Enabling Tabular Data Exploration for Blind and Low-Vision Users

Yanan Wang
yanan@cs.wisc.edu
Department of Computer Sciences,
University of Wisconsin-Madison
Madison, Wisconsin, USA

Arjun Srinivasan
arjun.srinivasan.10@gmail.com
Databricks, Inc.
Seattle, Washington, USA

Yea-Seul Kim
yeaseul.kim@cs.wisc.edu
Department of Computer Sciences,
University of Wisconsin-Madison
Madison, Wisconsin, USA

ABSTRACT

In a data-driven society, being able to examine data on one's own terms is crucial for various aspects of well-being. However, current data exploration paradigms, such as Exploratory Data Analysis (EDA), heavily rely on visualizations to unveil patterns and insights. This visual-centric approach poses significant challenges for blind and low-vision (BLV) individuals. To address this gap, we built a prototype that supports non-visual data exploration and conducted an observational user study involving 18 BLV participants. Participants were asked to conduct various analytical tasks, as well as free exploration of provided datasets. The study findings provide insights into the factors influencing inefficient data exploration and characterizations of BLV participants' analytical behaviors. We conclude by highlighting future avenues of research for the design of data exploration tools for BLV users.

CCS CONCEPTS

• **Human-centered computing** → **Interaction techniques**; **Empirical studies in HCI**; **Accessibility**.

KEYWORDS

data accessibility, data table

ACM Reference Format:
Yanan Wang, Arjun Srinivasan, and Yea-Seul Kim. 2024. Enabling Tabular Data Exploration for Blind and Low-Vision Users. In *Designing Interactive Systems Conference (DIS '24), July 01–05, 2024, IT University of Copenhagen, Denmark.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3643834.3661609

1 INTRODUCTION

Being able to investigate data on one's terms is critical for gaining a deeper understanding of the underlying phenomenon and making informed decisions. This empowers individuals to explore intricate patterns and extract information tailored to their specific information needs, leading to more effective problem-solving and knowledge discovery. This autonomy in data exploration is often facilitated by methodologies such as Exploratory Data Analysis (EDA), which is a well-established framework that assists users in identifying the questions they want to ask the data, creating meaningful representations, and inspecting data to form answers [6, 39, 55, 56]. EDA maximally utilizes visualization throughout the process to support viewers' cognitive processes during exploration. Indeed, visualizations are powerful interventions that summarize data and surface any emerging patterns, acting as a bridge between raw data and human cognition. Data exploration tools and practices have recognized the benefit of visualization, making it an integral part of data exploration.

However, this approach poses significant challenges for blind and low-vision (BLV) individuals. While accessibility features and efforts to make data tools screen reader-compatible offer some level of "access," inherent limitations exist as visualizations are fundamental to the EDA process. The absence of a user-suitable system also influences the formation of an established user base that can comfortably use the tools, discouraging further research into BLV individuals' analytical behaviors and cognitive processes that emerge while exploring data.

Our work began by asking how we could enable a similar depth of data exploration for BLV users who cannot rely on their visual perception. As a first step, we built a prototype that focuses on data exploration in a non-visual way to observe BLV users' analytical behaviors and investigate the needs and preferences of BLV users when exploring data. In the prototype, we employ interactive *data tables* to support data exploration, as prior work indicates that many BLV individuals interact with them frequently and fluently [53]. Through an observational user study with 18 BLV users using the prototype, we observed that participants performed a breadth of analytical tasks, including filtering, inferring correlations between variables, and deriving aggregate statistics for comparing data categories, among others. We also analyzed the sequence of interactions taken by the participants, providing insight into factors that influence inefficient data exploration.

We found that the accuracy of analytical tasks was influenced by both the complexity of the task and the number of variables involved in analytical tasks. Furthermore, participants exhibited more diverse interaction styles as the complexity increased. In free exploration, participants performed tasks such as gaining an overview, finding statistics, making comparisons, and inferring correlations, aligning with previous findings that sighted users typically engage in similar activities.

Through our exploration, we made several contributions. First, we conducted a formative user study to inform prototype development and reported findings around BLV participants' prior experience with data and potential challenges raised during data

DIS '24, July 01–05, 2024, IT University of Copenhagen, Denmark

ACM ISBN 979-8-4007-0583-0/24/07
https://doi.org/10.1145/3643834.3661609

exploration. Based on the formative study and prior work, we implemented a prototype that enables BLV users to explore data with keyboard interaction, utilizing data tables. Using the prototype, we ran an observational user study and characterized participants' analytical behaviors and interactions. Lastly, through the analysis of the user study, we identified avenues of future research to inform the design of data exploration system for BLV users.

2 FORMATIVE STUDY: UNDERSTANDING DATA EXPLORATION NEEDS

As a first step, we conducted a contextual inquiry with a follow-up interview with BLV individuals. Our primary goal was to 1) ensure the needs of data exploration 2) identify the challenges that BLV individuals have while exploring datasets with basic data tables, and 3) learn about the ideal technologies to support data exploration. The recent findings from a screen reader user survey by WebAIM [54] showed that 40.2% of participants use screen readers solely on desktop/laptop computers, while 49.5% use them across both mobile/tablet and desktop/laptop platforms, with only 10.2% exclusively employing screen readers on mobile/tablet devices. To maximize the impact of our work, we focused on supporting data exploration on computers.

2.1 Participants & Study Stimuli

We recruited participants through mailing lists of organizations hosting BLV people. The recruitment criteria were 1) at least 18 years old, 2) legally blind, and 3) screen reader users. We recruited participants until the findings were saturated on challenges they encountered and the suggested features, resulting in a total of six participants. The participants' ages ranged from 25 to 64 years old (M=40, SD=14.8). Participants were asked to use desktop computers or laptops to join the study. The sessions were conducted via Zoom, and each session lasted about an hour on average. Participants were compensated for their time with a $25 gift card. Upon interviewing 6 participants, we observed recurring themes in their behaviors without encountering new relevant insights to our research questions. As a result, we stopped further recruitment.

We prepared two web HTML tables of moderate complexity (i.e., ~500 rows and ~10 columns), one with worldwide COVID-19 case data (500 rows and 10 columns) and one with US housing data (500 rows and 13 columns). Four participants (P1, P4, P5, P6) chose the COVID-19 case data and two participants (P2, P3) chose the housing data to explore.

2.2 Procedure & Analysis

The study session comprised three parts. First, we asked participants about their general experience with data. Next, participants were instructed to navigate a dataset with their preferred assistive technologies. Before the exploration, we asked participants to share the screen so that researchers could observe their interactions. While exploring the dataset, participants were encouraged to think aloud to describe their thoughts and actions and to share when they had difficulty understanding or navigating the table. Also, we encouraged participants to share aspects of the dataset that they would want to know more about. Lastly, after exploring the dataset, participants were asked to share their opinions on ideal assistive technologies and systems for data exploration.

All sessions were recorded and transcribed. With the transcripts, we conducted a thematic analysis [9] to surface patterns of participants' experiences and preferences. One researcher created a codebook that could encompass the emerging themes and edited them iteratively as coded. Once the codebook is finalized through this iterative process, the researcher re-applied them to all transcripts to finalize the codes and corresponding quotes. The final codebook contains four themes (tasks, features, challenges, modalities) and 62 codes.

2.3 Results

2.3.1 *Prior Experience with Data.*

When we asked how often they encountered data tables online, three participants answered "More than once a week, " and two participants answered "Once a week." One participant answered that they encountered them fewer than once a month. P1 often reads the table on a sport-related website to know which team is predicted to win. P1 also shared they read the table on a relevant website when data-driven events happen: "The primary election that happened in June for the New York state. I went on the website." Several participants (P2-P4, P6) mentioned that financial data is reviewed most frequently by them. P4 shared, "For example, for keeping track of finances. Having numbers there." P2 used data tables extensively when they sold their house. "On the table, it had a representation of all the homes that sold in that area within the year." Some use data tables in professional settings (P3, P5). P5 said that they "look at responses to surveys, so large kind of national dataset surveys." P3 also shared they reviewed some spreadsheets from their nonprofit.

2.3.2 *Data Exploration Tasks.*

With the basic table, participants attempted to carry out various analytical tasks [3] to explore data. In the initial stage of the exploration, all participants wished to get an overview/trend of the dataset. We observed that the trends participants wished to review could be at the level of the table structure, datasets, or a data variable. For example, P3 shared "how I start typically is by knowing how many rows and columns, and then I look at the headings," whereas P2 specified, "First, [what I want to know] is the trend going up or is it going down, is it appreciating or is it depreciating?"

On many occasions, participants attempted to understand the summary statistics of a data attribute. For example, we observed that P1 tried to calculate the total number of COVID-related deaths across all countries by going through all cells. After that, they wanted to separate the deaths by country: "I would want to know what was the total number of deaths for this country." While P2 explored the housing dataset, they hoped to know more about the average of data variables. For example, "you could calculate the average price that you could ask for?" P5 also asked the researcher multiple times "do you know what's the average?"

Many participants attempted to gain insights into a subset of data. P1 shared "I'm trying to find Germany, but I have to go through all the rows here." P6 also noted "What are the numbers for July? So, kind of wish to have the July stats for all five countries." Sometimes, desirable filtering actions involve inference from one or more variables. For example, P2 mentioned "Virginia (filtering with variable

PID	Age	Gender	Edu.	Occupation	Diagnosis	Onset Age	Screen Reader	Frequency encountering data tables
P1	38	Male	M.S.	Educator	Pseudo-cerebral brain tumor leading to total blindness	7	JAWS, NVDA	Once or twice a week
P2	36	Male	A.A.	Accessibility analyst	Totally blind	19	JAWS	More than once a week
P3	27	Male	J.D.	Attorney	Retinopathy of prematurity, Stage 5.	1	JAWS	More than once a week
P4	64	Female	B.A.	Formerly Software Developer	Rod-Cone Dystrophy	56	JAWS	Once or twice a week
P5	50	Male	Ph.D.	Engineer	RP / CRD	35	JAWS	More than once a week
P6	25	Male	B.A.	Paralegal	Cateract gluocama	1	JAWS	Fewer than once a month

Table 1: Demographics of participants for formative study. Pid=Participant ID. Edu=Education (A.A.=Associate in Arts, J.D.=Juris Doctor, B.A.=Bachelors of Arts, M.S.=Masters of Sciences, Ph.D.=Doctor of Philosophy.)

#1 state) right here at the bottom. Its economy (variable #2 economy) is at 82. What was last year (variable #3 year)?" Indeed, many participants were explicitly interested in the relationship between two or more variables. P3 shared "Where's the best place for me to live (variable #1 state)? I like cool weather (variable #2 temperature) and good infrastructure (variable #2 infra score).

2.3.3 Challenges Arise During Data Exploration. The difficulties seem to stem from the size of the table mostly. Participants expressed frustration with how large the dataset is and attempted to locate themselves within the table when they felt lost. While P3 navigated down to scan all the rows, they shared "Woo this is really big." P1 shared the same sentiment and suggested having the ability to make a small table on demand to facilitate exploration: "The system should be able to pull all of the data together for that particular day for each country on the table. [...] They should be able to give me a simpler table for me to look at it rather than looking at the whole table."

Reference information like unit or column names, which are easily glanceable to sighted users, poses challenges for participants. P5 mentioned "I need to go back up and check because that's really typical that tables will be presented in units in thousands in quotation marks." P2 also expressed that "I sometimes have difficulties remembering the name of the row and column that I'm in." In terms of referencing column names, we observed participants leverage a screen reader's feature to overcome. P1 noted that "If you left arrow and come back then the right arrow and go back to where you were, it will announce which column it is you're reading. So sometimes when you suddenly forget where you are, just go rightward or leftward." We observed that P6 also exhibited the same behaviors, but they expressed frustration: "I would physically have to move, and then if I move, I lose touch with that value." P2 demonstrated how they could lose their position at a table if they wanted to see any other information presented outside of the table (e.g., unit, description of the table) while exploring the data. "So if I had to navigate off of this, for instance, where I'm at. Education row 81, and if I navigate it to the top of the page, out of the table heading. See, if I move back to the table, I can easily forget where I was."

2.3.4 Platform and Technologies. All participants were excited about the idea of online data exploration tools. Some participants (P2, P4, P6) shared their enthusiasm specifically for enabling data-driven decision-making. For example, P2 shared "Just imagine the type of possibilities that it could possibly create for people with visual impairments. They would be able to compare data and look at all that information, and they'd be able to build trends." P5 mentioned that the existence of the tool will encourage them to be more attentive to data: "I would probably pay a lot more attention to data than I do currently because right now sometimes it can be really difficult to navigate a large table or as I was referring to previously with like New York Times article."

In terms of the platform, all participants echoed that a browser interface would be the best way to support it. P4 shared that specifically because no initial learning to start the operation: "use it immediately and requires no knowledge of." The majority of participants (P1, P2, P4-P6) emphasized the interface should be in a "separate window" or make it easier to locate themselves within a website while navigating other information beyond data tables. Also, two participants (P1, P2) highlighted the automated approach in inputting tables to start exploring. For example, P1 shared "I can just go into the application and type in this URL then should be able to pull up that URL and just open it that way."

3 PROTOTYPE: SCREEN READER-BASED TABULAR DATA EXPLORATION

In this section, we described a prototype designed to observe BLV users' analytical behaviors. Instead of using existing software designed for sighted people with complex features (e.g., MS Excel), a prototype tailored to BLV users with more focused functionalities enables us to make meaningful observations centered on analytical behaviors without concerns about usability.

3.1 Design Goals

To guide prototype design and implementation, we compiled three goals based on the formative study and prior work on analytical tasks, systems for data exploration (e.g., [1, 13, 18, 28, 29, 53, 55]), accessibility guidelines [1, 18] and other software supporting tabular data such as Microsoft Excel [31].

- **G1: Provide overviews at multiple levels:** Many participants wished the prototype to provide an overview of the table structure (e.g., the number of rows and columns), the dataset (e.g., how many variables and what are they), as well as individual variables (e.g., the number of data categories).
- **G2: Support analytical tasks involving multiple variables:** Analytical tasks like understanding correlations and computing derived values (e.g., total covid cases by country) involving two or more variables are common tasks supported in prior tools [28, 29, 55] and were also observed during our formative study. To this end, the prototype should enable screen reader users to perform such analytical tasks by providing approaches to effectively select and/or compare columns of interest. To achieve this goal, we envision implementing "pivot table, " a popular feature in Microsoft Excel [31]. However, instead of and drop interface designed for sighted people in MS Excel, we should streamline the interaction to allow us to focus on observing participants' analytical behaviors.
- **G3: Support basic data management operations:** Depending on the number of items in the dataset or users' task, navigating data tables can be tedious and impede analysis, as we observed in the formative study. To help users manage the data and aid focused analysis, the prototype should provide the ability to flexibly filter and sort the table using one or more data columns.
- **G4: Provide contextual guidance:** In Web Content Accessibility Guidelines (WCAG) [1], providing context-sensitive help is considered helpful. Prior work also highlights the importance of providing comprehensive guidance [13]. As current systems do not provide data exploration-focused operations during screen reader-based interaction with tables, users may be unfamiliar with the possible set of operations. To help users operate the tool and effectively explore their data, the prototype should make users aware of the possible set of actions at any time. Furthermore, to serve as effective "next steps," the list of possible actions should be contextualized to the current state of the table and the users' location within the table.
- **G5: Work in conjunction with default screen reader actions:** Our formative study highlights the need for smooth integration into users' own environments to lower the barrier of using tools. ARIA Authoring Practices Guide [18] also emphasized the importance of the ease of learning and remembering and avoiding conflicts with assistive technology.
  In designing shortcuts, we envision following another principle suggested by ARIA Authoring Practices Guide [18]: prescribing the shortcut to be "easy to learn and remember by using a mnemonic (e.g., Control + S for "Save") or following a logical or spacial pattern" and "avoiding and managing conflicts with key assignments used by an assistive technology, the browser, or the operating system." We envision using both numbers and letter keys to support users' interaction and selected letters with a specific focus on mnemonic relevance to the intended functions, and review the document about keyboard shortcuts for JAWS, NVDA, and VoiceOver to avoid conflicts.
  While supporting the data exploration-oriented goals (**G1**-**G4**), the prototype should also ensure that users can leverage the default screen reader-based table navigation experience (e.g., using built-in shortcuts) and do not have to learn or memorize a slew of new keyboard commands to operate the interface. We listed all the keys we used in the prototype in Table 2.

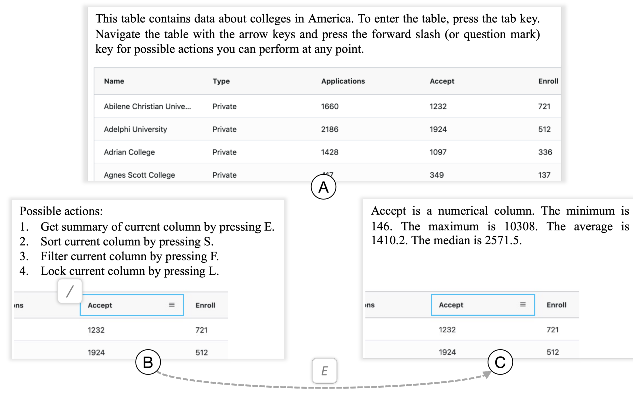

Figure 1: Interaction experience with the developed prototype. (A) The initial state when the table is loaded. The prototype lists basic instructions to use the table. (B) The contextual help menu is invoked from the column header. (C) The column summary action is invoked by pressing the 'E' key, resulting in the prototype providing the data type, range, mean, and median values for the *Accept* column.

3.2 User Experience & Implementation Details

Based on the derived goals, we designed a web-based prototype to help BLV users. All functions are implemented using JavaScript. We employed AG Grid [30] library for presenting the main table. AG Grid offers robust data storage capabilities by encapsulating data as objects and supports the feature "data type (e.g., categorical and numerical)", which makes it easy for the prototype to create meaningful descriptive statistics. The prototype keeps a trace of users' actions locally to inform the next action of the prototype, if necessary.

Below we describe user experience and implementation details of our prototype by key operations that operationalize the aforementioned design goals to support screen reader-based data exploration

Keys	Functions
Tab	Enter the table
Number keys	Apply the corresponding actions in the help menu
Arrow keys	Navigate cells
? or /	Provide contextual help menu
E	Get descriptive statistics about the current column
L	Locks/unlock the current column
M	Make pivot table/correlation
O	Go back to the origianl table and clear all changes
C	Change statistics in the pivot table
I	Reveal/hide the import table (upload or load from webpage) area
S	Sort the current column (cycles through ascending - >descending ->default).
F	Filter based on the current column (actions may vary based on the cell type of the current location)
Z	Clear all filters
X	Go back to the main table/last step

Table 2: A list of shortcuts used in the prototype and their functions

via a table. For consistency, we use a dataset of US colleges containing 500 rows and 12 columns, including 1 key, 3 categorical, and 7 numeric columns as a running example throughout this section.

3.2.1 Feature 1: Selecting (Locking) Columns. To support analytical tasks involving multiple columns (**G2**), the prototype provides a way to select/lock columns. Shortcut '`L`' is assigned to toggle between locking and unlocking a column (**G5**). For example, if users want to learn about the correlation between two columns, users can lock the two columns by pressing '`L`' on each column. Users can revert to the original state, where no column is selected, by pressing '`0`.' This basic unit of interactions is used in Feature 2 and Feature 3 to inform the prototype of the users' interest. It is used in Feature 4 to create a pivot table where we limit the number of locked columns to a maximum of three categorical and two numerical columns (a total of five variables) to ensure readability.

3.2.2 Feature 2: Invoking the Contextual Help Menu and Gaining an Overview of The Data. Figure 1A displays the initial state of the prototype upon loading a dataset. Specifically, the prototype provides a brief overview of the table's contents (**G1**) and states that users can enter the table to navigate it (**G4**). The paragraph shown in Figure 1A is rendered within an HTML division tag `<div>` whose `aria-live` property is set to 'polite' so it is also read out via the screen reader without interrupting its default narration (**G5**).

Once in the table, users can press the arrow keys to iterate through the table columns as in standard HTML tables. During this exploration, pressing the '`/`' forward slash key (cross-listed with the '`?`' question mark key) at any point generates a list of all possible actions in that state (**G4**). To make the help menu intelligible, the prototype checks the current position (header cell or value cell, data type of the column), the status of the current columns (whether locked or not), and the information of the currently locked columns. The full condition of combinatorial rules is shown in Table 3. For example, when users are on the header cell

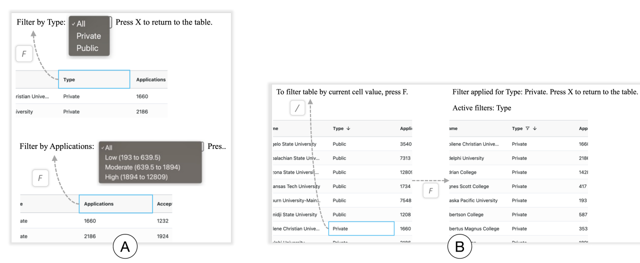

Figure 2: Data filtering workflows in the prototype. (A) When filtering is invoked from column headers, the prototype presents dropdown menus to select values to filter by. (B) When invoked from individual cells, the cell values are implicitly used to filter the table.

without having any locking columns, the help menu presents four actions for users to choose their next actions from (Figure 1B): 1) hearing descriptive statistics about the column, 2) sorting the table by the column's values, 3) filtering the table by the column's values, and 4) locking the column as context for subsequent actions.

To gain an overview of the different columns (**G1**), users can press '`1`' or the '`E`' key (**G5**) to hear the column's data type (categorical or numeric) as well as summary statistics such as the number of data categories and data distributions (Figure 1C). To create summary statistics for a categorical column, the prototype counts the number of categories and the number of rows for each category and computes the top 3 categories. For a numerical column, the prototype calculates the minimum, maximum, average, and median of the values in the column. Then, the prototype creates summary statistics text by combining the information based on the column's data type.

3.2.3 Feature 3: Sorting and Filtering. For the sorting features, users can press '`S`' to trigger the action (**G3**). By default, the prototype

Current Position	Current Column		Existing Locked Columns	Help Info Type	Help Info Content
Cell Type	Data Type	Locked ?			
-	-	-	-	Summary	Get summary of current column by pressing E.
-	-	-	-	Sorting	Sort the current column by pressing S.
Header	-	-	-	Filtering	Filter current column by pressing F.
Value	-	-	-	Filtering	To filter by the current cell value, press F.
-	-	Y		Locking	Unlock current column by pressing L.
-	Categorical	N	# Categorical <3	Locking	Lock current column by pressing L.
-	Numerical	N	# Numerical <2	Locking	Lock current column by pressing L.
-	-	-	# Column >0	Relationship Info	You've locked categorical column(s) [column name(s)], numerical column(s) [column name(s)].
-	Categorical	Y	# Column >0	Relationship	Press M if you want to see a pivot table between them and [current column name].
-	Numerical	Y	# Numerical >0 # Categorical = 0	Relationship	Press M if you want to see the correlation between them and [current column name].
-	Numerical	Y	# Categorical >0 # Numerical = 0	Relationship	Press M if you want to see a pivot table between them and [current column name].
-	Numerical	Y	# Categorical >0 # Numerical >0	Relationship	Press M if you want to see the correlation and pivot table between them and [current column name].

Table 3: The generation rule for the intelligible help menu. (-) sign indicates the condition does not impact the generation of the specific help menu.

sorts columns in ascending order and subsequently cycles through other options of 'descending' followed by 'none' as users press 'S'.

There are two scenarios where users can trigger the filtering features (**G3**) by pressing 'F': in a column header and an individual cell. When filtering the table via the column headers the prototype presents a dropdown menu for users to choose the filter value (Figure 2A). The filtering values are created differently based on the type of columns. For categorical columns, all the categories in the column are populated. For numeric columns, the prototype bins the values into three range buckets (low, moderate, high) corresponding to the interquartile ranges since widgets like range sliders may be tedious for screen reader users to operate, needing them to hear each value as it increments.

When the filter is triggered while users are in a cell, the prototype considers the value of the cell as a filtering value. If there are no other matching values available in the column (the case of a numerical column), the prototype sets the filter to the quantile range the cell's value falls within for numeric columns.

After examining the filtered table, users can return to the same column header without filtering by pressing 'X' (**G5**).

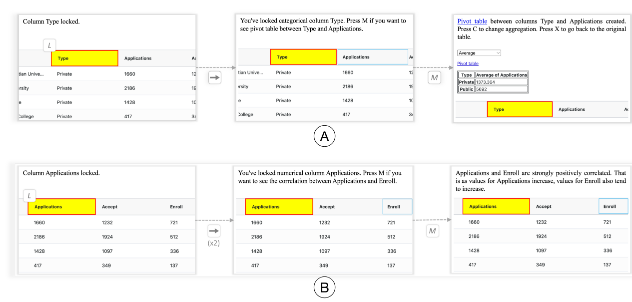

Figure 3: Analyzing a combination of columns. (A) Locking ('L') a categorical column and subsequently pressing 'M' on a numeric column creates a pivot table. (B) Locking a numeric column and pressing 'M' on a second numeric column computes the correlation between the two columns.

3.2.4 Feature 4: Computing Derived Values and Understanding Relationships Between Columns. The prototype offers a feature to create a pivot table to provide statistical information on one or more columns (**G2**). Consider the example workflow in Figure 3A where users first lock the categorical column *Type* (Figure 3A-left). As users navigate through other columns, the prototype now indicates that there is a locked column (**G4**) and the 'M' key can be used to create a pivot table with *Type* as the pivot column (Figure 3A-middle). Pressing the 'M' key results in the prototype creating a separate pivot table above the raw data table while also providing a dropdown to choose the aggregation for numerical columns in the pivot table (**G2**)(Figure 3A-right). At this stage, users can navigate the pivot table or adjust its aggregation using the dropdown or the shortcut key 'C' (**G2**), or revert to the original table by pressing the 'X' key. The possible statistic metrics the prototype supports calculating in the dropdown menu include average, minimum, maximum, median, sum, standard deviation, and count.

Alternatively, instead of locking *Type*, if one started by locking a numeric column (e.g., *Tuition*) when navigating through other numeric columns, the prototype presents an option to get the correlation between columns (as opposed to creating a pivot table), as shown in Figure 3B (**G2**).

To implement the pivot table, the prototype creates a new `<div>` and adds an `<table>` tag inside. Then, based on the sequence of the locked columns, the prototype creates a subset of rows for each combination of the categorical values in each column. Then, the prototype calculates the average value of the locked numerical column in each subset as default. If no numerical column is locked, the prototype calculates the count for each subset instead. Then, the prototype fills in the table with the calculated value. When users utilize the dropdown menu or go back to the original table and change the locked columns, the prototype updates the information within the table.

To detect the correlation between numeric columns (**G2**), the prototype computes the Pearson's correlation coefficient (r) and states that there is a strong positive correlation if $r \geq 0.75$; a moderate positive correlation if $0.5 \leq r \leq 0.75$; a strong negative correlation if $r \leq -0.75$; a moderate negative correlation if $-0.75 \leq r \leq -0.5$; and no notable correlation if $|r| \leq 0.5$.

3.2.5 Feature 5: Uploading or Extracting Data. Users can press 'I' to trigger an importing interface where they can upload their own CSV file or paste a link to a webpage that contains a table in an *<table>* tag (**G5**). To extract tables from a webpage, the prototype analyzes the structure of the tags (i.e. relationship among HTML tags including *<tr>*, *<th>*, *<td>* etc.) in the *<table>* and extracts the table and save them as a JSON array (which is the format that AG Grid expected). Then, the prototype judges the data type of each column by checking if all the values in the column are numerical or not, creates metadata for the table, and presents it in the main table area with the formatted data. Similarly, to import a CSV file into the prototype, it creates a JSON array to contain the data, create metadata for the table, and fill in the main table area with the formatted data.

4 OBSERVATIONAL USER STUDY: HOW DO BLV USERS EXPLORE DATA?

Using the prototype, we conducted a user study to observe how BLV participants perform data exploration, characterize their behaviors, and derive technical requirements for an ultimate data exploration tool for BLV users.

4.1 Participants

We solicited study participants through the same mailing list, and we recruited participants for the formative study with the same recruitment criteria. We recruited 18 BLV participants (9 females, 8 males, 1 non-binary, self-identified). The age of the participants varied between 21 and 52 years, with a mean age of 38.2 years and a standard deviation of 9.47. There was no overlap between the participants in the formative study and this study. The interviews were carried out using Zoom, lasting approximately 80.0 minutes (M=80.0, SD=13.79). Participants were compensated with a $25 gift card per hour of their participation.

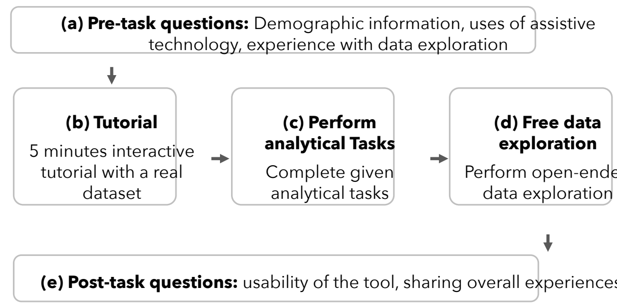

Figure 4: The study procedure.

4.2 Study Procedure

Figure 4 shows the overall procedure of the study. First, participants were asked to answer pre-task questions to collect demographic information and understand their familiarity with assistive technology and their prior experience with data exploration (Fig 4(a)). After this stage, participants were asked to share their screens so that researchers could observe their interactions. Following this, a 5-minute interactive tutorial session was conducted using a real dataset to familiarize participants with the prototype (Fig 4(b)). Specifically, we prepared a detailed walk-through of each function and asked participants to execute each function on their screen, one function at a time. For each function, participants were instructed to apply the function to the dataset by pressing the assigned shortcut. They were also requested to share the result of the action with us so that we could verify whether participants were able to parse the result correctly. Then, participants were instructed to perform specific analytical tasks using the prototype (Fig 4(c)). They were asked to open another page with a different dataset loaded. We would give them two minutes to familiarize themselves with the structure of the dataset. Then, we would ask them analytical questions. We prepared the tasks based on a well-established taxonomy of classifying analytical tasks [3]. Participants were expected to answer each question by exploring the dataset using the prototype. The detailed stimuli are described in Section 4.3. Subsequently, participants were asked to freely explore another given dataset (Fig 4(d)). We did not give any step-by-step instructions but shared that participants should "learn" about the datasets by exploring them. While performing analytical tasks and free exploration, participants were asked to "think aloud" to share their thoughts and behaviors. Finally, we asked post-task questions to assess the usability of the prototype and to gather participants' thoughts on their experience (Fig 4(e)).

4.3 Study Stimuli

We prepared three datasets that had moderate complexity (i.e., ~500 rows and ~10 columns). We wished to select datasets for which an average person might possess a decent level of familiarity—having heard about the topic but not being overly familiar with individual values. We ensured to have at least 3 categorical variables to observe participants' behaviors on a faceting dataset by categorical variable. We used a dataset about coffee sales in the U.S. for the tutorial (Fig 4(b)), a dataset about the housing market in the U.S. for

PID	Age	Gender	Edu.	Occupation	Light Perception	Functional Vision	Onset Age	Screen Reader	Years Used
1	29	Female	B.S.	Student	Y	N	0	JAWS	5
2	48	Female	Ph.D.	Consultant	N	N	0	NVDA	20
3	36	Female	H.S.	Unemployed	Y	Y	0	JAWS, VoiceOver	12
4	29	Female	M.S.	FMLA Claims expert	Y	N	0	JAWS, NVDA	21
5	26	Male	B.S.	Paralegal/Law	Y	N	0	JAWS	8
6	29	Non-binary	H.S.	Student	N	N	0	JAWS	15
7	21	Male	H.S.	Student	Y	N	14	NVDA	4
8	33	Female	B.S.	Instructor	Y	N	0	JAWS	20
9	39	Male	H.S.	Accessiblity consultant	N	N	0	NVDA	2
10	50	Female	A.A.	Homemaker	Y	Y	16	JAWS	23
11	52	Female	M.S.	Retired	Y	N	9	JAWS	30
12	52	Female	B.S.	ESL Facilitator	Y	N	0	JAWS	38
13	43	Male	B.S.	Teacher	N	N	2	JAWS, NVDA	25
14	32	Male	H.S.	Student	Y	Y	0	VoiceOver	12
15	37	Male	A.S.	Accessiblity analyst	N	N	20	NVDA	16
16	40	Female	H.S.	Unemployed	Y	Y	0	NVDA	5
17	47	Male	P.S.	Student	N	N	4	JAWS, NVDA	38
18	44	Male	M.S.	coordinator	N	N	0	JAWS	21

Table 4: Demographics of participants for the observational study. Pid=Participant ID. Edu=Education (P.S.=Primary School, H.S.=High School, A.A.=Associate in Arts, A.S.=Associate in Sciences, B.S.=Bachelor of Sciences, M.S.=Masters of Sciences, Ph.D.=Doctor of Philosophy.)

analytical tasks (Fig 4(c)), and a dataset about college admissions for open-ended exploration

For the analytical task phase (Fig 4(c)), we prepared a set of questions based on the taxonomy of analytical tasks proposed by Amar et al. [3]. In generating questions, we aimed to vary 1) the number of the required steps in the prototype (task complexity) and 2) the number of variables involved in answering (number of variables) to observe diverse behaviors based on the complexity of tasks. We first formulated all possible questions to cover the taxonomy fully. For example, the question "What is the range of baths in all states?" was generated for the determining-range task and "What is the minimum housing price in Alaska?" for the finding-extreme task. Then, we calculated the number of required steps to answer the questions and the number of variables involved in each question. To quantify the task complexity, we first identified the shortest sequence to answer the question. Then we added 1 point when the sequence required any functions listed here: filter (F), sort (S), summary statistic (E), lock (L), make correlation (M), make pivot table (M), change statistic of a pivot table (C). To count cell navigation, we added 1 point if the participant had to go through less than 10 value cells (Short) and added 2 points if they had to go through more than 10 value cells (Long). In this session, we chose questions from the easy ones (i.e., low number of required steps, low number of variables involved) to more complex ones and tried to cover the task variety as much as possible. Since we limited the study duration to mitigate participants' fatigue, participants were asked to answer as many analytical questions as they could in 30 minutes. To avoid the bias caused by the order of the questions, we provide the questions to the participants in a random order.

4.4 Analysis

We analyzed the correctness and time of the responses to the analytical questions. More importantly, we analyzed the sequence that participants took to accomplish tasks by analyzing the interaction logs. For the qualitative analysis, we recorded and transcribed all sessions and conducted a thematic analysis [9]. To analyze participants' quotes shared during the study session, one researcher first coded all the content and created themes for them, which resulted in 12 themes and 161 codes. Then, the researcher analyzed the existing codes and content and re-coded some of them to merge similar codes. The final codebook resulted in 11 themes and 150 codes.

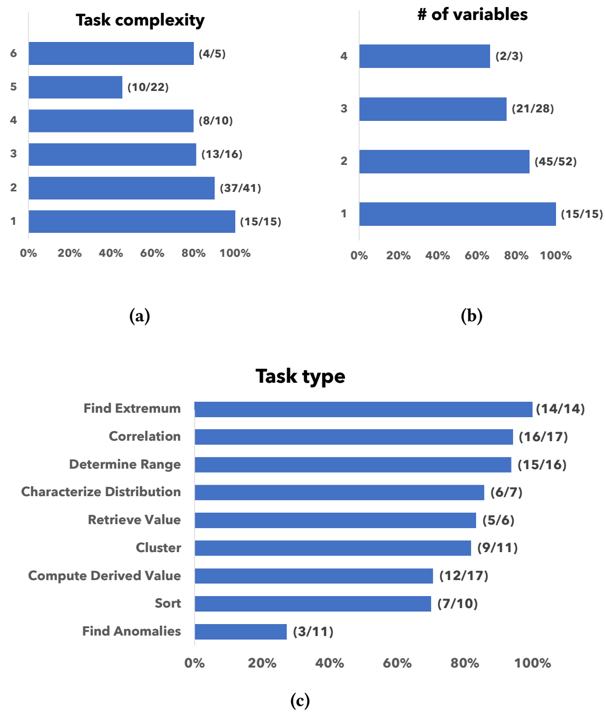

Figure 5: The accuracy of participants' analytical task performance (a) by task complexity, (b) by the number of variables, and (c) by task type. The numbers in the parenthesis are the number of questions correctly answered/the number of questions asked.

	Accuracy (%)		Response Time (s)	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Difficulty Level				
1	100.0%	0.00%	80.3	59.27
2	90.2%	16.14%	167.6	144.78
3	81.3%	32.57%	205.8	107.60
4	80.0%	42.16%	246.6	147.40
5	45.5%	48.06%	275.2	181.24
6	80.0%	44.72%	322.4	101.47
# of Variable				
1	100.0%	0.00%	120.9	87.85
2	86.5%	26.43%	184.7	146.31
3	78.6%	40.35%	286.5	168.61
4	66.7%	57.74%	242.0	112.66
Question Type				
Characterize Distribution	85.7%	37.80%	283.4	120.01
Cluster	81.8%	35.36%	130.5	96.20
Compute Derived Value	80.0%	44.72%	322.4	101.47
Correlation	94.1%	24.25%	136.8	63.80
Determine Range	93.8%	12.91%	79.0	57.51
difference	66.7%	49.24%	219.9	145.77
Find Anomalies	27.3%	46.71%	176.3	92.38
Find Extremum	100.0%	0.00%	265.1	192.22
Retrieve Value	83.3%	40.82%	122.8	97.78
Sort	70.0%	48.30%	385.4	199.06
Total	79.8%	18.39%	197.2	151.12

Table 5: The mean and standard deviation of participants' analytical task performance (accuracy and response time).

5 RESULTS

5.1 Part 1: How Do Participants Complete Analytical Tasks?

5.1.1 Accuracy & Response Time. On average, participants completed 6 analytical tasks (Sum=109, M=6.1, SD=1.55) in 30 minutes of duration. 12 out of 18 participants completed more than 6 tasks, whereas 2 participants completed 3 tasks, and four participants completed 4 tasks. Each task took around 200 seconds (M=200.8, SD=74.12). Fig. 5 shows participants' accuracy across the task complexity, the number of variables, and question types. Overall, as the task complexity and the number of variables involved increase, the participants' accuracy decreases (Fig 5a, Fig. 5b) and response time increases (Table 5). While participants completed most types of tasks accurately, the outlier identification task exhibited significantly lower accuracy rates (Fig 5c). We found that low accuracy on task complexity level 5 is associated with the anomaly identification task.

5.1.2 Sequence of Interaction to Accomplish Tasks. In figure 6, we illustrate the sequence of interactions taken by participants when engaging with tasks of varying levels of task complexity and the number of variables involved. We sampled a few questions that can represent our overall findings. As expected, with an increase in task complexity, participants tended to employ a broader array of approaches to accomplish the task. We observed the pivot tables (M) were more frequently used as the task involved more variables. As the task complexity increased, we found that participants made more traverses across cells (Long and short). While some sequences of interactions seem long, most of the participants conducted these tasks by chucking them into multiple small steps toward the final questions. Again, participants were able to utilize various hotkeys to complete these tasks, possibly thanks to the tutorial session as well as the help menu.

We identified a few recurring themes from which these divergent approaches seemingly stemmed.

- **How to apply a filter:** Some tasks required creating subsets of the data to examine a specific aspect within the subset. While the most efficient and common strategy would be to apply a filter on column headers and find the value of interest, some participants chose to apply a filter on a specific cell by navigating to the cell (e.g., the difference between Route 3-1 and Route 3-3, where instead of choosing "House" from the combo box, participants would go through the value cells in the *Type* column to find the cell that contains value "House" to do the filter; Similarly, Route 5-1 versus Route 5-2, etc.).

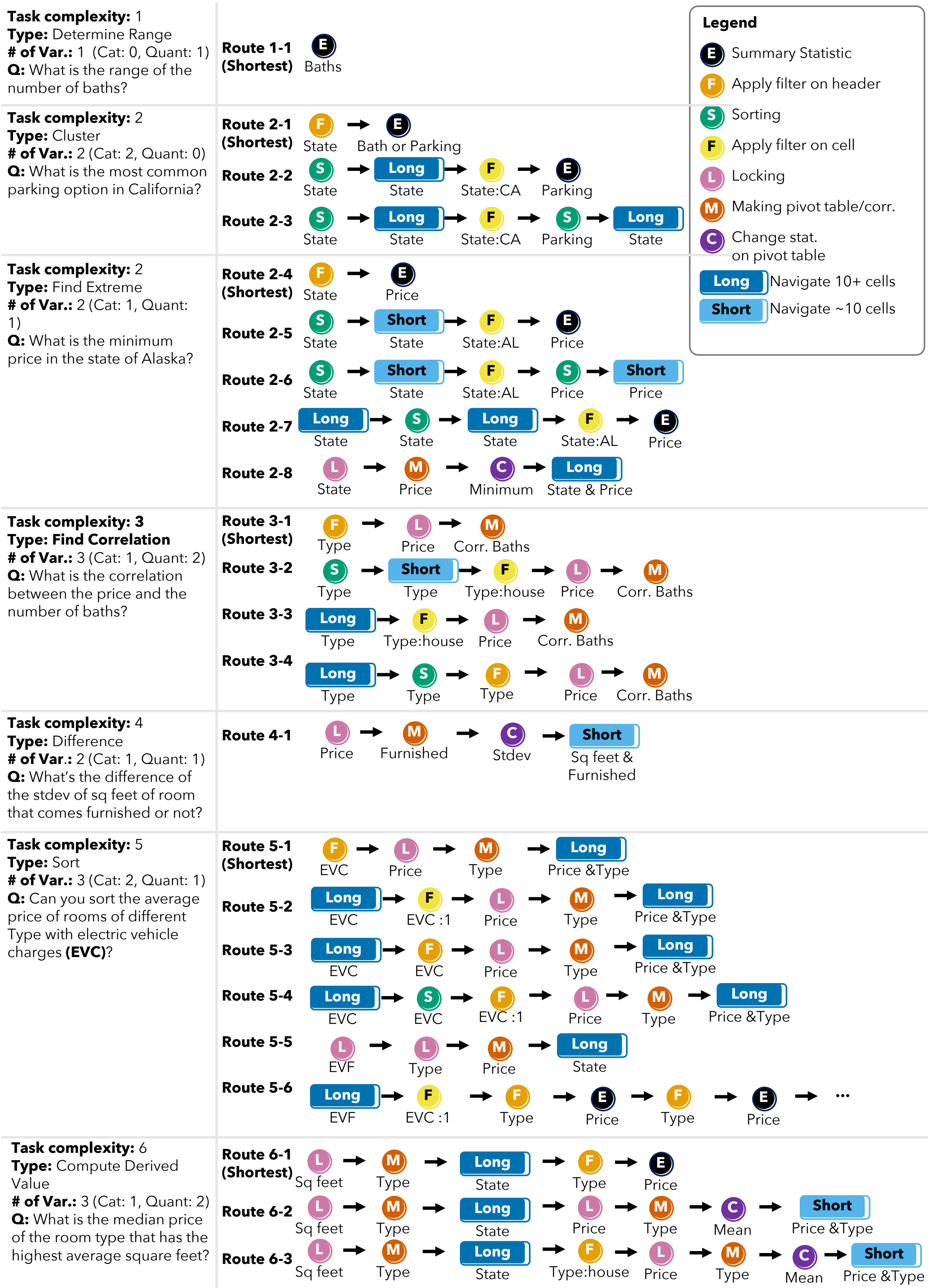

Figure 6: Sequences of interactions taken by participants when engaging with tasks of varying levels of task complexity.

- **Whether to use sorting function or not:** Sorting makes it easier to locate the value in mind as it follows an ascending or descending order. Not just extreme value that requires searching the top or the bottom of the column (e.g., the difference between Route 2-5 and Route 2-6, where instead of listening to the summary statistic of column *Price* to get the minimum price, some participants chose to sort the column and find the minimum value themselves), the sorted column help locate any values as the structure affords fast search through the ordered cells (e.g., the difference between Route 3-2 and Route 3-3, where with sort applied, participants are able to get to the value cell "House" with less movement). However, some participants were not utilizing the sorting functions when it could make their tasks more efficient. Instead, the participants navigate through in a natural order, looking for the target value by listening to individual values (e.g., Route 3-3). Moreover, without the sorting function applied, participants tended to miss the cell, especially when navigating quickly.
- **How to retrieve statistical values:** In many tasks, participants were required to find statistics of the variables. Despite the presence of summary statistics that provide basic details, participants sometimes used alternative routes. For example, some preferred to identify extreme values by sorting and going to the top or bottom (e.g., Route 2-6), while others constructed pivot tables and adjusted the pivot table's statistical metric to derive the minimum value (e.g., Route 2-8). As the cardinality of a categorical variable increased, pivot tables became increasingly advantageous when compared to filtering and summary statistics. However, certain participants relied extensively on a combination of filtering and summary statistics to perform tasks (e.g., Route 5-6) that could be efficiently addressed through the use of a single pivot table (e.g., Route 5-2) where P18 chose to manually find the average price of each room types by repeated filter and check the summary statistic. Some participants attempted to employ pivot tables for relatively straightforward tasks (e.g., Route 2-8), those that could be more efficiently accomplished using filters (e.g., Route 2-4) where a filter on column *State* to Alaska plus a summary statistic on column *Price* can solve the questions but P2 and P4 chose to make a pivot table to accomplish the task.

5.2 Part 2: What Did Participants Do In Free Exploration?

5.2.1 *Characterization of Data Exploration Tasks.*

Gain an overview of the dataset. All participants went through all column headers first to learn about the variables involved with the dataset. Participants achieved this task often by navigating through all the columns and applying the descriptive summary to learn the basic information of each column. As P1 shared "I think I understand the data frame here" after going through all the column headers. P15 explained "I'm just gonna explore, just to get familiar here with what my data points are." P5 also stated "I'm just looking at all these columns." In addition to learning about the column header, several participants (P5, P7, P10, P13, P16) also went through the first several rows to get a sense of the row information.

Find statistics (count, average, minimum, maximum, etc.). Some participants cared about the distribution of specific variables (P2, P3, P7, P11, P12). Participants achieved this task often by filtering and sorting the dataset, making pivot tables, and using descriptive summaries. P3 was interested in categorical column distribution and tried to find out the count of levels in a variable: "how many are private? How many are public?." P7 also wished to learn some basic statistics of a quantitative variable: "I just went on to enroll. For enrollment,[I am interested in] how many people in total."

Some investigated statistics in a subset (P2, P4, P7, P10 - P13, P17). For instance, P2 was interested in "average book cost in a public school" and P13 shared an interest in "enrollment in public schools." Participants also sought for extreme values of variables (P1 - P9, P12 - P14, P17, P18). For example, P1 shared an interest in knowing "which university has the maximum enrollment and minimum enrollment?" P2 also shared that "I want to see the highest one in book cost. Some participants calculated the extreme values when multiple variables were involved. P4 tried to find "the maximum full-time undergraduate under different student-faculty ratio types." P5 also examined the maximum, and minimum values by faceted by one categorical variable: "[maximum and minimum] values for the acceptance of public and private school."

The specific record also interests some participants (P10, P11, P16 - 18). As P16 stated "I kind of am just exploring a specific value." After finding extreme value, P18 further investigated the entire row of the corresponding college after knowing "Baldwin Wallace has the highest book cost" while P11 was interested in "Alaska Pacific University."

Making comparisons. Comparison was one of the most frequent goals that participants had while interacting with the dataset (P1, P3 - P5, P8 - P10, P14, P15, P17). Participants achieved this task often by applying filters and making pivot tables. Participants made different types of comparisons at different levels. Within a variable, participants made a comparison between categories (e.g., private vs. public) by aggregating numeric values across categories. For example, P1 and P3 investigated the tuition between public and private schools by locking the column *Type* and subsequently creating a pivot table using the column *Out of State Tuition.* P4 was interested in the maximum full-time undergraduate by "different student-faculty ratio." P5 examined the average, max, min, and standard deviation of "the acceptance rate between public and private schools."

Participants also compared the statistics across multiple columns. For example, P4 indicated that she wished to "compare [the statistics between] full-time undergraduate and part-time undergraduate." These comparisons were not limited to comparing the quantitative measure but also applied to categorical variables. P14 wished to "compare the graduation rate category at a public college versus a private college."

Infer the correlation between two variables. Correlation was another interesting aspect that participants wished to learn about (P1, P4, P5, P8, P9, P13 - P16, P18). Participants achieved this task using the lock feature illustrated in Figure 3B. P1 would like to see "a correlation between room and board and out-of-state tuition," while P5 tried to investigate "the correlation between application and the number of accept". While estimating the relationship between two variables, participants often noticed patterns that misaligned with their expectations. As P17 stated "That's ironic. Such high book cost and such low graduations."

5.3 Part 3: Other Qualitative Observations

When do participants envision exploring data? Participants shared several real-life scenarios that required data exploration. As a student, P14 mentioned it can be helpful to her schooling:"When it comes to looking at different classes throughout my undergrad. As I've been registering for classes, [it] would have been helpful to see what is the passing rate?" and "it'd be helpful to have a dataset that says, how many people said that they had a positive experience versus negative using data." As a teacher, P13 envisioned exploring students' data: "keep scores of their (students') performance, especially with kids with multiple disabilities like how they do things, how many times they try, how many times it works." Exploring price data in the context of shopping is another context mentioned by many participants. P2 envisioned filter can be used to "sort columns, for example, prices of items, and then select the kind of item, and then filter for the price or if you were on a looking at airline cause I've just come back over trips. That's what I'm thinking of looking at airline flights on certain days and being able to filter by day and check the price or compare the price to the day."

P18 shared a scenario of exploring a real-estate dataset: "one thing I love doing in my personal life is real estate, Looking at rental properties, looking at purchases." P15 also mentioned the "housing market", as he stated "we were just looking at some data renting a room, renting a house or an apartment." The prototype can be used "to see if you are being charged a fair amount of money by your landlord or your tenant. And where basically other areas that you can specifically live where the rent is lower. [It will help me] come up with some really intelligent decisions, good decisions from data." Being able to explore financial data raised participants' interests. As a business major student, P4 mentioned "Big economic tables of like country GDPs. it can be helpful to look at this giant spreadsheet and try to filter out and complete a report with it that has a ton of columns." P13 shared that "usually (in) like banking websites, online banking." Similarly, P17 envisioned investigating his "categories of spending."

Health-related information is also mentioned by several participants. P12 wished to "compare states within the Covid table." As she said, "I think something that would really help would be a table like this then you could compare how many deaths." P10 also has a similar vision as she stated "during the pandemic, we're trying to look at how many positive cases there were in your area, or any deaths, or especially like, if cases were on the rise and the tables were never accessible." P15 has a more personalized context in mind, which was about "comparing the glycemic indexes and bowling, correlations between the different types of foods that a person can eat like the different types of veggies, low calorie versus high calorie, fiber count."

How would participants explore data when the data exploration prototype is not available/accessible? Participants also shared their experience with calculating statistics and exploring data when a suitable tool is not available or accessible.

Regarding collecting necessary information, P14 said, "I have to go back and forth between the data points." P9 also stated, " I would just go up and down the columns to compare" which can be time-consuming as P9 stated "Examine it. record by record, which could take a lot of time. This is much more efficient." Thus, P4 also echoed "this [prototype] is much preferred. Once you get used to what you can do with it definitely."

To keep the information and find the expected value, four participants (P9, P13, P15, P18) said they would rely on their memory. P13 stated, "to find information like maximum or average, I try to remember." P18 shared that he attempted to create mental images of the dataset to infer the statistics from: "just doing a mental map."

Six participants (P3, P5, P10, P11, P16, P17) mentioned they would make their own notes. P16 shared, "I would probably have to write all that down." P3 shared "I will write it out and compare it using either Wordpad or Microsoft Word." P11 did similarly, but commented "just keep all in a Word document which is very cumbersome, as you can imagine. But that you know, that's how I do it. Just in a Word document." P17 shared their frustration with prior experience where he had to do manual exploration: "I've encountered tables that are like 1,000 rows, and it just sucks."

5.4 Part 4: Feedback about Prototype

In addition to reporting analytical behaviors, we summarized the feedback from participants related to our prototype to inform an ultimate data exploration tool for BLV users.

5.4.1 *Usability of the Prototype.*

Overall, participants shared that they could use the prototype without trouble. P5 shared, "It seemed very user-friendly to me." P13 also echoed: "The interface looks pretty accessible."

All participants agreed that the keystrokes are overall learnable within a reasonable time frame. P5 shared "seem very understandable." P13 also echoed the sentiment and said they are "straightforward."

More specifically, P8 thinks shortcuts were designed to be memorable. P8 shared that, "I do filtering as F and sorting as S. It makes perfect sense." P10 also shared, "L, for lock, is nice."

Regarding the usage, some of them think it needs some practice to remember the keys, As P4 stated, it is easy to track "once you get used to them." Initially, she "can't remember the function. (lock)" but after the study, she stated "it took me a little bit, but I felt like by the second time around I had most of them." P11 also shared that "It'll take some practice to remember the hotkeys" so she may need "a list" to "look over to shortcut keys."

5.4.2 *Perceived Usefulness of Functions.*

Many participants shared that *descriptive summary* was very useful in exploring the dataset. P10 mentioned that it is especially helpful when "tables and columns aren't tagged to work" because it can help them avoid "going all the way down, all the way up, all the way over to remind yourself the X and Y are for that piece of data." Also, P12 stated that "I could definitely see it being useful" because "what I usually do is not that easy to get the averages and stuff. And I do really like about this table [is that] it'll tell you what the averages are, and the mean and median, and it'll tell you which one has the highest of something."

While P1 shared that she enjoyed the prototype being efficient at calculating *correlation*: "just quickly trying to understand the correlation", P5 enjoyed what *pivot tables* can offer. As P5 stated "I think my favorite feature of all is, I think locking information you want and trying to compare whatever information you're trying to find." P10 also echoed the sentiment: "Lock one in place and then get it all in the same cell at the same time is very helpful."

P5 valued the functionality that allows him to choose various statistics in a pivot table. As he stated, "I like this is here where you can go in and change it." P13 also valued "I like that the table option. Being able to choose different statistical calculations." P2 especially liked the *sort* function "because then you can go up at the top as smaller and further down as larger. That is usually pretty helpful." P12 shared the sentiment: "Sorting, I think, would be really good if you wanted to sort like years of something."

P1 mentioned she could learn about the trend and others by sorting the data: "If you're trying to determine which has the most frequent count, or which has the greatest value, and trying to understand the trend. I think the sort might be helpful." However, P10 pointed out the limitation of the usefulness of sort as she stated "Sorting is definitely helpful to make ascending or descending. If you're trying to get something near the low or high end, if it's in the middle, it doesn't make that much difference." P16 liked *filtering* capability. As she stated, "the date or the time that I'm going to be hosting (the event); otherwise the tables get kind of jumbled up." P17 shared that "if you don't know what you're looking for already, it's hard to find it in big tables. That's why filtering and comparing is super useful." and "You could make a lot of inferences based on the data, and it would probably be easier using this [prototype] because the filtering and the comparisons options. I mean, you could do a lot with [this prototype]."

Participants also commented positively on the overall value of the prototype. P5 advocated that "[with the prototype] you can do many things much more quickly than having to just read it yourself and try to digest all of the information that you need. so I would actually think it's pretty useful." P12 also shared, "I figured it actually does help like when we were sorting those things by state, I mean that actually was really cool, so I could see doing it if I was looking at a table with statistics." For pivot tables, she stated that "[I] can compare things. It's actually really cool. That would be really new feature." P14 thought that this prototype could be a great starting point to build upon.

5.5 Potential Features to Support Data Exploration

Streamlining textual summary & description. Some participants wished for the summary and description to be more concise. For example, as P9 stated, " [Instead of saying] 'minimum is X' 'the maximum is Y,' it could just say 'minimum' and pause and say '300'. It's a small thing, but when you're hearing it a lot, it really adds up over time." Maybe due to the verbose summary, we observed that a few participants tended to skip the summary and search for the information by themselves. For example, when P6 was trying to find the ID (college) for the lowest book cost, instead of hearing the information that was going to be provided ("Appalachian State University has Estimated Book Cost of 96"), she moved quickly to the column *ID* and found the college name by herself.

Capability to configure/personalize information. We observed that participants' informational needs, in terms of granularities and types of information, could be varied. While others were content with the function, P15 complained that "The screen reader will read the entire pivot table out if not get into it which can be hard to understand since that is a lot of information." P2 shared that she needs more reminders about the filtering information: "Unless I remember, I don't know what my filter type has set to" suggesting that announcing filters when applied and persisting the global indicator with active filters was insufficient (Figure 2B-right).

Some participants also explicitly mentioned it would be useful to have the ability to configure the information presented by the prototype. For example, P17 suggested making the components of the summary customizable. As he stated "I wish I had more customization over that. I wish I could just completely turn off everything except it is a key column." Also, he suggested that the function can be on and off by being aware of the context: "turn off the cell messages once you get to not need them [because you are familiar with it]. I think would be a cool option." P9 echoed: "When you arrow onto a numerical column, instead of automatically reading the minimum, maximum, and so on, make a command to read that."

Multimodality support. While we implemented this feature to work with sighted research team members, for people who still have a remaining vision, highlighting cells was considered useful as feedback to the participants' actions. For example, P3 stated "having something highlighted [is like] having a confirmation."

P1 raised the need to transmit the provided information to the Braille display to support them in better reading the content. As she stated, "I think it can be a little clearer if it was also transferred to reflected under Braille display." P10 also envisioned "if I had a little key like in Braille here of the commands until I got familiar with them. That would help me because when I hear all the talking, a lot of stuff goes out of my head."

Copy and Paste function. Several participants hoped to have a copy-and-paste function so that they could re-use the pivot table they generated for their report, as P1 stated "If I'm writing a paper and I want to insert the table of specific information, copy the table that I've generated using this prototype, and then I would go on to my paper and then just paste it there." P15 also mentioned "I wanted to copy and paste information from the table." P18 wanted "If I'm getting information or putting together a report, I want to make sure I can copy and paste that information into my report." P5 used a more general expression to describe his need: "export certain information that you have."

Support quick navigation around tables. Since the prototype aims at supporting data exploration with potentially large datasets, participants suggested implementing advanced features to navigate tables, beyond what screen readers offer for HTML tables. For example, P4 asked about the functionality to jump from the last column to the first column: "Once you get to the last column, is there a way to really quickly get to the first column without scrolling all the way back?" P8 also envisioned a functionality to be able to "get back up to the top" that allows her to "to jump directly to the column headers from the last row." Indeed, JAWS offers this function, but not other screen readers such as NVDA or VioceOver. Some participants said the support for navigating to a cell would be helpful. As P1 stated "I think it will be helpful to have the function to navigate me to, like on Excel, like we have the letter column, like G5, for example, if there is a good way to just navigate the specific cell." P18 echoed the needs: "I want to go back to the heading, and go to the cell."

6 DISCUSSION

This research area of supporting BLV individuals to explore data has remained significantly underexplored. The absence of tools tailored to their unique needs resulted in a lack of empirical understanding of how they perform analytical tasks. This creates a challenging cycle where the absence of foundational knowledge hinders the development of effective tools. Existing reseach [5, 23, 33, 57, 59] toward providing BLV individuals with access to raw data demonstrate the necessity and feasibility of extending assistance to them. However, exploring and deriving further insights from the data has been accomplished through manual processes by users, such as memorization and note-taking.

As a first step, we presented some observations through a user study using a prototype built based on our formative study, prior work, guidelines, and other relevant software. Many gaps have to be filled to create a data exploration system that serves all the needs of BLV users, but we hope our initial results contribute to such a system. To mitigate the challenges associated with formulating appropriate queries that possible alternative approach like visual question answering [27] need from users, our tool facilitates easy data transformation, empowering users with visual impairments to uncover salient insights tailored to their needs. In our studies, participants displayed great enthusiasm for the prospect of data exploration that could be comfortably facilitated by familiar assistive technology. Many participants noted that such a tool would enhance their attentiveness to the data. We encourage further research and intervention development in this area to provide much-needed support for BLV individuals living in a data-driven society. Plenty of features suggested by participants highlighted the needs for enhancement that have been overlooked within current technologies. These suggestions will provide guidance for a system that facilitates effective data exploration for BLV individuals.

6.1 Design Implication

From the design process of our prototype and the user study, we have derived several design implications for a system that supports data exploration for BLV individuals.

User-Centric Design. While the concise information should be prioritized, allowing users to customize the level of detail of information based on preferences can make the support more efficient. In terms of interface and functionality as well, designing with the flexibility to accommodate diverse user preferences and requirements can improve the usability of the tools from another perspective.

Multimodality. Incorporating multimodal support and compatibility with assistive technologies can greatly improve the accessibility of data. Specifically, features like cell highlighting, transmission to Braille displays, and auditory feedback are useful approaches to enhance usability.

Efficient Navigation and Exploration. Advanced navigation capabilities, such as quick access to specific sections and jumping between columns, can enhance efficient navigation. Intuitive navigation features supporting the exploration of complex datasets, such as offering cell movement via position ID, will further contribute to usability.

Integration and Interoperability. Standard features like copy-and-paste functionality, which facilitates data exchange with other software solutions, can be valuable, particularly in the context of data exploration aimed at sharing results with a wide audience. Additionally, seamless compatibility with external tools and platforms, including ensuring support for default screen reader actions and avoiding conflicts with assistive technology, are essential considerations, especially for a tool targeting BLV individuals who rely on screen readers.

Contextual Guidance and Support. Providing comprehensive guidance and contextually relevant actions tailored to the user's current state and location within the interface can ease the cognitive burden associated with remembering extensive information.

6.2 Future Avenues of Research to Support Data Exploration

Through an observational user study, we were able to characterize BLV participants' analytical behaviors when exploring datasets. Participants were able to complete around six analytical tasks within a 30-minute timeframe with decent accuracy using our prototype. However, we observed that as the complexity of the tasks and the number of variables involved increased, participants tended to achieve lower accuracy rates. This result suggests that providing additional support could enhance the quality of data exploration, especially as users investigate deeper into the exploration process with more variables. One major issue that we observed during the study session was that as the number of variables involved in an analytical task increases, the representation of the pivot table becomes more complicated. Parsing this type of complex table through screen readers is not a trivial task. Future research should look into designing screen reader rules for complex tables by considering users' mental capacity. In addition to streamlining the screen reader rules to parse the complex table, investigating the optimal strategy to split the complex table into a digestible size could be an interesting solution.

While participants were generally able to perform tasks accurately, there was one task that the majority of participants couldn't correctly perform, which was anomaly detection. For sighted users, this task often involves visually identifying data points that deviate from the majority of data points in the visualization, which is a task quickly accomplished by human vision. However, with tabular data, this task was demonstrated to be challenging. An intriguing avenue for future work is to explore alternative modalities beyond vision to compensate for tabular data's limitations in supporting analytical tasks required to understand spatial relationships. For example, spatial audio can be an option where the data is rendered with audio channels, and the listeners can identify the topology of outliers by seeking a sound that is distant from the majority of data points.

The sequence of interaction taken by participants was more varied as the complexity of tasks increased. We identified the recurring inefficient steps taken by participants, alluding to an opportunity to analyze the causes of the deviation further. For example, it may be due to the participants' low data literacy or due to the mental model toward the functions formed differently during the tutorial session. Alternatively, a future system can support a simplified interaction through natural language interaction to conduct analytical tasks instead of prompting users to execute a sequence of functions via keyboard (e.g., create pivot table → filter out by a variable and so on). Allowing users to state their questions and then presenting a formulated table for immediate examination would help BLV users engage better with data exploration. Indeed, we observed that participants were able to articulate the task in a structured way, highlighting the opportunity for a natural language-based data exploration system.

In the later part of the observational user study, where participants freely navigated the dataset, we observed that participants started the exploration by constructing some overview of the dataset and proceeded with understanding the statistics of each data variable. Since the quality of the overview constructed by a user impacts the quality of the following data exploration, future work should investigate how to provide a comprehensive overview of datasets through text using automated technologies such as LLMs.

After that, participants made many comparisons to build the underlying datasets' comprehensive landscape. The findings are similar to a study that targeted sighted people with exploring data with data visualization [56]. Further comparison between the two populations, in conjunction with different affordances of tools, would be an interesting avenue for future investigation to characterize which aspects we can transfer from studies targeted at sighted individuals.

6.3 Limitations

Our current prototype focuses on quantitative and categorical variables. Expanding support to other data types, such as temporal and geographic attributes, will allow observation of a wider range of behaviors and allow researchers to characterize the behaviors based on different data types.

In our observational study, we tried to choose datasets moderately familiar to the average person. However, we acknowledge that participants might have varying degrees of familiarity with the datasets, potentially introducing bias in their responses. Future research can investigate the implications of individuals utilizing their own data, potentially offering richer insights into user behaviors.

In our prototype, we have incorporated functionality for loading users' own data. While we evaluated its usability, we did not utilize this feature in the observational study setting. However, this feature will enable future work to study users' analytical behaviors with their own data.

Despite our careful development and testing with various screen readers, two participants encountered conflicts with specific advanced features in their screen readers. One possible future solution would be to configure the shortcut and the rules differently by detecting the type of screen readers, the version, and their installed features.

7 CONCLUSION

Our work focuses on enabling data exploration for BLV users using data tables. We conducted a formative study and subsequently developed a prototype tailored to the needs of BLV users. This prototype enables various analytical operations through keyboard-based interactions. Our observational user study using the prototype shed light on how BLV users conduct data exploration, offering valuable insights into the analytical behavior of BLV users.

REFERENCES

[1] 2021. Web Content Accessibility Guidelines 2.1, W3C World Wide Web Consortium Recommendation Updated 27 July 2021, 1.3.1: Info and Relationships. https://www.w3.org/WAI/WCAG21/Understanding/info-and-relationships.html

[2] Iyad Abu Doush, Enrico Pontelli, Dominic Simon, Tran Cao Son, and Ou Ma. 2009. Making Microsoft Excel™ accessible: Multimodal presentation of charts. *ASSETS'09 - Proceedings of the 11th International ACM SIGACCESS Conference on Computers and Accessibility* (2009), 147–154. https://doi.org/10.1145/1639642.1639669

[3] Robert Amar, James Eagan, and John Stasko. 2005. Low-level components of analytic activity in information visualization. In *IEEE Symposium on Information Visualization, 2005. INFOVIS 2005.* IEEE, 111–117.

[4] Dagmar Amtmann, Kurt Johnson, and Debbie Cook. 2002. Making Web-based Tables Accessible for Users of Screen Readers. *Library Hi Tech* 20, 2 (Jan. 2002), 221–231. https://doi.org/10.1108/07378830210432589

[5] Chieko Asakawa and Takashi Itoh. 1999. User Interface of a Nonvisual Table Navigation Method. (1999), 214–215.

[6] Leilani Battle and Jeffrey Heer. 2019. Characterizing exploratory visual analysis: A literature review and evaluation of analytic provenance in tableau. In *Computer graphics forum*, Vol. 38. Wiley Online Library, 145–159.

[7] Matthew Blanco, Jonathan Zong, and Arvind Satyanarayan. 2022. Olli: An Extensible Visualization Library for Screen Reader Accessibility. *IEEE VIS Posters. http://vis. csail. mit. edu/pubs/olli* (2022).

[8] Roopa Bose and Helmut Jürgensen. 2014. Accessibility of e-commerce websites for vision-impaired persons. In *International Conference on Computers for Handicapped Persons*. Springer, 121–128.

[9] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.

[10] S. Brewster. 2002. Visualization Tools for Blind People Using Multiple Modalities. *Disability and Rehabilitation* 24, 11-12 (Jan. 2002), 613–621. https://doi.org/10.1080/09638280110111388

[11] Lorna Brown, Stephen Brewster, Ramesh Ramloll, Wai Yu, and Beate Riedel. 2002. Browsing Modes For Exploring Sonified Line Graphs. In *In Proceedings of Bcs-Hci 2002*. 6–9.

[12] Vladimir Bulatov and John Gardner. 1998. Visualization by People without Vision. In *Content Visualization and Intermedia Representations (CVIR'98)*.

[13] Davide Ceneda, Theresia Gschwandtner, Thorsten May, Silvia Miksch, Hans-Jörg Schulz, Marc Streit, and Christian Tominski. 2016. Characterizing guidance in visual analytics. *IEEE transactions on visualization and computer graphics* 23, 1 (2016), 111–120.

[14] Mechmet Chiousemoglou and Helmut Jürgensen. 2011. Setting the table for the blind. In *Proceedings of the 4th International Conference on PErvasive Technologies Related to Assistive Environments*. 1–8.

[15] Stephen H. Choi and Bruce N. Walker. 2010. Digitizer Auditory Graph: Making Graphs Accessible to the Visually Impaired, In Proceedings of the 28th of the International Conference Extended Abstracts on Human Factors in Computing Systems - CHI EA '10. *Conference on Human Factors in Computing Systems - Proceedings*, 3445. https://doi.org/10.1145/1753846.1753999

[16] Robert F Cohen, Arthur Meacham, and Joelle Skaff. 2006. Teaching Graphs to Visually Impaired Students Using an Active Auditory Interface. *ACM SIGCSE Bulletin* 38, 1 (2006), 279–282.

[17] Chetz Colwell and Helen Petrie. 2001. Evaluation of Guidelines for Designing Accessible Web Content. *ACM SIGCAPH Computers and the Physically Handicapped* (2001), 11–13.

[18] World Wide Web Consortium. 2023. ARIA Authoring Practices Guide (APG). https://www.w3.org/WAI/ARIA/apg/
[19] Seniz Demir, David Oliver, Edward Schwartz, Stephanie Elzer, Sandra Carberry, Kathleen F. McCoy, and Daniel Chester. 2010. Interactive SIGHT: Textual access to simple bar charts. *New Review of Hypermedia and Multimedia* 16, 3 (2010), 245–279. https://doi.org/10.1080/13614568.2010.534186
[20] Iyad Abu Doush, Enrico Pontelli, Tran Cao Son, and Dominic A Simon. 2010. Multimodal presentation of two-dimensional charts: An investigation using open office XML and microsoft excel. November (2010). https://doi.org/10.1145/1857920.1857925
[21] Google. 2023. Google Sheets. https://docs.google.com/spreadsheets.
[22] Waqar Haider and Yeliz Yesilada. 2020. Tables on the web accessible? unfortunately not!. In *Proceedings of the 17th International Web for All Conference*. 1–5.
[23] Rushil Khurana, Duncan McIsaac, Elliot Lockerman, and Jennifer Mankoff. 2018. Nonvisual interaction techniques at the keyboard surface. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–12.
[24] Johan Kildal and Stephen A. Brewster. 2006. Non-visual overviews of complex data sets. *Conference on Human Factors in Computing Systems - Proceedings* May 2014 (2006), 947–952. https://doi.org/10.1145/1125451.1125634
[25] Johan Kildal and Stephen A Brewster. 2006. Providing a size-independent overview of non-visual tables. In *12th International Conference on Auditory Display (ICAD2006)*. 8–15.
[26] Jeongyeon Kim, Yoonah Lee, and Inho Seo. 2019. Math Graphs for the Visually Impaired: Audio Presentation of Elements of Mathematical Graphs. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, ACM, Glasgow Scotland Uk, 1–6. https://doi.org/10.1145/3290607.3308452
[27] Jiho Kim, Arjun Srinivasan, Namwook Kim, and Yea-Seul Kim. 2023. Exploring Chart Question Answering for Blind and Low Vision Users. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. ACM.
[28] Doris Jung-Lin Lee, Dixin Tang, Kunal Agarwal, Thyne Boonmark, Caitlyn Chen, Jake Kang, Ujjaini Mukhopadhyay, Jerry Song, Micah Yong, Marti A Hearst, et al. 2021. Lux: always-on visualization recommendations for exploratory dataframe workflows. *arXiv preprint arXiv:2105.00121* (2021).
[29] Hae-Na Lee, Sami Uddin, and Vikas Ashok. 2020. TableView: Enabling efficient access to web data records for screen-magnifier users. In *Proceedings of the 22nd International ACM SIGACCESS Conference on Computers and Accessibility*. 1–12.
[30] AG Grid Ltd. 2023. AG Grid. https://www.ag-grid.com
[31] Microsoft. 2023. Microsoft Excel. https://www.microsoft.com/en-us/microsoft-365/excel.
[32] Microsoft. 2023. MS Power BI. https://powerbi.microsoft.com/.
[33] Toshiya Oogane and Chieko Asakawa. 1998. An interactive method for accessing tables in HTML. In *Proceedings of the third international ACM conference on Assistive technologies*. 126–128.
[34] Enrico Pontelli, D Gillan, Gopal Gupta, A Karshmer, Emad Saad, and W Xiong. 2002. Intelligent non-visual navigation of complex HTML structures. *Universal Access in the Information Society* 2 (2002), 56–69.
[35] Enrico Pontelli, D Gillan, W Xiong, Emad Saad, Gopal Gupta, and Arthur I Karshmer. 2002. Navigation of html tables, frames, and xml fragments. In *Proceedings of the fifth international ACM conference on Assistive technologies*. 25–32.
[36] Enrico Pontelli and Tran Cao Son. 2002. Planning, reasoning, and agents for non-visual navigation of tables and frames. In *Proceedings of the fifth international ACM conference on Assistive technologies*. 73–80.
[37] Enrico Pontelli, W Xiong, Gopal Gupta, and Arthur I Karshmer. 2000. A domain specific language framework for non-visual browsing of complex html structures. In *Proceedings of the fourth international ACM conference on Assistive Technologies*. 180–187.
[38] Rameshsharma Ramloll, Stephen Brewster, Wai Yu, and Beate Riedel. 2001. Using non-speech sounds to improve access to 2D tabular numerical information for visually impaired users. In *People and Computers XV—Interaction without Frontiers: Joint Proceedings of HCI 2001 and IHM 2001*. Springer, 515–529.
[39] Dominik Sacha, Andreas Stoffel, Florian Stoffel, Bum Chul Kwon, Geoffrey Ellis, and Daniel A Keim. 2014. Knowledge generation model for visual analytics. *IEEE transactions on visualization and computer graphics* 20, 12 (2014), 1604–1613.
[40] Prabodh Sakhardande, Anirudha Joshi, Charudatta Jadhav, and Manjiri Joshi. 2019. Comparing User Performance on Parallel-Tone, Parallel-Speech, Serial-Tone and Serial-Speech Auditory Graphs. In *Human-Computer Interaction – INTERACT 2019*, David Lamas, Fernando Loizides, Lennart Nacke, Helen Petrie, Marco Winckler, and Panayiotis Zaphiris (Eds.). Vol. 11746. Springer International Publishing, Cham, 247–266. https://doi.org/10.1007/978-3-030-29381-9_16
[41] Ather Sharif, Katharina Reinecke, Andrew M Zhang, and Jacob O Wobbrock. 2023. Understanding and Improving Drilled-Down Information Extraction from Online Data Visualizations for Screen-Reader Users. (2023).
[42] Ather Sharif, Olivia H. Wang, Alida T. Muongchan, Katharina Reineck, and Jacob O. Wobbrock. 2022. VoxLens: Making online data visualizations accessible with an interactive JavaScript plug-in. In *CHI '22: CHI Conference on Human Factors in Computing Systems*. ACM. https://doi.org/10.1145/3491102.3517431
[43] Ather Sharif, Andrew Mingwei Zhang, Anna Shih, Jacob O Wobbrock, and Katharina Reinecke. 2022. Understanding and Improving Information Extraction From Online Geospatial Data Visualizations for Screen-Reader Users. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility*. 1–5.
[44] Tableau Software. 2023. Tableau. https://www.tableau.com/.
[45] Dimitris Spiliotopoulos, Panagiota Stavropoulou, and Georgios Kouroupetroglou. 2009. Acoustic rendering of data tables using earcons and prosody for document accessibility. In *International Conference on Universal Access in Human-Computer Interaction*. Springer, 587–596.
[46] Dimitris Spiliotopoulos, Gerasimos Xydas, and Georgios Kouroupetroglou. 2005. Diction based prosody modeling in table-to-speech synthesis. In *International Conference on Text, Speech and Dialogue*. Springer, 294–301.
[47] Dimitris Spiliotopoulos, Gerasimos Xydas, Georgios Kouroupetroglou, and Vasilios Argyropoulos. 2005. Experimentation on spoken format of tables in auditory user interfaces. In *Proceedings of the 11th International Conference on Human-Computer Interaction (HCII'05)*. 361–370.
[48] Dimitris Spiliotopoulos, Gerasimos Xydas, Georgios Kouroupetroglou, Vasilios Argyropoulos, and Kalliopi Ikospentaki. 2010. Auditory universal accessibility of data tables using naturally derived prosody specification. *Universal Access in the Information Society* 9, 2 (2010), 169–183.
[49] Brianna J. Tomlinson, Jared Batterman, Yee Chieh Chew, Ashley Henry, and Bruce N. Walker. 2016. Exploring Auditory Graphing Software in the Classroom: The Effect of Auditory Graphs on the Classroom Environment. *ACM Transactions on Accessible Computing* 9, 1 (Nov. 2016), 1–27. https://doi.org/10.1145/2994606
[50] Bruce N Walker and Joshua T Cothran. 2003. SONIFICATION SANDBOX: A GRAPHICAL TOOLKIT FOR AUDITORY GRAPHS. (2003), 3.
[51] Ruobin Wang, Crescentia Jung, and Y Kim. 2022. Seeing through sounds: Mapping auditory dimensions to data and charts for people with visual impairments. In *Computer Graphics Forum*, Vol. 41. Wiley Online Library, 71–83.
[52] Yanan Wang and Yea-Seul Kim. 2023. Making Data-Driven Articles more Accessible: An Active Preference Learning Approach to Data Fact Personalization. In *Designing Interactive Systems Conference*.
[53] Yanan Wang, Ruobin Wang, Crescentia Jung, and Yea-Seul Kim. 2022. What makes web data tables accessible? Insights and a tool for rendering accessible tables for people with visual impairments. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. ACM.
[54] WebAIM. [n. d.]. WebAIM: Screen Reader User Survey #10 Results. https://webaim.org/projects/screenreadersurvey10/ Accessed Apr 29, 2024.
[55] Kanit Wongsuphasawat, Dominik Moritz, Anushka Anand, Jock Mackinlay, Bill Howe, and Jeffrey Heer. 2016. Voyager: Exploratory analysis via faceted browsing of visualization recommendations. *IEEE transactions on visualization and computer graphics* 22, 1 (2016), 649–658.
[56] Kanit Wongsuphasawat, Zening Qu, Dominik Moritz, Riley Chang, Felix Ouk, Anushka Anand, Jock Mackinlay, Bill Howe, and Jeffrey Heer. 2017. Voyager 2: Augmenting visual analysis with partial view specifications. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 2648–2659.
[57] Yeliz Yesilada, Robert Stevens, Carole Goble, and Shazad Hussein. 2003. Rendering tables in audio: the interaction of structure and reading styles. *ACM SIGACCESS Accessibility and Computing* 77-78 (2003), 16–23.
[58] Haixia Zhao, Catherine Plaisant, and Ben Shneiderman. 2005. I Hear the Pattern - Interactive Sonification of Geographical Data Patterns", (Extended Abstracts. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*. 1905–1908.
[59] Yichun Zhao, Miguel A Nacenta, Mahadeo A Sukhai, and Sowmya Somanath. 2023. TADA: Making Node-link Diagrams Accessible to Blind and Low-Vision People. *arXiv preprint arXiv:2311.04502* (2023).
[60] Jonathan Zong, Crystal Lee, Alan Lundgard, JiWoong Jang, Daniel Hajas, and Arvind Satyanarayan. 2022. Rich Screen Reader Experiences for Accessible Data Visualization. *arXiv preprint arXiv:2205.04917* (2022).