

**1 Sound, Touch, or the Full Monty? A Comparative Study of Data Accessibility**  
2 **Techniques for Blind Users**

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Blind and low-vision (BLV) individuals encounter significant challenges in accessing and interpreting data, a critical component in many data-intensive fields. Traditional screen readers, which convert text to speech, have been the primary solution, but recent developments such as the Monarch refreshable tactile display and hybrid approaches such as TactualPlot, which combines sound and touch, offer new possibilities for data accessibility. Our first study explores the efficacy of these modalities—sound, touch, and their combination—through an empirical investigation conducted with Blind individuals. Participants engaged in tasks of varying complexity using the Monarch, Olli screen reader, and TactualPlot, with data presented in scatterplots, line charts, bar charts, and pie charts. Next, we conducted a co-design session to understand how blind individuals can utilize the Monarch in their data exploration workflow. Our findings reveal the strengths and limitations of each modality and provide qualitative insights into blind individuals' preferences. Our findings show that TactualPlot generally led to better task accuracy, although confidence intervals overlapped across devices. Pie and bar charts exhibited higher accuracy across all devices compared to line and scatterplots, suggesting that certain visual structures translate more readily to non-visual modalities. The Monarch often resulted in the lowest task completion times, indicating efficient access for some tasks, but it faced challenges with complex visualizations like scatterplots due to occlusion. We find that prior experience with tactile media facilitated quicker adaptation to the Monarch, and screen reader users found Olli more familiar. Overall, participants expressed a desire for hybrid systems combining the overview capabilities of touch and audio, with the precision of text. This work contributes empirical findings on the effectiveness of different modalities, qualitative perspectives from blind participants, enhancements to the TactualPlot technique to support more chart types, and findings from a co-design session exploring visual analysis with refreshable tactile displays.  
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**33 CCS Concepts:** • **Do Not Use This Code → Generate the Correct Terms for Your Paper;** *Generate the Correct Terms for Your*  
**34 Paper;** *Generate the Correct Terms for Your Paper;* *Generate the Correct Terms for Your Paper.*  
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**36 Additional Key Words and Phrases:** data visualization, multimodal accessibility, sonification, refreshable braille displays.  
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**60 1 INTRODUCTION**

62 Information professionals who are blind or have low vision (BLV) face significant challenges in accessing and interpreting  
 63 data, an essential aspect of many data-rich disciplines [19]. Screen readers have traditionally been the primary tool for  
 64 navigating digital content by verbalizing text into sound to convey information [9]. However, recent advancements  
 65 have introduced tactile devices such as the Monarch by HumanWare [29], which offer an alternative by providing haptic  
 66 feedback (touch) to represent data. In addition, hybrid approaches, such as TactualPlot [10], combine both sound and  
 67 touch to enhance data accessibility. Understanding when and how to deploy these different modalities—sound, touch,  
 68 or a combination—remains a crucial yet underexplored area in ensuring equitable access to data for BLV professionals.  
 69

70 To address this gap, we conducted an empirical study that compares the efficacy of these modalities—sound, touch,  
 71 and their combination—in real-world settings. Our study was designed in the tradition of cognitive psychology but  
 72 adapted to the field, engaging blind professionals in their actual work environments. Given the sensitive nature of  
 73 working with a protected population, our study involved traveling to participants' locations to conduct qualitative  
 74 interviews and observational assessments. This approach provided a nuanced understanding of how BLV professionals  
 75 interact with data using different modalities and offered insights into their cognitive processes and preferences.  
 76

77 Our study involved three specific tasks with varying levels of complexity: single-item data reading, two-item  
 78 comparison, and multi-item distribution characterization. Participants used three distinct devices across these tasks: the  
 79 Monarch tactile display, the Olli data table screen reader [3, 58], and the TactualPlot method that generates sonification  
 80 of the user's touch interaction on a capacitive touch display [10]. To ensure a comprehensive analysis, we included four  
 81 types of data visualizations: scatterplots, line graphs, bar charts, and pie charts. Incidentally, this required enriching the  
 82 TactualPlot technique to support these additional chart types beyond scatterplots.  
 83

84 This work makes several key contributions: (1) empirical findings from our user study, which highlight the strengths  
 85 and limitations of each modality across different tasks; (2) qualitative insights from blind participants, offering valuable  
 86 perspectives on the use of sound versus touch in data interpretation; (3) enhancements to the TactualPlot technique,  
 87 extending its capabilities to support a broader range of data visualizations; and (4) findings from a co-design session  
 88 with a blind participant to understand the challenges of visual analytics tasks when using novel refreshable tactile  
 89 displays.  
 90

**95 2 RELATED WORK**

96 Data accessibility for blind and low-vision (BLV) individuals has been a growing concern in the fields of human-computer  
 97 interaction, visualization, and assistive technology [8, 19, 37]. As data-intensive professions become increasingly  
 98 prevalent, the need for effective methods to convey complex information through non-visual means to enable blind  
 99 professionals has become more pressing. This section explores the evolution of data accessibility techniques, from  
 100 traditional screen readers to more recent innovations in sonification and tactile displays, highlighting the ongoing  
 101 challenges and potential solutions in this domain.  
 102

## 105 **2.1 Screen Readers and Verbal Descriptions**

106 Screen readers have long been a fundamental assistive technology for blind and low-vision (BLV) individuals to access  
107 digital content, including data representations. As Cook and Polgar note, screen readers are essential tools that convert  
108 on-screen text to synthesized speech, allowing users to navigate and interpret information aurally [12]. However, when  
109 it comes to complex data visualizations, traditional screen readers struggle to convey the spatial relationships and  
110 patterns inherent in visual representations such as charts and graphs [21]. To address this, researchers have explored  
111 ways to enhance screen reader functionality for data accessibility. Jung et al. proposed comprehensive guidelines for  
112 writing alternative text descriptions for visualizations, aiming to cater to the diverse needs of blind individuals [32].  
113 Their study investigated how to effectively communicate visualizations without visuals, providing insights into creating  
114 more accessible alternative text for people with visual impairments.  
115

116 Recent efforts have focused on improving the integration of charts with screen readers. Zong et al. developed  
117 methods to optimize chart structure, navigation, and descriptive content for rich screen reader experiences [58]. Their  
118 work introduced new techniques for making data visualizations more accessible, including hierarchical navigation  
119 and semantic bundling of chart elements. Building on these advancements, Thompson et al. presented Chart Reader, a  
120 system designed to create accessible visualization experiences specifically for screen reader users [52]. Their approach  
121 combines natural language processing and chart semantics to generate rich, interactive experiences that allow BLV  
122 users to explore data visualizations more effectively. While these advancements have improved the accessibility of data  
123 through verbal means, they still face challenges in conveying spatial relationships and allowing users to quickly grasp  
124 overall patterns and trends in the data [21]. This limitation has led researchers to explore alternative modalities, such as  
125 sonification and tactile displays, to complement or replace purely verbal descriptions.  
126

## 127 **2.2 Sonification: Hearing the Data**

128 While screen readers primarily rely on verbal descriptions to convey information, sonification offers an alternative  
129 approach by using non-speech audio to represent data [35]. In other words, sonification maps data attributes to various  
130 sound properties such as pitch, volume, and timbre, potentially conveying complex relationships and patterns that are  
131 difficult to describe verbally [24, 25]. The field traces its roots back to the founding of the International Community for  
132 Auditory Display (ICAD) in 1992 [34].

133 Early research in this field demonstrated the potential of sonification for spatial data representation. For instance,  
134 the iSonic system used spatialized audio to convey geographic data, allowing blind users to navigate and query maps  
135 using physical key mappings [56]. More recent developments have focused on making sonification more intuitive and  
136 accessible. Hoque et al. [28] explored the use of natural sounds in sonification, demonstrating how familiar everyday  
137 sounds can be leveraged to represent data in an intuitive and accessible manner. Their approach suggests that using  
138 recognizable sounds may reduce the learning curve often associated with abstract sonifications. Similarly, Wang et  
139 al. [53] conducted studies to rank the effectiveness of different audio channels in conveying data, providing valuable  
140 insights for designing more effective sonifications. Finally, advancements in web technologies have made tools such as  
141 Highcharts Sonification Studio [5] able to support flexible data exploration using sound in web-based environments.  
142

143 Chundury et al. [9] investigated the role of sonification for data accessibility by conducting an interview study to  
144 understand sensory substitution techniques. Their findings emphasize the potential of sonification as a complementary or  
145 alternative method to visual representations, particularly in professional settings where BLV individuals need to interact  
146 with complex datasets. Accordingly, empowering BLV individuals to create their own sonifications has also been a focus  
147

of recent research. Potluri et al. introduced PSST, a toolkit enabling blind developers to author sonifications of streaming sensor data [43]. However, sonification can be challenging to create. As noted by Kramer et al., the transformation of data relations into perceived relations in an acoustic signal requires careful design considerations [35]. While the approach can be particularly effective for representing temporal or continuous data serially, parallel presentations—at which visual displays excel—are more challenging, which can make it difficult to provide quick overviews or comparisons of large datasets. Additionally, interpreting sonified data often requires specialized training, as people generally have less practice in deriving meaning from abstract sounds compared to visual representations.

### 2.3 Tactile Displays: Feeling the Data

While sonification leverages the auditory sense, tactile displays aim to make data tangible, allowing BLV users to explore information through touch. Tactile graphics have been a longstanding tool for making visual information accessible to BLV individuals, but recent technological advancements have led to more sophisticated and interactive tactile display methods. Traditional tactile graphics, such as raised line drawings and embossed prints, have long been used to create static representations of visual information [12]. However, these methods are limited in their ability to represent dynamic or interactive data. To address this, researchers have explored various forms of digital and dynamic tactile displays.

One area of development is in the creation of 3D printed tactile models. Holloway et al. [26] compared the effectiveness of 3D printed models with traditional tactile graphics for accessible maps. Their study found that while 3D printed models can offer unique benefits, such as the ability to represent complex spatial relationships, they also present challenges in terms of production time and cost. The concept of data physicalization has also emerged as a promising approach for making data tangible. Jansen et al. [30] explored the opportunities and challenges of data physicalization, discussing how physical representations of data could enhance understanding and interaction for all users, including those with visual impairments.

While not exclusively designed for BLV individuals, data physicalization techniques offer potential benefits in terms of tactile exploration and spatial understanding of data. Guinness et al. [22] introduced RoboGraphics, a system that uses mobile robots to create dynamic tactile graphics. Taher et al. [51] demonstrated that refreshable technologies could effectively translate visual representations of bar charts into touch-perceivable equivalents. Even more sophisticated refreshable tactile displays are being developed. The Monarch device, previously known as the Dynamic Tactile Device (DTD), represents a significant step forward in making tactile displays more accessible and versatile for professional use [29]. Developed by HumanWare and the American Printing House for the Blind, this technology promises to provide refreshable tactile graphics, potentially revolutionizing how BLV individuals interact with visual information in various professional and educational contexts.

### 2.4 Multimodal Data Access

Recognizing the strengths and limitations of individual modalities, researchers have increasingly turned to multimodal approaches that combine different sensory inputs to create more comprehensive and accessible data representations. These hybrid solutions aim to leverage the complementary nature of different senses to enhance overall data comprehension and exploration. The concept of *sensory substitution*, where information typically acquired through one sense is conveyed through another, forms the foundation of many multimodal approaches [9, 12]. Deroy and Auvray provide a comprehensive perspective on sensory substitution, exploring how information can be effectively communicated

209 through alternative sensory channels [13]. Building on this, Nanay introduces the concept of multimodal mental imagery,  
210 suggesting that our mental representations of data can integrate information from multiple senses simultaneously [38].  
211

212 One promising approach is the combination of sonification and tactile feedback. Nikitenko and Gillis explored the  
213 potential of combining touch and sound for data exploration on mobile devices [39]. Their work demonstrates how the  
214 integration of tactile interaction with sonification can create more intuitive and engaging data exploration experiences.  
215 The TactualPlot system [10] adopted in this study is another example of this multimodal approach, combining sound  
216 and touch to represent data. Such hybrid systems have the potential to overcome some of the limitations of single-  
217 modality solutions. For instance, while tactile displays may excel at conveying spatial relationships, sonification could  
218 complement this by providing quick overviews or highlighting temporal patterns in the data.  
219

220 Researchers have also explored the potential of other sensory modalities in data representation. Patnaik et al. [41]  
221 investigated the use of olfactory display for data communication, proposing “information olfaction” as a novel  
222 approach to convey data through scent. While still in its early stages, this work highlights the potential for engaging  
223 additional senses in multimodal data representations. This adaptability is particularly valuable in professional settings,  
224 where BLV individuals may need to work with a wide variety of data types and complexities. However, care must be  
225 taken to ensure that the different modalities complement rather than interfere with each other, and that the cognitive  
226 load of integrating multiple sensory inputs does not become overwhelming for the user. Additionally, as Chundury  
227 et al. [9] noted in their interview study, it’s important to consider the practical aspects of using these technologies  
228 in professional settings, where compatibility with existing tools and workflows is crucial. More recently, researchers  
229 conducted a wizard-of-oz study on the use of refreshable tactile displays (RTDs) to make accessible charts, and explored  
230 how data and charts can be combined with the speech modality—both for interaction and for verbalization. Reinders et  
231 al. [4] conducted a systematic review of touch-based accessibility and identified the need for more comparison studies  
232 of presentation technique (sensory modalities) for a wide variety of charts. In our work, we use speech (verbalization)  
233 to read out labels and data values, and additionally compare the effectiveness of: sound—textual descriptions that use  
234 the Olli [3]; touch—tactile graphics on the Monarch [29]; and an audio-touch—sonified charts that support touch  
235 interaction using the TactualPlot [10] system. We explore differences across four chart types: pie charts, bar charts, line  
236 charts, and scatterplots.  
237

### 238 3 DESIGN SPACE: MULTIMODAL ASSISTIVE TECHNOLOGIES FOR REPRESENTING DATA

239 Multimodal assistive technologies are emerging as powerful tools for representing complex information. By leveraging  
240 multiple sensory channels, these approaches aim to create more inclusive and effective data experiences. This section  
241 explores the design space of multimodal assistive technologies, with a focus on their application in representing data  
242 for people who are blind or have low vision (BLV).  
243

#### 244 3.1 Definition: Multimodal Data Access

245 *Multimodal data access* refers to the use of two or more sensory *modes* (or sensory channels) to represent and interact  
246 with data. In this context, modalities are different types of sensory input or output that can be used to convey information.  
247 The key principle of multimodal data access is that these modes should support and complement each other, providing  
248 a richer and more accessible experience for users. An example of multimodal access is the use of touch for spatial  
249 interaction with information presented in the form of audio—this principle is used in systems such as TactualPlot [10]  
250 and ChartA11y [55].  
251

252 The combination of multiple modalities allows for:  
253

- 261 (1) **Redundancy:** presenting the same information through different channels;  
 262 (2) **Complementarity:** using different modalities to present different aspects of the data; and  
 263 (3) **Enhanced understanding:** leveraging the strengths of each modality to improve overall comprehension.

265 While various sensory modalities can be employed in data representation, this paper focuses primarily on those  
 266 most relevant to individuals who are blind or have low vision (BLV). For BLV individuals, the main modalities that can  
 267 be utilized include

- 269 • **Sound (Auditory):** Utilizing audio cues and speech to represent data. – *examples:* sonification, text-to-speech  
 270 (TTS), earcons (audio icons).
- 271 • **Touch (Haptic/Tactile):** Using physical sensations to convey information. – *Examples:* Braille, tactile graphics,  
 272 vibration patterns.
- 273 • **Vision (for individuals with low vision):** Enhancing visual elements for easier perception – *Examples:*  
 274 High-contrast displays, magnification, color-coding

275 While less common, other sensory modalities can also be explored for data representation:

- 278 • **Smell (Olfactory):** Using scents to convey information or enhance other modalities. – *Potential applications:*  
 279 Associating scents with data categories or intensity levels [2, 41].
- 281 • **Taste (Gustatory):** Employing taste sensations to represent data. – *Potential applications:* Using different flavors  
 282 or intensities to represent data points.

283 For the purposes of this paper and its focus on BLV individuals, we will primarily explore the combination of touch  
 284 and sound as complementary modalities for data access. Combining modalities allows designers and programmers to  
 285 convey more data and information to translate a visual chart into a more accessible representation. Novel multi-line  
 286 refreshable braille displays such as the Monarch [29] and the Graphiti [44] provide access to pin-based haptic feedback  
 287 while also having hardware features capable of providing audio and verbal feedback. Such tactile displays offer a unique  
 288 design challenge for data visualization accessibility: visualization designers can make their charts accessible using  
 289 touch, while also utilizing the audio and speech rendering capabilities of these devices. However, these RTDs are very  
 290 expensive, and cheaper touchscreen displays such as the iPad, Android tablets, and smartphones can also be used to  
 291 provide audio output, and parallel access to chart elements through *direct touch interactions*. Rich screen reader chart  
 292 descriptions are also used as an *audio only* way of interacting with charts that are otherwise inaccessible to the visual  
 293 sense for blind individuals. Our goal was to perform a qualitative and task-based *comparison of audio only, touch only,*  
 294 *and a combination of audio and touch accessibility systems*, to isolate and better understand the benefits and challenges of  
 295 a particular sensory modality. We derived insights that can help future visualization designers adapt their visualization  
 296 to a combination of sensory modalities.

301 **Table 1. Comparison of Different Chart Characteristics and Interaction Modes**

304	Standard Charts	Olli	TactualPlot	Monarch
305 <b>Chart Characteristics</b>	Vision	Audio	Audio	Touch
306 <b>Data Characteristics</b>	Vision	Audio	Audio	Touch
307 <b>Chart Interaction</b>	Vision	Keyboard	Touch	Touch

309 We designed pie charts, bar charts, line charts and scatterplots using Vega-lite [45] for our study and adapted them  
 310 to work with *Olli* and the *Monarch* display. We implemented D3.js charts and extended the design space for *TactualPlot*  
 311 Manuscript submitted to ACM

313 to work with the aforementioned chart types used in our comparative study. The *Olli* system generates a hierarchical  
314 set of textual data descriptions that users can navigate through a standard keyboard and *listen* to using their screen  
315 reader. TactualPlot is a multimodal system in which users can directly *touch* chart elements such as data encodings  
316 (visual elements such as shapes, labels, titles, and axes) and *listen* to the relevant sonification and verbalization. And  
317 finally, the *Monarch* is a system in which users rely solely on their sense of *touch* to both interact and feel the chart  
318 elements. Our choices allowed us to isolate and map design challenges for systems that use single sensory modalities  
319 (*touch, sound*) and multimodal interaction (*sound plus touch*). In the next three sections, we describe the interaction  
320 techniques used by our participants to complete visualization tasks on each device.  
321  
322

### 323 3.2 TactualPlot: A Crossmodal Data Access Technique

324 TactualPlot is an innovative crossmodal technique that combines touch input with auditory output to represent visual  
325 data [10]. The core concept of TactualPlot is as follows:  
326  
327

- 328 (1) **Input:** Users explore a spatial representation on a touchscreen using their fingers;
- 329 (2) **Processing:** The system tracks the user's touch input and correlates it with the underlying data that has been  
330 spatially laid out on the screen; and
- 331 (3) **Output:** Data touched by the user's fingertips is sonified in real-time, providing auditory feedback based on the  
332 user's exploration.

333 This technique allows BLV users to “feel” the structure of a visual representation while simultaneously hearing the  
334 data values through sound. The original TactualPlot focused on scatterplots, enabling users to explore data points in a  
335 two-dimensional space.  
336  
337

338 3.2.1 *Design Principles for TactualPlot.* *TactualPlot* was originally designed to work with scatterplots. We retained the  
339 original design principles, and added our own design goals to ensure that our study participants can easily learn and  
340 use the sonification-based system. To that end, we employ the following design principles:  
341  
342

- 343 • **Sampling area size:** Provide users the sensation of “touching” chart elements by fixing the sampling area to a  
344 circular lens that is roughly the size of the user’s fingertip.
- 345 • **Employ audio representation:** Integrate auditory feedback to the elements of the chart, ensuring that the  
346 underlying data or structure is discernible through sound and the spatial layout being discernible through  
347 tactile feedback.
- 348 • **Minimize target hunting:** Reduce cognitive and physical effort in locating and interacting with small or sparse  
349 elements. Avoid leaving large empty regions that force users to search extensively for interactive features.
- 350 • **Leverage the entire display:** Utilize the full available screen space to provide a consistent reference frame.  
351 By allowing interaction across the entire display, users can better orient themselves and understand spatial  
352 relationships.
- 353 • **Allow interaction with single or multiple data series:** Present data in manageable segments that allow  
354 users to focus on one series at a time or allow comparison among multiple data series. Restricting the display to  
355 a single series minimizes complexity and fosters clarity, making interpretation simpler. However, comparison  
356 between multiple data series, for example, in a line chart, enables users to perform higher-level data comparison  
357 tasks.
- 358 • **Use differentiable and pleasant audio scales:** TactualPlot represents the density of data within the sampling  
359 area using pitch: higher densities produce higher pitches. To align with the continuous drag interaction, the  
360

365 system continuously modulates a pleasant tone [10] in real time as the user’s finger moves. Through piloting,  
 366 we created 5 distinctly yet pleasant instrument scales where the pitch can be modulated to sonify quantitative  
 367 values. For multiple data classes, TactualPlot employs polyphonic sound (e.g., different instrument voices) so  
 368 each class is heard simultaneously without breaking the continuous audio stream.  
 369

- 370 • **Highlight empty space and chart element boundaries:** Clearly indicate the absence of data in the sampling  
 371 area and trigger sounds or vibrations when chart boundaries or chart elements are touched. This allows users  
 372 to better understand the spatial or “visual” position of the chart elements such as lines, points, bars, and slices.  
 373 Using sounds to signify chart boundaries and axis tick marks provides better positional awareness to users with  
 374 respect to the entire chart view—zoomed or otherwise. As stated earlier, clearly differentiating blank space and  
 375 interactive elements can help minimize target hunting.  
 376
- 377 • **Enable On-demand labels:** Allow users to retrieve labels or descriptions through simple, direct interactions  
 378 such as tapping. This approach facilitates focused exploration and reduces audio clutter when labels are not  
 379 needed immediately.  
 380

381  
 382 3.2.2 *Sound Design and Mapping.* For TactualPlot, we use a discrete audio space based on MIDI notes that starts from  
 383 MIDI note 21 (which is **A0** in the musical scale) and goes up to a maximum of 120 (which is **C9** in the musical scale).  
 384 This ensures exactly 100 distinct audible steps, spanning A0 to C9. We choose a discrete audio space because we do  
 385 not encode sound directly from the data domain to the sound domain. Instead, the values from the visual scales or the  
 386 axis scales to our discrete sound domain. Users can compare the pitches between two different notes to distinguish  
 387 them while dragging their fingers across the display. While dragging, the users touch the chart elements, and the  
 388 corresponding tone is played, and is sustained for 1.5 seconds before being muted. If the user comes into contact with  
 389 another sonified element before the 3 seconds are completed, a new audio note corresponding to the new value is  
 390 played. Encountering empty space produces a muffled noise to indicate the absence of sonified chart elements under  
 391 their finger. Users are not required to identify the musical notes to complete visualization tasks. To retrieve the absolute  
 392 data value, they can tap on an element to have the system verbalize it. Using a combination of dragging and tapping,  
 393 users can make sense of the underlying chart. For all chart types, we use the same audio scale. However, the mapping  
 394 between the visual elements and the audio notes changes based on chart type. For every relevant item (e.g., tick marks,  
 395 bar segment, pie slice, point density, point on a line) in the chart domain, we apply a linear interpolation function to  
 396 find the corresponding MIDI value. Given a value  $x$  from 0 to some positive maximum  $x_{\max}$ , we wish to map every  
 397 data value  $x \in [0, x_{\max}]$  to one of the 100 integer MIDI notes  $\{21, 22, \dots, 120\}$ . The mapping is defined by:  
 398

$$403 \quad \text{noteIndex}(x) = \left\lfloor \frac{x}{x_{\max}} \times 99 \right\rfloor, \quad \text{MIDI}(x) = 21 + \text{noteIndex}(x).$$

404 Here,  $\lfloor \cdot \rfloor$  denotes the floor function. For any  $x \leq 0$ , no note is played (treated as **silence**). When  $x > 0$ , the function  
 405 linearly interpolates  $x$  to a discrete note index in  $[0, 99]$ , then shifts it by 21 to cover the MIDI note range from 21 (for  
 406 very small  $x$ ) to 120 (for  $x = x_{\max}$ ). Once a user touches a chart element, the corresponding  $\text{MIDI}(x)$  value is sonified.  
 407

408 For different classes of sounds, we change tone parameters in ToneJS,<sup>1</sup> a JavaScript toolkit based on the Web Audio  
 409 W3C API,<sup>2</sup> rendering a MIDI note’s pitch value as an audibly different tone. This allows us to sonify a quantitative  
 410 value from different data series as categorically different sound notes. This allows us to create “*audio instruments*” that  
 411

412 413  
 414 <sup>1</sup><https://tonejs.github.io/>

415 <sup>2</sup><https://www.w3.org/TR/webaudio/>

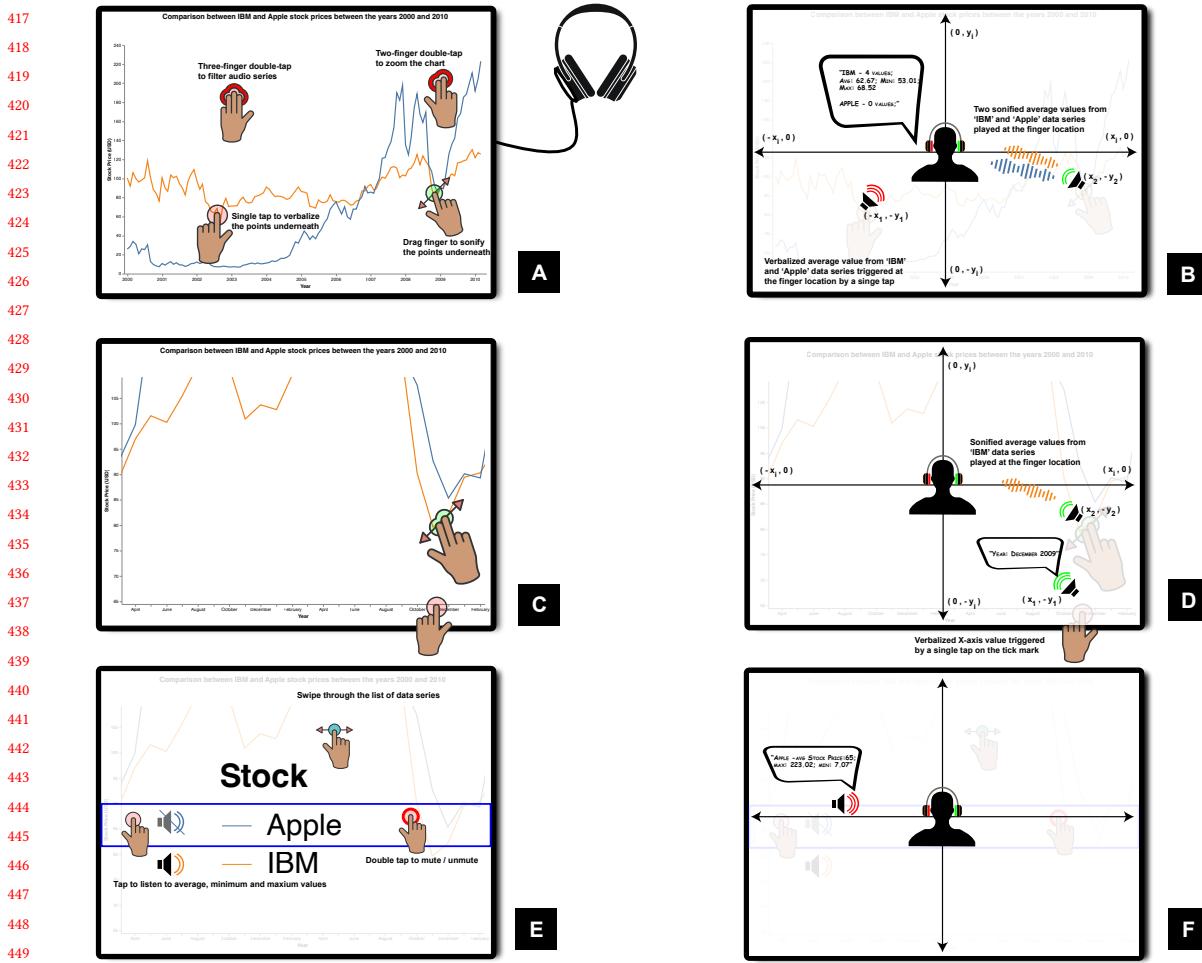


Fig. 1. **TactilePlot interactions.** An overview of the TactilePlot system's interactive techniques for line charts. Panels (A–F) illustrate key gestures such as dragging to continuously sonify data, tapping to trigger verbalization of data values, and multi-finger actions for filtering and zooming. These interactions enable blind users to explore and interpret visual data through a combination of touch and auditory feedback.

can be assigned to different data series, and thereby adapt charts that have nominal variables encoded using color or shape.

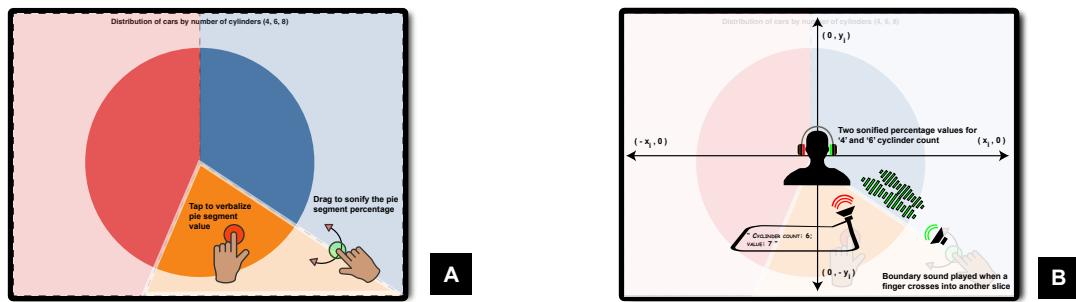
While we utilized multi-finger touch interactions across the system, we restricted our audio-sampling lenses to two fingers. In other words, users can continuously touch and drag two fingers around the display to trigger the non-speech sounds that are mapped to the data values and chart elements. Two-finger sampling still enables our users to hear sound from two different regions of the chart and make comparisons. We believe that such comparisons allow users to better trace chart elements in a step-by-step manner—i.e., users can use a combination of tapping for verbalizing and dragging to find their way around a chart.

We adopt the axis and title sonification schemes from TactualPlot [10] in our implementation. For charts that have multiple categories such as line charts, scatter plots, and stacked bar charts, users can filter the audio stream for each category by using the audio legend panel. Users can perform a *three finger double tap* to open and close the *audio legend panel*. In this panel, users can swipe through a list of audio streams and choose to mute a particular category by *double tapping* a category. For example, while exploring a line chart with 3 data series, a pairwise comparison is possible by only selecting two of the three data series. As users drag their fingers across the screen, we provide stereo panning of the audio stream to convey the horizontal and vertical touch positions of each sampling lens—also the same as the touch location of the user’s finger(s). This is made possible using the *Panner3D* node of ToneJS. We initialize the Z-axis as 0 to restrict audio to a two-dimensional space.

**3.2.3 Adapting TactualPlot For Different Charts.** Here, we discuss our specific interactive sonification approach for the four chart types used in our study:

**Pie charts:** a circular statistical chart that is used to convey numerical proportions (e.g., the market share of different smartphone manufacturers) by dividing a circle into *segments or slices* - each slice representing a single data point.

- **Spatial layout:** The visual space is split into circle segments or “slices”, one per data point, originating from the center of the space. Each circle segment has an arc proportional to its data point value in relation to the other data values. The order of the circle segments follow the order of data points in the dataset.
- **Chart interaction and sonification:** The proportion of the currently selected data item—normalized against the full 100% of the entire pie chart—is sonified as pitch. The TactualPlot pie chart does not have an outer perimeter; it fills the entire available visual display space. This eliminates the need for the user to “hit” the circular shape; they can instead drag their fingers along the perimeter of the touchscreen. The proportion of the currently selected data item—normalized against the full 100% of the entire pie chart—is sonified as pitch. Tapping on a circle segmented representing a data item will verbalize the textual label for the item. Dragging a finger across a pie slice boundary triggers a drum beat to indicate crossing between slices.



**Fig. 2. TactualPlot—Pie Charts.** Users can drag their finger along pie segments to sonify proportional values and tapping actions that verbalize labels, with auditory cues (earcons) signaling transitions between slices for improved spatial awareness.

**Bar and stacked bar charts:** a statistical graphic using rectangular bars of varying lengths to show comparisons among categories.

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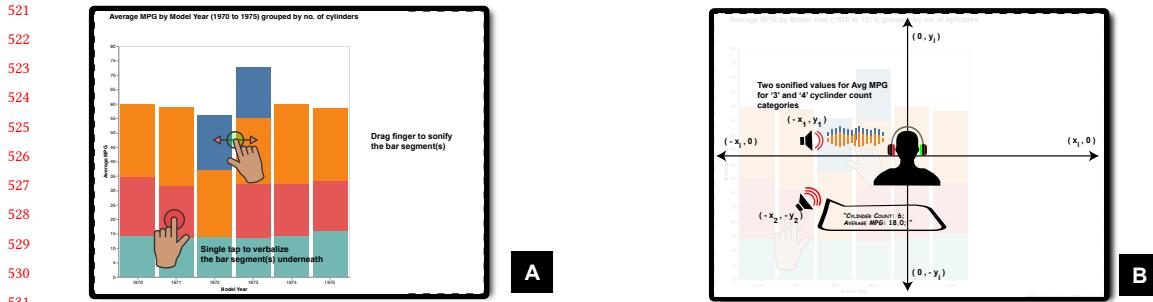


Fig. 3. **TactualPlot—Bar Charts.** Users can drag across bar segments to receive sonified representations of quantitative values—where pitch maps to bar height; and tap to obtain precise numerical feedback.

- *Spatial layout:* The visual space is split into bar segments, one per data point, originating from horizontal axis. The height of each bar corresponds to the quantitative values of the data points. In the case of a stacked bar chart, the bar segments of each data series are stacked on top of one another for each data point in the dataset. The order of the bar segments follow the order of data points in the dataset. Users can continuously drag up to two fingers to sonify or verbalize the bars and the axes.
- *Chart interaction and sonification:* The proportion of the currently selected bar—normalized against the full 100% of the entire bar height—is sonified as pitch. Therefore, a percentage value for each bar segment is calculated with the total height possible being equal to the maximum value shown on a given axis. This percentage value is then mapped to a MIDI note to indicate size of a bar segment as an audio note. Normalizing the value allows bar charts with different scales to sound similar. For example, two bar charts with a y-axis range—[0, 7.5] and range—[0, 80] can be mapped to notes that sound similar. Tapping on a bar segment verbalizes the corresponding value of the bar in the data domain. For a stacked bar chart, users can similarly drag their fingers across the chart to touch a bar segment of a particular category. On being touched, the MIDI note corresponding to the audio instrument mapped to that particular category of the bar segment is played.

*Single and multi-series line charts:* a statistical graphic that displays continuous information as a series of points connected by lines (such as the Google stock market value over time).

- *Spatial layout:* A data point's  $x$  and  $y$  values are plotted against the  $x$ -axis (horizontal) and  $y$ -axis (vertical) respectively. For example, a line chart showing monthly Apple stock price values between the years 2000 and 2010. Users can place their fingers on the chart, and listen to the sonified vertical ( $y$ ) values of points under their finger. First, we count the number of points within the sampling area, and then calculate an average value. This aggregated value serves as an indicator of the average vertical position ( $y$ -value) of the data in that region of the chart. For a multi-line chart, one average per data series is calculated when a sampling area contains points from multiple data series.
- *Chart interaction and sonification:* On touching a line segment, the average  $y$ -value of the points under a sampling lens—normalized against the full 100% of  $y$ -axis—is sonified as pitch. This average value is then mapped to a MIDI note to indicate height of the line segment as an audio note. If more than one line segment is under the sampling area, the average value from each series that is touched is sonified using the *audio instrument*

573 corresponding to each data series. Every note is played in unison, and the tone of the note allows users to  
 574 differentiate between the data series. Tapping on a line segment verbalizes: 1) the number of values in the  
 575 sampling area, and 2) the *extrema*—maximum value and minimum value. For a multi-line chart, the verbalization  
 576 is repeated for every point on the line segment from each data series.  
 577

- 578 • *Zooming*: a zoomed view of a particular sampling area can be rendered by choosing an area of interest using  
 579 one finger, and then performing a *two-finger double tap* with the other hand. This modifies the chart view by  
 580 changing the extents of the x-axis and the y-axis to the data ranges from the area of interest. In the refreshed  
 581 view, we also include one step on either side of the sampling area’s data range. The zoomed view follows the  
 582 same sonification structure as the non-zoomed view. This is done to ensure that leave a trail of data from  
 583 the original non-zoomed view. If the display is untouched for 30 seconds, we reset the zoom level. Users can  
 584 verbalize the current zoom level in the chart by performing a two-finger tap anywhere on the display. For our  
 585 study, only one level of zoom is enabled for the sake of simplicity, and visualization tasks can be accurately  
 586 completed with one additional level of zoom.  
 587

588 *Single and multi-class scatterplots*: a type of statistical graphic that displays data as a collection of points. Each point’s  
 589 position on the x-axis and y-axis indicates values for two quantitative variables. Multi-series scatterplots use different  
 590 colors or symbols to distinguish among multiple categories or data series.  
 591

- 592 • *Spatial layout*: A data point’s x and y values are plotted against the *x-axis (horizontal)* and *y-axis (vertical)*  
 593 respectively. For example, a scatter plot that compares petal lengths (quantitative) and petal widths (quantitative)  
 594 of iris flowers across 3 different flower species (nominal). Users can place their fingers on the chart, and listen  
 595 to the sonified density of points under their finger. We count the number of points that are within the circular  
 596 sampling areas under the users’ finger(s). For a multi-class scatterplots, the count of values for each class of  
 597 points that are within the sampling area is calculated.  
 598
- 599 • *Chart interaction and sonification*: On touching a chart region, the total count of the points under the sampling  
 600 lens (finger) is sonified as pitch by mapping the point density to the corresponding MIDI note. The (x, y)  
 601 positions of the points are also mapped to 2D positions in the auditory space using the spatial audio rendering  
 602 capability of Tone.JS—as users move horizontally and vertically, the sound location changes with every move of  
 603 the finger. If more than one class of points lie under the sampling area, point density from each data series or  
 604 class is sonified using the *audio instrument* corresponding to the data series. Every note is played in unison, and  
 605 the tone of the note allows users to differentiate between the data series. Tapping on a region verbalizes: 1) the  
 606 number of points in the sampling area, and the *extrema*—maximum value and minimum value. For a multi-class  
 607 scatterplot, the verbalization is repeated for each data series.  
 608
- 609 • *Zooming*: the zoom technique is similar to that of line charts. In the refreshed view for scatterplots, we only  
 610 include the sampling area’s data range.  
 611

### 612 3.3 Olli: Screen Reader Accessibility Solution That Uses Only Audio

613 Olli is an open-source framework that makes data visualizations accessible to blind and low-vision (BLV) users through  
 614 structured text descriptions and interactive navigation [3]. Olli parses common chart specifications (e.g., from libraries  
 615 such as D3, Chart.js, or Vega-lite) for metadata underlying a visualization. This includes details such as chart type,  
 616 scales, axes, and individual data points. Having gained access to the semantically rich representation of the visualization,  
 617 Olli generates textual descriptions that communicate both high-level insights (e.g., overall trends or comparisons) and  
 618 Manuscript submitted to ACM

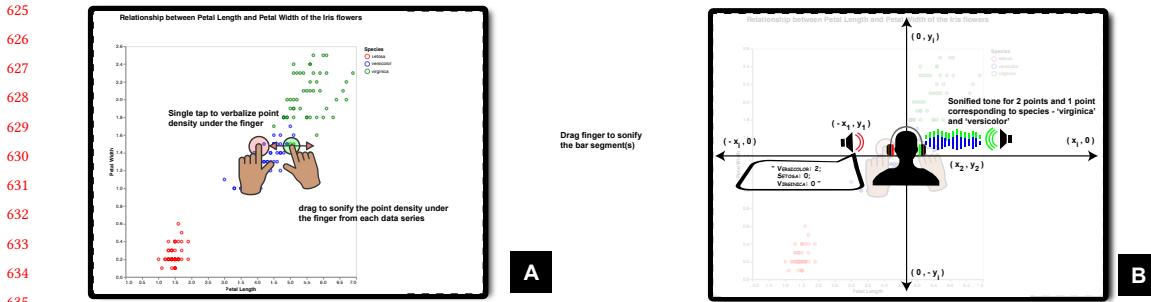


Fig. 4. **TactuPlot—Scatterplots.** Continuous finger dragging triggers real-time auditory feedback based on point density and distribution, while tapping provides verbal summaries of the data within a given region, facilitating multi-series comparisons.

low-level details (e.g., exact data values) in a textual format. This text is then rendered as a hierarchical tree of textual descriptions or text nodes which are nested at 4 or 5 different levels. While Olli primarily focuses on generating textual descriptions of static charts, it also supports interactions akin to “drilling down” for more information or comparing multiple views.

The steps for generating accessible output in Olli are:

- (1) **Specification Parsing:** Olli takes a chart specification (e.g., a JSON file describing a bar chart) and reads information about the data fields, encoding channels, and visual mappings.
- (2) **Semantic Extraction:** Next, Olli interprets the chart’s structure (axes, labels, legends) and extracts the main data elements (bars, lines, points) along with their relationships (e.g., groupings, stacks, or comparisons).
- (3) **Text Generation:** The system uses pre-defined templates or rules to transform these extracted elements into meaningful text. This can include brief summaries (e.g., “This bar chart compares quarterly revenues for 4 products”) and specific details (e.g., “The tallest bar represents Product C with \$3.2 million in revenue”).
- (4) **Interactive Exploration:** Through screen readers, keyboard navigation, or other assistive interfaces, users can navigate the described chart. They can query specific segments, drill down into the data, or request summaries, allowing for dynamic data exploration without relying on sight.

3.3.1 *Encodings.* The hierarchical structure of the system is driven by the underlying encodings of the visualization. Because of this direct mapping, each hierarchy follows the visual format of the original chart or graph.

- **Top-Level Summary (L1):** This root node notifies the user that a hierarchical representation is available and provides a concise overview of the visualization (e.g., the chart type and data domain). If the visualization contains multiple chart facets (multi-series line charts), each facet (line) is nested as a separate node in the level below the summary level.
- **Encodings (L2):** The next level contains individual nodes for each axis or legend from the original visualization.
- **Intervals or Categories (L3):** Each axis or legend node expands into child nodes that represent discrete intervals (e.g., ranges along a numeric axis) or categories (e.g., distinct labels in a legend).
- **Data Points (L4):** The last level of detail is a table listing all individual data points in the selected interval or category.

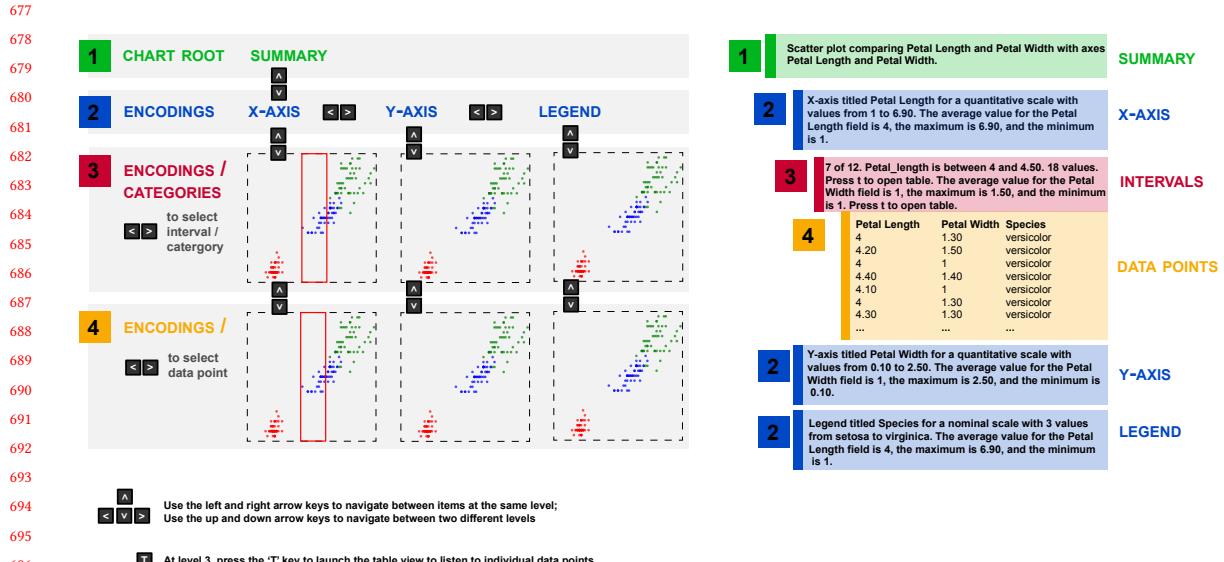


Fig. 5. **Olli interactions.** This figure has been adapted from Zong et al. [58] A chart is broken down into levels—from an overall summary to axis encodings, categorical intervals, and individual data points; enabling structured, audio-guided exploration.

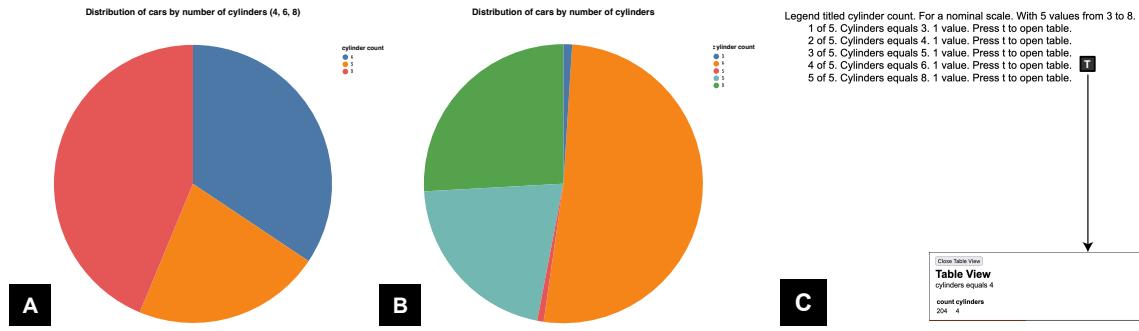
3.3.2 *Interaction.* Users explore and refine their understanding of the data hierarchy through a set of keyboard controls, making the system navigable for blind or low-vision (BLV) users. The text is then read aloud by the native screen reader. By pressing the **arrow keys**, they can move between levels and sibling nodes:

- **Down Arrow:** Moves down one level in the hierarchy, revealing a finer granularity of information (e.g., from the X-axis node to specific intervals along that axis).
- **Up Arrow:** Moves up one level, returning to a higher-level view of the data.
- **Left/Right Arrows:** Switch between sibling nodes at the same level of detail (e.g., moving from one interval or category to the next).
- **Table View - T:** the final level or the data table for an interval along an axis or category in a legend can be opened by pressing the “T” key when the focus is on an interval level node (L3).

For instance, imagine a scatterplot comparing penguin body mass (Y-axis) against flipper length (X-axis). Starting at the top-level summary, the user learns that they are examining data about penguins. Pressing the Down Arrow moves into the axis-level nodes, landing first on the X-axis (flipper length). A second press goes deeper, revealing intervals of flipper length divided into 10-millimeter ranges (e.g., 170–180 mm, 180–190 mm, etc.). The user can then press Right to scan through these ranges. If they discover an interval with an interesting distribution (e.g., a large number of points), they can press Down again to open a table listing each data point, including details such as species or precise measurements. This step-by-step approach—moving from broad summaries to precise details—echoes the “overview first, details on demand” model. It leverages both hierarchical encoding (for structured exploration) and straightforward

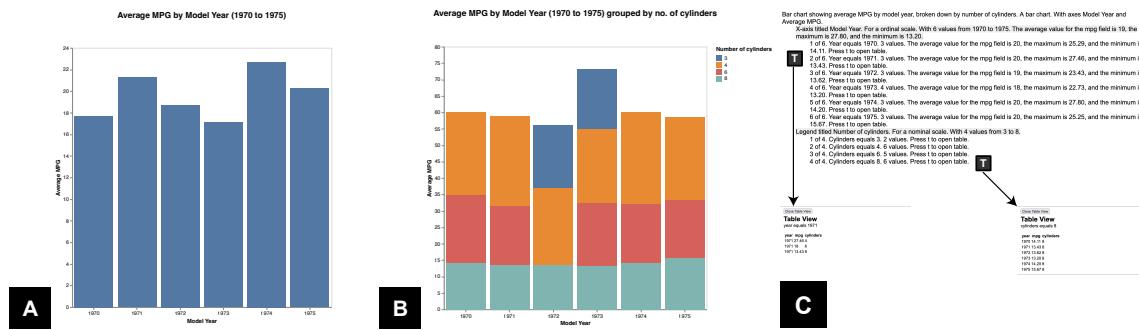
729 keyboard interactions (for intuitive navigation), ensuring that users can efficiently understand and analyze the data  
 730 without relying on traditional visual cues.  
 731

732 *3.3.3 Adapting Olli For Different Charts.* The Olli library supports the generation of multi-level textual descriptions  
 733 for various chart types, including stacked bar charts, multi-series line charts and scatterplots. We created charts using  
 734 Vega-Lite and provided the chart specifications to Olli.  
 735



746 Fig. 6. **Olli—Pie Charts.** Panels (A–C) show the progression from a top-level summary to detailed descriptions of individual pie  
 747 slices, supporting an screen reader exploration of categorical proportions.  
 748

749 For pie charts, olli generates a high-level summary (level-1), and items for each slice of the pie segment (see Figure 6.).  
 750



751 Fig. 7. **Olli—Bar charts.** Panels (A–C) illustrate a hierarchical approach—from chart summary to axis intervals and detailed data  
 752 points—facilitating navigation through both simple and stacked bar charts using auditory feedback.  
 753

754 For bar charts, olli generates a high-level summary—level-1, and items for the X-axis—level-2, followed by items for  
 755 X-axis intervals—level-3, and users can use the table view by pressing the ‘T’ key while on an interval item to access  
 756 individual data points—level-4. For stacked bar charts, there is also a legend item at level-2 (see Figure 7.).  
 757

758 For line charts, Olli generates a high-level summary—level-1, and items for each line or data-series—level-2, followed  
 759 by items for X-axis and Y-axis intervals—level-3. At level-4 are items for intervals for the axes nested under level-3. And  
 760 users can use the table view by pressing the ‘T’ key while on an interval item to access individual data points—level-5  
 761 (see Figure 8.).  
 762

763 For scatterplots, Olli generates a high-level summary—level-1, and by items for X-axis and Y-axis intervals—level-2.  
 764 At level-3 are items for intervals for the axes nested under level-2. And users can use the table view by pressing the ‘T’  
 765

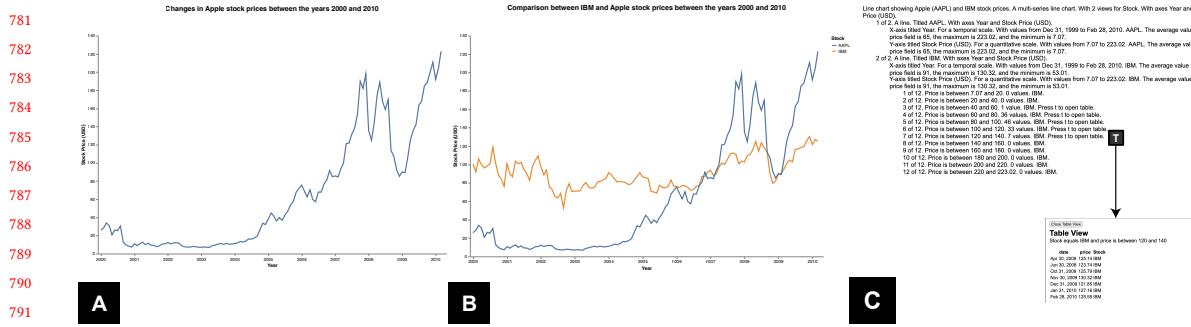


Fig. 8. **Olli—line charts.** Panels (A–C) detail the breakdown from a high-level summary to specific X and Y-axis intervals, allowing users to drill down into trends and compare multiple data series.

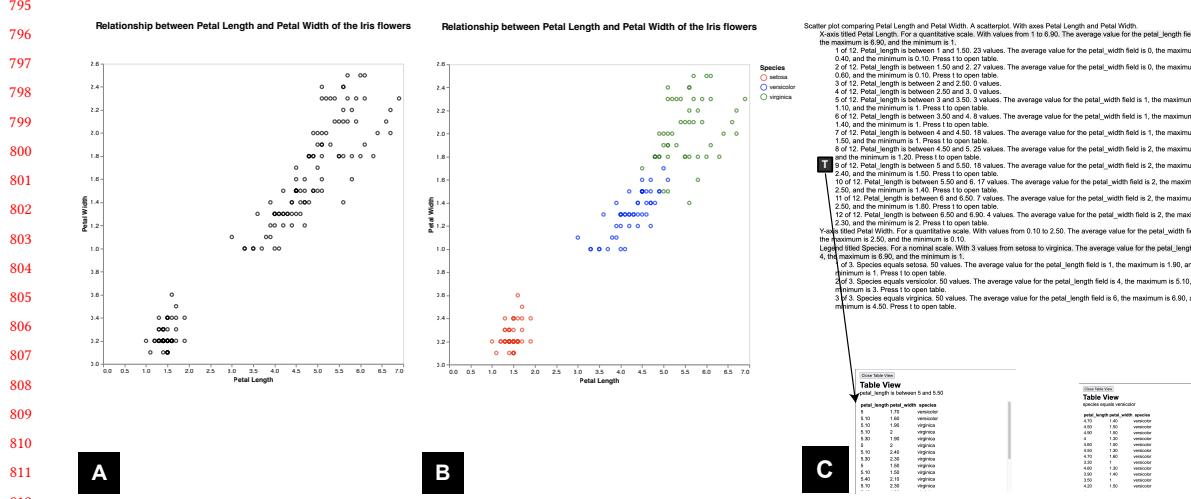


Fig. 9. **Olli—Scatterplots.** Panels (A–C) guide the user from an overall chart summary to detailed intervals that capture the distribution and density of data points across different categories.

key while on an interval item to access individual data points—level-4 (see Figure 8.). For a scatter plot with multiple categories, a legend item is added at level 2. Nested under the legend are items for each category of the nominal variable being visualized.

### 3.4 Monarch: Multi-line Refreshable Braille Display That Uses Only Touch

Monarch is a RTD designed to provide tactile access to both text and graphics for blind or low-vision users. Figure 10 shows an annotated schematic of the device.

**3.4.1 Device Layout and Interaction.** When placed on a flat surface, the Monarch tablet is oriented such that the *Braille keyboard* is closest to the user (front edge). On the left edge, from front to back, users will find a USB-A port, the square-shaped Power button, and a USB-C port (for charging or data transfer). On the right edge, the device provides an HDMI port, a 3.5 mm audio jack, and volume keys. The *tactile display* occupies the central region, with 10 lines of 32 Braille characters each. Monarch’s tactile display is made up of an array of pins forming multiple lines (up to 10 lines).

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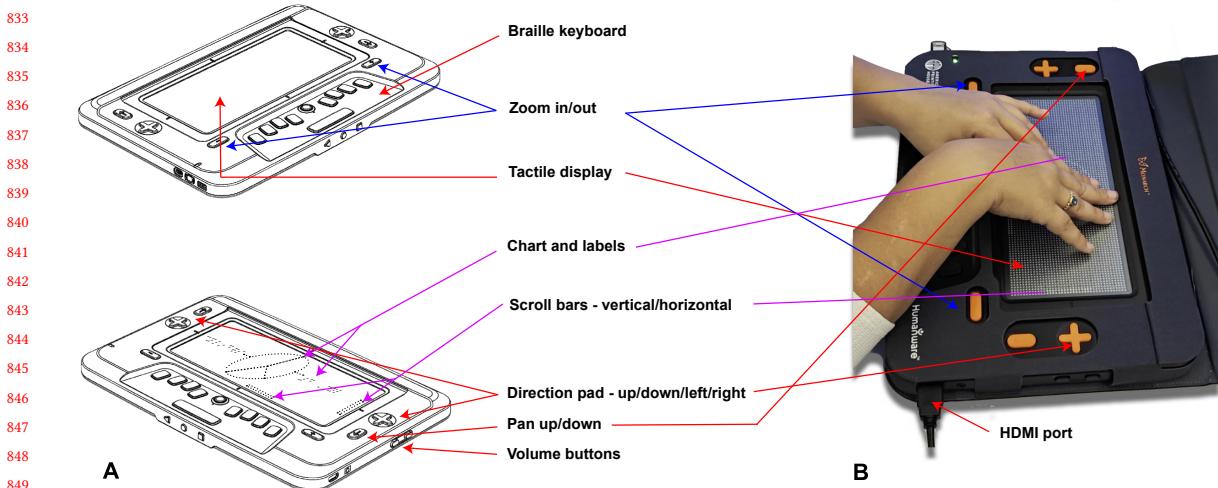


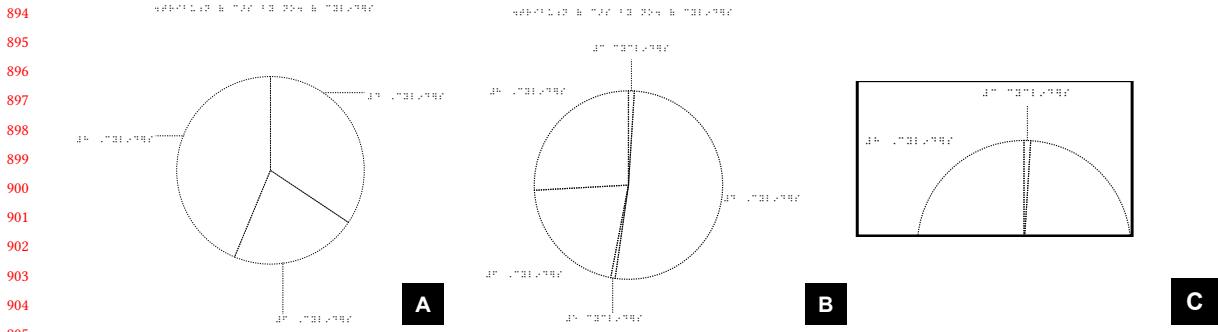
Fig. 10. **Monarch Interactions.** Panels (A–B) highlight key features such as the Braille keyboard, tactile display, and navigation buttons that enable blind users to access both static text and graphical content through touch.

10 lines; 32 Braille cells per line), enabling dynamic refresh of Braille text or tactile graphics. The pin dimensions are  $96 \times 40$  ( $W \times H$ ). Each cell is composed of 8 pins (dots 1–6, plus dots 7–8). A dedicated orange *Refresh button* near the Braille keys can refresh the pin array in a case of pin actuation errors. The device supports *zoom in/out* buttons that adjust the spacing and number of Braille lines displayed. This zooming allowed our participants to zoom into the chart, if needed, while performing the tasks. Two *D-Pads* (directional pads—one on each side of the tactile display) for panning the view after zooming in. There are *Pan Up* and *Pan Down* physical buttons for panning large documents or multi-page text content. Along the front edge, users have a conventional 6-dot Braille input layout plus dot 7 (Backspace), dot 8 (Enter), and a Space bar.

**3.4.2 Designing Charts for Monarch.** The Monarch device runs the Android operating system, and comes pre-installed with apps to view documents, a mobile browser, and access to tactile graphics through an app called **Tactile Viewer**. We designed charts to work with the Tactile Viewer application as the mobile browser was only able to render text from websites, and not images or SVG charts. Tactile viewer uses a *thresholding* approach to segment an image into the foreground and background. We created charts using the Vega-Lite library and exported the charts as PDFs to be rendered on the Monarch device. Tactile Viewer applies the thresholding technique and then scales the image to be viewable on the tactile display. Through piloting, we identified a web-chart resolution that would be appropriately rendered on the pin display. The application did not support a focus zoom, where users could point to a section of the chart to zoom into. However, users can zoom into the current view and use the d-pad to pan the zoomed view. This meant that users would lose the reference axes while viewing a region far away from the x-axis and y-axis. With these constraints in mind, we designed simple grayscale charts with minimum clutter. Although the device supports interactions through buttons and the tactile display, the charts we designed were “static visualizations”.

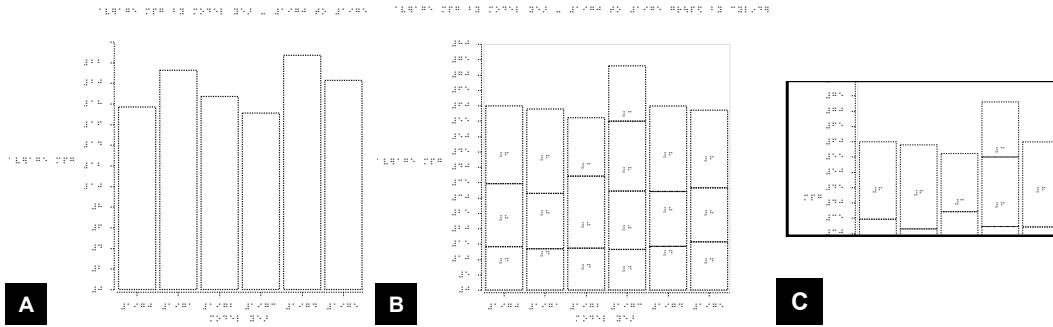
Every chart included a title, x and y-axis (when applicable), axes labels, tick marks, and tick mark labels. While creating the charts, we converted labels and titles to ASCII Braille characters using a simple character mapping function. We adjusted the font size to ensure that the braille text is readable after zooming in. For charts that had multiple data

series being visualized, we also included a legend with a title, and labels for each category. Overall, we only used borders for the chart elements, and did not fill the elements such as bars, pie slices, and scatter plot symbols. We piloted the designs within the research team (one author is blind), and decided to use the space within to include annotations or other labels. For visual charts, annotations and labels are laid out at various angles (for example, a y-axis label could be printed vertically). However, considering the nature of braille, we had to ensure that labels were horizontally rendered (see Figure 10). To estimate the sizes and data values of the chart elements, users would have to use the tick mark labels on the axes.



**Fig. 11. Monarch—Pie Charts.** Panels (A-C) show a pie chart adapted for the Monarch device, where each segment is annotated with an external Braille label connected by a guiding line.

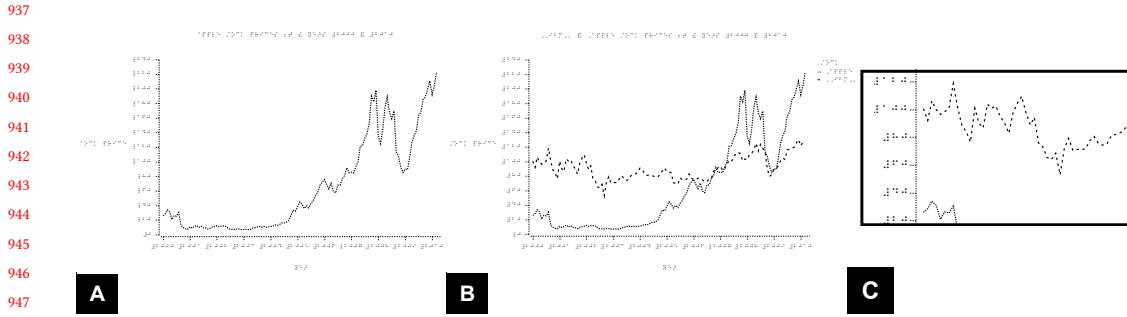
For *pie charts*, we included labels for each pie segment outside the pie. When pie segments were smaller, we included a line to connect the label to the pie segment (see Figure 11).



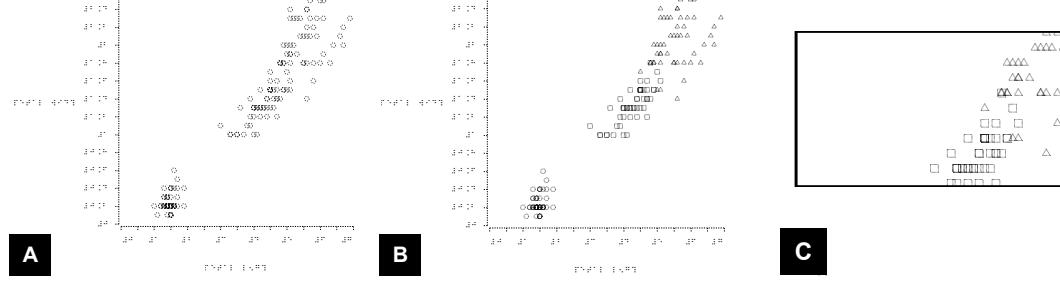
**Fig. 12. Monarch—Bar Charts.** Panels (A-C) show a simple and stacked bar chart. The tick marks and in-cell labels allow users to identify quantitative differences and categorical groupings through tactile exploration.

For *bar charts*, each bar segment was assigned a tick mark and labeled. In the case of stacked bar charts (see Figure 12.B), the category of a bar segment is included as a label inside every bar segment corresponding to that particular data series.

For *line charts*, we used different line stroke patterns to encode the categorical values. We ensured that each pattern was perceptually differentiable to the sense of touch through internal piloting. In the case of multi-series line charts (see Figure 13.B), the category of a series is included as a label inside every bar segment corresponding to that particular data series. We chose not to annotate the points on the line because of clutter; especially in multi-series line charts.



**Fig. 13. Monarch—Line Charts.** Panels (A–C) show a single and multi-series line charts created for the Monarch. Panel B shows that for multi-series line charts the design embeds different line types (dashed vs. dots) for each data series.



**Fig. 14. Monarch—Scatterplots.** Panels (A–C) show the tactile rendering of scatter plots where different shapes (such as circles, squares, and triangles) encode categorical values.

For *scatter plots*, we used different shapes (circle, square, and triangle) to encode the categorical values. Based on the data distribution, there is a possibility of occlusion (see Figure 14.B), and despite zooming, the positions of the points remain the same, and the zooming algorithm of Tactile Viewer simply magnifies the size, and does not introduce spacing to make points more perceivable while zooming. This is a limitation of our implementation, and we ensured that the tasks used in our comparison study did not require such granular zooming.

#### 4 USER STUDY

In this section, we describe a comparison study to understand the tradeoffs and strengths of each data accessibility approach.

##### 4.1 Overview

Our goal was to explore how blind and low-vision (BLV) professionals interact with different data representations using various devices, focusing on the efficacy and user experience of each method. In order to better design multimodal experiences, we compared inclusive data visualization access through 1) screen-reader access to chart descriptions, 2) interactive sonification, and 3) tactile representations on a refreshable braille display. Participants were expected to complete data visualization tasks by exploring bar charts, pie charts, line charts, and scatter plots. Each chart was

adapted for three systems: 1) Olli [3] for screen reader access 2) TactualPlot [10] for sonification, and 3) Monarch [29] for tactile representation, and completed 3 tasks per chart type ( $n = 4$ ). The study was approved by the National Federation of the Blind (NFB) in Baltimore and our university's Institutional Review Board (IRB).

## 4.2 Participants

We recruited participants through NFB's mailing lists, and snowball sampling. Our inclusion criteria was that participants had to: *be blind or have low vision, have experience with data analysis, and live in the U.S.* As part of the consent and scheduling process, participants filled an online survey through which we collected demographic information, information on their blindness, assistive technology usage, experience with data visualization, and familiarity with non-visual analysis techniques (sonification and tactile graphics).

**4.2.1 Demographics and background.** Ten blind adults ( $n = 10$ ) were recruited after our screening and consent process. Table 2. outlines key demographics and background information for each participant. Our participants were between the ages of 18 and 60, with the average age being 40.2 years. Seven participants identified as female, two as male, and one chose not to specify their gender. Majority of our participants reported being "totally blind" ( $n = 7$ ), and three participants reported that they were "legally blind". Most of our participants ( $n = 7$ ) were blind since birth; two reported onset between 0-5 years of age, and one experienced onset between 13-18 years. All participants had at least a high school diploma: five had completed master's degrees, three completed bachelor's degrees, and two had completed high school. Six participants reported that they can read braille fluently; and four can read with some difficulty. Eight participants reported that they can write braille fluently; and two can write with some difficulty. A summary of the participant demographics can be found in table 2.

Table 2. Participant demographics.

ID	Age	Gender	Blindness	Onset	Braille Reading	Braille Writing	Education
P1	49	F	Totally blind	From birth	Some difficulty	Fluently	Master's
P2	41	F	Legally blind	13-18 years	Some difficulty	Fluently	Master's
P3	36	F	Legally blind	From birth	Some difficulty	Some difficulty	Master's
P4	37	N/A	Totally blind	From birth	Fluently	Fluently	Master's
P5	39	M	Totally blind	From birth	Fluently	Fluently	High school
P6	59	F	Totally blind	From birth	Some difficulty	Some difficulty	Master's
P7	60	F	Totally blind	0-5 years	Fluently	Fluently	Bachelor's
P8	18	M	Totally blind	From birth	Fluently	Fluently	High school
P9	35	F	Totally blind	0-5 years	Fluently	Fluently	Bachelor's
P10	28	F	Legally blind	From birth	Fluently	Fluently	Bachelor's

**4.2.2 Technology usage.** All of our participants used screen readers daily. Similarly, all participants reported using desktop/laptop computers and smartphones; with four participants additionally using a Tablet/iPad. All of our participants reported having using Microsoft Windows; five participants also used Apple MacOS; and one participant was familiar with Linux. In terms of smartphone operating systems, all participants were familiar with Apple iOS; and two participants were familiar with Android. Among the ten participants, data analysis experience ranged from "Little to no experience" ( $n=1$ ) to "Moderate experience, such as advanced coursework, or occasionally using charts

and statistics for work" (n=2), with the remaining seven reporting "Some experience, such as an introductory course in school, but no advanced training". Comfort with bar and pie charts was most commonly "Somewhat comfortable" (n=7) though a few reported "Very comfortable" (n=2) or "Not very comfortable" (n=1). Line and scatterplot familiarity followed a similar pattern, and one participant indicated "Very comfortable" with scatterplots while another indicated "Not at all comfortable". Most participants were at least "Somewhat comfortable" (n=5) with tactile graphics, while exposure to sonification tended to be "Not very comfortable" (n=5) or "Somewhat comfortable" (n=3); with two "Not at all comfortable". Comfort level with screen reader access to charts was split among "Somewhat comfortable" (n=5), "Not very comfortable" (n=2), and "Very comfortable" (n=3). Overall, these responses showcase a range of comfort and experience levels across different chart types and sensory modalities. A summary of the participants' technology usage and data analysis experience can be found in table 3.

Table 3. Technology and data analysis experience.

ID	Data Analysis	Bar Charts	Pie Charts	Line Charts	Scatter Plots	Tactile Graphics	Sonification	Screen Reader Chart Access
	(Exp.)	(Comfort)	(Comfort)	(Comfort)	(Comfort)	(Familiar)	(Familiar)	(Familiar)
P1	Some	Somewhat	Somewhat	Very	Somewhat	Very	Not Very	Very
P2	Some	Somewhat	Somewhat	Not Very	Not Very	Somewhat	Not at all	Not Very
P3	Some	Somewhat	Somewhat	Somewhat	Somewhat	Somewhat	Not very	Somewhat
P4	Some	Very	Very	Very	Somewhat	Very	Not at all	Somewhat
P5	Some	Somewhat	Somewhat	Not very	Not very	Somewhat	Not very	Very
P6	Some	Not very	Not very	Not very	Not at all	Somewhat	Somewhat	Somewhat
P7	Little	Somewhat	Somewhat	Somewhat	Somewhat	Not Very	Not very	Not very
P8	Moderate	Very	Very	Somewhat	Somewhat	Very	Somewhat	Very
P9	Moderate	Somewhat	Somewhat	Somewhat	Somewhat	Somewhat	Somewhat	Somewhat
P10	Some	Somewhat	Somewhat	Somewhat	Very	Very	Not very	Somewhat

### 4.3 Apparatus

Our study used three different approaches to data accessibility, each representing a different modality or combination of modalities for presenting data to BLV users. These approaches were chosen to cover a range of current and emerging technologies in the field of accessible data visualization.

- (1) **TactualPlot**: installed on an Apple iPad Pro 128 GB with an 11-inch (diagonal) Liquid Retina display; the actual screen dimensions were  $247.6\text{mm} \times 178.5\text{mm}$ —providing a hybrid audio-tactile interface for data exploration.
- (2) **Monarch device**: a HumanWare tactile tablet featuring a  $96 \times 40$  ( $W \times H$ ) retractable and refreshable pin grid to generate tactile experiences.
- (3) **Screen reader**: participants used screen reader software (Apple VoiceOver) in conjunction with the Olli navigator for accessing textual chart descriptions.

### 4.4 Dataset, charts and tasks

We utilized basic multidimensional statistics datasets commonly provided in R, matching each dataset to a specific representation:

- 1093 • mtcars dataset (fuel consumption and automobile design) - pie charts, bar charts and scatterplots;
- 1094 • auto-mpg dataset (fuel efficiency data) - pie and bar charts;
- 1095 • stocks dataset (monthly stock price of companies between years 2000 and 2010) - line charts; and
- 1096 • iris dataset (Measurements of iris flowers) - scatterplots.

1098 In total we created 24 charts, with 6 charts per visual representation so that every participant does not encounter  
 1099 the same chart while using all three devices. To introduce some complexity in the charts, we created two levels of  
 1100 difficulty—**CD01**, and **CD02**. For pie charts, difficulty was based on number of pie segments. For bar charts, CD01  
 1101 did not have a nominal variable visualized, CD02 was a stacked bar chart (includes nominal variable). For line charts,  
 1102 CD01 include only data from one series, and CD02 included a multi-series line chart with data from two series. For  
 1103 scatterplots, CD01 included a relationship between two quantitative variables, and CD02 included a nominal variable  
 1104 where the chart included a third encoding to group data by categories. Participants completed three types of tasks for  
 1105 each chart, introduced through the concept of “cardinality” (one item, two items, all items):  
 1106

- 1107 T1 **Single-Point Identification** (cardinality: one item): Identify specific data points (e.g., “What was the average  
   1108 MPG of 3 cylinder cars”);
- 1109 T2 **Pairwise Comparison** (cardinality: two items): Compare two data points or categories (e.g., “Which has a  
   1110 higher MPG: 3-cylinder or 4-cylinder cars?”); and
- 1111 T3 **Trend Analysis** (cardinality: all items): Describe overall trends or patterns in the data (e.g., “What is the  
   1112 relationship between petal length and petal width”)

#### 1113 4.5 Experimental Factors

1114 Our study considered the following factors:

- 1115 • **Device (DT)**: Olli (**OLL**), TactualPlot (**TAP**), and Monarch tactile graphics (**MON**)
- 1116 • **Visual Representation (VR)**: pie charts (**PIE**), bar charts (**BAR**), line charts (**LINE**),  
   1117 and scatterplots (**SCATTER**)
- 1118 • **Task Type (TT)**: single-point identification (**SP**), pairwise comparison (**PC**), trend analysis (**TA**)

#### 1119 4.6 Experimental Design

1120 Considering the experimental factors, each participant attempted 36 tasks—3 tasks per chart (VR) across the three  
 1121 devices (DT). We chose an experimental design within subjects where all participants experienced all conditions during  
 1122 the study. The order of presentation of the devices (DT) was counterbalanced using a Latin square design. We did not  
 1123 include chart difficulty as an experimental factor to restrict the number of tasks in the experiment, and to reduce fatigue  
 1124 during the study session. However, we ensured that the participants performed 18 tasks on each CD01 and CD02 charts  
 1125 on the three devices.

#### 1126 4.7 Procedure

1127 After obtaining informed consent online, we administered a demographic survey to gather background information  
 1128 on each participant’s visual impairment, professional experience, and familiarity with assistive technologies. On the  
 1129 scheduled date, we met participants in a laboratory space in our university or in their personal space of choosing to  
 1130 ensure comfort and familiarity with the environment. We gave participants an introduction to the session, and explained  
 1131 the study procedure. Participants received a 10-minute hands-on training on each device and data representation  
 1132

method before performing tasks. While we dedicated 10-minutes for the training, training times often varied between participants, with a maximum of 17 minutes. Participants typically learned to use Olli and the Monarch faster than TactualPlot. This training phase was designed to ensure that all participants had a baseline understanding of how to interact with each device and interpret the different data representations.

Following the training, we conducted timed and recorded trials for each of the 36 task combinations. Participants were encouraged to think aloud during the trials, providing verbal insights into their thought processes and any challenges they encountered. Considering the novelty of some of these devices, participants could also ask the researcher for help if they were stuck during a task. Tasks were read out loud to the participant, and we informed participants about the 4-minute time limit for a task. To reduce study demands, the researcher recorded task times, and also selected the task answer after receiving verbal confirmation from the participant. Completion times were measured with the start time being the moment after the task was read-out loud to the participant, and the stop time was when a task option was chosen. We restricted the task time to ensure that participants attempted all the tasks on all three devices. Upon completion of all trials, we conducted a semi-structured interview with each participant. Participants also filled the NASA Task Load Index (TLX) workload questionnaire to collect subjective ratings for each of the devices. These interviews allowed us to gather qualitative feedback on the participants' experiences with each device and representation, their preferences, and any suggestions for improvement. The average duration of the study session was 3 hours and 18 minutes (breaks were offered to prevent fatigue).

#### 4.8 Data Metrics and Analysis

We collected the following data for analysis:

- **Accuracy:** correctness of responses for each task.
- **Task completion time:** measured for all trials across all devices.
- **Qualitative feedback:** gathered through post-task interviews and think-aloud protocols during the trials.

Our analysis involved both quantitative and qualitative methods:

- **Quantitative analysis:** Analysis of effect sizes and 95% confidence intervals to compare task completion times and accuracy across devices, representations, and task types.
- **Qualitative analysis:** Thematic analysis of interview transcripts and think-aloud data to identify recurring themes, preferences, and challenges associated with each approach.

This mixed-methods analysis helped provide a comprehensive understanding of the strengths and limitations of each data accessibility technique in the context of BLV individuals' real-world data exploration needs.

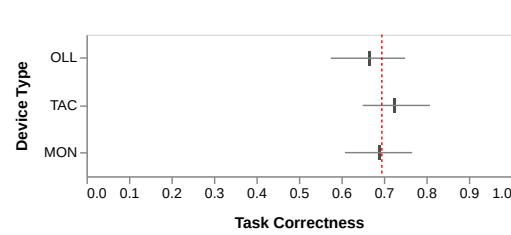
### 5 RESULTS

In this section, we present results from our analysis of 360 tasks from n=10 participants. The tasks were distributed as follows for each condition: DT—120 per device type; VR—90 per visual representation; TT—120 per task type. We analyzed all our data using estimation methods to derive 95% confidence intervals (CIs). We employed non-parametric bootstrapping [15] with R = 1,000 iterations— to follow current best practices for fair statistics in the field of HCI [14]. The goal of our analysis was to explore challenges with performing analysis tasks (TT) on each device (DT), and to understand what kind of challenges different chart types (VR) pose while using a particular device. We measured accuracy (task correctness) and task completion times. Since we used a think-aloud protocol, the completion time measure includes time spent on performing a task as well as any time taken for any communication between the

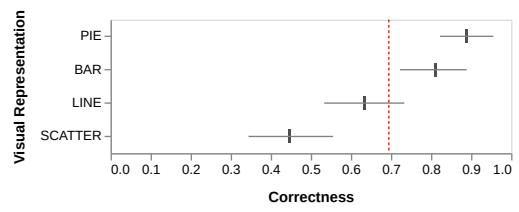
researcher and participant. However, we note that completion time can be a good indicator for how difficult or easy a task was to perform. Additionally, we report subjective NASA TLX ratings, and include a thematic analysis [36] of the post-task completion interview, and participants' thoughts while performing the tasks.

### 5.1 Task Correctness

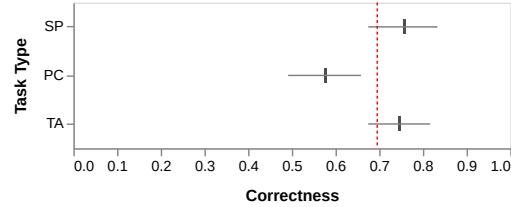
Our analysis results show that participants completed 250 (out of 360) tasks correctly with an accuracy of 69.4%. First, we compared task correctness between devices, and observed that the accuracy with: Olli (OLL) was 69.2%; TactualPlot (TAC) was 72.5%; and the Monarch (MON) was 66.6%. Participants had accurately completed 80/120 tasks with Olli; 87/120 tasks with TactualPlot; and 83/120 tasks with the Monarch. Thus, TactualPlot resulted in marginally better accuracy than Olli and the Monarch. However the error bars (see figure 15a.) for all three devices have a large overlap and do not have too much of a separation despite the mean values being apart.



(a) Comparing task correctness between device type (DT) levels (error bars represent 95% confidence intervals).



(b) Comparing task correctness between visual representation (VR) levels (error bars represent 95% confidence intervals).



(c) Comparing task correctness between task type (TT) levels (error bars represent 95% confidence intervals).

**Fig. 15. Analysis of correctness (accuracy) across the experimental factors.** Results from an analysis of 95% CIs after bootstrapping ( $R = 1000$ ).

We compared task correctness between different visual representations (VR), and observed a clear separation between the means. The accuracy for: pie charts was 88.9%; followed by 81.1% for bar charts; 63.3% with line charts; and only 44.4% for scatterplots. Participants had accurately completed 80/90 tasks with pie charts; 73/90 tasks with bar charts; 57/90 tasks with line charts; and 40/90 tasks with the scatterplots. We can clearly notice a separation between the means of each visual representation (see figure 15b.) and the overlap between the error bars of each VR is very minimal. This shows that participants found certain chart types easier than the others.

We compared task correctness between task types (TT), and observed that the accuracy with: single-point identification (SP) was 75.8%; pairwise comparison (PC) was 57.5%; and trend analysis (TA) was 75%. Participants had accurately completed 91/120 single-point tasks; 69/120 pairwise comparison tasks; and 90/120 trend analysis tasks. Thus, pairwise comparison tasks, which involved comparing two different data values by navigating, and locating the right chart

element (TP and MON) or textual description (OLL) were harder than single-point identification and trend analysis. In figure 15c., we can see that the means of task types TA and SP are higher than the overall average (red line); with the mean value and error bars of PC tasks clearly separated from both the overall average and the other task types.

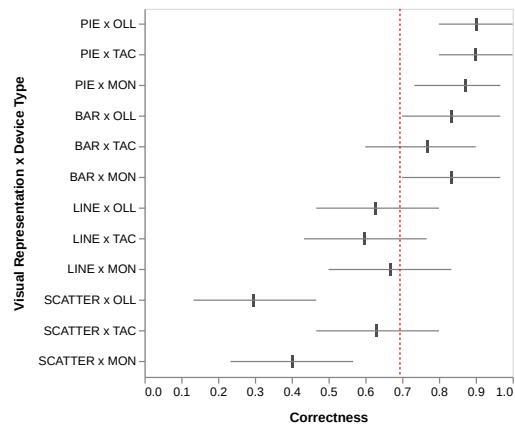
Table 4. **Comparison of mean task correctness for a combination of Device Types (DT) across Visual Representations (VR) and Task Types (TT).** Task correctness values are reported as percentages, and we also show the number of correct tasks for each condition.

	Pie	Bar	Line	Scatter
<b>Olli</b>	90.0% 27/30	83.3% 25/30	63.3% 19/30	30.0% 9/30
<b>TactualPlot</b>	90% 27/30	76.66% 23/30	60.0% 18/30	63.3% 19/30
<b>Monarch</b>	86.6% 26/30	83.3% 25/30	66.6% 20/30	40.0% 12/30

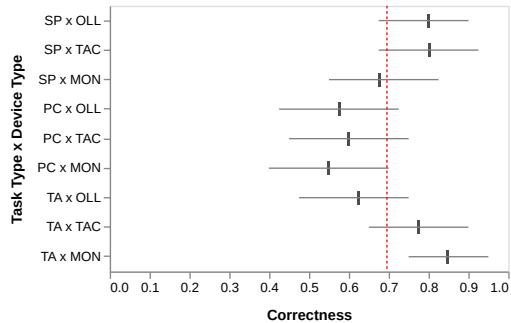
(a) Visual Representation (VR) x Device Type (DT).

	Single point	Pairwise	Trend
<b>Olli</b>	80.0% 32/40	57.5% 23/40	62.5% 25/40
<b>TactualPlot</b>	80.0% 32/40	60.0% 24/40	77.5% 31/40
<b>Monarch</b>	67.5% 27/40	55.0% 22/40	85.0% 34/40

(b) Task Type (TT) x Device Type (DT).



(a) Comparing mean task correctness between visual representation type (VR) x device type (DT) (error bars represent 95% confidence intervals).



(b) Comparing mean task correctness between task type (TT) x device type (DT) levels (error bars represent 95% confidence intervals).

Fig. 16. **Analysis of correctness (accuracy) across a combination of experimental factors.** Results from an analysis of 95% CIs after bootstrapping ( $R = 1000$ ).

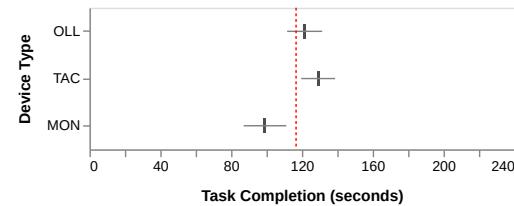
Next, we wanted to further explore and understand the relationship between device type (DT) and visual representation (VR); especially considering scatter plots and line charts had lower task correctness. The mean task correctness for each combination of factors are shown in Table 4a. Figure 16a demonstrates the trend in our data, where scatterplots and line charts had lower task completeness, compared to bar charts and pie charts; with pie charts being the most accurate across all device types. The error bars for bar and pie charts overlap indicating that both visual representations were similar in task correctness; with bar charts on Tactualplot showing the least accuracy. With scatterplots, TactualPlot

1301 showed more task correctness compared to Olli and the Monarch; and the error bars of TactualPlot and Olli do not  
 1302 overlap. Olli and the Monarch showed higher task correctness as compared to TactualPlot for bar charts and line charts;  
 1303 However, the error bars (CIs) in figure 16a overlap when comparing all three devices for pie, bar, and line charts.  
 1304

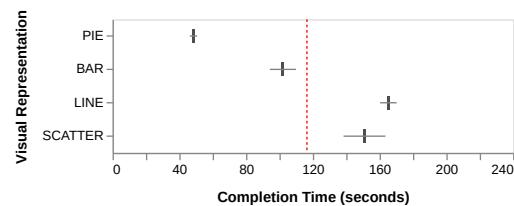
1305 Finally, we compared task correctness for a combination of task type (TT) and device type (DT). The mean task  
 1306 correctness for each combination of factors are shown in Table 4b. Figure 16b displays these means along with 95%  
 1307 confidence intervals generated from bootstrapping. For PC tasks, we note that the confidence intervals largely overlap  
 1308 across devices—indicating comparable performance. For the TA condition, non-overlapping error bars between Monarch  
 1309 and Olli, suggesting that there was a large difference in task correctness.  
 1310

## 1312 5.2 Task Completion Time

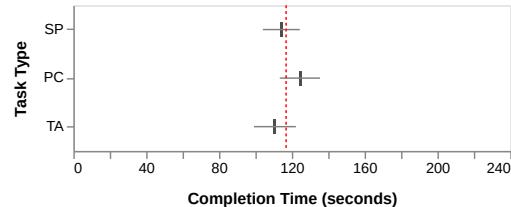
1314 We performed a similar analysis of task completion times (maximum trial limit of 240 seconds) using the bootstrapping  
 1315 technique. The mean task completion time was 116.6 seconds ( $SD = 60.7$  s). A comparison of the means of correct (94.5  
 1316 s) and incorrect (166.8 s) tasks indicated that participants spent more time on incorrect tasks. We note that the increased  
 1317 time could also be impacted by the time spent by the participant on thinking out loud (some individuals expressed more  
 1318 thoughts than others) and discussing the task with the researcher. We compared task completion time between devices,  
 1319 and observed that the completion: Olli (OLL) was 121.4 s; TactualPlot (TAC) was 129.3 s; and the Monarch (MON) was  
 1320 98.9 s. The error bars (see figure 17a.) for the mean completion times for Olli and TactualPlot show that participants  
 1321 spent more than the average task completion time (116.6 s—indicated by the red line) on Olli and TactualPlot tasks.  
 1322 Figure 17a. also shows that the error bars for the Monarch do not overlap with those of the other two device types (OLL  
 1323 and TAC).  
 1324



1327 (a) Comparing mean task completion time between device  
 1328 type (DT) levels (error bars represent 95% confidence inter-  
 1329 vals).



1330 (b) Comparing mean task completion time between visual  
 1331 representation (VR) levels (error bars represent 95% confi-  
 1332 dence intervals).



1333 (c) Comparing task completion time between task type (TT)  
 1334 levels (error bars represent 95% confidence intervals).

1335 Fig. 17. **Analysis of mean task completion time across the experimental factors.** Results from an analysis of 95% CIs after  
 1336 bootstrapping ( $R = 1000$ )

1353 Next, we compared completion times between different visual representations (VR), and observed a clear separation  
 1354 between the means. The completion time (lowest to highest) for: pie charts was 48.4 s; followed by 101.6 s for bar charts;  
 1355 150.9 s for scatterplots; and the highest values was 165.3 s for line charts. We can clearly notice a separation between  
 1356 the means of each visual representation (see figure 17b.) and there is no overlap between the error bars of each VR. This  
 1357 shows that participants spent more than average time with line charts and scatter plots, as compared to pie and bar  
 1358 charts.

1359  
 1360 We compared mean completion times between task types (TT), and observed that the time for: single-point identifi-  
 1361 cation (SP) was 114.4 s; pairwise comparison (PC) was 124.7 s; and trend analysis (TA) was 110.7 s. This indicates  
 1362 that participants spent the least time on trend analysis tasks, followed by single-point identification, and most time on  
 1363 pairwise comparison tasks. In figure 17c., we can see that the means of task types TA and SP are lower than the overall  
 1364 average (red line). And, the mean completion time for PC tasks was the highest.  
 1365  
 1366

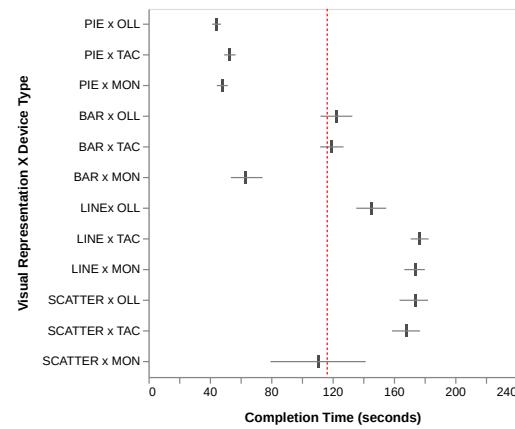
1367  
 1368 **Table 5. Comparison of mean completion times for a combination of Device Types (DT) across Visual Representations**  
 1369 (**VR**) and Task Types (TT). The completion time is measured in seconds (s).

	Pie	Bar	Line	Scatter
Olli	44.2	122.4	145.2	173.8
TactualPlot	53.0	119.3	176.8	168.2
Monarch	48.1	63.0	173.9	110.9

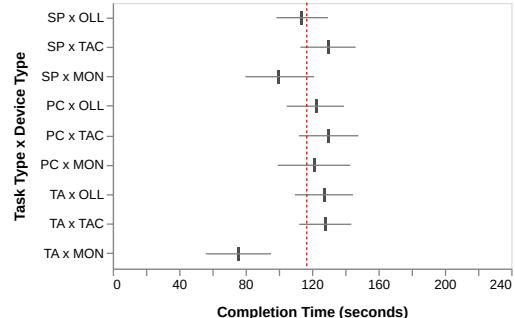
1370 (a) Visual Representation (VR) x Device Type (DT).

	Single point	Pairwise	Trend
Olli	113.6	123.3	127.4
TactualPlot	129.5	129.6	128.9
Monarch	99.9	121.3	75.8

1371 (b) Task Type (TT) x Device Type (DT).



1372  
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 1374  
 1375  
 1376 (a) Comparing mean task completion time between visual  
 1377 representation type (VR) x device type (DT) (error bars rep-  
 1378 resent 95% confidence intervals).



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 1392 (b) Comparing mean task completion time between task  
 1393 type (TT) x device type (DT) levels (error bars represent 95%  
 1394 confidence intervals).

1395  
 1396 Fig. 18. **Analysis of mean task completion times.** Comparison across a combination of experimental factors—results from an  
 1397 analysis of 95% CIs after bootstrapping (R = 1000)

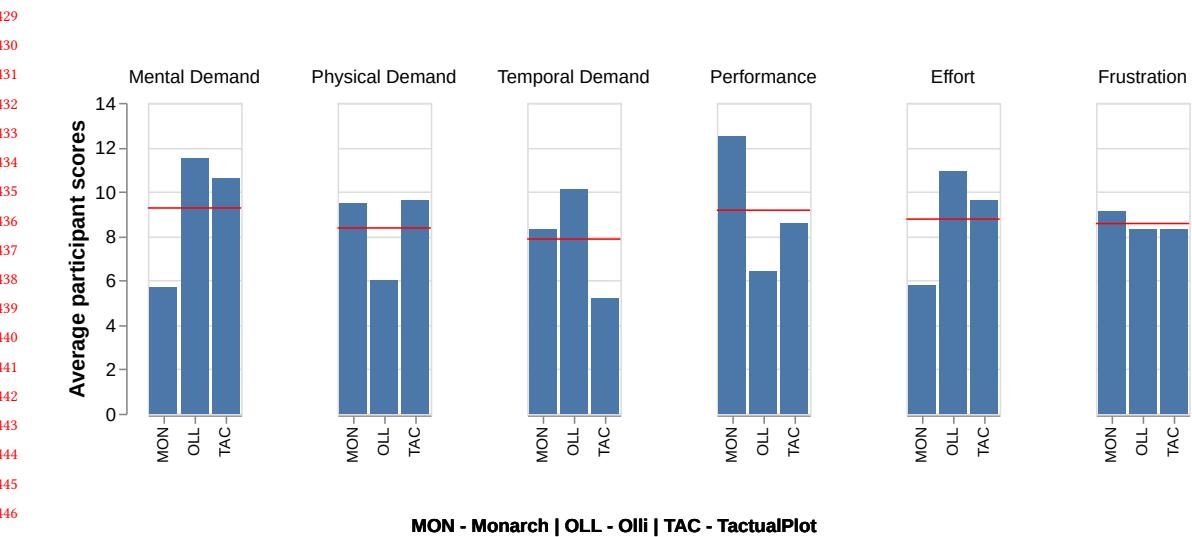
1398 Next, we wanted to further explore and understand the relationship between device type (DT) and visual represen-  
 1399 tation (VR). The mean completion times for each combination of factors are shown in Table 5a. Figure 18a indicates

1405 small error bars (95% CIs) for each condition except for scatterplots on the Monarch. Pie charts showed the lowest  
 1406 mean completion times on all three devices, followed by bar charts on the Monarch. Scatterplots on the Monarch  
 1407 also had a mean completion less than the study mean (red line). We suspect this was because participants struggled  
 1408 with scatterplots on the Monarch considering the occlusion that required multiple levels of zooming and panning;  
 1409 with participants often feeling lost. Some of our participants gave up and chose the “unsure of the answer” option to  
 1410 complete the task (incorrectly). For line charts, the mean completion time for Olli was lower than TactualPlot and the  
 1411 Monarch—both of which had similar mean completion times.  
 1412

1413 Lastly, we compared mean completion times for a combination of task type (TT) and device type (DT). The mean  
 1414 completion times for each combination of factors are shown in Table 5b. We note that the Monarch had the lowest  
 1415 mean task completion time among all the three task types; followed by Olli, and the highest was TactualPlot. Single  
 1416 point tasks (129.5 s) on TactualPlot had higher mean completion time than every combination of task type and devices  
 1417 except for pairwise tasks on the TactualPlot (129.6 s). The error bars (see Figure 18b.) after bootstrapping do overlap for  
 1418 many of our conditions; but trend analysis tasks on the Monarch shows a clear separation between all the conditions,  
 1419 except single point tasks on the Monarch.  
 1420

### 1421 5.3 Subjective Ratings: NASA TLX

1422 Figure 19. shows the mean NASA TLX subscale scores (0–20) reported by our participants for each device type. We  
 1423 assessed the devices across six dimensions: *Mental Demand*, *Physical Demand*, *Temporal Demand*, *Performance*, *Effort*,  
 1424 and *Frustration*. In every dimension, a lower score indicates a better rating.  
 1425



1448 Fig. 19. **NASA TLX Ratings.** Comparison of mental demand, physical demand, temporal demand, performance, effort, and frustration  
 1449 on a 20-point scale between the three device types. A lower score indicates a better rating.  
 1450

- 1451 • **Mental Demand.** Participants rated Olli (OLL) the highest (11.5) on mental workload, whereas TactualPlot  
 1452 (TAC) tended to be lower (10.6). Mental Demand rating for Monarch (MON) was the lowest (5.7).

- **Physical Demand.** MON (9.5) and TAC (9.6) both received moderate physical demand scores. OLL had the lowest rating (6.0) for physical demand, possibly due to minimal physical interaction beyond keyboard or gesture navigation.
- **Temporal Demand.** Participants using OLL felt slightly time intensive (10.1). MON ratings (8.3) indicated that participants felt less time than OLL while performing tasks. TAC ratings (5.2) indicated lowest temporal demand.
- **Performance.** OLL was rated at 6.4, TAC was rated at 8.6, and MON scored 12.5. This suggests that participants felt they performed best with OLL, moderately with TAC, and least effectively with MON.
- **Effort.** OLL's rating was 10.9, TAC was 9.6, and MON only 5.8. Participants perceived MON as requiring the least effort, with TAC in the middle, and OLL demanding the most effort.
- **Frustration.** Both OLL and TAC received a rating of 8.3; while MON scored slightly higher at 9.1. These results indicate that participants experienced similar levels of frustration with OLL and TAC, but slightly more frustration with MON.

#### 5.4 Qualitative Findings

We present results from a thematic analysis [36] of 10 participants' interview and other study responses. Participants explored bar charts, pie charts, line charts, and scatter plots, performing tasks like identifying largest slices, spotting trends, or comparing data points. We highlight major themes, challenges, and benefits of each modality.

*5.4.1 Initial Learning Curve and Familiarity.* Participants who had significant practice with tactile media (e.g., embossed Braille) adapted faster to the Monarch, while those accustomed to screen readers found Olli more familiar: “*I already had experience with tactile, so there’s less of a learning curve than a purely verbal system.*” (P5). Others (P2, P3) reported inconsistent exposure to tactile in past schooling, which led to early hesitation but quick adaptation: “*I’ve used charts before but not often. After a few minutes of feeling the pins on Monarch, it made sense.*” (P3). Despite initial confusion, most participants mentioned a turning point where the interface “clicked”: “*When the beep in TactualPlot got higher for bigger values, that’s when it all made sense. I was like, ‘Oh, that’s the pattern!’*” (P2). Similarly, users initially had to get accustomed to the features of the Tactile Viewer application: “*I struggled with the scroll bars on Monarch at first, but once I zoomed in properly, it was straightforward.*” (P1).

*5.4.2 Spatial Overview vs. Precise Detail.* Many participants praised Monarch for broad overviews: “*I can run my fingers along the bars and see which one is tallest, without reading five lines of text.*” (P1). However, dense or closely spaced data (e.g., scatter plots) could become a “blur of pins” if there was no filtering or zoom: “*When there’s a big cluster of data, it’s all lumps. I’d need more zoom or maybe fewer points at once.*” (P3). Participants used Olli to verify exact numeric values, though some worried about verbosity: “*If it’s 53 vs. 54, I’d rely on Olli’s text. But it can get overwhelming when it rattles off 10 lines in a row.*” (P4). They liked hierarchical breakdowns but wanted quick summaries, and had personal preferences on what information receives priority: “*Just give me the min and max upfront, so I don’t arrow through everything to find it.*” (P8) TactualPlot helped participants “feel” a chart while hearing real-time sonification: “*I love hearing a beep go higher with a taller bar, then tapping for the exact label. It’s a great combo.*” (P2) Yet interpreting pitch differences posed challenges for some: “*I’m not musically trained, so if the pitch difference is small, I can’t tell if it’s a bit bigger or a lot bigger.*” (P1)

*1509     5.4.3 Chart-Specific Observations.* Bar chart visual structures were familiar to some of the participants, and having  
*1510     this prior knowledge helped users to adapt to various device types: "If it's a stacked or grouped bar chart, I can still figure*  
*1511     out each segment, or just arrow through the categories."* (P8). P2 emphasized how past experience provided ease of access:  
*1512     "Bars are very direct in tactile or audio. I recognized them from past math classes, so it felt natural."* Pie charts made it easy  
*1513     to spot the largest or smallest slice: "*I can immediately tell if something's half the circle, but guessing it's 20% or 25% is**

*1514     *trickier without labels.*"* (P10). Line charts effectively showed peaks or dips: "*I can trace with my finger. It's super obvious*

*1515     *where it spikes around 2007, then dips slightly after.*"* (P6). However, multiple lines overlapping each other confused  
*1516     participants without a way to isolate lines or reduce clutter with TactualPlot. Participants often struggled with locating*

*1517     *previously explored areas during comparison tasks. Scatter plots presented the greatest challenge, especially with**

*1518     *overlapping points: "When points bunch together, I'd need more zoom or a filter, or it's just lumps of pins or lumps of beeps."** (P9)  
*1519     Scatter plots consistently posed challenges. P1 explains: "Scatter. Scatter plots have been hard for me to understand*

*1520     *because there's so much going on in so many different areas."* This difficulty was largely attributed to overlapping data*

*1521     *points and the lack of distinct tactile cues (Monarch). Similarly, shape encoding or polyphonic audio (for multiple**

*1522     *categories) demanded a lot of attention from the participants.**

*1523     5.4.4 Sonification Challenges & Opportunities.* Below are key challenges and benefits specific to TactualPlot's audio and  
*1524     touch design. We fold in additional quotes that highlight pitch perception, multi-category audio, and the need for text*  
*1525     *confirmations. P4 discusses how it was important to be able to differentiate pitches for overview tasks: "I'm okay with**

*1526     *moderate pitch intervals, but if it's too subtle, I miss it. A bigger jump is easier to detect."* Participants noted that accidental*

*1527     *touches could obfuscate trends in the chart while tracing the display by touching: "If I accidentally touch two data points,**

*1528     *I get two beeps simultaneously. Then it's a bit confusing."* (P10). Participants also indicated that unexpected sounds can*

*1529     *be overwhelming: "More than two categories can create chords. That's neat but also overwhelming if I'm not expecting**

*1530     *it."* (P3) We note that having an understanding of the dataset or distributions can assist in audio-tactile exploration.*

*1531     Participants emphasized the need for verbal confirmation to interpret the pitch values, and how TactualPlot's tapping*

*1532     *feature can help with validating data values: "Even if the beep helps me see it's bigger, I'd still tap for the label. I want to**

*1533     *know if it's 53 or 62 exactly."* (P2). We observed that the spatial audio rendering became harder to interpret when there*

*1534     *were multiple musical tones playing for each category. P6 explains: "But I do worry about ear fatigue after too many**

*1535     *pitch streams in a row. We might need breaks or varied sounds."**

*1536     5.4.5 Implications For Multimodal Accessibility.* For Olli, participants appreciated the depth of data-related information  
*1537     *that users had access to, but for a better experience, they emphasized the need to customize verbosity of the text: "I**

*1538     *like Olli's exact values, but I'd prefer a short summary. I don't need to hear all intervals unless I want them."* (P9). The*

*1539     *Monarch provided participants with a quick understanding of the overview of a chart. However, participants explained**

*1540     *that displaying a large number of data points at the same time made them zoom and pan extensively; with overlapping**

*1541     *pins causing confusion: "It's so satisfying to feel the chart's shape directly. But if there's a lot of points, I'd like a smaller**

*1542     *view or smaller region."* (P3) Participants who were familiar with printed tactile graphics, explained that having the*

*1543     *ability to render pins at different heights could be helpful; especially considering the need for grid lines to assist with**

*1544     *exploration: "So the traditional way, you make the axis at 100% dot height, you make the line at 100% dot height, and you**

*1545     *make the grid lines at 50% dot height. But this [Monarch] doesn't offer that capability."* We find that a combination of*

*1546     *direct touch and sonification fosters immediate feedback—good for scanning. However, audio clutter with overlapping**

*1547     *pitches, and subtle audio-intervals require user training. Additionally, we also note that our participants were least**

*1548     *familiar with sonification(see table 3). For both the Monarch and TactualPlot, participants emphasized that clear and**

1561 effcient labeling was crucial to improving multimodal accessibility. For example, P4 explained how more labels could  
1562 have helped with line charts on the Monarch: "*I would have liked to have the [stock] prices in Braille somewhere.*" This  
1563 was echoed by other participants as well, especially when considering charts that were not used in the study such  
1564 as maps which "lose a lot of information" (P6) without labels. Overall, no single modality solved all the user needs;  
1565 participants saw them as complementary, wishing for a hybrid system that combines tactile for overview, audio for  
1566 quick magnitude cues, and text for precise numbers.  
1567

## 1569 6 DISCUSSION

1570 This study provides insights into the efficacy of different modalities for data accessibility—sound (Olli), touch (Monarch),  
1571 and combined sound and touch (TactualPlot)—for blind individuals. Our within-subjects methodology (section 4.), where  
1572 ten blind participants with diverse backgrounds and technology usage (section 4.2) completed a range of data analysis  
1573 tasks across four common visualization types (pie, bar, line, and scatter charts). This allowed for a direct comparison of  
1574 their strengths and weaknesses so that future tools that have both audio-tactile capabilities such as the Monarch can  
1575 combine modalities effectively.  
1576

### 1577 6.1 Sound, Touch, Or The Full Monty?

1578 The findings on task correctness (section 5.1) reveal that TactualPlot generally led to better accuracy, although with  
1579 overlapping confidence intervals across devices overall. However, a clear trend emerged based on visualization type,  
1580 with pie and bar charts exhibiting higher accuracy across all devices compared to line and scatterplots. This aligns with  
1581 observations from related work suggesting that certain visual structures might translate more readily to non-visual  
1582 modalities than others. For instance, the inherent part-to-whole relationship in pie charts and the discrete comparisons  
1583 in bar charts may be more easily conveyed through sound or touch than the continuous and often overlapping data  
1584 in line and scatterplots. The analysis of task completion time (section 5.2) indicated that the Monarch generally had  
1585 the lowest completion times, compared to Olli and TactualPlot. This suggests that for certain tasks and visualizations,  
1586 direct tactile exploration might offer a more efficient means of accessing information for BLV users familiar with  
1587 tactile media. However, the higher completion times for scatterplots on the Monarch, potentially due to occlusion and  
1588 navigation challenges, highlight the importance of considering the interaction design and the complexity of the data  
1589 being represented in tactile formats. The longer completion times for TactualPlot and Olli underscores the cognitive  
1590 load and potential difficulties associated with interpreting data through non-tactile modalities. The subjective NASA  
1591 TLX ratings (section 5.3) provided further insights into the user experience. Olli was rated highest in mental demand,  
1592 while the Monarch received the lowest rating in this dimension. This could reflect the cognitive effort required to  
1593 process sequential auditory information compared to the spatial overview afforded by touch. However, the slightly  
1594 higher frustration score for the Monarch might be linked to the aforementioned challenges with complex visualizations  
1595 and occlusion (for example, scatterplots that visualized multiple shape).  
1596

1597 Olli (screen reader) leverages existing familiarity with auditory interfaces for many BLV users and excels at delivering  
1598 precise, albeit sequential, data. However, its limitations in conveying spatial relationships and the potential for  
1599 information overload are significant HCI challenges. The Monarch offers the potential for direct spatial comprehension  
1600 but requires careful design to avoid clutter and to provide effective navigation and labeling, especially for complex  
1601 datasets. The need for consistent tactile encoding, as highlighted in the co-design study is crucial for effective interaction.  
1602 TactualPlot (audio-tactile) attempts to bridge the gap by offering real-time multimodal feedback, potentially enhancing  
1603 both spatial awareness and value perception. However, the effectiveness of sonification is dependent on learnability  
1604

1613 and the design of intuitive sound mappings, and the combination with touch needs to be carefully orchestrated to avoid  
 1614 sensory overload or conflicting cues. The study also corroborates the long-standing recognition of screen readers [52]  
 1615 as essential tools for accessible data visualization, while also empirically demonstrating their limitations with complex  
 1616 charts that visualize a large amount of data (e.g., scatterplots and scatterplot matrices).  
 1617

## 1618 6.2 Towards Multimodal Chart Accessibility

1619 Our study contributes to the growing body of research exploring the potential of tactile displays and sonification as  
 1620 complementary or alternative approaches. The findings particularly highlight the complexities of designing accessible  
 1621 visualizations for modalities beyond vision, emphasizing the need for user-centered design approaches, and the  
 1622 consideration of individual user preferences and prior experiences. The performance variations across visualization types  
 1623 and tasks underscore that a one-size-fits-all solution is unlikely, and future research should focus on developing adaptive  
 1624 and multimodal systems that can tailor the presentation modality to the specific chart representation, visualization tasks,  
 1625 and analytical goals of blind individuals.  
 1626

1627 *6.2.1 Extending Accessibility Features For Complex Charts.* Complex charts such as UpSet plots [18] may also consider  
 1628 tactile and audio representations for future accessibility implementations. Systems such as TADA [57], ChartA11y [55],  
 1629 and TactualPlot [10], can further extend their design space to support more complex charts on devices such as the  
 1630 Monarch and Graphiti. The availability of the tactile modality will help with better tracing of trends and overviews.  
 1631 Brushing across modalities might lower the cognitive demand on the user. However, sufficient training and practice is  
 1632 required to become familiar with the different modalities used for specific visualization tasks in a multimodal system.  
 1633 Combining hierarchical description of text along in the form of audio narratives [27, 49]; and personalizing options  
 1634 to control verbosity and configure other statistics [31] that may help further personalize the experience for blind  
 1635 individuals.  
 1636

1637 *6.2.2 Expanding The Sonification Design Space.* As stated by our participants, their experience with sonification was  
 1638 minimal, with more comfort and familiarity with tactile graphics. The MAIDR system [46] utilizes: 1) a sequence of  
 1639 audio tones (repetition) to convey box plot features such as whiskers and outlier values, and 2) uses point-density for  
 1640 regions in a heat map. Similarly, Chartreader and ChartA11y use non-speech tones to represent point densities for  
 1641 scatterplots. Stereo-audio panning is often used to encode positional values; and in TactualPlot spatial audio is used to  
 1642 vary the sound source location using the panner3D node. In our study, we did not specifically evaluate the effectiveness  
 1643 of spatial audio. Considering the increasing use of sonification for accessibility, we believe that further research is  
 1644 needed to establish validated audio scales (akin to Colorbrewer [23] for colors) so that standards can be established  
 1645 for accessible solutions that use non-speech audio. Sequential sonification and verbalization of charts is supported by  
 1646 existing sonification tools such as Highcharts [6] and sonification grammars such as Erie [33]. Both these solutions  
 1647 offer default audio scales, but do not support 2D or 3D spatial audio. Spatial audio and audio scales are important to  
 1648 sonify multi-dimensional visualizations; especially those that map data to visualize visual variables such as color and  
 1649 texture. For example, our implementation of TactualPlot only handles 100 unique tones based on musical scales—we  
 1650 adopt musical scales with a range that spans a full-sized piano to ensure that each tone can be differentiable when  
 1651 played in sequence.  
 1652

1653 *6.2.3 Combining Sound And Touch Modalities.* Recent audio-tactile design studies [55, 57] shows the usefulness of  
 1654 touch-based interactions and audio representation for common charts such as—bar charts, pie charts, line charts,  
 1655 Manuscript submitted to ACM

1665 scatterplots, and graph visualization such as node-link diagrams [57]. Scatterplots are 2D visualizations that can often  
1666 include a third visual variable to encode multiple data series values. These audio-tactile systems use touch interactions  
1667 to gain spatial awareness and tactile feedback, with non-speech audio used (sonified tones with pitch variation) being  
1668 mapped to data or chart elements. Recent theoretical work on audio-visual analytics characterizes audio having a  
1669 temporal component [20]. But, combining audio and touch interactions enables parallel access to audio, which can  
1670 be triggered when elements are touched by multiple fingers. This reduces the need for sequential sonification or  
1671 verbalization, thereby reducing the cognitive and temporal demand to remember the audio sequences. When designed  
1672 effectively, simultaneously played tones can help users compare the individual data values in a region (for example, a  
1673 bar's height being mapped to a pitch value) or the aggregated values (point density in scatterplots or hues in a heatmap).

1674 To help easily create tactile graphics from visual charts, Pineros et. al [7] extended the vega-lite visualization library  
1675 by implementing features that can encode textures and braille labeling automatically. However, our study shows that  
1676 Braille labels often take up large amounts of space on RTDs such as the Monarch and Graphiti. These devices, unlike  
1677 printed tactile graphics, are refreshable, and can support chart interactions such as zooming, panning; and direct  
1678 manipulation of chart elements. We recommend that speech interaction [48] be combined with non-speech audio and  
1679 tactile representation to assist in visualization tasks—especially to save time and improve direct access to data values.  
1680 We believe further research is needed to design accessible charts for this unique multimodal device—especially to make  
1681 the grid view of pins responsive to user interactions. We suggest using spatial audio to help with tracing tasks [40] for  
1682 better audio-tactile interactions. To the best of our knowledge, research to understand accessibility of RTDs [44] has  
1683 explored combining tactile exploration with speech-input; with blind individuals taking on the role as consumers of  
1684 charts and not the authors.

## 1691 7 CO-DESIGNING TACTILE GRAPHICS

1692 Although our large study provided quantitative and qualitative insights into the performance of sound, touch, and  
1693 multimodal interactions, it also prompted further research questions on how such systems could be used as part of  
1694 a user's data analysis workflow [11]. For instance, how can blind users author charts for devices with multimodal  
1695 capabilities such as the Monarch. Prior work has explored authoring sonification and structured navigation [59] using  
1696 a screen reader. Refreshable Tactile displays are novel systems that help blind people consume visuals in a tactile  
1697 manner. While multimodal data exploration on RTDs has been recently explored [44], there is limited work on authoring  
1698 visualizations [4] for these devices.

1699 We conducted a 3-hour co-design session with a blind individual where a researcher and the participant co-created  
1700 and explored charts created using Python and rendered on the Monarch. Our goal was to understand how novel  
1701 refreshable braille displays are used by blind individuals as part of their data analysis process. For this study, we adopted  
1702 the pair analytics method [1] to drive the analysis and chart creation process. In this method, a subject matter expert  
1703 (SME)—the participant, collaborates with a visual analysis expert (VAE)—a researcher to analyze data. The role of the  
1704 participant as the SME was to drive the analysis by working with the VAE whose role it was to assist the SME with  
1705 inputs on the visual analysis process. The VAE only provided expertise on refining the charts, and did not drive the  
1706 analysis goals of the participant. This method allowed us to understand the challenges and opportunities that the blind  
1707 participant faces while creating charts for the Monarch.

### 1708 7.1 Methodology

1709 Here, we describe the procedure used to conduct the design session.



Fig. 20. **Co-design study setup.** Panel A and C illustrate the participant’s workstation where charts are iteratively created using a personal laptop and the Monarch. Panel B displays the tactile chart in a visual form in an external monitor connected to the Monarch.

**7.1.1 Recruitment.** Our study participant—D1 (P8) was recruited for the design session after indicating an interest in creating charts using his own dataset. D1 was interested in learning about stock market investments, and wanted to understand how to use the Monarch to visualize a stream of stock market data to learn how to make investment decisions. The demographic and analysis experience of our participant can be found in table 2 and table 3.

**7.1.2 Apparatus.** The Monarch was used as the main visual analytical tool and the participant was responsible for controlling the device. We did not enforce any constraints on the chart creation process—the participant was free to use a dataset, and visualization tool of their choice. The participant used a personal laptop to create and iterate the charts to be viewed on the Monarch’s Tactile Viewer application. Our participant chose to use Matplotlib (Python visualization) for chart creation. A monitor was connected to the Monarch to ensure that the researcher could view the charts that were being rendered on the Monarch (see figure 20.).

**7.1.3 Procedure.** Our design session consisted of 4 stages after we scheduled the participant session. We received consent from the participant through an online consent form (approved by our IRB), and offered a compensation of \$250 for the 3-hour session.

**Pre-study Stage and Datasets.** Our participant (D1) curated data based on Tesla (TSLA) stock prices. The participant (SME) created two data files for the session and emailed the data to the researcher (VAE) ahead of time. The first data file contained 286 items where each item contained the stock’s ‘high’, ‘low’, ‘volume’, and ‘WMA’ (weighted moving average). The second data file contained 4224 items where each item contained the stock’s ‘open’, ‘high’, ‘low’, ‘close’, and ‘volume’. The participant mentioned having an interest in exploring candlestick charts. So, we created a sample candlestick chart using a different dataset as a reference for the participant.

**Establishing Session Goals.** On the day of the session, we completed the study setup at the participant’s home, and received consent for recording the session. The Monarch device was placed next to D1’s personal laptop (see figure 20.) so that the participant could quickly iterate on the chart design using Python, and upload every iteration to the Monarch. Since D1 had already participated in our comparative study, he was comfortable with using the Monarch. Although interested, the participant mentioned having very little to no experience with exploring candlestick charts beyond understanding the concept of the chart. While we provided a sample candlestick chart, we did not mandate the participant to create a candlestick chart; and D1 could create any chart type. We wanted to understand the entire data exploration process as opposed to only limiting the session to creating only a particular chart type.

**Pair Analytics.** We explained the roles of each member of the analytics dyad (VAE and SME), and emphasized to the participant that the researcher will only provide support and feedback on the chart iteration, and guidance on design changes to make the session charts useful. We ensured that the researcher would not provide insights on the data, and explained to D1 that he would have to come up with analysis questions to drive chart exploration. For example, it was up to the participant to: choose variables that need to be visualized, choose any chart types beyond the candlestick chart, and explore the charts and derive insights. The participant spent approximately 2 hours of the 3-hour session designing and iterating on the charts. The researcher provided syntax hints for Matplotlib to help the participant iterate on the chart designs. After every design iteration of the chart encodings, such as adding grids, changing thickness, filtering data, we loaded the chart on the Monarch for the participant's review. We provided breaks when needed, and concluded the pair analytics stage of the session after the participant was happy with his progress. In total, D1 spent 1 hour and 52 minutes iterating on the chart design and exploring the datasets.

**Design Debrief.** After the pair analytics stage, we conducted a design debrief (semi-structured interview) and asked questions about the challenges faced with exploration using the Monarch.

Throughout the session, we collected audio records, photos, and chart images for every design iteration, and qualitatively analyzed the data.

## 7.2 Findings

In this section, we present the key findings from the co-design session, structured around the design decisions during the iterative design session, and the themes identified through qualitative thematic analysis. Our analysis reveals insights into the participant's chart design and data exploration strategies, and usability of tactile displays.

**7.2.1 Chart Iterations.** While viewing the tactile candlestick chart for the first time, the participant discussed the visual encodings and structures with the researcher to better understand how to interpret the candles ("popsicles"). This quote shows the initial reaction from the participant:

*"Oh, boy. See, I've...I've never felt this is a really good way to show this, because I've never felt a candlestick chart in real life. I don't even know what they look like. I know the idea, but I have no clue what they look like. So this is really good and like this is, I don't know what it looks like visually, but it feels like a mess...Yeah, um, let's increase let's zoom in, I guess. Let's increase detail. Hold on, let me...tell me if this is, you know, the wrong way to say it, but like the way I envision a candle, I think of a cylinder in the middle, or a rectangle in the middle, and then out of the top and the bottom of that rectangle are sticks that come up and down. So those Yes, so the cylinder goes, or the rectangle ocean, the high to the low, and then the stick goes from the open to the or, sorry, the the cylinder. The way I would describe it is, imagine a popsicle stick, yes. A popsicle stick can go up and down, right, yes. And the middle, the size of the Popsicle. Popsicle is open to close. And high low the stick is, yeah, how low is the stick?"*

The participant preferred to use a line chart to start the data exploration. Line charts were a more familiar representation for the participant because of prior experience with analyzing stock data using tables, and having used a Braille embossed line chart. Overall, D1 performed seven different iterations (see figure 21) of line charts during the study. We describe the iterations (I1–I7) below:

- **I1:** The participant wanted to compare the High values and the weighted moving average values. To gain an overview, all the items were visualized using a solid blue line for high values, and an dashed orange line for WMA. The participant initially struggled to find patterns because of issues with chart resolution as the default Matplotlib chart resolution did not match the resolution of the Monarch.

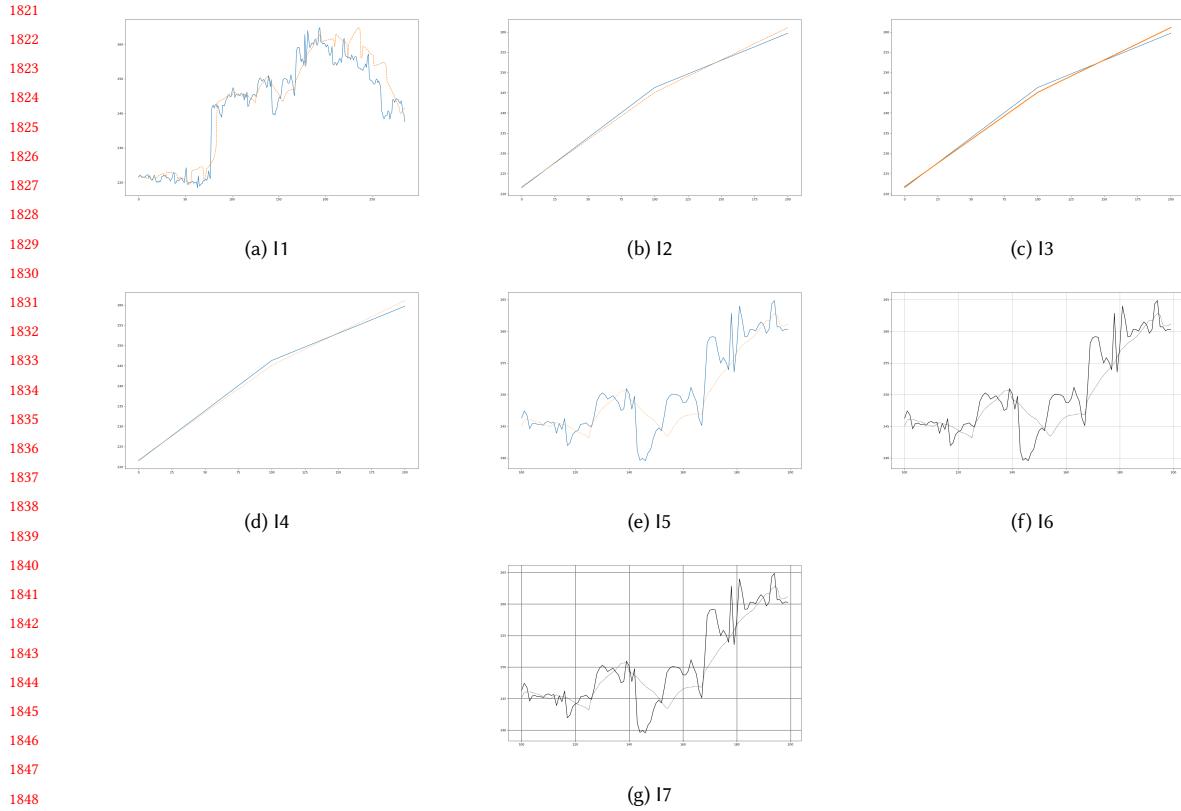


Fig. 21. Sequence of design iterations.

- **I2:** Rather than spending time trying to resize the chart using trial and error, the participant instead chose a filtering approach to find a larger trend in the data. D1 only visualized three items—the first item, the 100th item, and the 200th item. The goal was to understand how moving averages varied with the high values in the trading date. D1 faced the same issue as in I1, where the resolution of the chart did not appropriately fit the entire view of the Monarch. Considering the data distribution, the two overlapping lines made it difficult to perceive each data series individually.
- **I3:** Next, D1 tried to make the lines more perceivable by using line thickness to encode the two data series. While the Monarch rendered the two lines to be noticeably different, D1 remarked that it was still difficult to understand regions where the lines overlapped.
- **I4:** D1 felt that the spacing between the dashed lines, in conjunction with the data distribution sometimes made both the solid and dashed lines “feel” the same. So, D1 used a dotted line instead of the dashed line to represent WMA. At this stage, D1 was satisfied with the idea of having to differentiate a solid blue line and a dotted orange line.
- **I5:** Next, the participant employed the encoding scheme from I4 to all of the data, and generated a variation of the chart from I1; but with only the first 200 items.

- 1873 • I6: At this stage, D1 was curious if the contrast in the images could influence the thresholding-based rendering  
 1874 approach of the *Tactile Viewer* app. Additionally, D1 added grid lines to better understand the values of the  
 1875 peaks and dips. However, after multiple levels of zoom, D1 was uncertain if he was touching a grid line or the  
 1876 data series.
- 1877 • I7: For the last iteration, D1 increased the thickness of the grid lines to make them noticeably different.

1878 After the last iteration, D1 mentioned gaining a better understanding of the data. However, these insights were  
 1879 not gained from just one of the versions; rather each iteration built up the insights gained. This quote illustrates the  
 1880 advantage of an iterative design process for blind individuals: *“Like, this is all good information. And I really think what*  
 1881 *we what we have determined, and, you know, correct me if I’m wrong—but, what I think we need is an interface that all of*  
 1882 *this that we just did...most of the graphs, I can think of, at least four graphs that we’ve created today that could be useful*  
 1883 *all in the same workflow, right? Like the first graph with no grid lines to determine the trends, right? And then, and then*  
 1884 *another graph where, maybe, you know, like the first graph was just that, that just the first 100 data points where it was*  
 1885 *very easy to see...And then the the third thing would be the, I guess, the idea that you know, you can see all of the data*  
 1886 *points. And then the fourth thing would be like, add grid lines. So that way you can, you know, know exactly where you are*  
 1887 *on the thing. Once you once you already know, like, what you’re feeling, then it might be easier to have the grid lines. So*  
 1888 *all four of those graphs would be great...Obviously, more useful would be if we could figure out how to throw the graphics*  
 1889 *directly up here with an application, because then the graphs could be up, you know, could be here in, like a live preview.*  
 1890 *And I think that would more allow for blind people to create the graphs.”*

1891 7.2.2 *Chart Design Decisions.* The participant’s approach to chart design was highly iterative, involving multiple  
 1892 refinements to improve the legibility and interpretability of stock market trends. A key observation was the participant’s  
 1893 emphasis on aligning the chart with the grid structure of the Monarch, which aided in understanding spatial relationships  
 1894 in the data: *“It’s very helpful that I’m looking at this graphic on a pinned display that’s in a grid, because this graph is*  
 1895 *obviously designed on a grid, and so it makes it a lot easier and more intuitive to understand that I’m looking at it on a grid.”*  
 1896 However, despite the benefits of a structured tactile layout, the participant struggled with certain visual encodings,  
 1897 particularly dashed lines. The participant found the tactile representation of dashed lines misleading, as the spacing  
 1898 between dashes was inconsistent and could be mistaken for rendering artifacts rather than intentional design choices:  
 1899 *“Like, you can tell it’s dashed, don’t get me wrong, right? But it’s so infrequently dashed that it’s almost like it’s just artifacts*  
 1900 *that the display is not doing it correctly.”* This finding suggests that current tactile design conventions may need to be  
 1901 reevaluated, particularly in how line styles are encoded for pin-based displays.

1902 7.2.3 *Challenges With Tactile Viewer.* Throughout the session, the participant encountered several usability challenges  
 1903 related to rendering stock market visualizations on the Monarch. One major issue was the difficulty in distinguishing  
 1904 overlapping data series, particularly with multiple zoom levels: *“All the way zoomed out, definitely one. Okay, let’s try one*  
 1905 *level zoom... The tick marks actually, on the x-axis, went away. But I’m not sure if that’s because there’s no room for them.”*  
 1906 The participant initially struggled to perceive whether there were one or two distinct lines, an issue exacerbated by the  
 1907 Monarch’s display resolution, and the data density and distribution. Additionally, zooming and panning operations  
 1908 were described “arbitrary” and “unpredictable”, leading to difficulties in maintaining context while navigating the chart:  
 1909 *“I had to be pretty zoomed in, and then I lost the context. You know what I mean?”* This suggests a need for more intuitive  
 1910 zooming and navigation controls. The participant proposed adding “adaptive zooming”, where contextual grid lines  
 1911 and axis references are preserved across zoom levels, to prevent disorientation when focusing on finer details. While  
 1912

1925 the structured layout of the device was an asset for understanding slopes and relationships, the limited resolution  
 1926 and unpredictable rendering of certain elements reduced confidence in decision-making: “Literally, it becomes one line.  
 1927 They physically cross over each other, and then up here at the top, you can very much see that it’s dotted.” This issue  
 1928 became more pronounced when attempting to determine precise crossover points in stock data, which are critical for  
 1929 making trading decisions. The participant emphasized that grid lines and axis labels should persist across all zoom  
 1930 levels, preventing loss of reference points. Additionally, the participant recognized the trade-offs between resolution  
 1931 and accessibility, noting that higher resolution displays (similar to printed tactile graphics), or more granular control  
 1932 over tactile rendering would significantly enhance usability: “If we had that granular control, when we zoom in and out,  
 1933 and we knew exactly where we were, it would be so much better.”  
 1934

1935  
 1936  
 1937 **7.2.4 Data Exploration Strategies.** The participant engaged in self-driven data exploration, leveraging the tactile charts  
 1938 to extract meaningful stock market trends. One key approach was iteratively adjusting zoom levels to verify perceived  
 1939 trends, particularly in identifying when stock prices represented by the lines crossed: “Now that I am zoomed in, I’m  
 1940 up in the part of the line where I start to see this weighted moving average really drop below the line, and that’s when I  
 1941 know, okay, this is definitely an uptrend.” The participant suggested experimenting with alternative encodings, such as  
 1942 replacing dashed lines with discrete points to perceive initial trends rather than focusing on creating the ideal chart:  
 1943 “Instead of drawing a line for the weighted moving average, could we put a point at each x value? Just put a point that is  
 1944 the y value. So almost like making a scatter plot out of WMA values.” This highlights a potential design opportunity  
 1945 to provide multiple encoding options within tactile stock charts, allowing users to select representations that best  
 1946 suit their perception and analytical needs. By maintaining the participant’s role as the primary analyst, the study  
 1947 avoided introducing bias from the researcher’s visual perception. The participant reflected on how access to real-time,  
 1948 dynamically updating charts could enhance independent stock analysis: “If I want to trade stocks, it would be so useful to  
 1949 be able to connect with the Yahoo Finance API, pull down this stuff, apply the settings I configured, and then show them  
 1950 on the display.” This underscores the need for accessibility tools to move beyond static representations, and adapt to  
 1951 support a diverse set of data exploration strategies.  
 1952

1953  
 1954  
 1955  
 1956 **7.2.5 Reflections On The Design Process And Future Improvements.** The session provided the participant with a novel  
 1957 way to engage with stock market data, which differed significantly from previous experiences relying on tables or  
 1958 textual representations. The ability to feel stock trends in real-time enhanced comprehension and intuition: “I’ve heard  
 1959 all of that stuff, but it’s like, you just, it changes your perception when you actually get to feel it for real.” Reflecting on  
 1960 future improvements, the participant discussed the need for a dedicated tactile charting tool that simplifies the process  
 1961 of generating and iterating on financial visualizations: “We could write some type of interface where you configure all this  
 1962 stuff, throw in a CSV file, and then it makes PNGs that you could put on a thumb drive. That could be really useful.”  
 1963

1964  
 1965  
 1966 **8 DESIGN GUIDELINES FOR AUTHORIZING ACCESSIBLE MULTIMODAL VISUALIZATIONS**  
 1967 Our findings show the importance of automation and accessibility in visual data analysis, suggesting future research  
 1968 should focus on streamlining chart creation while preserving the user’s control over data interpretation. Recent work by  
 1969 Potluri et al. [42] shows the critical need for blind individuals to be empowered as expert users, while also highlighting  
 1970 the need for development tools (such as accessibility “linting” in Python notebooks) to assist sighted and blind individuals  
 1971 during data exploration. Studies also show that chart libraries need to be made accessible [47], and an adaptive approach  
 1972 of sonification and textual description solutions is an effective way to also support the authoring - such as tactile  
 1973 Vega-lite [7]. When considering sonification-based accessibility, we argue for an immediate need for better theoretical  
 1974  
 1975  
 1976 Manuscript submitted to ACM

frameworks [20] and standards—for example, a pitch-based encoding is a common sonification technique, but for users to authors multimodal charts, we need to develop more validated audio-visual and audio-tactile scales. We believe these efforts can help design audio tones and systems that can minimize audio fatigue, and sound more pleasant and user-friendly [47]. Most importantly, blind individuals will have more flexibility with audio-encoding for both chart consumption and authoring in multimodal authoring systems such as Umwelt [59] and MAIDR [46].

The co-design session revealed that while a user can identify trends and adapt chart design strategies, technical limitations, such as rendering inconsistencies and unpredictable zooming on RTDs, can hinder efficiency and limit confidence. Future work should explore improving tactile encoding methods, enhancing navigation controls, and developing interactive stock visualization tools tailored for blind individuals that can be integrated into their current data analysis workflow.

The study highlights the strengths and limitations of different modalities for data access by blind and low-vision (BLV) users, which has direct implications for adhering to WCAG principles on both desktop and touch interfaces. Additionally, existing auditing methods such as Chartability [16], which also adopts WCAG principles for creating accessible data visualization, can be extended to multimodal contexts. Below we illustrate the implications of our study findings on some of the existing WCAG 2.1 [54] guidelines. We discuss how WCAG 2.1 [54] success criteria (SC) can be addressed by multimodal charts:

## 8.1 Perceivable

- **Text Alternatives (SC 1.1):** The success of Olli demonstrates the importance of providing structured text alternatives for data visualizations. This directly aligns with WCAG SC 1.1. However, the study also points out that verbosity and the need for quick summaries are important considerations for usability. WCAG guidelines should emphasize not just the presence of text alternatives, but also their conciseness and adaptability to user needs.
- **Alternatives for Time-based Media (SC 1.2):** While not directly addressing time-based media, the study's exploration of sonification in TactualPlot can be seen as an auditory alternative for visual data. WCAG SC 1.2 principles could be extended to consider the design of effective non-visual (auditory or tactile) representations for dynamic or complex data that is often presented visually over time.
- **Adaptable (SC 1.3):** The study reveals that different visualizations and tasks are better suited to different modalities. This shows the importance of making data presentations adaptable to various sensory outputs (speech, touch, and audio). WCAG SC 1.3 should encourage the provision of data in multiple formats or through interfaces that allow users to choose their preferred modality. The challenges with zoom and context loss on the Monarch also highlight the need for adaptable content that remains understandable at different magnification levels.
- **Distinguishable (SC 1.4):** In the context of tactile displays, ensuring clear and distinguishable tactile patterns and labels (as emphasized by participants) is a tactile equivalent of WCAG SC 1.4. The difficulties with distinguishing dashed lines on the Monarch point to the need for careful consideration of tactile contrast and distinctness.

## 2029 8.2 Operable

- 2030 • **Keyboard Accessible (SC 2.1):** Olli relies on keyboard navigation for exploring the hierarchical textual  
 2031 descriptions. This is a direct application of WCAG SC 2.1. The study highlights the effectiveness of this approach  
 2032 for detailed data exploration.
- 2033 • **Enough Time (SC 2.2):** The study imposed time limits on tasks, indicating the practical considerations of data  
 2034 exploration. WCAG SC 2.2 emphasizes providing users with enough time to read and use content. For non-visual  
 2035 modalities, this might translate to ensuring screen reader users have sufficient time to process information, and  
 2036 limiting searching and navigation time on audio-tactile systems.
- 2037 • **Seizures and Physical Reactions (SC 2.3):** Our study findings may not apply to seizures and other physical  
 2038 reactions.
- 2039 • **Navigable (SC 2.4):** Olli's hierarchical structure provides a form of navigation through the data. For tactile  
 2040 interfaces like the Monarch, the challenges with panning and zooming indicate that intuitive and consistent  
 2041 navigation mechanisms are crucial for operability. The "adaptive zooming" proposed by a participant suggests  
 2042 a need for navigation that maintains context. For touch-based sonification in TactualPlot, the risk of accidental  
 2043 touches highlights a potential barrier to smooth operation could be addressed through principles of discrete and  
 2044 structured division of the touch area. Existing toolkits such as Data Navigator [17] can help designers create  
 2045 structured navigation schemes across modalities.
- 2046

## 2047 8.3 Understandable

- 2048 • **Readable, Understandable, Predictable (SC 3.1 and SC 3.2):** Olli's structured text aims for readability  
 2049 and understandability. However, the study's findings on the need for verbosity customization imply that  
 2050 "understandable" can be user-dependent. The consistency of sound mapping in TactualPlot (using the same  
 2051 audio scale across chart types) contributes to predictability (WCAG SC 3.2). The challenges some users faced in  
 2052 interpreting pitch differences indicate a potential barrier to understandability.
- 2053 • **Input Assistance (SC 3.3):** While we did not directly explore input assistance in our study, we believe that  
 2054 interaction features such as the directional lock mechanisms and dynamic sampling sizes in ChartA11y [55] can  
 2055 help Blind individuals gain more spatial awareness and better understanding of the current view in relation to a  
 2056 previous view. Such input and navigation assistance is essential, especially with large data volumes, interactive  
 2057 charts, and complex charts.
- 2058

## 2059 8.4 Robust

- 2060 • **Compatible with Assistive Technologies (SC 4.1):** Our study revolves around the use of assistive technologies  
 2061 like screen readers (with Olli) and tactile displays (Monarch), as well as a novel audio-tactile technique (TactualPlot).  
 2062 The findings directly inform the compatibility and effectiveness of these technologies for multimodal  
 2063 access to data visualizations. Finally, robust systems and chart libraries should strive to help Blind individuals  
 2064 both create, explore, and communicate data visualizations. While not directly designed for accessibility, Large  
 2065 Language Model (LLM)-powered tools such as Pluto [50] offers bi-directional chart and summary editing.  
 2066 Such tools can help Blind individuals by generating textual summaries to gain an overview of current data  
 2067 transformations, chart view, and data values. Chen et al. [7] recommend designing tactile-first data visualizations  
 2068 to counter empty space in tactile visualizations. However, considering the robustness aspect of accessibility,  
 2069

2081 care should be taken to not completely change the visual structure of commonly used charts to facilitate better  
2082 collaboration between sighted and Blind individuals.  
2083

2084 This study provides empirical evidence that can inform and strengthen WCAG 2.1 guidelines related to non-visual  
2085 data accessibility. It emphasizes the need to move beyond basic text alternatives to consider multimodal approaches,  
2086 the importance of user-centered design, and the specific challenges and opportunities presented by different assistive  
2087 technologies and interaction paradigms on both desktop and touch platforms. Future updates to WCAG guidelines  
2088 for blind and low-vision individuals could benefit from incorporating more specific guidance on designing accessible  
2089 sonifications, tactile graphics, and multimodal interfaces for data visualization. In summary, authoring for RTDs and  
2090 multimodal accessibility requires a multi-faceted approach encompassing: accessible authoring tools, standardized  
2091 multimodal scales, improved tactile rendering and navigation, and combinations of audio, touch, and speech to empower  
2092 blind individuals in the creation and exploration of data visualizations.  
2093  
2094

## 2095 9 LIMITATIONS AND CONCLUSION

2096 While our study provides valuable insights into the efficacy of sound, touch, and combined modalities for data accessibility,  
2097 we acknowledge the limitations in our study. The study involved ten blind adults with diverse backgrounds and  
2098 technology usage. While this allowed for within-subject comparisons, the sample size might limit the generalizability  
2099 of the quantitative findings to the broader population of blind individuals. Additionally, the tasks were performed  
2100 within a controlled study environment, although efforts were made to conduct sessions in participants' preferred spaces.  
2101 The 10-minute training provided on each device, and method may have been sufficient for a baseline understanding,  
2102 but more extensive training can potentially impact task performance and user preferences. We also note that the  
2103 implementation of TactualPlot was limited to 100 unique tones based on musical scales, which might not be sufficient  
2104 for all complex datasets. Future work can explore how to expand the sonification design space; and can consider  
2105 layering the audio—with audio mapping to overviews, and textual descriptions to read data values at deeper zoom  
2106 levels when fewer points are available to sample. The charts designed for the Monarch were static visualizations due to  
2107 limitations with the Tactile Viewer application, potentially not fully leveraging the interactive capabilities of the device.  
2108 The co-design session, while insightful, involved only one participant, limiting the breadth of understanding regarding  
2109 tactile chart creation by BLV individuals; especially considering the variability in blind individuals' technical expertise  
2110 and experience with data analysis.

2111 In conclusion, this comparative study contributes to the growing body of research on data accessibility for blind  
2112 individuals by empirically evaluating the strengths and weaknesses of screen readers, tactile displays, and audio-tactile  
2113 approaches. Our findings show that TactualPlot generally led to better accuracy, while the Monarch often resulted  
2114 in lower completion times, suggesting a trade-off between these modalities depending on the task and visualization  
2115 type. The study shows that pie and bar charts were generally more accessible across all devices compared to line charts  
2116 and scatterplots. Qualitative feedback highlighted the importance of prior experience and learning curves associated  
2117 with each modality, as well as user preferences for specific features like hierarchical textual descriptions in Olli, and  
2118 the direct manipulation of chart elements in TactualPlot. The co-design session provided valuable insights into the  
2119 challenges and opportunities of using refreshable braille displays for creating tactile graphics, emphasizing the need  
2120 for improved tactile encoding, navigation controls, and integration with existing workflows. Our research emphasizes  
2121 the need for user-centered design approaches in developing accessible visualizations and highlights the potential of  
2122 multimodal systems that can adapt to different data characteristics, tasks, and individual user needs. Future work  
2123

should focus on developing standardized multimodal scales, enhancing tactile rendering and navigation, and exploring combinations of audio, touch, and speech to empower blind individuals in both the consumption and creation of data visualizations. Finally, we discuss the direct implications of our findings for strengthening accessibility guidelines (WCAG), and advocate for more specific guidance on designing accessible sonifications, tactile graphics, and multimodal interfaces for data visualization.

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