on ensuring that water [93] or technologies [89] are available and usable for a broad range of users. This interpretation aligns with the idea of removing barriers to access, but it differs from the more specific focus on making visualizations accessible to individuals with disabilities.

Accessibility of Maps

A specific consideration must be made regarding maps, which are often overlooked in accessibility discussions related to visualizations. Within the papers included in our SLR, only two explicitly addressed map accessibility. Notably, [42] focused on the accessibility of standard geographic maps but acknowledged a limitation in not addressing choropleth maps. This gap was later addressed by a subsequent study [53], which specifically analyzed choropleth maps and their accessibility challenges. Additionally, three papers excluded from our final analysis [94–96] concentrated on maps designed to help wheelchair users find accessible locations, rather than improving the accessibility of the maps themselves. This distinction highlights an important research gap: while there is interest in accessible spatial information, there is comparatively less attention given to making different types of maps themselves more accessible. Beyond these visualization-focused studies, recent advances in LLMs have opened new avenues for integrating natural language understanding with cro:gisGeographic Information System (GIS). For example, one study introduced an autonomous GIS system powered by LLMs as its core reasoning engine. This system combines automatic geographic data acquisition, analysis, and visualization to address complex spatial challenges [97].

Taken together, these findings underscore the need for a broader exploration of accessibility across diverse map types, including choropleth, bubble maps, and other complex spatial visualizations. Future research should focus

not only on the data represented but also on making the maps themselves more accessible, potentially harnessing the emerging capabilities of LLMs-powered GIS technologies.

5.8 Real-world integration

The application of accessibility guidelines in widely used visualization and publishing tools reveals several practical barriers. For instance, Power BI includes features such as keyboard navigation, screen reader compatibility, high-contrast modes, and the ability to add alternative text [98], but many of these elements require manual configuration by the report author, and accessibility may be lost when reports are embedded or published in constrained environments. Tableau similarly supports color-blind friendly palettes, alternative text for visualizations, and compliance with WCAG standards [99], yet accessible design heavily depends on authoring practices, and embedded dashboards or authentication flows may introduce non-compliant elements. Furthermore, open-source software such as R provides color-blind friendly palettes [100]. In the case of D3.js and other JavaScript-based libraries, the potential for fully accessible visualizations exists, as developers can directly implement ARIA roles, semantic HTML, and WCAG-compliant interactions. However, this requires substantial expertise, time, and testing, making accessibility highly contingent on developer skills and organizational priorities. These practical constraints underscore that accessibility in visualization is not only a matter of following guidelines but also of overcoming technical, organizational, and workflow-related challenges in real-world contexts.

5.9 Limitations

This work faces several limitations that should be considered when interpreting the results.

First, the number of studies retrieved and analyzed was relatively limited. Although a comprehensive search strategy was employed, the scarcity of directly relevant papers indicates that research on ML-driven accessibility in data visualization remains fragmented. This highlights a need for systematic efforts to consolidate findings across related domains and develop a shared body of knowledge.

Second, the methodological diversity among the reviewed studies, including differences in datasets, evaluation metrics, and experimental settings, complicates direct comparison and synthesis. Future work should prioritize the development of standardized evaluation frameworks to enable reproducible and comparable assessments of ML-based accessibility tools.

Third, given the rapid pace of technological advancement in ML, some emerging techniques may not have been captured by this review. A continuous and iterative mapping of the literature would help maintain the relevance of findings and capture the evolution of best practices in the field.

Finally, the study concentrated on a subset of dimensions identified as most significant for accessibility. Future research could broaden this scope by incorporating cross-disciplinary perspectives (e.g., cognitive psychology) and intersectional accessibility factors to better understand the multifaceted role of ML in data visualization accessibility.

6 Conclusion and future works

This paper has examined the emerging intersection of accessibility, data visualizations, and machine learning through a comprehensive SLR. Our investigation provides a detailed synthesis of how ML and DL techniques, including recent advances in LLMs, have been applied to enhance the accessibility of visual data.

Despite the significant potential of ML, DL, and LLMs to automate and scale the generation of accessible alternatives to visual content, our review highlights that this field is still in its early stages. Most existing studies focus on limited visualization types or isolated accessibility features, and few adopt holistic, user-centered design approaches. Moreover, we found that empirical validation with target users–especially those with varying

degrees and types of visual impairment–is often lacking or insufficiently reported. Due to the limited number of papers resulting from the analysis, we are unable to extract many significant insights. However, we were able to identify some promising research directions and open challenges that could be explored in future works.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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