Understanding the Visualization and Analytics Needs of Blind and Low-Vision Professionals

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Abstract

Inclusivity for blind and low vision (BLV) professionals in data science and analytics is limited by a gap in understanding their unique data analysis needs. We contribute to the literature by reporting on a two-step online survey delving into the experiences and challenges faced by BLV individuals engaged in data-related roles. Our findings highlight that despite expertise in programming and GUI-based analysis tools, BLV professionals faced accessibility issues at various points in the data analysis pipeline—issues ranging from data loading and transformation, availability and compatibility of data tools with assistive technology, and visualization authoring. The prevalent use of tools such as Excel, Python, and SAS alongside heavy reliance on assistive technologies highlights persistent accessibility challenges. Furthermore, frequent collaboration with sighted colleagues indicates compromised independence. These results underscore the urgent need for "born accessible" tools that ensure the inclusivity and autonomy of BLV professionals in the field of data science.

CCS Concepts

• **Human-centered computing → Empirical studies in accessibility**; **Visualization**.

Keywords

Accessible data visualization, blind and low vision users, inclusive data analysis

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1 Introduction

As the field of visualization and data science continues to expand, it is becoming increasingly inclusive of blind individuals [2, 3, 5, 8, 9, 12, 14]. Despite these advancements, there remains a profound lack of understanding regarding the specific data analysis needs of blind and low vision (BLV) professionals. Existing data analysis tools are designed for sighted users, which marginalizes blind professionals by not accommodating their unique interaction paradigms. This not only restricts access to the field but also curtails the potential contributions of BLV professionals within the broader information landscape. But to know how to mitigate the shortfall in the first place, we will need to know the specific needs of BLV professionals for data analysis in situations where they differ from sighted users. To address this significant knowledge gap, we designed a two-step online survey aimed at understanding the data analysis practices of BLV information professionals. We uncover the specific challenges and strategies employed by BLV professionals in navigating the data-driven aspects of their careers. Accessibility challenges were prevalent, with heavy reliance on assistive technologies like screen readers. Collaboration with sighted colleagues was often necessary for creating and interpreting visual data, highlighting the need for inherently accessible data visualization tools. To support BLV professionals, we must innovate and develop "born accessible" [10] tools to ensure full inclusivity and independence in data science.

2 Background

We review the literature on accessible visualization and data analysis practices; focusing on the challenges faced by BLV individuals in learning and using visualizations, and employment. Historically, accessibility in data visualization for BLV users relied on equivalence methods. Smaller visualizations had textual descriptions, while larger datasets were accessible through downloadable files for flexible analysis. An example from a recovery.gov case study [11] states: "*Because visualizations are inherently inaccessible, allowing for download of data sets allows users to analyze the data in any manner that they prefer.*". However, limited research in this area highlights the need for further development [9, 14]. Recent advancements, such as Jung et al.'s guidelines for writing effective alternate texts for visualizations, recommend concise, plain language descriptions to accommodate the diverse needs of blind users [8]. Kim et al.'s research highlights the importance of context in visualization, identifying distinct literacy tasks for reading and creating visualizations, and emphasizing the varying experiences of BLV users based on the visualization's purpose, whether exploratory or explanatory [9]. These insights drive our study to enhance understanding and improve accessibility of data visualizations.

Education at all levels, especially in STEM, often includes inaccessible data analytics modules. Butler et al. [1] highlight significant accessibility barriers for vision-impaired students in Australia, particularly affecting their participation in STEM fields. These barriers influence BLV students' academic and career choices due to visually-focused curricula in subjects like math and science. The lack of affordable assistive technologies in classrooms exacerbates these challenges [7]. However, more recent "born accessible" teaching approaches are examples of solutions that support BLV individuals at early stages of their data analysis learning [19]. Traditional low-tech teaching methods, like using pins and rubber bands to construct graphs [5], pose risks and limitations, and often lead students to avoid using graphs post-education [25]. Despite efforts to introduce data visualization early in education, BLV students struggle with independent data exploration in higher studies due to inadequate tools, impacting their career choices [2, 25]. Despite legislative efforts to foster workplace inclusion, people with disabilities face significant employment barriers compared to non-disabled peers. Negative employer attitudes often lead to discrimination in hiring, promotion, and other employment aspects [16]. Furthermore, employment rates for blind and visually impaired individuals have not significantly improved [17]. Employers may view BLV employees as less capable due to inaccessible workplace technologies, which hinder job performance and reinforce employment barriers. A contributing factor to these persistent perceptions is that employers may view BLV employees as less capable due to the use of inaccessible workplace technologies. These technologies not only hinder BLV individuals' job performance but also reinforce barriers to effective employment.

3 Survey Methodology and Findings

We designed an online survey instrument to collect data about the analysis and visualization practices of BLV professionals. To ground our research in real-world experiences, we consulted a panel of four blind professionals with advanced degrees who regularly conduct data analysis. They advised us to explore the broader conceptual knowledge of data analysis and understand personal accessibility workarounds and challenges. Our panel explained that BLV students can stay in K-12 until age 22, potentially entering the workforce later than their sighted peers. We developed a survey to explore the challenges, workarounds, and experiences of data analysis among BLV individuals, making adjustments based on our panel's recommendations to ensure inclusivity. We developed survey questions focusing on demographics, assistive technology, and data analysis tools; making adjustments based on our panel's recommendations to ensure inclusivity. Given the broad scope of data analysis and visualization, we included statistical, evidence, qualitative, geographic, marking, and free-form analysis types (as recommended by our panel).

We screened participants based on these criteria: *(1) adults 21+, (2) some degree of blindness, (3) currently employed, and (4) professional experience in data analysis*. We sent survey invitations via listservs for blind professionals (e.g., National Federation of the Blind) and AccessComputing. The survey was hosted on Qualtrics and underwent accessibility checks with a screen reader. Our panel recommended that we broadly understand the types of data analyses performed by BLV individuals, and also the varying levels of disability. In our work, we adopt a social model of disability [13], and wanted our participants to self-report their lived-experiences and identities as analysts (as recommended by our panel). Through our screening questions (see supplementary material), we were able to collect data on a broad list of data analysis types (e.g., text analysis) and workflows; allowing us to screen our participants for the longer survey. We received 2,000 responses within 48 hours, likely boosted by a social media post ("freegiftcard") that we were not involved with, leading to many fraudulent entries. To address this, we revised the protocol, added open-ended screening questions, and warned about fraud consequences. After consulting our Institutional Review Board, we increased outreach through local NFB chapters, excluded multiple submissions from single IPs, and filtered out inconsistent responses. Two researchers reviewed open-ended responses and invited 47 participants to the main survey, eliminating fraudulent and outlier responses to yield 28 valid responses. Given the potential for fraudulent responses, we took a very conservative and careful approach. Screened participants received a $10 gift card for completing the main survey. We used descriptive methods for fixed-response data and deductive thematic analysis for open-ended responses, starting with initial codes and adding emergent codes.

Our participants self-identified themselves with diverse degrees of visual impairment: 8 were legally blind, 7 visually impaired, 5 with low-vision, 3 with light perception only, and 5 with no light perception. Eight had congenital vision loss, 6 began losing vision between 6 months to 10 years, and 16 experienced vision loss after the age of 10. Perceptions of impairment vary among BLV individuals, as Massof notes [15], are often influenced by whether individuals identify with having low-vision or blindness, affecting their use of assistive technologies and handling of daily challenges. Our survey offered varied response options to accommodate such personal blindness perspectives. As described by our Blind co-author: legal blindness definitions can vary across countries; and from an individual's perspective, a person who is legally blind may or may not have light perception. Some individuals with some light perception, or other visual impairments may choose to identify as Blind or Low-vision. For the sake of data analysis, we have combined the categories of 'no light perception', 'legally blind', and 'Blind' into 'Blind'; and combined 'light perception', 'visually impaired', and 'low-vision' into 'Low-vision'. This resulted in our data having responses from **13 Blind**, and **15 Low-vision** individuals (indicated by SurveyID-B/SurveyID-LV in our quotes).

All participants had at least a high school diploma, with 18 holding bachelor's degrees, 6 master's degrees, and 2 doctorates. Professionally, they worked as data or business analysts, and in roles like operations manager, accessibility consultant, and research staff; indicating broad engagement with data analysis and visualization. Most participants had at least 2 years of programming experience, with 15 having 5-10 years, and at least 10 had experience in web, mobile, desktop development, or data science.

3.1 Data Analysis Goals, Types, and Tools

Open-ended survey responses indicate that individuals conduct a variety of analyses, ranging from descriptive to predictive, and their data analysis goals include steps like data cleaning, data manipulation through querying, and analysis using both visualization and non-visual statistical methods. Participants worked on tasks such as data collection through surveys or focus groups, identifying trends, patterns, and other statistical relationships, and were often responsible for database management, from simple spreadsheet maintenance to manipulating and querying data, as well as visualizing data. Tool use was widespread and diverse, commonly involving spreadsheet/tabular data analysis using Excel, Python, R, SAS, and other tools depending on the analysis task. *S10-B*, a JAWS screen-reader user, used SAS for analysis, along with Excel for data manipulation: "*I actually use SAS for all 'real' statistical analysis, but find that it often displays/reads better with Jaws in Excel, so I often copy from SAS to Excel. I also use Excel/CSV for organizing, cleaning and organizing data prior to importing into SAS.*"

Most participants used assistive technology like screen readers and magnification to access data and charts, listing devices such as screen readers, tactile graphics, audio graphs, magnifiers, and Braille keyboards. They also benefited from predictive text *(S28-B)* and screen sharing with sighted colleagues *(S3-B)*, using Zoom features for both data visualizations and tabular views like tables and spreadsheets. The use of screen readers for visualizations suggests access to alt-text, captions, or advanced screen reader features such as auto-captioning or OCR (e.g., JAWS). Oftentimes managing data and analyzing data involves collaboration with other individuals. *S6-B* described the various actors involved as follows: "*Currently I determine the type of information collected and then I analyze it from a team of outreach consultants that work with local school districts, cooperative regions, parents, etc., concerning the services we provide.*"

3.2 Collaboration Practices

Consistent with findings from prior work [2], most participants collaborate with sighted individuals as part of their analysis workflow, though the goals varied—sometimes after completing their tasks independently, sometimes during the analysis process. Collaboration was not always for accessibility purposes, as *S6-B* noted: "*Yes, but not for accessibility, more interpretation of results.*" Sighted colleagues often helped with visual tasks such as creating charts and providing feedback, acting as visualization authors by taking summarized data and creating visual presentations (S12-B). Participants appreciated feedback on visual aesthetics to ensure reports were *(S1-B; no light perception)* "*formatted in a visual, pleasing manner.*". This quote from *S8-LV* illustrates how the participants may work with colleagues, but take ownership of an analytical task: "*Typically my analysis is independent. I will often send graphs or summaries to sighted individuals, but that is not really part of my workflow. I like to get feedback from them on how the graph looks aesthetically and if anything needs to be improved.*".

While collaboration was viewed positively, participants also expressed a desire for independence, with *(S9-LV)* stating, "*sometimes I feel like [an] annoyance for needing help and would like to be independent.*" Accessibility issues in the analytical tools used by BLV users often required assistance from sighted colleagues, which would not have been necessary otherwise. *S10-B* explained how layout and visual aesthetics that sighted individuals rely on could introduce accessibility issues during non-visual access: '*I find that sighted people using Excel like to leave blank columns or rows for better visual layout, which sucks using JAWS and can mess up data analysis. So I am constantly cautioning against merged cells or blank rows or columns. Also, I have discovered that with text entries, JAWS may read the entire contents of a cell but visually much is cut off, so this causes confusion between sighted and blind persons.*"

3.3 Authoring Data Visualizations

Participants' goals for creating data visualizations focused on clear and effective communication, improved data accessibility, and elements like labels, color use, and visual structure complexity. They aimed to present data in an understandable format for colleagues and clients, including BLV users; preferred tools integrated with assistive technology; used Tableau, Power BI, and Excel; and consulted sighted colleagues for assistance. Data communication goals help with choosing relevant chart types: *(S11-B; legally blind)* "*All depends on the data and the story you are trying to tell with that data when it comes to choosing the various chart types. Building test charts with a subset of data to experiment is helpful.*" Choice of charts are governed by the data, and visualization goals: *(S5-LV)* "*There is not one or two types of data visualization that are more helpful to me than others.* In general, common bar charts, pie charts, and line charts were most popular. Visualizations are hard to create when tools are inaccessible, or when data is complex *(S19-B; legally blind)*: "*The more complex a visualization is, the more difficult it can be for people with low vision to understand. For example, when I was working on a project to visualize data from different sensors, I used only one type of chart, the bar chart, and kept the number of bars in each chart to around four or five. This made it easier for me to see how much each sensor was contributing to the total amount of data being collected.*" Visualizations that offer a clear linear path of data, or comprehensive overviews were preferred. *S1-B* mentioned the difficulty in being confident about colleagues' visualization work, especially without being able to independently verify the representation: "*I would say the greatest challenge is not being 100% confident in the ability of my colleagues to render the information visually. I couldn't double check on my own.*"

3.4 Accessible Visualization Practices and Challenges

BLV individuals developed various strategies to access data visualizations, often relying on existing technologies or human assistance, and employing alternative, more accessible means such as tactile representations, alt-text, or other sensory methods. *S1-B* mentioned, "*asking questions, using AI, and finding alternative means of representing the data [in tactile form] worked well.*" Some individuals manually adjust data presentations to better suit their needs, including enlarging images or altering colors and fonts to enhance readability. "*I've copied many graphs into PowerPoint and enlarged them to fill a slide," S7-B; legally blind* explained. Tools that adjust the display settings like magnification, contrast, and color settings are crucial for those with low vision: *(S5-LV)* "*screen enlargement, contrast tools, magnifiers have been helpful.*" Accessible color palettes and comprehensive text descriptions aid those with color blindness or low vision: *(S11-B; legally blind)* "*General design principles make a big difference. Keeping in mind color palettes that are usable by individuals with color blindness and designing dashboards with good alternative text to be used by screen readers.*" Some participants revert to purely statistical data analysis techniques, or other non-visual methods to extract necessary information: *(S15-LV)* "*When data visualization is not accessible, I will try to use other data analysis methods, such as statistical analysis, data mining, etc.*" Though not always effective, *sonification*, which converts data points into sound, can be beneficial for understanding simpler data relationships: *(S8-LV)* "*I tried sonification, but that did not work for me. The sound of the data was not interpretable to me, except with very simple linear relationships.*"

BLV users have personal preferences for alternate sensory modalities: "*I prefer them to be some sort of a tactile representation, but if I have to hear the audio, I prefer them to be different sounds to represent different lines on the chart.*"*(S5-LV)*. Preparing and transforming data into a format that can be visualized was challenging: *(S21-LV)* "*When creating data visualizations, I faced two main challenges. First, I had to figure out how to get the data into a format that could be visualized. This meant ingesting large amounts of raw data and then transforming it into something usable for analysis. Second, I had to create a visual representation that made sense and was easily understood by others.*" Perceiving and interpreting the overview of a chart was challenging: *(S8-LV)* "*The largest challenge is getting a view of the entire graph at once (i.e., to understand the relationships between data points). I took a statistics class that required interpreting whether certain assumptions held based on the shape of the graph, and this was very challenging. This is where I learned the method of using a preview image.*"

4 Discussion and Conclusion

Our study findings add to the growing literature [6, 23, 24] on the lived data visualization experiences of BLV individuals. Our data, from both Blind (legally blind; no light perception; blind), and low-vision (visually impaired; low-vision; light perception) demonstrates ways in which a person's abilities, impairments, and personal experiences influences the preferred workarounds such as magnification, screen-readers, multimodal approaches, and dependency on colleagues, to accessibility challenges at different stages of data analysis (data wrangling, analysis, and presentation). We find that Blind individuals needed to create visual data representations (visualizations and reports) for the sake of their sighted colleagues. While magnification and collaboration were most observed accessibility solutions for Low-Vision individuals, a few participants (e.g., S8-LV) also tried multimodal approaches such as sonification. Considering the breadth of challenges for individuals the spectrum of blindness, we believe that finding solutions for specific data analysis tasks, making data science education accessible [19], and focusing future work on data science and analytical tasks in collaborative professional settings can lead to more "born accessible" technology.

BLV professionals face pervasive accessibility challenges in data science due to the lack of implementation of accessibility guidelines (e.g., WCAG 2.2) in tooling solutions such as notebooks [18]. We found ambivalent views on multimodal accessibility options like sonification; while also finding the utility of traditional textual and tactile forms [6]. Learning to use alternate forms can be challenging, but their potential ought not to be disregard prematurely. Combining modalities such as sound, touch, and speech to carry larger information bandwidths [20] can be advantageous. Future work must continue to explore efficient alternative to textual representations; particularly as many BLV professionals may not have experienced optimally designed sonification systems, which could offer a more intuitive understanding of data when well-executed [3, 21, 22]. As recommended by Potluri et al. [18] and as seen in our data, there is a need to adapt data artifacts such as charts, reports, and data-rich notebooks to work with assistive technology such as screen-readers and magnifiers. We recommend finding solutions in which data artifacts can be easily translated to be equal and accessible non-visual data representations [24]. Such methods can ensure that current data-rich environments can be accessed through individual or combined multimodal approaches such as sonification, refreshable braille displays, refreshable tactile displays (e.g., Graphiti and Monarch).

Our findings suggest an immediate need to create systems that enable BLV individuals, whether they are programmers or GUI users, to author visualizations independently [26]. By developing tools that are inherently accessible ("born accessible" [10]), we can shift the narrative from dependency to autonomy, allowing collaboration with sighted colleagues to stem from a desire for enhanced productivity [4] rather than a necessity due to inaccessible practices. We wish to conclude by discussing our future research direction: we want to conduct contextual inquiries with our survey participants to gather nuanced insights into the daily challenges and successes. Furthermore, we also intend to contribute to the effort for more inclusive visualization authoring for BLV workers.

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