

ORIGINAL RESEARCH

Understanding How Older Adults Comprehend COVID-19 Interactive Visualizations via Think-Aloud Protocol

Mingming Fan^{a,b} and Yiwen Wang^c and Yuni Xie^c and Franklin Mingzhe Li^d and Chunyang Chen^e

^aThe Hong Kong University of Science and Technology (Guangzhou), China; ^bThe Hong Kong University of Science and Technology, Hong Kong SAR China; ^cRochester Institute of Technology, USA; ^dCarnegie Mellon University, USA; ^eMonash University, Australia

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ABSTRACT

Older adults have been hit disproportionately hard by the COVID-19 pandemic. One critical way for older adults to minimize the negative impact of COVID-19 and future pandemics is to stay informed about its latest information, which has been increasingly presented through online interactive visualizations (e.g., live dashboards and websites). Thus, it is imperative to understand how older adults interact with and comprehend online COVID-19 interactive visualizations and what challenges they might encounter to make such visualizations more accessible to older adults. We adopted a user-centered approach by inviting older adults to interact with COVID-19 interactive visualizations while at the same time verbalizing their thought processes using a think-aloud protocol. By analyzing their think-aloud verbalizations, we identified four types of thought processes representing how older adults comprehended the visualizations and uncovered the challenges they encountered. Furthermore, we also identified the challenges they encountered with seven common types of interaction techniques adopted by the visualizations. Based on the findings, we present design guidelines for making interactive visualizations more accessible to older adults.

KEYWORDS

Older adults; interactive visualization; COVID-19; accessibility; visualization comprehension; digital inequality; think aloud; aging; elderly; seniors

1. Introduction

While people of all age groups have been affected by the COVID-19 pandemic (WHO, 2020a), older adults have disproportionately suffered the most severe COVID outcomes (Nanda, Vura, & Gravenstein, 2020; Shahid et al., 2020) and have the highest death rate among all age groups (CDC, 2020b; CDPH, 2020; Ourworldindata, 2020; Worldometer, 2020). One critical step to cope with the pandemic is to stay informed about the rapidly evolving situation by acquiring the latest COVID-19 information, such as the latest confirmed cases in one's local area. Such real-time COVID-19 information (e.g., the daily new cases) has been widely presented and updated on a daily basis in live dashboards (e.g., (1Point3Acres, 2020; CDC, 2020a; JHU, 2020; WHO, 2020b)) and news media websites (e.g., (Reuters, 2020a, 2020b)) in the form of visualizations.

Visualizations are widely adopted online to convey insights in today's data-driven world. Research suggests that visualizations can help older adults deal with age-related declines (John & Cole, 1986; Salthouse, Hancock, Meinz, & Hambrick, 1996; Strayer, Wickens, & Braune, 1987), such as lowering working memory demands (Price, Crumley-Branyon, Leidheiser, & Pak, 2016), enhancing prospective memory (Burkard et al., 2014), and facilitating communication (Le et al.,

2015; Mynatt, Essa, & Rogers, 2000; Mynatt, Rowan, Craighill, & Jacobs, 2001; Reeder, Chung, Le, Thompson, & Demiris, 2014). However, older adults often encounter difficulties when reading visualizations (Backonja et al., 2016; Bock et al., 2016; Hakone et al., 2016; Le et al., 2015). Such difficulties are further exacerbated by the increasingly popular *interactive* visualizations that require users to actively interact with to reveal hidden information. As COVID-19 visualizations shown in live dashboards and government and new media websites (e.g., (1Point3Acres, 2020; CDC, 2020a; JHU, 2020; Reuters, 2020a, 2020b; WHO, 2020b)) are often interactive, it is critical to understand whether older adults are able to effectively interact with and comprehend these interactive visualizations and the challenges that they might encounter. Such an understanding could inform the design of interactive visualizations that are more accessible to older adults.

Toward this goal, we adopted a user-centered approach by inviting older adults into the evaluation of COVID-19 interactive visualizations that are critically relevant to their lives during the pandemic. We focused on two research questions (RQs) to explore how older adults interact with COVID-19 interactive visualizations and the challenges that they encounter:

- **RQ1:** What are older adults’ thought processes and the associated challenges when they comprehend COVID-19 interactive visualizations?
- **RQ2:** What difficulties do older adults encounter with the common *interaction techniques* adopted by the COVID-19 interactive visualizations?

To answer RQs, we first reviewed COVID-19 related live dashboards and news media websites to identify common types of interactive visualizations and curated a set of representative interactive visualizations. These visualizations covered all common types of interaction techniques adopted in interactive visualizations based on a well-known taxonomy (Yi, Kang, Stasko, & Jacko, 2007). We further studied the types of data shown in these visualizations and designed a set of tasks for participants to work on in the user study. To better understand how they comprehend the visualizations, we asked older adult participants (N=14) to think aloud while working on the tasks during the study. We chose to use the think-aloud protocol because it is a well-known method for understanding users’ thought processes that are otherwise invisible to researchers (Nielsen, 2012) and widely used in industry to identify user experience problems (Fan, Shi, & Truong, 2020; McDonald, Edwards, & Zhao, 2012).

By analyzing participants’ think-aloud verbalizations as well as the corresponding session recordings, we identified five representative thought processes that reflected how older adults comprehended and interacted with the visualizations. Moreover, we uncovered the key challenges associated with each type of thought process. Furthermore, we identified the issues that older adults encountered with the seven types of interaction techniques used in visualizations (Yi et al., 2007). Based on the findings, we derived design guidelines for making interactive visualizations more accessible for older adults. Finally, we discuss the limitations and future work. In summary, this work makes the following three contributions:

- Identification of four types of thought processes that reflect how older adults comprehend COVID-19 interactive visualizations and the associated challenges.
- Identification of the difficulties that older adults encounter with the common interaction techniques adopted by the visualizations.
- Design guidelines for making interactive visualizations more accessible for older adults.

2. Background and Related Work

Our work was inspired and informed by prior research on *Visualization for Older Adults* and *Visualization Comprehension Theory*.

2.1. Visualization for Older Adults

Aging is a global challenge, and technologies have been studied to understand challenges faced by older adults and support them to age with dignity. Visualization is one such technology and has been explored to understand older adults' behaviors, such as their mobility (Franke, Winters, McKay, Chaudhury, & Sims-Gould, 2017; O'Brien, McDaid, Loane, Doyle, & O'Mullane, 2012) and face-to-face interactions in the community (Masumoto et al., 2017).

Visualization has been shown to be beneficial for older adults to deal with many age-related declines. Visualization can lower older adults' working memory demands. For example, in the context of choosing a medicare prescription drug plan, Price et al. found that older adults made more accurate decisions in less time when performing a computerized decision-making task to find the best health care plan with the assistance of a simple visualization (i.e., a color-coded table) than without it (i.e., a typical data table) (Price et al., 2016). Similarly, visualization has also been shown to be beneficial for enhancing prospective memory (Burkard et al., 2014).

Visualization can also facilitate communication between older adults and their healthcare providers (Le et al., 2015; Reeder et al., 2014) and promote conversations between them and their family members (Mynatt et al., 2000, 2001). Moreover, visualizations can also help older adults maintain an awareness of the progress of their health goal (Pham, Mejía, Metoyer, & Hooker, 2012), gain a better understanding of their health conditions (Backonja et al., 2016), and learn potential interaction effects between different medicines (De Croon, Cardoso, Klerkx, Abeelee, & Verbert, 2017).

Despite these potential benefits of visualizations, few visualizations have been designed *with* and *for* older adults (Backonja et al., 2016). The age-related declines among older adults present unique challenges for designing effective visualizations. Firstly, it is common that older adults would encounter problems when comprehending visualizations (Bock et al., 2016; Le et al., 2015). For example, older adults felt that too much information was presented within the visualization, and they were uncertain about what elements of the visualization to focus on (Le et al., 2015) or had difficulty interpreting abstract visualizations (Backonja et al., 2016). Secondly, not all visualizations are equally effective for older adults. For example, Hakone et al. found that pie charts sampling along temporal dimensions were more effective at communicating change-over-time data when compared to temporal area charts among older patients (Hakone et al., 2016). Consequently, without taking older adults' experiences into consideration, the increasingly pervasive visualizations might become inaccessible to them.

One key step to making visualizations more accessible to older adults is to understand how they comprehend visualizations. For example, Ahmed et al. conducted a participatory design with older patients to design visualizations for data generated from cardiac re-synchronization therapy devices to increase their engagement in care for a patient-facing dashboard (Ahmed et al., 2019). Similarly, Le et al. conducted a participatory design with older adults (Le, Reeder, Chung, Thompson, & Demiris, 2014) to design health visualizations and later interviewed older adults to understand how they used health visualizations and potential barriers (Le, Chi, Chaudhuri, Thompson, & Demiris, 2018). They found that older adults felt that contextual information about visualizations was helpful and that their computer literacy might have affected their understanding.

Inspired by this line of research that primarily focused on non-interactive visualizations for older adults (Ahmed et al., 2019; Le et al., 2018; Le, Reeder, et al., 2014; Le et al., 2015), we seek to understand how older adult use and perceive *interactive visualizations*. In this work, we focused on interactive visualizations related to COVID-19, which is critically relevant to older adults' lives. To do so, we adopt *usability testing with the think-aloud protocol* to better understand older adults' thought processes, that are otherwise unavailable to researchers, when they comprehend interactive visualizations.

2.2. Visualization Comprehension Theory

Building on top of earlier work investigating human visualization comprehension processes in 1980s and 1990s (e.g., Bertin (1983); Cleveland and McGill (1985); Pinker (1990)), Carpenter and Shah proposed a **three-process visualization comprehension theory** to explain how people comprehend visualizations: *encoding visual information*; *relating visual features to concepts*; *associating concepts with existing knowledge* (Shah & Hoeffner, 2002). Further, their experimental results showed that visualization comprehension often involves multiple, integrated, and iterative cycles of these three processes (Carpenter & Shah, 1998).

Encoding visual information involves identifying visual characteristics of a visualization, which influence how effective a viewer can encode graphical information (Bertin, 1983). Bertin characterized visual variables for building graphs: position, size, shape, value, color, orientation, and texture (Bertin, 1983). Cleveland and McGill identified six similar elementary perceptual tasks that people carry out when extracting quantitative information from graphs (Cleveland & McGill, 1984) and conducted a study to rank people’s judgments on these six tasks from the most accurate to the least accurate: position along a common scale, position along a nonaligned scale, length and angle, area, volume, shading (Cleveland & McGill, 1986).

Relating visual features to concepts is the translation of visual features into the conceptual relations represented by those features (Kosslyn, 1989; Pinker, 1990). Pinker proposed a set of cognitive operations that are executed when processing a graph to create a mapping that relates visual features to conceptual relations found in the display (Pinker, 1990). Specifically, visualization is mapped into conceptual relations such as differences in size, changes in trend, and differences in spatial location (Bertin, 2011; Kosslyn, 1989). Thus, this process involves interpreting visual pattern quantitatively, such as an upwardly curved line means an accelerating trend (Carpenter & Shah, 1998). Further, the translation process is complicated by multiple graphical features, such as multiple lines in a graph (Carpenter & Shah, 1998). Thus, errors in interpretation may occur when visual characteristics do not effectively get translated into concepts or relationships (Kosslyn, 1989; Larkin & Simon, 1987; Pinker, 1990). Moreover, the relative ease of mappings between visual features and referents in visualizations can also affect this translation process. For example, horizontally oriented bars may be better for representing variables for which the horizontal dimension is more meaningful than the vertical dimension, such as in depicting data about distance traveled (Kosslyn, 1994).

Associating concepts with existing knowledge refers to the process of leveraging existing knowledge in the interpretation of visualizations. Existing knowledge may provide contexts to comprehend conceptual elements (Bertin, 1983). Shah found that students’ existing knowledge and expectations of content affected their interpretations of graphs (Shah & Carpenter, 1995; Shah & Shellhammer, 1999). A viewer may make an error in the interpretation of a visualization when its visual feature does not automatically evoke a particular fact or relationship for her (e.g., Larkin and Simon (1987); Pinker (1990); Shah and Shellhammer (1999); Stenning and Oberlander (1995)). Le et al. suggested that the knowledge gap in health information among older adults may contribute to the challenges that they encounter in comprehending health-related visualizations (Le, 2014; Le et al., 2015).

The three-process theory of visualization comprehension was developed and validated with mostly *static* visualizations on printed paper or computer screen in the 1980s and 1990s. In the recent decade, *interactive* visualizations have become increasingly popular on the web, such as in news media reports and dashboards. Compared to static visualizations, interactive visualizations allow users to explore data dynamically from different perspectives through interactions. As interactive visualizations are often not designed and evaluated with older adults, they may encounter difficulties in comprehending and interacting with such interactive visualizations. Thus, it is important to examine whether the three-process theory is still applicable by studying how *older adults* comprehend *interactive* visualizations and to identify ways to improve such interactive visualizations for older adults by uncovering potential challenges they may encounter.

3. Method

To answer RQs, we conducted online think-aloud usability testing with older adults. During think-aloud usability testing, older adults worked on tasks related to the COVID-19 interactive visualizations while at the same time verbalizing their thought processes. Compared to other approaches such as survey or interview, this approach allowed us to gain insights into older adults' invisible thinking processes while they were comprehending interactive visualizations.

We followed three design considerations while curating the dataset of interactive COVID-19 visualizations and corresponding tasks for the study. Firstly, we reviewed commonly appearing interactive visualizations in major news media websites and live dashboards about COVID-19 to ensure that our dataset covered all common types of visualizations. Secondly, we consulted the visualization literature to understand the interaction techniques widely adopted in interactive visualizations and ensured that common interaction techniques were well represented in our dataset. Lastly, we studied the information conveyed in these COVID-19 interactive visualizations and designed the corresponding tasks based on the information. In the next three subsections, we explain these three steps in detail.

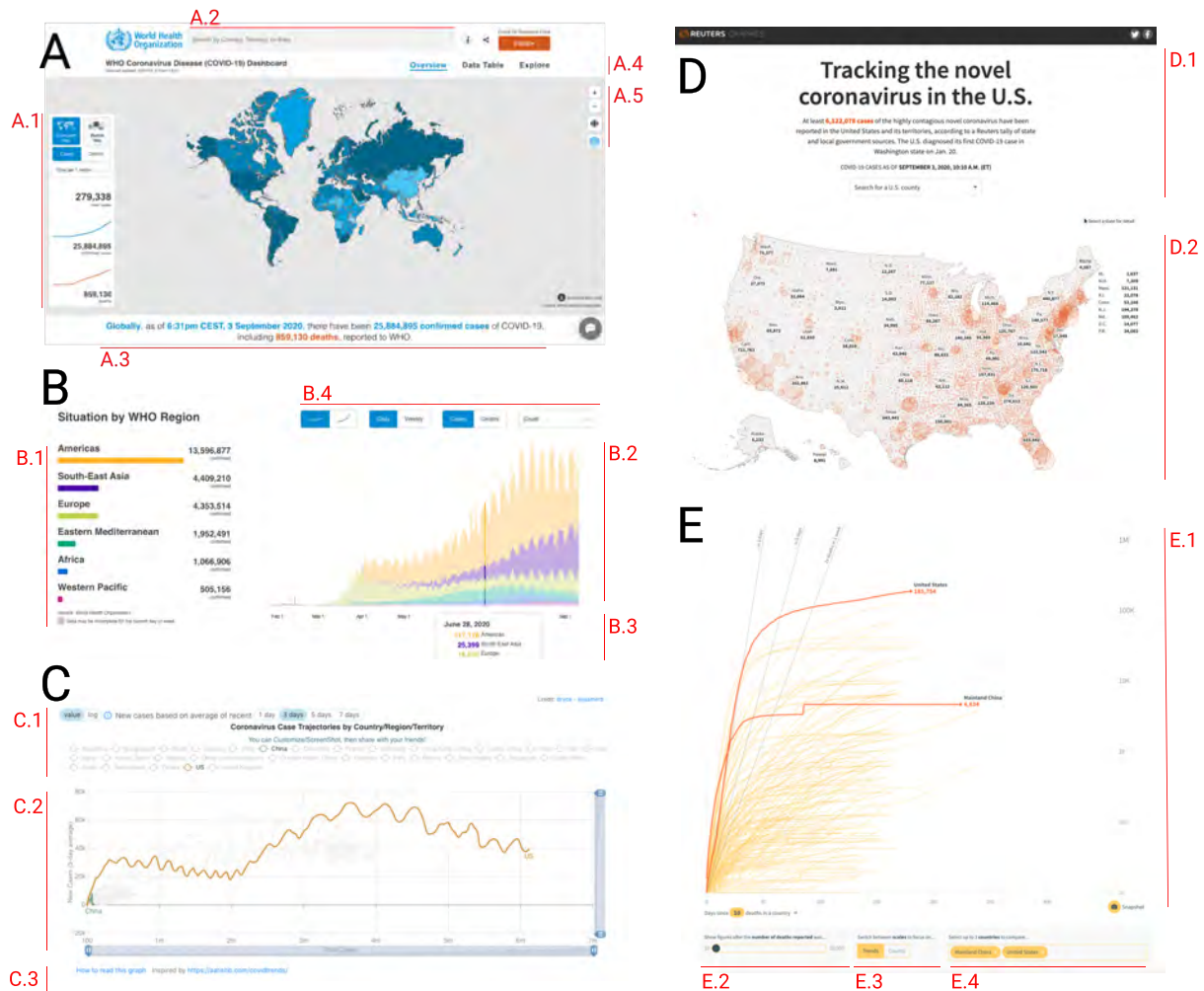


Figure 1.: The five interactive visualizations (labeled A to E) used in the study

3.1. Interactive Visualizations for the Study

We searched the following keywords in Google: *COVID*, *coronavirus*, *COVID-19*, *covid*, *case*, *data*, *interactive*, *visualization*, *chart*, and *graphic*. From the top 10 pages of the search

results up until June 30, 2020. we identified 57 dashboards and news reports about COVID from 16 well known organizations. The number of dashboards or news reports from these 16 sources was as follows: Word Health Organization (WHO) dashboard (1), 1point3acres dashboard (1), Johns Hopkins University (JHU) dashboard (1), The New York Times (10), Reuters (7), Bloomberg (6), CNN (5), Forbes (5), NBC (5), The Economist (5), The Washington Post (3), BBC (2), NPR (2), The World meters (2), ABC (1), and state government COVID website (1).

From these 57 dashboards and news reports, the first three authors identified 172 COVID-related visualizations. They analyzed the visualization types (e.g., line graph, bar chart) and interaction techniques (e.g., zoom, filter) used in these visualizations and chose five examples for the user study. Figure 1 shows the five interactive visualizations, which are labeled from A to E. These five example visualizations were chosen to cover the common visualization types and interaction techniques; the exact number of visualizations chosen was determined after two rounds of pilot studies to ensure that the duration of the study was around an hour. The interaction techniques used in these visualizations will be elaborated on in the next section.

3.2. Interaction Techniques in the Visualizations

The visualization community has proposed taxonomies to characterize interaction techniques used in visualizations (Dimara & Perin, 2019; Yi et al., 2007). We compared two primary taxonomies (Dimara & Perin, 2019; Yi et al., 2007) and chose to use Yi et al.’s taxonomy (Yi et al., 2007) because this taxonomy characterized the interaction techniques in our visualizations better and was also more widely used. Yi et al.’s taxonomy includes seven types of interaction techniques commonly used in visualizations: *Select*, *Explore*, *Reconfigure*, *Encode*, *Abstract/Elaborate*, *Filter*, and *Connect*. (Yi et al., 2007).

To illustrate how each of the seven interaction techniques is instantiated, Figure 2 shows one example drawn from our visualizations in Figure 1. Next, we explain how these interaction techniques are instantiated in details. We have included more details to explain how each visualization instantiates all the relevant interaction techniques in the supplemental file.

Select: Select interaction techniques allow users to mark a data item(s) of interest visually distinctive so that they could easily keep track of it when there are too many data items on a view or when representations of data are changed. Figure 2A shows an example Selection technique.

Explore: Exploration interaction techniques enable users to examine a different subset of a data set. Due to some combination of the large scale of the data set, view, and/or limited screen space, users often only see a limited number of data items at a time. Thus, Exploration interaction techniques allow users to gain understanding and insights from a subset of the data before moving to view different subsets of the data. Figure 2B shows an example. The panning interaction on this map-based visualizations allows users to explore different parts of the data set one at a time.

Encode: Encode interaction techniques enable users to alter the visual representation of the data, including the visual appearance (e.g., color, size, and shape) of data items. Visual representations are important because they affect pre-attentive cognition and are related to how users understand relationships and distributions of the data items.

Changing how the data is represented, such as from a bar chart to a map, is an example of Encode. Another example of Encode is to alter the color encoding of a data set. Similarly, altering size, orientation, font, and shape encodings are also examples of Encode. Figure 2C shows an example Encode interaction technique.

Abstract/Elaborate: Abstract/Elaborate interaction techniques allow users to adjust the level of abstraction of data representation. One example is details-on-demand techniques, such as the tool-tip interaction, which provide more details when a mouse cursor hovers over a data item. Another example is geometric zooming. Geometric zooming allows users to change the scale of represented data so that they could see an overview of a larger data set (with zoom-out) and a detailed view of a smaller data set (with zoom-in). The representation of underline data is

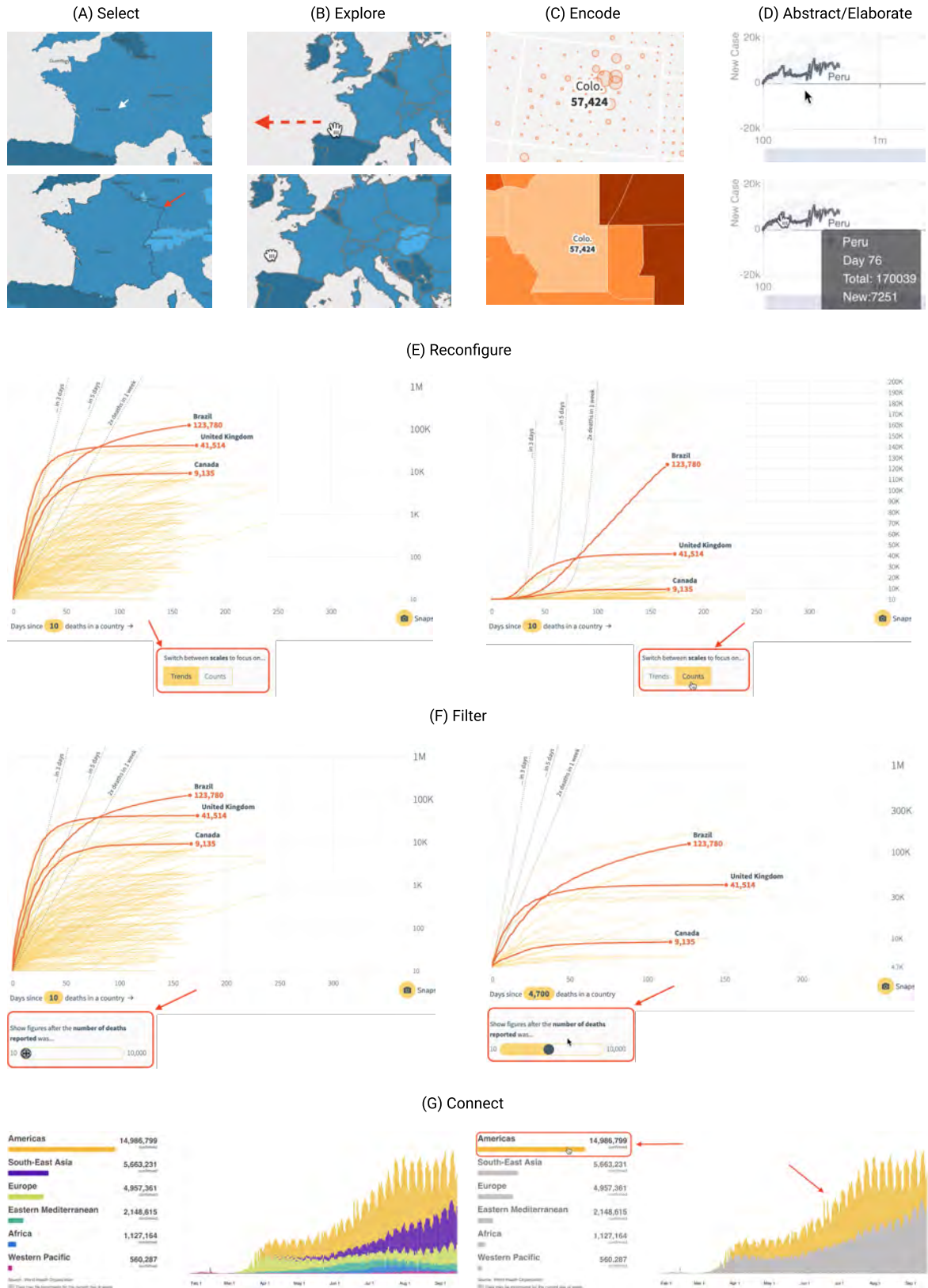


Figure 2.: The instantiation of each interaction technique (Yi et al., 2007) in example visualizations in Figure 1. The appendix includes all the relevant interaction techniques that each visualization in Figure 1 instantiates.

not altered during geometric zoom. Figure 2D shows examples of Abstract/Elaborate in our data set.

Reconfigure: Reconfigure interaction techniques allow for changing the spatial arrangement of data representations (e.g., how data items are arranged or aligned) to have different perspectives onto the data set.

Sorting and rearranging columns are examples of Reconfigure interaction techniques. Further, changing the attributes assigned to x- and y-axes is another example, which changes the relationships between the data items visualized and thus provide different perspectives. What distinguishes “Reconfigure” from “Abstract/Elaborate” is that the representation is changed in “Reconfigure”. Figure 2E shows an example in our data set.

Filter: Filter interaction techniques allow users to change the set of data items being visualized based on some specific conditions. When using this type of interaction, users specify a range or condition so that only data items meeting the criteria are shown. Because the actual data items are usually unchanged, the view would resume when users remove the filtering criteria. In a similar vein, filter interaction techniques do not change the perspective on the data but just specific conditions for data to be shown. This category includes interaction techniques that allow users to specify ranges, keywords, or queries. Figure 2F shows an example in our data set.

Connect: Connect interaction techniques highlight associations and relationships between data items. When more than one view is used to show different representations of the same data set, it can be difficult to find the corresponding item of a data point in a different view. To alleviate such difficulty, Connect interaction techniques often highlight the corresponding item in a different view when the user selects an item in one view. Similarly, Connection interactions also apply to the same view by highlighting the related items to a selected data point. Further, Connect interactions can also reveal data items that are originally hidden in the view. Figure 2G shows an example in our data set. When hovering over a horizontal bar (e.g., Americas) in Figure 1B.1, the corresponding part of the stacked bar chart in Figure 1B.2 is highlighted.

Table 1 shows how these interaction techniques are instantiated in each of the visualizations in Figure 1.

Table 1.: The types of Interaction techniques instantiated in each of the five visualizations in Figure 1. The visualizations collectively cover all the interaction techniques.

Vis. IDs	Source	Type	Select	Explore	Reconfigure	Encode	Abstract / Elaborate	Filter	Connect
A	WHO 1 ¹	Map	✓	✓	✓	✓	✓	✓	✓
B	WHO 2 ¹	Bar			✓	✓	✓		✓
C	1Point3Acres ²	Line	✓		✓		✓		
D	Reuters 1 ³	Map		✓		✓	✓	✓	
E	Reuters 2 ⁴	Line	✓		✓		✓	✓	

3.3. Tasks for the Visualizations

We had three design considerations when designing the tasks that participants would work on when comprehending the visualizations during the think-aloud usability testing. First, the tasks should utilize the information shown in the visualizations. To do this, the first three authors independently analyzed the captions and the labels of the axes of the COVID-19 visualizations in our data set and extracted terms and phrases from the captions and the labels to construct a taxonomy of COVID-19 information. They further discussed their results to gain a consensus of the key terms and phrases. Then, they applied an affinity diagramming

approach on these terms and phrases to derive two themes related to COVID-19: *expressions* and *impacts*. Within the COVID-19 expressions theme, there were five sub-themes: *Cases* (cases by region, population, day, condition, people, active cases, recovered cases); *Deaths* (deaths by region, day, people, estimated deaths, other deaths); *Rates* (fatality rate, Change frequency, growth rate); *Tests* (tests by day, region, people); and *Others* (population, time). Within the COVID-19 impacts theme, there were four sub-themes: *Health* (symptoms, mental, psychological health, other diseases), *Behaviors* (activities, spreading index), *Resources* (hospitals, transportation), and *Economy and Policies* (finance, government policies).

Table 2.: The tasks for the visualizations in Figure 1.

Vis. IDs	Tasks
A	find out the confirmed COVID cases “per 1 million population” in France
B	find out the daily confirmed COVID cases on June 28 in Americas; find out the date when Americas exceeded Europe in terms of the cumulative COVID cases
C	find out which country the light-color line that is above the line representing the US represents
D	find out the county that has the lowest positive COVID-19 cases in Nevada
E	find out which country has the least number of COVID cases: Brazil, Canada, and Germany; find out which countries have over 10, 000 death cases for more than 100 days

Second, the tasks should cover all common interaction types in Section 3.2. Third, the tasks should be of different levels of complexity. Following these design considerations, we designed the tasks for the visualizations in Table 2. Note that the tasks were different for each visualization.

4. User Study

4.1. Participants

This research was approved by IRB at our institution. We recruited participants through advertisements posted on social media platforms, word-of-mouth, and snowball sampling. We first conducted a pilot study with two older adults (one female and one male, aged 64 and 77) and used the data to revise the visualizations and the corresponding tasks and to ensure the study procedure was appropriate. We then conducted the formal online think-aloud usability testing with eighteen older adults (eight females and ten males). Participants lived in Canada ($N = 15$) and USA ($N = 3$). Their ages were between 60 and 78 ($M = 67$, $SD = 5$, $median = 65.5$, $IQR : 64 - 71$). No one was colorblind.

4.2. Procedure

The eighteen older adults participated in the study online from their homes using their own devices as they normally would do when using computers. Sixteen participants used their laptops, and two used their desktop computers. Based on the experience of the pilot studies, we moved some setup procedures into the *pre-study* session so that participants could better focus on the tasks during the actual user study.

¹<https://covid19.who.int/>

²<https://coronavirus.1point3acres.com/en>

³<https://graphics.reuters.com/HEALTH-CORONAVIRUS-USA/0100B5K8423/index.html>

⁴<https://graphics.reuters.com/HEALTH-CORONAVIRUS/yxmvjookdpr/index.html>

4.2.1. Pre-study Session

We emailed participants the consent form before the study so that they would have sufficient time to read it and ask us questions. We sent the computer literacy questionnaire (Boot et al., 2015) so that they could finish it before the study. Because we conducted our study through Zoom, we scheduled with each participant to help them set up Zoom, if they had not already done so, and provided a short tutorial, such as how to share their screen. The goal of the pre-study was to receive informed consent from participants and ensure that the technical setup was sound for the study.

4.2.2. Online Think-Aloud Usability Testing

We conducted the online think-aloud usability testing through Zoom and audio- and screen-recorded the study to understand how they comprehended the interactive visualizations. Two research team members were presented in each study session. One acted as the moderator to deliver the instructions and moderate the study. The other was the note taker who observed the session and noted down important observations.

At the beginning of the study, the moderator explained the think-aloud protocol (Nielsen, 2012) and asked the participant to work on a task with an interactive visualization that would not be used in the formal study. The goal of this process was to get each participant familiar with the think-aloud protocol. Next, the moderator presented the participant with the visualizations (Figure 1) and the tasks (Table 2). The order of the visualizations and the corresponding tasks were randomized. The moderator reminded the participants to keep talking if they felt into silence for a long period and monitored the time to remind participants to stop if the allocated time for each task was out. The order of the visualizations was randomized. Each participant was compensated with \$25.

4.3. Data Analyses

We audio- and screen-recorded the user study sessions. We transcribed the audios to acquire participants' think-aloud verbalizations. We applied thematic analysis on think-aloud verbalizations. First, two coders independently coded the verbalizations to identify different comprehension thought processes. As think-aloud verbalizations may contain fragmented utterances (Charters, 2003; Nielsen, Clemmensen, & Yssing, 2002), we referred to the screen recordings whenever needed to better understand participants' verbalizations during the entire analysis. Afterward, the two coders discussed their codes to gain a consensus on their codes. The third coder joined the discussion to resolve potential conflicts and consolidate the final codes. The coders applied affinity diagramming to group the codes into themes, which characterized different types of thought processes. Finally, we compared the final themes of thought processes with the three-process visualization comprehension theory (see Section 2.2) to derive the commonalities and differences.

We followed a similar approach to identify the challenges that participants encountered with the visualizations. We then organized the challenges based on the seven types of interactions (Yi et al., 2007). Findings will be presented in Sec 5.2.

5. Findings

5.1. Comprehension Thought Processes and the Associated Challenges (RQ1)

Our analyses uncovered four types of thought processes that older adults had when interacting with and comprehending the interactive visualizations: 1) *Encoding visualization information*, 2) *Relating visual features to concepts*, 3) *Associating concepts with existing knowledge*, and 4) *Recovering from errors*. The first three types of thought processes are consistent with the three-process comprehension theory discussed in Sec 2.2. Furthermore, we also identified challenges associated with each thought process.

Next, we explain these four types of thought processes and the corresponding challenges in detail. We provide participants’ think-aloud verbalizations as quotes and annotate each quote with “P#, letter” to indicate the corresponding participant ID and the corresponding visualization ID in Figure 1.

5.1.1. Encoding visual information

While comprehending visual characteristics of visualizations, participants encountered challenges with *colors*, *labels*, *texts*, and *layouts*. Two issues were associated with colors: brightness and contrast. While it is common to use light-grey colors to indicate inactive or unchecked visual elements, our participants did not notice their existence in the first place, such as in Figure 1.C: “My issue was trying to see something that wasn’t there. There appears to be a very, very, very faint background graph”- P15, C.

Participants also had difficulty perceiving differences between colors: “The difference between Europe and the Americas is not as clear as it is between Southeast Asia and Eastern Mediterranean.”- P15, B. When turning Figure 1B into gray-scale, we noticed that Europe and Americas were indeed barely distinguishable.

The key issue with labels was the lack of them. This happened to legends and axis labels. For example, Figure 1D did not have a legend to explain what COVID data the circle size represents for: “I just didn’t know what the circle was referring to, was it a place?”-P7, D; “The diameter of the circle, what they represent is not clear.” -P10, D. Second, the axes of some visualizations lacked necessary labels. Figure 1E.1 did not have labels for both its axes. This caused the misinterpretation of data. “So the hundred [a number on the horizontal axis] must be days [it actually referred to the number of deaths]. But why the hell they didn’t say that.” - P13, E.

Two issues were associated with texts in the visual. First, some font sizes were perceived too small, such as texts in Figure 1A.1. Second, some texts lacked sufficient brightness or clear borders. “I think they should make the printing a little brighter, so I can read it.” - P6, C.

One challenge with layouts was overlaps between visual elements. For example, Figure 1D.2 had many overlapped circles. Some participants even thought the overlapped visual elements were a single element. Many countries’ lines were too close to each other or partially overlapped with each other in Figure 1E, such as the ones for Germany and Canada. Some participants did not even realize there were two lines. Moreover, the sheer amount of visual elements could also be overwhelming. “You ask me to find one line, but there are too many lines” - P1, C.

5.1.2. Relating visual features to concepts.

This type of thought process included cognitive operations creating a mapping from visual features to conceptual relations represented by those features. In general, participants were able to relate the continuous changes in visual features to the trends of underlying data. For example, participants intuitively associated different shades of blue in Figure 1A and different sizes of the bubbles in Figure 1D with the severity of COVID conditions. However, participants often had difficulty understanding mappings between visual features and the underlying COVID information they represented. Think-aloud verbalizations revealed three reasons for such difficulties.

Ambiguous Language: The language used in some visualizations was ambiguous. Three factors contributed to ambiguity. The first factor was *use of technical terms*. For example, participants were confused about the meaning of the technical term “log” in Figure 3, which is the top-left corner of Figure 1C.1. Similarly, participants also had hard time making sense of the terms “trends” and “count” in Figure 1E, which were used for the “log” and “linear” scales.



Figure 3.: Technical terms, such as “log”, caused confusion to participants.

Another factor was the *use of abbreviations*. For example, the labels on the horizontal axis used the letter “m”. Although it was intended to mean “million,” some participants misunderstood it as “month.” Such misunderstanding was reasonable because it was not uncommon to show time on the horizontal axis.

The last factor was *use of incomplete labels*. Short words or phrases are often used in visualization labels to maintain a “clean” looking as complete descriptions might make visualization cluttered. However, such incomplete labels caused confusions. For example, it was unclear to some participants what the word “total” in Figure 1A referred to because it could mean the “total” confirmed cases, “total” new cases, or even “total” global cases. Similarly, it was also unclear whether the word “cases” in Figure 1B referred to the cumulative or daily cases.

Mental model mismatches: Confusions were also caused by two types of mismatches between participants’ mental models and the information organization in the visualizations. One mismatch was related to the *grouping of options in the visualization*. For example, Figure 1A organized the “total per 1 million population” option into the drop-down list with the default option as “total.” However, many participants did not expect that the “total per 1 million population” option belonged to the same category as the “total” option.

Another mismatch was related to *the mappings between graphical components*. For example, the slider-bar at the bottom-left corner of Figure 1E allowed users to change the number of *deaths* to change the number of *days* displayed on the x-axis of the visualization. However, such mapping was counter-intuitive, and many participants were confused about whether they actually changed the number of deaths or days.

Affordance mismatches: Confusions also occurred when participants’ perceived affordance of visual elements did not match with what they represented. For example, the “wiggling” and “smooth” line icons in Figure 4 (part of Figure 1B.4) represented the “daily change” and “cumulative” cases respectively. Unfortunately, no participants perceived the meanings of the two line icons correctly.



Figure 4.: The affordance of graphical elements, such as “wiggling” and “smooth” lines, did not match with what they represented (i.e., “daily change” and “cumulative” cases).

Another common perceived affordance issue was the misuse of buttons and drop-down lists. For example, although the visual element with an “eye” icon in Figure 5 (part of Figure 1A) functioned as a drop-down list, it visually resembled a button. Consequently, many participants did not expect it to show a list of options once clicked.

Moreover, the affordance of an “eye” often suggested revealing some hidden content, such as a password, which was also unrelated to a drop-down list. “*The eye on some of the software I use ... allows me to see my password.*” - P11, A.



Figure 5.: The visual affordance of the “eye” icon, which was a button, mismatched with its actual function, which was a drop-down list.

Although it was common to use different colors to distinguish the active and inactive tabs in a toggle button, participants were confused about which color represented the active tab.

For example, the blue “Daily” tab of the toggle button in Figure 1B.4 was supposed to be the activated one. However, many participants felt that the white “weekly” tab was activated because it seemed to be protruding up. While it might be possible to infer the active tab by clicking each option and observe the change in the visualization, such a trial-and-error approach was not widely used by participants.

Furthermore, affordance issues also occurred with the *stacked bar* chart. Many participants perceived all bars in the stacked bar chart in Figure 1B.2 starting from the same horizontal axis, and shorter bars simply overlapped on the top of tall bars. *“I thought the Americas was starting on the same axis as all the others. It just shows that how the Americas went higher.”* - P4, B. Consequently, as Americas was always shown as the top portion of the stacked bar chart, many participants thought that Americas’ cases were always higher than other continents. As a result, they were confused when noticing that the number for Europe was higher than that of Americas in some parts of the chart.

5.1.3. Associating concepts with existing knowledge

Participants tended to use their familiar tools, personal knowledge, and prior experiences with similar products or to follow general design principles when comprehending the visualizations. Confusion arose when visualization designs conflicted with their prior knowledge and experiences.

Familiar tools: General tools, such as Google and common commands in browsers, were used in their comprehension processes. For example, to find out the confirmed cases “per 1 million population” in France in Figure 1A, many participants first found the total cases from the visualization, then searched in Google to find out the population of France, and finally calculated the number themselves. Although the map visualizations had + and - icons for zooming, some participants still chose to zoom in the entire website. What’s more, we also observed that some participants used common hotkeys, such as Ctrl+F, to search for information in the visualizations.

Prior experiences with similar software: Participants’ prior experiences with similar software also affected their expectations of the visualizations. When clicking on the state name in Figure 1D.2, they expected that would lead to more details of the state based on their prior experience with a similar website. *“If I click [states on the map], do they go anywhere? No... So the New York Times site has, like, if you click Tennessee, it will go to Tennessee.”* - P14, D. Moreover, when hovering over a line in Figure 1C, participants expected to see more information popping up. *“Often in this kind of tool when you hover over the line. It tells you what you’re looking at. But this one does not.”* - P14, C. Similarly, when zooming in the world map in Figure 1A, participants expected more information would pop up immediately, just like Google Maps. However, the world map did not reveal any further information after the first click on the “+” icon in Figure 1A.5.

General design principles: General design principles guided participants’ expectations and comprehension processes. One such principle was *consistency*. For example, when participants zoomed in the map as shown in Figure 6 (a part of Figure 1A), not all countries’ names appeared at the same time. This design was inconsistent with their experiences of using common digital maps, such as Google Maps. As a result, it confused participants as they would expect the country name to appear at the same time.

Another consistency issue was caused by a mismatch between the perceived meaning of an *icon label* and the *visualization it represented*. For example, two line icons were used in the toggle button in Figure 1B.4 to represent the bar charts in Figure 1B.2. *“This is confusing for me [pointing to the two line icons] because they are lines, not the bar graph [pointing to the bar graph in Figure 1B.2].”* - P5, B.

Furthermore, the violation of consistency guidelines also happened when icons and textual labels were mixed together in the same group of visual elements. For example, while one toggle button in Figure 1B.4 used icons as labels, the other two toggle buttons used texts as labels. Participants felt puzzled about the meanings of the icons and also the inconsistent design. *“Why not just put words in there [pointing to two line icons]? Because words are used there [pointing*



Figure 6.: Consistency issue: not all countries’ names appear at the same time when the map was zoomed in, which was inconsistent with participants’ experiences with common digital maps.

to the Daily and Weekly icons].” - P14, B.

Another design principle violated was *Gestalt principles*. Gestalt principles are principles of human perception that describe how humans group similar elements and recognize patterns (Koffka, 2013). One of these principles was the law of proximity. When two visual items were separated, they would not be perceived as connected. For example, because the tool bar as shown in Figure 1A.1, was so distant from the world map view that many participants did not realize that the tool bar was connected with the map. “Maybe it [the tool bar] can be placed around here, closer to the map... if it is closer, then it becomes more obvious [that it is part of the map].” - P10, A. Consequently, when selecting a different option from the dropdown list in the tool bar, many did not notice that the colors in the map changed accordingly. Similarly, the search bar at the top (A.2) was also so far away from the map in Figure 1A that many participants did not realize that it was connected to the map.

5.1.4. Recovering from Errors

Some of the participants’ thought processes were related to figuring out and recovering from errors. One error-recovery approach was *trial-and-error*. For example, when trying to figure out why Germany was not added in E.4 for the task on Figure 1E, P2 attempted different options in E.3 and verbalized: “...Trends, Counts...[clicking the Counts button]... Should be a different graph? Let’s see what happens” - P2, E.

Another error-recovery approach was to adopt their familiar non-digital workarounds. For example, when P11 could not figure out how to add multiple countries in Figure 1E at the same time, he eventually decided to add one country at a time and wrote down the country name and the case number shown in the figure on a piece of paper. Later, he compared these written numbers to complete the task.

5.2. Challenges with Interaction Techniques (RQ2)

In addition to understanding participants’ comprehension thought processes, we analyzed the challenges they encountered with the seven interaction techniques (see Section 3.2). We found that they encountered problems primarily with the following five interaction techniques: Abstract/Elaborate (e.g., hover-over tooltips and zooming), Select (e.g., pinning a visual element and making it always visible), Filter, Encode (e.g., visual encoding), and Reconfigure (e.g., changing spatial arrangement of underlying data).

5.2.1. Abstract/Elaborate

Hover-over tooltips and zooming were two examples of Abstract/Elaborate. A common issue with hover-over tooltips was precise pointing and selection. Selecting an item from many closely arranged visual elements was challenging. For example, stacked bars in Figure 1B.2 were so close together that a slight motion slip resulted in a different bar than the intended one. Hovering over thin lines, such as the ones in Figure 1C, to reveal tooltip was an issue for participants as this required them to move their mouse with fine motor control.

Accidentally triggered hover-over tooltips caused confusion. For example, as Figure 7 (a part of Figure 1E) shows, after selecting the three required countries (i.e., Brazil, Canada, and France) as indicated in the bottom right corner of the figure, P2 was surprised to find that another country’s data was also shown up and became confused: “*Why am I getting China?*”. This was because he did not realize that his cursor was still on the chart and the cursor triggered a pop-up tooltip at that place, which displayed the data for China.



Figure 7.: An accidentally triggered hover-over tooltip, an example of Abstract/Elaborate interaction technique, can cause confusion to participants.

Participants anticipated zooming in on a map would reveal more information similar to how Google Map works. However, zooming in on a country in Figure 1A did not reveal more details. Another issue with zooming was that the “+” and “-” buttons were so far away from the map in Figure 1A that they were not perceived to be related to the map and thus were rarely used. This was the violation of Gestalt principles (see Sec 5.1.3).

5.2.2. Select

While Abstract/Elaborate (e.g., hover-over tooltip) can reveal additional information, Select techniques allow for marking a visual element and pinning associated information to facilitate comparison. The task for Figure 1B required participants to compare the numbers between Americas and Europe. Participants hoped to click on the bars representing Americas and Europe to select/pin them there so that they could see numbers for both at the same time. Unfortunately, Figure 1B did not support Select techniques.

Although Figure 1C and E supported Select techniques by allowing for clicking a country option in C.1 to activate the corresponding line in C.2 or adding a country in E.4 to highlight the corresponding line in E.1, such Select techniques were realized through separated UI elements (i.e., C.1 and E.4 respectively) outside of the main visualization areas. However, participants tended to directly click on the lines that they want to activate. In other words, Select techniques could be improved by supporting *direct manipulation* on the visualization instead of relying on a UI element physically separated from it.

5.2.3. Filter

While participants were familiar with standard drop-down lists, many did not realize that they could filter options in the country drop-down list in Figure 1E.4. As a result, they scrolled through the long list of country names to find the target. One common issue with scrolling a long list was that the list would disappear if their cursor was accidentally moved out of the list area. As a result, they were confused and had to start over again. Another issue was caused by the misalignment between the visual indicator of the selected item in the list and their mouse

cursor, which might be caused by poor internet speed or computer configuration.

Some filters lacked real-time feedback. For example, while dragging the scroll bar in Figure 1E.2, participants were confused that nothing happened in the visualization. This was because the visualization was only updated when the mouse was released.

Furthermore, similar to their expectation for Select techniques, participants also expected to use Filter techniques by *direct manipulation*. For example, although the scrollbar in Figure 1E.2 allowed for filtering lines in the visualization, few participants used it. Instead, many participants directly clicked on a number label in Figure 1E.1 and anticipated it to filter lines in the visualization based on the number.

5.2.4. Encode

Participants found the visual encoding of some visualizations ambiguous and hard-to-understand and consequently attempted to interact with the visualization in the hope of changing the visual encoding to better understand the data. “*I see a bubble in the place where Germany, Italy, and Switzerland joined, so is the statistics based on Italy, Germany, or Switzerland? It’s hard to tell... [click A.1 to switch from bubble map to choropleth map]*” - P8, A.

5.2.5. Reconfigure

Reconfiguration allowed participants to change the spatial arrangement of underlying data (e.g., sorting and rearranging columns or changing x- and y-axes). Figure 1B and E allowed participants to use slider bars (B.4, E.3, and E.4) to reconfigure data shown in different axes. However, participants found that it was not always clear which option in a slider bar was activated. One potential reason was mismatched affordance, which has been explained in Sec 5.1.2.

6. Discussion

We understand how older adults comprehend COVID-19 interactive visualizations through the lens of their think-aloud verbalizations. In this section, we discuss these thought processes in the light of the literature and the challenges that older adults encountered when using these interactive visualizations.

6.1. Visualization Comprehension Thought Processes and Challenges

6.1.1. Thought Processes of Comprehending Interactive Visualizations

Our analyses uncovered four main types of thought processes that explained how older adults comprehended the COVID-19 interactive visualizations: *encoding visual information*, *relating visual features to concepts*, *associating concepts with existing knowledge*, and *error-recovery*. Older adults experienced an integrated and iterative cycle of these thought processes.

Previous research studied how *young adults*, mostly college students, comprehend *static visualizations* and identified the first three types of thought processes: encoding visual information, relating visual features to concepts, and associating concepts with existing knowledge (Barnard, Bradley, Hodgson, & Lloyd, 2013; Carpenter & Shah, 1998; Shah & Hoeffner, 2002). Our research extends this line of research by studying how *older adults* interact with and comprehend *interactive visualizations* that are closely related to their lives. We found the same three types of thought processes. Moreover, our research further revealed one additional type of thought processes: *error-recovery*. These four types of thought processes provide a lens to understand how older adults comprehend information from interactive visualizations at a micro-level.

6.1.2. Challenges in Comprehending and Interacting With the Visualizations

Our study revealed challenges older adults encountered with each type of thought process (see Sec. 5.1). These challenges were caused by inappropriate visual designs (e.g., colors, texts, layouts), insufficient information (e.g., lack of labels, missing legend), confusing information (e.g., unfamiliar labels, ambiguous language), mismatches in mental models as well as in affordance, conflicts with prior knowledge and experiences, and violations of design principles. While prior research focused mostly on static visualizations, our work focused on interactive visualizations and extended our understanding of how older adults perceive and use interactive visualizations. For example, prior work found that static stacked bar charts takes longer for older adults to comprehend than bar charts (Le, Aragon, Thompson, & Demiris, 2014). In contrast, our study found that dynamical rearrangement of stacked bars in a bar chart after a user interaction can affect older adults' understanding of the chart.

Furthermore, our study found that older adults encountered challenges with five of the seven types of interaction techniques (see Sec 5.2). Specifically, they encountered more challenges with Abstract/Elaborate, Select, and Filter techniques than with Encode and Reconfigure techniques. These challenges were primarily caused by inadequate responsiveness of interactive visualizations (e.g., delay between user actions and visual feedback), demand of precise pointing (e.g., being able to move cursor in a fine-granular way), and unfamiliar or confusing visual elements (e.g., the filter within a text box). Such challenges might be exacerbated with aged-related perception and motor declines, such as presbyopia and finger coordination (Shim, Lay, Zatsiorsky, & Latash, 2004), and thus are more likely to appear among older adults than young adults. However, more controlled comparative studies are needed to validate this conjecture.

Our analyses also revealed ways to improve the user experience of interaction techniques commonly used in interactive visualizations: balance complementary interaction techniques (e.g., Abstract/Elaborate and Select), consider using direct manipulation that allows for moving visualization directly on it instead of relying on controls physically distant from the visualization, match the perceived affordance of a UI element with the function that it supports, and allow for alternative ways of exploring visualizations to increase the chance of success.

6.2. Design Guidelines

Based on our findings, we derive five design guidelines (DGs) for creating user-friendly interactive visualizations for older adults. We further discuss how these DGs corroborate with and extend the literature as well as how they might be implemented.

DG1: Increase the legibility of visual designs. This guideline entails three sub-guidelines. First, the color scheme used in the visualization should have sufficient contrast. Second, texts should have sufficient size and contrast. Low contrast color schemes and small font sizes can be hard for aging eyes. These two sub-guidelines are consistent with the general guidelines for creating user friendly instructions for older adults (Fan & Truong, 2018). Previous research suggests that the font size should be at least 12-point to accommodate aging vision (Becker, 2004; Bernard, Liao, & Mills, 2001; Chadwick-Dias, McNulty, & Tullis, 2002; Chisnell, Lee, & Redish, 2004). However, these prior works focused on static charts on paper or screen. In contrast, our work shows that these guidelines are also applicable to interactive visualizations.

Lastly, visual elements representing important information should be spaced out properly. The densely-distributed lines in Figure 1E and bars in Figure 1B represent many data visualizations commonly found online. Although such visualizations might not cause severe issues for young adults who have fine motor skills and good eyesight to explore the meaning of each line or bar by moving their cursor from one to another, our study shows that older adults struggled to do so and often overshot the intended line or bar. Thus, visual elements (e.g., lines or bars) representing important information should be spaced out generously so that it does not require fine motor skills and good eyesight to navigate them. While prior work suggests that this guideline is necessary for designing user interfaces on a small mobile phone for older adults (De Barros, Leitão, & Ribeiro, 2014), our work extends the prior work and shows that such guideline is also

necessary for designing interactive visualizations for older adults.

DG2: Facilitate the understanding of the affordance of visual elements by adding textual labels and using plain language. First, important interactive visual elements, such as buttons, should be labeled with text even when icons are used. While prior work shows the necessity of this guideline for mobile user interface design, our study suggests that icons alone were not always interpreted correctly by older adults with the intended affordance and thus text labels should be added to assist the understanding of interactive visualizations (De Barros et al., 2014). Moreover, our study shows that short labels can be misinterpreted and cause confusion. Thus, visualization designers should balance between keeping texts succinct to maintain visual aesthetics and informative to make it self-explanatory.

Second, plain language should be used to explain technical terms or abbreviations that appear in the visualization, such as in the labels and legend. Technical terms often cause confusions to older adults and abbreviations can be interpreted differently due to their different historical, cultural, and educational backgrounds. This is consistent with prior work studying the usability of website and instructions for older adults (Chadwick-Dias et al., 2002; Fan & Truong, 2018).

It is worth noting that DG2 raises a tension between keeping the texts concise, which often requires using technical terms and abbreviations, and using plain and easy-to-understand language, which might result in lengthy explanations. Future work should explore better ways to balance between these two aspects when designing visualizations.

DG3: Match visual designs with older adults’ expectations by understanding and following their existing knowledge and experiences. Older adults, as any users, bring their personal experiences and knowledge when interacting with and comprehending visualizations. Thus, visualizations following their expectations can reduce their cognitive load and learning effort.

One possible approach to implementing DG3 is to follow similar designs of typical software and tools that older adults commonly use. For example, if a map is used to visualize geolocation-related data (e.g., COVID cases in different cities), it would be desirable for the visualization to follow common visual designs (e.g., +/- icons to zoom in/out) and interaction techniques (e.g., click and drag the cursor to pan the map) in digital maps (e.g., Google Maps).

DG4: Support trial-and-error exploration and error recovery. Previous research found that older adults used a trial-and-error approach to learn information technology and use mobile phones (Leung et al., 2012; Mitzner et al., 2008; Selwyn, Gorard, Furlong, & Madden, 2003; Tang, Leung, Haddad, & McGrenere, 2013). Our study extends prior work and shows that trial-and-error approach was also used by older adults to recovery from errors when using *interactive visualization*. However, our work also shows that such trial-and-error approaches often did not help older adults recover effectively from errors. One reason was that once entering a wrong path, older adults could not easily find a way back (Ziefle & Bay, 2005). One possible way to support trial-and-error exploration is to identify when older adults enter a wrong state, for example by sensing their subtle verbalization patterns (e.g., slowed-down speech and more frequent use of negative or filler words) (Fan, Zhao, & Tibdewal, 2021), and promptly help older adults return to a previous step or a “safe” home state so that they could easily start over again.

Another potential reason was that the interactive visualizations never provided any timely error messages. Without informative error messages, even if participants realized that they made a mistake, they did not know what caused the problem. Consequently, they were unable to recover from it with the aimless trial-and-error approaches. This suggests that informative error messages should be provided promptly to inform older adults the potential cause of the problem and ideally a potential solution.

Finally, participants suggested another error-recovery solution, which was to provide effective instructions about how to read and interact with the visualizations. While prior research provides guidelines for creating senior-friendly instructions to help them use technology products (Fan & Truong, 2018; Tang et al., 2013), our work points out that showing instructions on a visualization may make it cluttered and negatively affects its clarity. Thus, how to balance the number of instructions and a clean visual design is still a challenge. Future work should explore ways to balance the number of instructions and visual design, such as showing instructions on-demand.

DG5: Provide responsive, reliable, and intuitive interactions. Based on the interaction challenges described in Section 5.2, we provide six possible directions to implement this DG: 1) ensure synchronicity between user inputs and feedback (and informing users when a delay is unavoidable); 2) avoid interactions that depend on precise pointing (e.g., the densely distributed bars and lines in Figures 1B and E. If precision pointing is unavoidable, consider to adopt assistive pointing techniques for older adults, such as PointAssist (Hourcade, Nguyen, Perry, & Denburg, 2010); 3) prevent unwanted interactions from being accidentally triggered (e.g., accidentally activated tooltips); 4) support Select when Abstract/Elaborate (e.g., tooltip information) is used so that users can choose to pin the elaborated information if needed; 5) support direction manipulation with the visual elements of the visualization instead of asking older adults to operate controls (e.g., buttons, slide bars) positioned far away from the visualization; and 6) provide multiple ways to understand data by supporting Encode and Reconfigure; 7) Tangible user interfaces have been shown to be intuitive for older adults to comprehend visualizations. For example, MeViTa was a tangible Augmented Reality (AR) based system that projected relevant medical information (e.g., side effect) beside physical medicine packages placed on a table De Croon et al. (2017). The combination of tangible objects (i.e., medical packages) and corresponding visualizations helped older adults understand their side effects and interactions among those medicine packages. Future work could explore tangible user interfaces to provide intuitive interactions for older adults to better comprehend visualizations.

Last but not least, it is worth noting that our proposed guidelines would likely make interactive visualizations more usable in general and thus benefit both older and young adults at the same time. More research is needed to tease out the general guidelines for all age groups and specific ones more applicable to older adults.

6.3. Limitations and Future Work

Effects of Visualizations. We studied how older adults interacted with COVID-19 interactive visualizations as these visualizations were critically relevant to their daily lives. COVID-19 data represents a typical type of temporal data that is frequently updated (e.g., on a daily basis) and contains multiple data properties (e.g., new cases, cumulative cases, death cases). Thus, our findings could potentially inform the design of the visualizations of future pandemic data for older adults. However, it remains an open question of how older adults would comprehend visualizations of other data sources and how the design guidelines might need to be adapted.

We chose five visualizations to cover common types of interaction techniques highlighted in the literature (Dimara & Perin, 2019; Yi et al., 2007) in our study. These interaction techniques, however, might not be equally important from older adults’ perspectives. For example, some interaction techniques might be more frequently used than others. Future work should investigate the usage frequency of different interaction techniques and focus on optimizing more frequently used interaction techniques if simultaneously optimizing different ones is too costly or impossible.

Effects of Tasks. We explored older adults’ thought processes and challenges when using interactive visualizations with *goal-oriented tasks*. In other words, the participants had clear goals in mind when interacting with the visualizations. While this is a common usage scenario of visualizations, users might also explore visualizations without a specific goal in mind and perform a free-style exploration. We suspect that there might be differences in users’ interaction patterns and comprehension thought processes. For example, there might be more open-ended trial-and-errors. Future work should explore how older adults comprehend and interact with visualizations without a specific goal to compare with and enrich the findings of this study.

We designed the tasks in our study so that they utilized key information in the COVID visualizations. Alternatively, another approach to constructing tasks is through a needs-finding study. For example, by observing how older adults actually use COVID visualizations, we might be able to derive more representative tasks for them.

Effects of Older Adults’ Background Information. Older adults are not a homogeneous group of users. Our study participants did not report any physical, perceptual, or cognitive

impairments. As older adults’ physical, perceptual, and cognitive abilities may vary widely and can affect the way how they interact with and comprehend visualizations, it is imperative to understand how older adults’ varied abilities may affect how they interact with visualizations and to adapt the design guidelines accordingly. Moreover, our participants lived in North American cultures. As cultures can affect the way how people read, reason, and communicate, more research is warranted to investigate how older adults of different cultures may comprehend visualizations and how the guidelines might need to be tuned accordingly.

Effects of Device Configurations. Our participants joined the study remotely using their own computers in their homes. This setup allowed them to interact with and comprehend interactive visualizations on their familiar devices in their familiar environments. As a result, their thought processes and interaction patterns were more likely to reflect their natural behaviors than those observed in a controlled lab study. That said, with this natural setup, we had limited control over their devices (e.g., screen resolution and size), internet connectivity (e.g., speed), and environmental factors (e.g., lighting condition). Previous research suggests that device constraints could result in problems because interactive visualizations depend on screen real estate and mouse-based interaction (Chittaro, 2006; Ghose, Goldfarb, & Han, 2013; Ghosh, Parikh, & Chavan, 2003; Roberts et al., 2014). Thus, further work should conduct more controlled lab studies to understand how device configurations (e.g., screen size, resolution, internet speed) may affect older adults’ comprehension of and interaction with interactive visualizations.

Effects of Age. Last but not least, a natural follow-up question is whether our design guidelines are older adults specific or they would also make interactive visualizations accessible to other age groups, such as young adults. Future work could conduct similar studies with young adults and compare the similarities and differences to understand the applicability of the guidelines to other age groups.

7. Conclusion

Visualization has become an important tool to make sense of ever-increasing data in this data-driven world. Thus, ensuring its accessibility to all populations is key to digital equity. In this research, we conducted think-aloud usability testing and interviews with older adults using COVID-19 interactive visualizations that were relevant to their daily lives. By analyzing participants’ think-aloud verbalizations, we identified four types of thought processes reflecting how they interacted with and comprehended the visualizations: *encoding visual information*, *relating visual features to concepts*, *associating concepts with existing knowledge*, and *recovering from errors*. These four types of thought processes confirm and extend the three-process visualization comprehension theory that was developed with *static visualizations* and *young adults* by examining how *older adults* comprehend *interactive visualizations*.

We further uncovered the challenges that older adults encountered with each thought process. Moreover, we also highlighted the challenges they encountered with the seven common types of interaction techniques adopted in the interactive visualizations.

Based on our findings, we present five design guidelines to make interactive visualizations more accessible to older adults: *increase the legibility of visual designs*, *facilitate the understanding of the affordance of visual elements by adding textual labels and using plain language*, *match visual designs with users’ expectations by following their existing knowledge and experiences*, *support trial-and-error exploration and error recovery*, and *Provide responsive, reliable, and intuitive interactions*.

Future work should examine whether and to what extent the content of the visualizations (e.g., non-COVID related information) might affect the findings and the design guidelines. We used goal-oriented tasks to study how older adults comprehended COVID-19 interactive visualizations. It remains an open question of how the types of tasks (e.g., non-goal oriented freestyle exploration) might affect the findings. Furthermore, as older adults are not a homogeneous group, it is worth exploring how their physical and cognitive abilities as well as their culture backgrounds might affect the findings and the design guidelines. Last but not least, future work could conduct

similar studies with young adults and compare the similarities and differences to understand the applicability of the guidelines to other age groups.

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8. Biographies

Mingming Fan is an Assistant Professor in the Computational Media and Arts Thrust and the Division of Integrative Systems and Design at The Hong Kong University of Science and Technology (HKUST) in both Guangzhou and Clear Water Bay campuses. He leads the Accessible & Pervasive User EXperience (APEX) Group to research at the intersection of Human-Computer Interaction and Accessibility.

Yiwen Wang is a graduate student in the School of Information at the Rochester Institute of Technology. She has been working with Dr. Mingming Fan on aging and accessibility research.

Yuni Xie recently graduated from the School of Information at the Rochester Institute of Technology. She has been working with Dr. Mingming Fan on aging and accessibility research.

Franklin Mingzhe Li is a PhD student in the Human-computer interaction institute at Carnegie Mellon University. His research focuses on accessibility.

Chunyang Chen is a lecturer (Assistant Professor) in the Faculty of Information Technology, Monash University, Australia. He received his PhD from the School of Computer Science and Engineering, Nanyang Technological University (NTU), Singapore. His research focuses on Software Engineering, Deep Learning and Human-Computer Interaction.