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► **To cite this version:**

Tanja Blascheck, Lindsay Macdonald Vermeulen, Jo Vermeulen, Charles Perin, Wesley Willett, et al.. Exploration Strategies for Discovery of Interactivity in Visualizations. IEEE Transactions on Visualization and Computer Graphics, In press, 10.1109/TVCG.2018.2802520 . hal-01705792v1

HAL Id: hal-01705792

<https://hal.science/hal-01705792v1>

Submitted on 9 Feb 2018 (v1), last revised 29 Oct 2018 (v2)

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Exploration Strategies for Discovery of Interactivity in Visualizations

Tanja Blascheck, Lindsay MacDonald Vermeulen, Jo Vermeulen, Charles Perin, Wesley Willett, Thomas Ertl and Sheelagh Carpendale

Abstract—We investigate how people discover the functionality of an interactive visualization that was designed for the general public. While interactive visualizations are increasingly available for public use, we still know little about how the general public discovers what they can do with these visualizations and what interactions are available. Developing a better understanding of this discovery process can help inform the design of visualizations for the general public, which in turn can help make data more accessible. To unpack this problem, we conducted a lab study in which participants were free to use their own methods to discover the functionality of a connected set of interactive visualizations of public energy data. We collected eye movement data and interaction logs as well as video and audio recordings. By analyzing this combined data, we extract exploration strategies that the participants employed to discover the functionality in these interactive visualizations. These exploration strategies illuminate possible design directions for improving the discoverability of a visualization's functionality.

Index Terms—Discovery; Visualization; Open Data; Evaluation; Eye Tracking; Interaction Logs; Think-Aloud;

1 INTRODUCTION

Many governments worldwide strive to make their data available online in open formats. This *open data* movement has been pursued as a political priority in countries such as Canada [1], the United Kingdom [2], Germany [3], and the European Union as a whole [4]. This data is typically only available in raw formats like spreadsheets and CSV files [5], making it hard for the general public to access and explore. Moreover, citizens often lack the means or skills to process, visualize, and understand the data [6].

A popular way of making open data more accessible is via web-based interactive visualizations. Some examples include the OECD Better Life Index [7], the NCDRisk Height Map [8], the Crime Maps of UK cities [9], or the Live London Underground Map [10]. However, it remains unclear how the general public makes use of these visualizations, and whether citizens are able to discover how to interact with them. In particular, recent work by Boy et al. [6] suggests that viewers often not notice the functionality in interactive visualizations. To date, visualization research has not deeply explored how viewers discover interactive functionality. This knowledge gap makes it difficult to develop data visualizations that are accessible for the general public.

We contribute a detailed mixed-methods study from which we identify a variety of exploration strategies that people use when discovering how to interact with a visualization. We report the results from our observations of 24 participants as they used their own methods to discover the functionality of an open data visualization on a government website dedicated to providing information on energy data.

We collected and integrated eye movement data and interaction logs as well as video and audio recordings to extract exploration strategies that participants employed to discover the visualizations' functionality. These exploration strategies are: eyes only, reading text, opportunistic interactions, entry points, structural interactions, permutation interactions, and leveraging the familiar. Some of these exploration strategies have been documented previously, including eyes only [11], reading text, opportunistic interactions [12], permutation interactions [13], and choosing personally relevant entry points [14]. However, additional exploration strategies we observed shed new light on how people explore interactive visualizations. These include using the structure of available controls for sequential search and leveraging the familiar by comparing a familiar view and a new view to discover functionality.

Interactivity can be a powerful tool to enable visual exploration and insight generation [15]. Despite the ubiquity of interactive visualizations, it remains a challenge for people who create visualizations to determine when interaction is appropriate, and how people discover functionality when it exists. We investigate strategies people use to discover the functionality of a specific set of visualizations of energy data. While these are only a subset of the broad and diverse space of interactive visualization techniques, our study presents a first step towards a better understanding of how people discover a visualization's functionality. Based on our exploration strategies, we contribute suggestions on how to design for discovery by inviting interaction, pro-

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Manuscript received XXX XX, 2017; revised XXX XX, 2017.

viding entry points, using spatial organization, combating oscillation, supporting transitions, and scaffolding complex interactions.

2 RELATED WORK

Our work is related to existing research in two main areas: proliferation of open data visualization and research examining the discovery of functionality in visual interfaces.

2.1 Proliferation of Open Data Visualizations

Many countries and institutions are increasingly interested in making government data open and accessible to citizens. However, for most non-experts, making sense of huge and often technical public datasets can be difficult. For example, most institutions only make open data available to the general public as raw tabular data files [5], for which few citizens have the tools or expertise to examine. Creating interactive visualizations that enable analysis by the general public poses an important challenge [16]. Research systems such as ManyEyes [17] and commercial tools like Tableau Public [18] have provided generic mechanisms for visualizing public data online. While these represent a great step forward as general purpose tools, they offer little specific help for introducing novices to either the data, the visualizations, or their interactive functionality. An increasingly popular alternative is to produce tailored interactive visualizations that present specific types of public data in ways that require less expertise. Interactive visualizations like Wattenberg's NameVoyager and BookVoyager [19] and Heer et al.'s sense.us [20], along with more recent examples like the OECD Better Life Index [7] feature tailored interactive visualizations of individual datasets intended for consumption by non-experts. However, the visualization community still knows little about how to craft these kinds of interactive visualizations for the general public in ways that can reliably enable novices to discover the functionality.

2.2 Discovery of Functionality in Visual Interfaces

Interactive visualizations face concerns about discovery and accessibility of functionality, especially when intended for novices. Although prior work has investigated graphical literacy and comprehension [21] for static charts, little is known about how novices approach more complex interactive visualizations. As a result, interactive open data visualizations, like Slingsby et al.'s Place Survey [22], have put considerable emphasis on designing for public accessibility. However, the results of these efforts have been mixed. In their own analyses, Slingsby et al. found that novices often failed to understand and use the more advanced functionality, even when they were explicitly introduced to it via tutorials. Perin et al.'s interactive ranking tables for soccer [23] — also designed with novices in mind — suffered from similar issues. While an introduction to the soccer visualizations explained the novel interaction techniques, novices often still failed to discover their functionality or use them when examining the data.

Recent work by Boy et al. [6] suggested a number of potential exploration strategies for revealing interactive functionality to novices. In a study of visualizations from

the OECD's Better Life Index [7], Boy et al. tested three different suggested interactivity techniques, including overt animations that used feedforward [24] to highlight interactive functionality. Their findings indicate that strong visual emphasis can encourage novice awareness of specific functionality in interactive visualization tools. However, the overall process by which novices discover functionality of new interactive visualizations still remains largely unstudied. This makes it difficult for designers to know which interaction techniques to include for a given visualization and how to best highlight them. With this in mind, our work explicitly examines how the general public uncovers novel visualizations and describes exploration strategies they use to make sense of unfamiliar interfaces.

As interactive visualizations are essentially interfaces, related work in the field of human-computer interaction on the discovery of functionality is relevant as well. Discovery of functionality is one of the most important characteristics of good interface design. Norman stresses that designers must always be cognizant of whether it is possible for a person "to even figure out which actions are possible and where and how to invoke them" [25, pg. 3]. In fact, usability guidelines often suggest that all functionality and possible actions should be immediately visible in an interface [25]. As a result, interfaces for novices tend to be heavily reliant on visual search [26]. Supporting visual search often involves removing features and suppressing more advanced functionality, with the goal of reducing search time and improving novice performance. However, this can lead to tools that fail to accommodate experts, and give novices little room to grow or to investigate more deeply. Ideally, an interactive system should support discovery of functionality for both novices and experts, encouraging awareness and understanding of its functionality [27] while also facilitating novice-to-expert transitions [26].

In contrast to prior research, which has primarily used interaction logs to evaluate discovery of functionality in online interactive visualizations (e.g., [6], [23], [28]), our study combines log data with eye movement data, video and audio recordings to produce detailed records of the discovery process.

3 STUDY: DISCOVERING VIS INTERACTIONS

To improve our understanding of how the general public discovers the interactions available in a visualization, we conducted a study of an interactive open data visualization on a government website dedicated to energy data.

We used a controlled environment and collected eye movement data and interaction logs as well as video and audio recordings. While eye tracking has been used to evaluate visualizations in general [29]–[34] and to specifically evaluate how novices remember visualizations [35], [36], it has not previously been used to tease out the discovery of functionality in a novel visualization. Using eye movement data makes it possible to examine which areas of the visualization viewers attend to and how their attention switches during a task. By contrast, usability studies tend to rely heavily on interaction logs, often supplemented by think-aloud protocols [37]–[39] which can provide insight into participants' thought processes [40], [41]. Combining

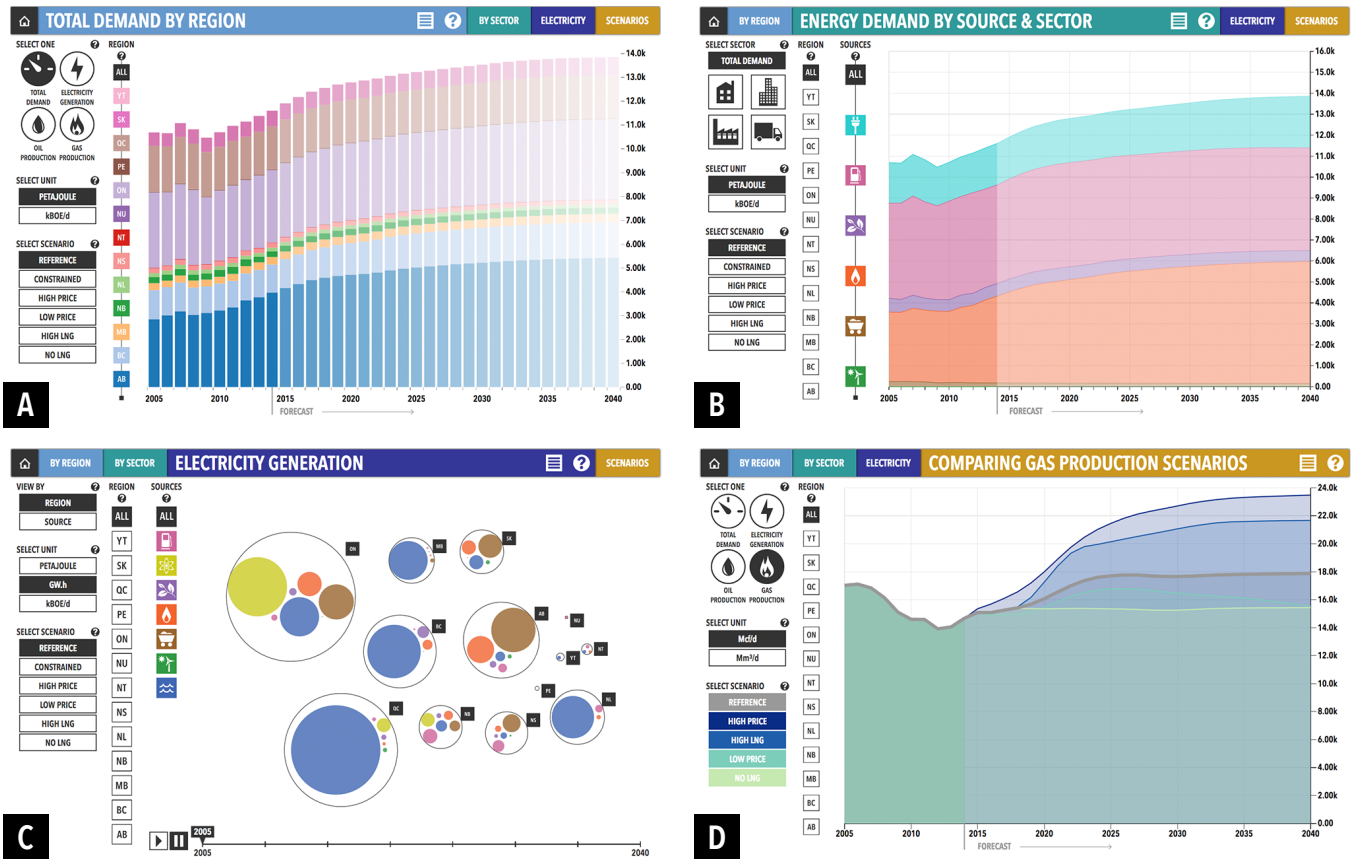


Fig. 1. The four views available on the NEB website: (A) STACKED BAR CHART showing total energy demand by regions, (B) STACKED AREA CHART depicting energy demand according to the energy source and sector, (C) BUBBLE CHART presenting electricity generation by region or source, and (D) LINE CHART showing different possible energy production scenarios.

these methods and collecting a more diverse set of data allowed us to analyze participants’ actions both in terms of attention and more explicit actions. This rich data provides a better understanding of the barriers participants faced and made it possible to identify specific exploration strategies that participants employed to discover the visualizations’ interactive functionality.

While there are trade-offs associated with conducting a controlled lab study, triangulating data from a range of different sources allowed us to extract strategies participants used and examine them in detail. In Section 8, we reflect further on the limitations of our approach.

3.1 The Interactive Visualization Website

We asked participants to explore a set of interactive visualizations: “Exploring Canada’s Energy Future” created by Canada’s National Energy Board (NEB) [42]. Like some of the other open data efforts mentioned previously, the NEB created these interactive visualizations to help both the general public and data experts examine data that was previously published in a less accessible format. The visualization website consists of a START PAGE shown in Figure 2, as well as four interactive views shown in Figure 1, each highlighting a different kind of energy data. The STACKED BAR CHART (Figure 1 A) shows energy demand, electricity generation, oil, or gas production by region. The STACKED AREA CHART (Figure 1 B) depicts the energy demand

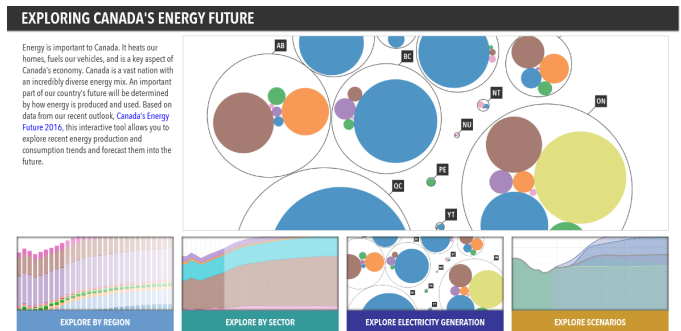


Fig. 2. The START PAGE of the website evaluated in the study showing across the bottom the option to select one of four views.

according to the energy source and sector. The BUBBLE CHART (Figure 1 C) presents electricity generation by region or by source. The LINE CHART (Figure 1 D) supports comparison of possible production scenarios, for total energy demand, electricity generation, oil, or gas production.

All four views use a similar layout with groups of controls on the left, a chart representing the energy data on the right, and one or two axes. Viewers can switch between views using the menu bar at the top. The menu bar also includes help (?) and description (≡) buttons, which provide more information about each view and how to use it. Question marks (?) next to each group provide more

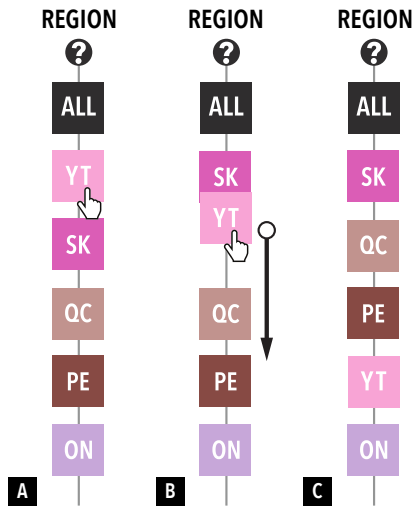


Fig. 3. The sliding rail supports reordering of elements in the views, here represented by two-letter codes of regions from Canada. A region is selected (A) and dragged to a new position (B), which causes other regions on the rail to make space for the region that is being dragged. When the region is dropped, the reordering is shown in the chart (C).

information specific to the associated interactive controls.

In addition to standard buttons and check boxes, the interface also includes two unconventional interface widgets. Both the STACKED BAR CHART (Figure 1 A) and STACKED AREA CHART (Figure 1 B) include a *sliding rail* control (Figure 3). By clicking the boxes on the sliding rail, viewers can hide and show related information in the chart. Viewers can also drag and drop boxes along the sliding rail to reorder the series as shown in Figure 3. The BUBBLE CHART (Figure 1 C) includes an interactive timeline that can be used to play back changes in the data over time.

3.2 Participants

In order to examine a diverse cross-section of the general public, we recruited three different types of participants: *novice*, *savvy*, and *experts*. The *novice* group consisted of i) students who were not studying a computer science-related discipline and ii) non-students who had never worked in the energy sector. The group of *savvy* participants consisted of computer science students. We recruited this group of participants because their technical background makes them experts in using interfaces despite being novices in the field of energy data. Finally, the *expert* group consisted of participants with experience in the energy sector (average 8.38 years experience; min 8 months, max 35 years). We recruited 8 participants for each group via posters, mailing lists, and word-of-mouth. Due to a variety of technical issues including poor English skills and hardware malfunctions that made the data unusable, we dropped and replaced 6 of the initial participants to obtain the final set of 24 participants (8 per group), which we report in this paper. Fourteen of the 24 participants were female and 10 were male. Fifteen participants were students. Six participants were 18–24 years old, 13 were 25–34 years old, 3 were 35–44 years old, and 2 were 55–64 years old. All participants had normal or corrected-to-normal vision. We also asked participants about their knowledge of energy issues — 21 stated they had some knowledge. Fourteen also

noted that they were familiar with infographics — 6 on the web, 13 in the media (multiple answers were possible).

3.3 Equipment and Set Up

To record eye movement and interaction data, we used a Tobii X2-60 compact eye tracker (accuracy 0.4 degrees, precision 0.34 degrees) on a Dell XPS 27 all-in-one machine (27" screen with a resolution of 2560×1440 px) running Windows 8.1. We recorded the eye movement data at 60 Hz. We aggregated gaze points using the IV-T classifier with a velocity threshold of 30 degrees/second, and a window length of 20 ms. We merged adjacent fixations up to a maximum time between fixations of 75 ms and a maximum angle between fixations of 0.5 degrees and discarded fixations with a duration below 60 ms. We used an additional video camera placed behind the participant to capture the participant and the screen.

We ran our study using an Internet Explorer 11.0.33 window with a size of 1235×910 px positioned 520 px from the left of the screen and 210 px from the top. The size of the browser window was constrained to maintain a consistent view size. We conducted the study in a room isolated from outside distraction. To ensure constant illumination, we closed the blinds and switched on the room light.

3.4 Study Procedure

We asked participants to investigate the Canada's Energy Future website and the four views associated with it. The experimenter did not provide participants with any explanation of the views. Participants could only use the information available on the website. The experimenter instructed the participants to freely explore the views and to talk about their thought process as they did so. We removed the header and footer of the website to eliminate distractions, to focus participants' attention on the views, to maintain consistency in view size, and to avoid scrolling that could disrupt the eye tracker.

At the beginning of each trial, an experimenter asked the participants to sign a consent form and fill out a demographic questionnaire. Participants then had to pass a visual acuity test utilizing a Snellen chart and a color vision test. We checked for color blindness and red-green blindness using nine of the 24 Ishihara test plates [43]. Next, we used a nine-point calibration procedure to calibrate the eye tracker. When the study was completed, participants filled out a NASA TLX questionnaire and a questionnaire for rating the views. At the end of the session, participants could make final remarks and received \$20 for their participation.

3.5 Data Collection

We collected eye movement data, interaction logs, and the time participants took to explore the interactive views. We also recorded the screen and audio using the eye tracker's integrated camera, and utilized a second camera to capture audio and video of participants. In addition, we collected demographic information, NASA TLX, and view-rating questionnaires. During the study, the experimenter also had a checklist to record each interactive function the

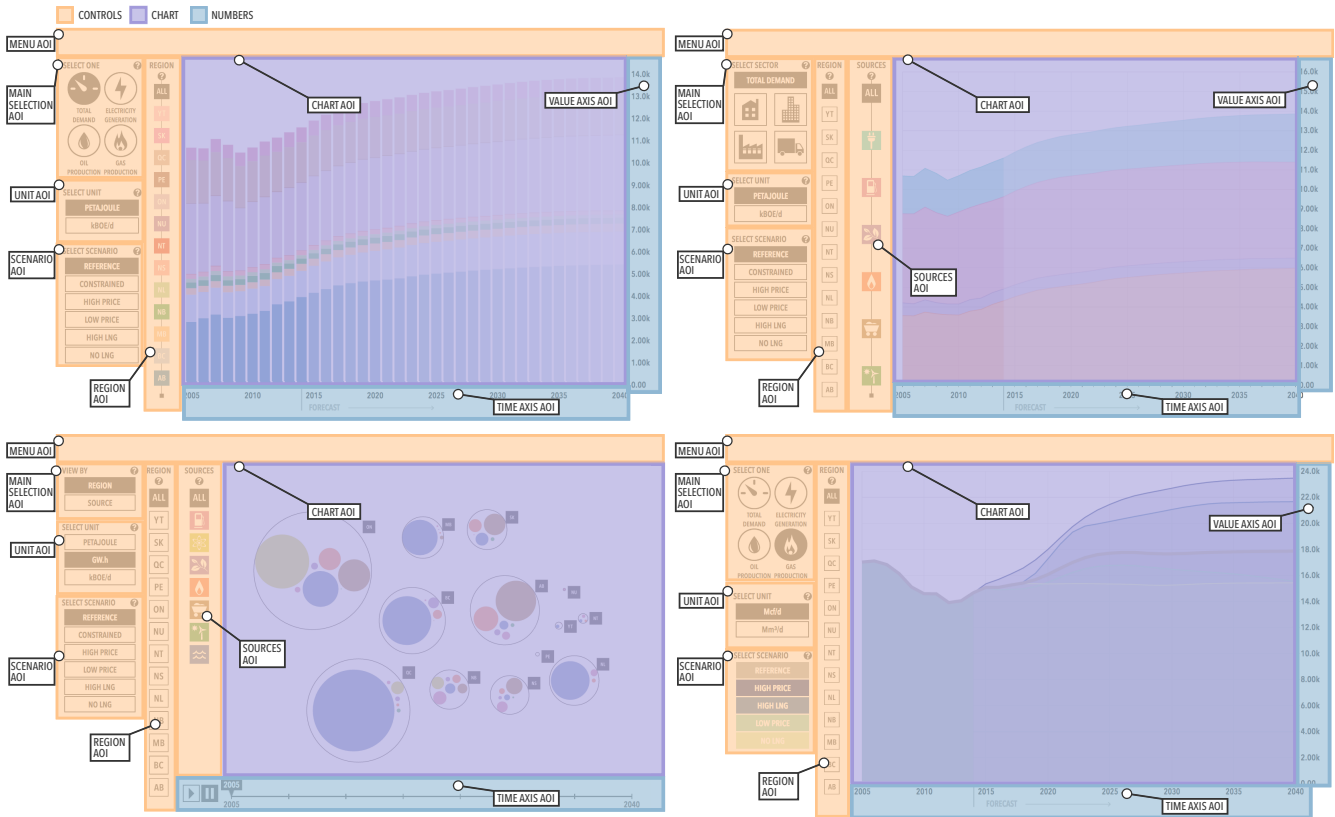


Fig. 4. The AOIs for each view. Each AOI is indicated by a color overlay based on the AOI group. The controls AOIs are shown with orange rectangles, indicating how the controls are grouped. The numbers AOIs for the axes are depicted with blue rectangles and the chart AOI is shown with a purple rectangle.

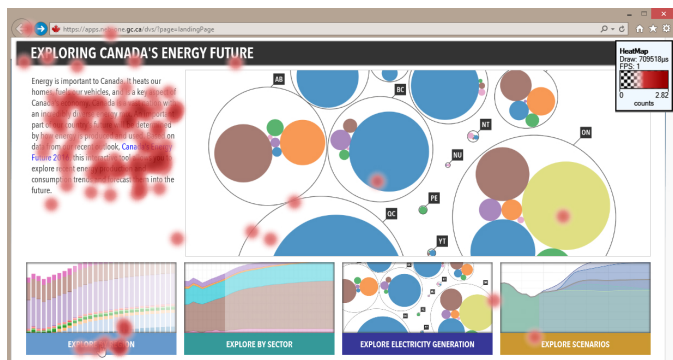


Fig. 5. The START PAGE of the website overlaid with an attention map for one participant showing high attention on the text snippet and some on the STACKED BAR CHART. The thumbnail in the top right corner shows the data mapping of the transparent to red color ramp.

participants used. We provide the complete data collected during the study on a supplemental website¹.

4 PROCESSING OUR STUDY DATA

To analyze our collected data, we first define areas of interest. Then, we describe three eye tracking visualizations we used for our analysis — attention maps, scanpaths, and AOI timelines. Last, we summarize the numerical data collected in the study.

1. <http://innovis.cpsc.ucalgary.ca/supplemental/Exploration-Strategies/>

4.1 Defining Areas of Interest

We analyzed the eye movement data using areas of interest (AOIs) for each view. We define AOIs based on the visual structure of the website (i.e., the control groups, chart, axes, and menus). Figure 4 shows the AOIs we defined for each view. We used one AOI for the chart (*chart AOI*), one AOI for each group of interactive controls including a *menu AOI*, *main selection AOI*, *scenario AOI*, *unit AOI*, *region AOI*, and *source AOI*. Since the controls vary according to the view and the data, the main selection AOI is different in each view. It contains the controls for choosing the energy type in the STACKED BAR CHART and LINE CHART, for choosing the sector for the STACKED AREA CHART, and for switching between a region and source option for the BUBBLE CHART. We used AOIs for the numerical parts of the views: the horizontal (*time axis AOI*) and the vertical axis (*value axis AOI*). We also refer to the horizontal time slider in the BUBBLE CHART as a *time axis AOI*.

As part of our analysis, we grouped these AOIs into three high-level groups which are shown in Figure 4: the *controls* group (shown in orange), the *chart* (shown in purple), and the *numbers* group (shown in blue). Although the individual AOIs are specific to the views in our study, the AOI groups reflect classes of elements common to most visualizations. The majority of interactive visualizations have one or more chart elements as well as a set of interactive controls. Furthermore, most visualizations feature numbers, either as axes or as temporal interaction controls.

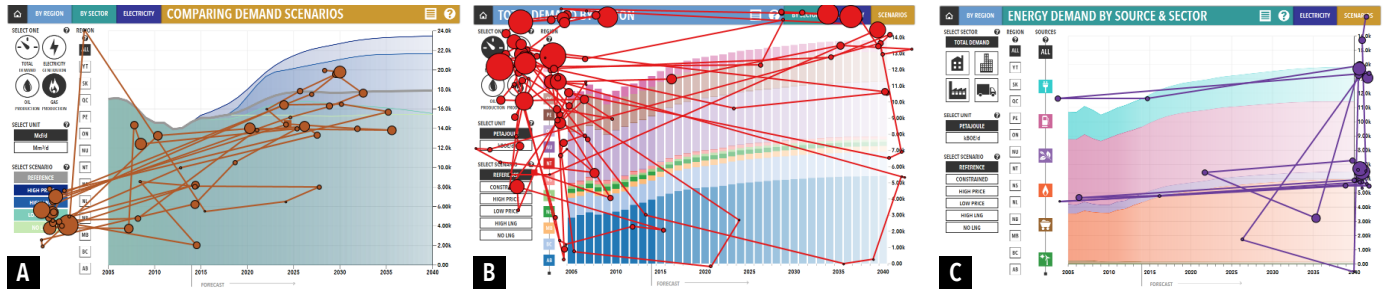


Fig. 6. Three different scanpaths showing the participants focus: (A) largely on the chart (P16), with some attention on the lower controls; (B) largely on the controls (P20), with some attention on the chart and on the numbers; and (C) largely on the numbers (P14), with some attention on the chart.

P10 - LINE CHART

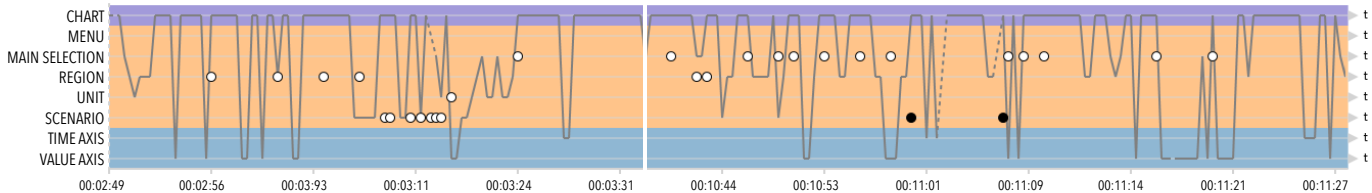


Fig. 7. A part of an AOI timeline for one participant for the LINE CHART. All AOIs for one view are represented by a horizontal light gray line. The background color of each AOI encodes its AOI group. The white circles show interactions in AOIs. Black circles mean that a participant opened the help menu. The dark gray line depicts the eye movements over time. If the eye movement line is dotted, it means that fixations are not assigned to any AOI. A vertical gap (white) indicates that a participant switched to another view and later came back to this view again.

4.2 Eye Movement Visualizations

We used three types of eye movement visualizations: attention maps, scanpaths, and AOI timelines.

Attention maps, like the one in Figure 5, represent the distribution of a participant’s attention on top of a stimulus. Our attention maps use a heat map metaphor where darker red indicates a higher amount of sustained attention while lighter red shows less attention. Areas without attention are not color coded. Attention maps are useful for identifying which parts of a view received participants’ attention and which ones did not.

Scanpaths, like those in Figure 6, depict the sequence of fixations on top of a view. Each circle represents one fixation and lines connect consecutive fixations. The circle radius encodes fixation duration. Scanpaths are useful for revealing the order in which participants focus on each element.

AOI timelines [44], like the one in Figure 7, show fixations and saccades — rapid eye movements between fixations — for an individual participant in a single time-based view. We created five AOI timelines per participant: one for the START PAGE and one for each of the four views. In each AOI timeline, individual AOIs are indicated by horizontal lines. The background of the AOI timeline is colored according to AOI group: purple for the *chart* (at the top), orange for the *controls* (in the middle), and blue for the *numbers* (at the bottom). The gray path represents the sequence of fixations of a participant. The longer the path stays in the same AOI (horizontal segments), the longer the fixation. Dotted segments of the path represent fixations that are not assigned to any AOI. These are times when, for instance, the participant may have looked away from the screen. White circles indicate an interaction such as a mouse click, while black circles mean that a participant opened or closed the help menu. Vertical gaps indicate the times at which a participant temporarily switched to

another view and later returned to work with the current one. AOI timelines are particularly useful for examining detailed temporal information for individual participants.

4.3 Coding Process

In our coding process, we drew upon the eye tracking visualizations as well as the video and audio recordings to identify exploration strategies that participants applied when exploring the views. First, one author developed an open coding scheme based on observations of eye movement visualizations and videos from several participants. A second author then verified this pass. Next, a group of four authors (including the initial two) discussed, refined, and presented the coding scheme to the rest of the research team. The team then refined these through a series of iterations until they reached consensus on a set of 10 exploration strategies. Then, using poster-sized printouts of the AOI timeline visualizations, one author coded the data from all 24 participants to identify all instances of these strategies. The larger group then discussed the results of this process and used axial coding to regroup, consolidate, and rename the strategies to arrive at a final set of seven. We provide the AOI timelines for all five views and all 24 participants on a supplemental website¹.

4.4 Times, Fixations, and Interactions

We now summarize the data we collected in our study before explaining the exploration strategies that we identified. On average our participants took approximately 15 minutes to finish their initial exploration of the interface ($M = 920s$, $SD = 478s$). During this time, every participant examined all four views. Figure 8 shows all participants’ fixations across the four views. Although we recruited a variety of participants from different backgrounds and assigned them

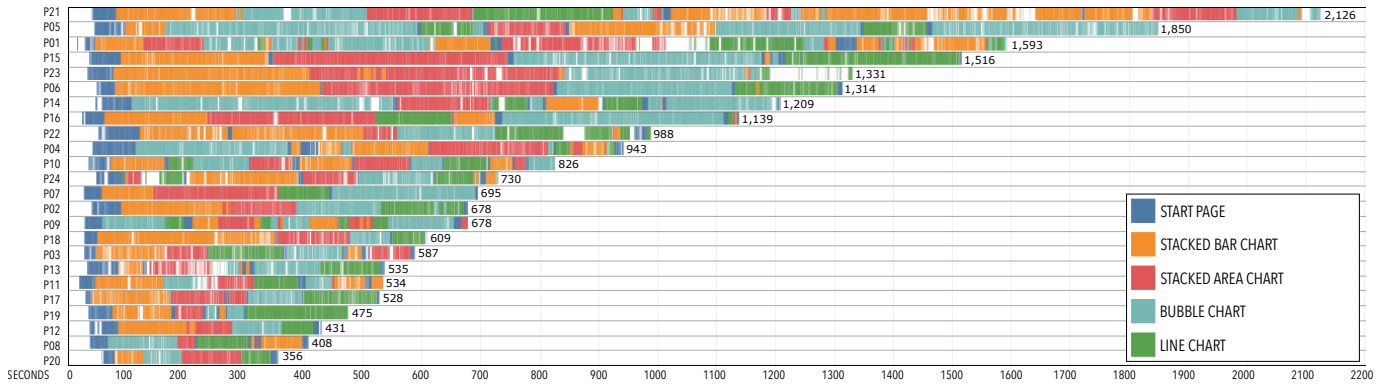


Fig. 8. All fixations recorded for each participant, colored by view, and sorted by total completion time in seconds. The white spaces indicate no eye movement data for that moment, for instance, when a participant looked away from the screen.

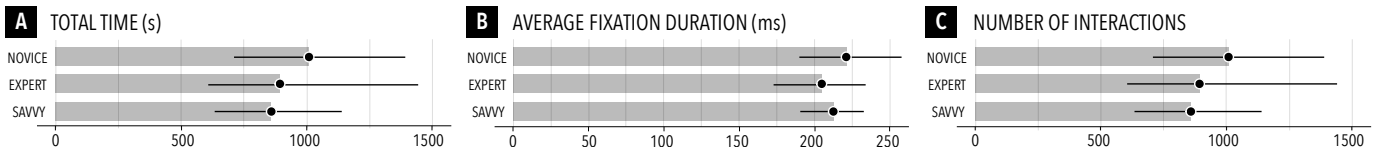


Fig. 9. Total time (A), avg. fixation duration (B), and number of interactions (C) for the three groups — with 95% bootstrapped confidence intervals.

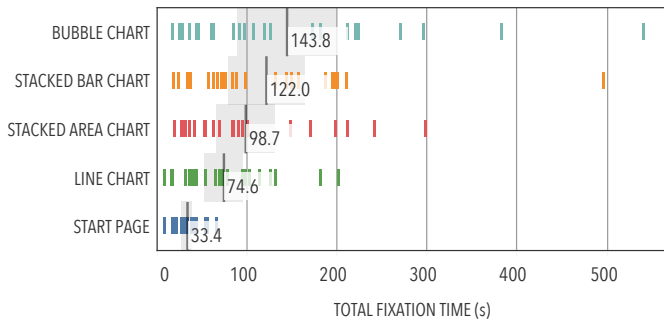


Fig. 10. Total per-participant fixation times on each view with averages and 95% confidence intervals indicated by the gray areas. The colors refer to the different views.

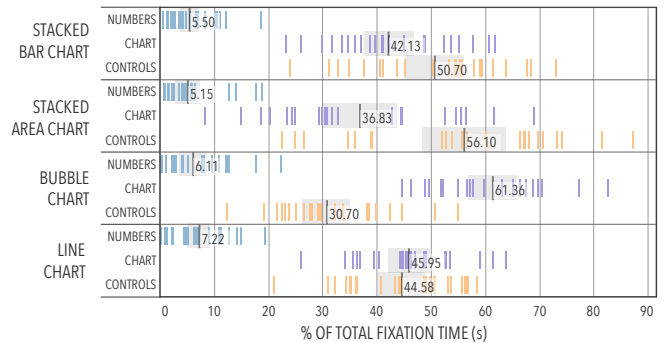


Fig. 11. Percentage of the total fixation time of AOI groups for each view with averages and 95% confidence intervals indicated by the gray areas. The colors refer to the different AOI groups.

to three groups (novice, savvy, and expert), we observed no clear difference between these groups in terms of total time, fixation duration, or total number of interactions (see Figure 9 for details). For example, participants from the expert group had both the longest and the shortest times. In general, for the timings shown in Figure 8, participants from all three groups were quite evenly spread across the time variations. We therefore collapse the groups for the rest of the analysis in this paper.

Overall, 19 of 24 participants started with the STACKED BAR CHART, 4 participants (P04, P08, P09, P14) started with the BUBBLE CHART, and P24 jumped quickly between several views before returning to the STACKED BAR CHART. Eleven participants (P06, P07, P08, P12, P13, P15, P16, P17, P18, P19, P20) visited all four views in sequence, without returning to any previous view for more than a few seconds.

Figure 10 shows participants’ total fixation time for the four views. Each vertical bar represents one participant’s total fixation time for that view. Participants generally spent the most total time on the BUBBLE CHART, followed by the STACKED BAR CHART, the STACKED AREA CHART, the

LINE CHART, and the START PAGE. Figure 11 breaks down the percentage of the total fixation time spent on the three AOI groups. When examining the STACKED BAR CHART and the STACKED AREA CHART participants spent the most time focusing on the *controls*. For the BUBBLE CHART, participants spent the most time on the *chart*. For the LINE CHART, participants spent a similar amount of time on the *chart* and on the *controls*. Participants spent less time looking at the *numbers* than the *chart* or *controls* in all four views. The largest difference between *chart* and *controls* occurred in the STACKED AREA CHART, where participants spent more time looking at the *controls*, and the BUBBLE CHART, where participants spent more time looking at the *chart*.

Across all views, we observed a noticeable pause before participants started interacting. Figure 12 shows the time to first interaction, the time it took participants to start interacting with each view. This delay to interact is interesting because during this gap the participants spent their time scanning visually (cf. Section 5.1). The average time to first interaction was longest for the STACKED BAR CHART, followed by the BUBBLE CHART, then the STACKED

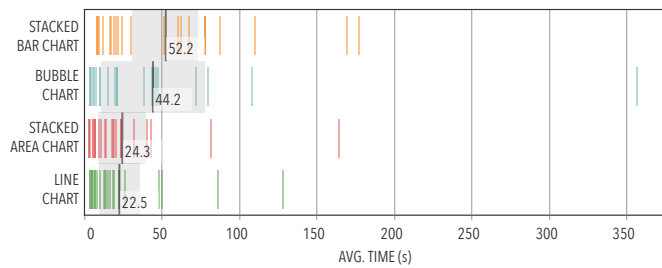


Fig. 12. Time to first interaction for each view with averages and 95% confidence intervals indicated by the gray areas. The colors refer to the different views.

AREA CHART, and the LINE CHART. Time to first interaction varied considerably for the BUBBLE CHART.

5 EXPLORATION STRATEGIES

We identified seven exploration strategies (ES) that participants employed to discover functionality in the views: eyes only ($ES_{\text{eyes only}}$), reading text (ES_{text}), opportunistic interactions ($ES_{\text{opportunistic}}$), entry points (ES_{entry}), structural interactions ($ES_{\text{structure}}$), permutation interactions ($ES_{\text{permutations}}$), and leveraging the familiar (ES_{leverage}). Our findings both highlight the use of novel strategies and confirm the use of relatively well-known exploration strategies. Additionally, the presented exploration strategies, their prevalence, and the ways in which they were combined, are contributions in themselves and shed new light on how people discover interactive visualizations. Icons next to each exploration strategy indicate the combination of data sources that we used to identify it: eye movement data (\odot), interaction data (☒), and think-aloud data (☞).

5.1 $ES_{\text{eyes only}}$: Eyes Only (\odot , ☒)

When using $ES_{\text{eyes only}}$, participants visually examined a view, but did not interact with it. By scrutinizing a view while preserving its current state, participants engaged in what Spence [11, p. 141] calls passive interaction – interactions that have no physical component, but constitute a complex visual and cognitive performance during which a viewer’s mental model changes. In our study, participants usually employed this exploration strategy when they were first exposed to a view or immediately after completing a sequence of interactions that altered the view.

To extract occurrences of $ES_{\text{eyes only}}$ we examined the eye movement data and interaction logs to identify all time spans longer than five seconds that did not include any interaction. Within each time span, we calculated the total dwell time for each AOI group, using the AOIs defined in Section 3.5. The dwell time is the sum of all durations of fixations assigned to any AOI in a group. This resulted in three sub-strategies of $ES_{\text{eyes only}}$ differentiated by the AOI group the participants focused most of their attention on. We observed 1102 total occurrences of this pattern across the *chart* (691 instances), *controls* (385 instances), and *numbers* AOI groups. All 24 participants used $ES_{\text{eyes only}}$ at least once while focusing on the *chart* (showing scan patterns similar to Figure 6 A) and on the *controls* (showing scan

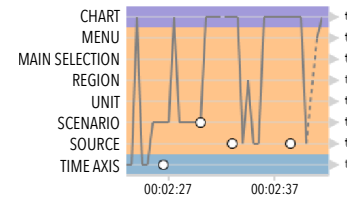


Fig. 13. This part of a participant’s AOI timeline shows $ES_{\text{opportunistic}}$ on the BUBBLE CHART. The white interaction circles show different types of controls being selected and between each selection the chart is viewed.

patterns similar to Figure 6 B). Thirteen participants also used $ES_{\text{eyes only}}$ when examining the *numbers* (showing scan patterns similar to Figure 6 C).

5.2 ES_{text} : Reading Text (\odot , ☒)

Most participants also read the documentation provided by the visualization designers to help them understand a new view. The attention map in Figure 5 shows a participant reading the entry text. ES_{text} is slightly more interactive than $ES_{\text{eyes only}}$, because aside from the entry text on the START PAGE, reading the available documentation required the participants to select a help button.

Most participants used the help functions by accessing the website description (☒), the main help button from the menu bar across the top of the page (☒), and the contextual help available for each control group (☒). Nineteen participants used ES_{text} a total of 170 times.

- In discussing opportunistic interactions (sec 5.3), the authors write that subjects “typically selected a random option from any group of controls”. I’m not sure what is meant by “random” here. I doubt the subjects themselves were truly deciding randomly (in a probabilistic sense), though perhaps that is what it (colloquially) looks like to an external observer. Perhaps instead it could be noted that subjects appeared to lack a clear rationale for the decision of which controls to interact with?

5.3 $ES_{\text{opportunistic}}$: Opportunistic Interactions (\odot , ☒)

In our study, when participants interacted opportunistically, they typically selected an arbitrary option from any group of controls, examined the chart to assess what changes their action caused, and then relatively rapidly moved on to a different control to repeat this process. Participants appeared to lack a clear rationale for the decision of which controls to interact with. *Opportunistic* interactions are characterized by being free-ranging, relatively effortless, and usually not carefully planned [12].

Figure 13 shows part of an AOI timeline for a participant interacting *opportunistically*. In this example, the participant first changed the year on the *time axis*, then selected a *scenario*, before selecting two different *sources*. To assess the frequency of *opportunistic* interactions we coded all instances in which a participant interacted with controls from multiple different groups in sequence. All 24 participants used this strategy at least once, for a total of 351 occurrences.

5.4 ES_{entry} : Entry Points (☒ , ☞)

When using ES_{entry} , participants started their investigation with a view by gravitating towards familiar factors in the

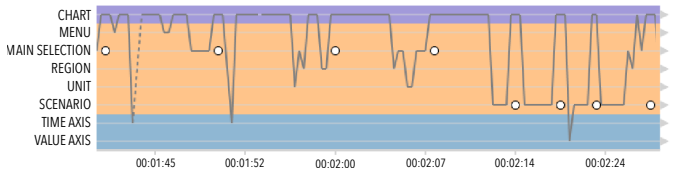


Fig. 14. This part of a participant's AOI timeline shows $ES_{structure}$ on the STACKED BAR CHART, where the participant sequentially selected all options in the main selection and then switched to the options in the scenarios controls.

controls, the charts, or the content. These familiar factors served as entry points into the view. Several participants noted looking at the geographic region they grew up in or currently live in. Some examples include: “[...] I guess but maybe that’s just because we live in Alberta [...]” (P01); “[...] got Ontario here because that’s my home province [...]” (P03); “[...] of course I want to look at Alberta first cause that’s where I’m [...]” (P05); and “[...] right away I am interested in my region, that is why I clicked this [...]” (P07). This selection of factors of personal interest corresponds strongly to Bates’ description of *berrypicking* — conducting exploration “by a series of selections of individual references and bits of information at each stage of the ever-modifying search” [14]. To count the occurrences of participants using entry points, we listened to the audio recordings for any indication of a statement referring to personal information. We also coded all selections of “Alberta” as an entry point, because the study took place in Alberta, Canada. Thirteen participants explored views by selecting familiar entry points, for a total of 36 occurrences.

5.5 $ES_{structure}$: Structural Interactions (👁️, 🗑️)

When using *structural* interactions, participants leveraged the structure that is visually apparent in the interface. For example, a participant would choose one control group and then iterate over all of the available options in that group. Participants often followed the spatial organization of the controls — for example, moving from top to bottom through the control group. Although they vary from view to view, the control panels contain groups of controls that are related by icon style as well as by spatial proximity. Figure 14 shows a section of an AOI timeline from a participant who used this approach. Here, the participant iteratively tested all options in the *main selection* control group, always oscillating between the chart and the controls to observe changes. After finishing with the *main selection* control group, the participant then explored the options in the *scenarios* group. All 24 participants used *structural* interactions at least once, for a total of 644 occurrences.

5.6 $ES_{permutations}$: Permutation Interactions (👁️, 🗑️)

Permutation interactions are a careful, methodical approach that reveals some understanding of the relationship between control groups. Similar to a comparative measure or dimension walk [13], participants would select one control item in a given control group (A) and then take a different control group (B) and iterate through all the options in B. Then, they would return to A, select a new item, and iterate through all the options in B again. We call this *permutation*

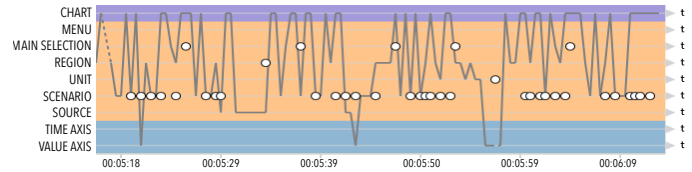


Fig. 15. This part of a participant's AOI timeline shows $ES_{permutations}$ on the STACKED AREA CHART. The interactions with the main selection control are separated by a series of interactions with the scenario control.

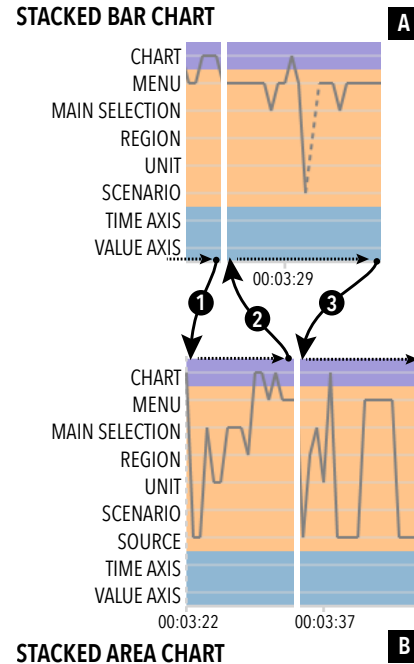


Fig. 16. This part of a participant's AOI timeline shows $ES_{leverage}$. Here, the participant moved from view A to view B (arrow 1). After quickly inspecting B the participant briefly revisited A, (arrow 2). The participant then returned to B and remained on that view (arrow 3).

interaction because in this manner participants could ensure that they had seen all permutations and combinations of the two groups. Figure 15 depicts a part of an AOI timeline for a participant using this method. After selecting an option in the *main selection* group, the participant selected all options from the *scenarios*. After seeing how the *scenarios* had changed for the first *main selection* option, the participant selected the next *main selection* item and again investigated each of the *scenarios*.

Permutation interactions were the least used exploration strategy: 6 participants used it at least once, for a total of 7 occurrences. Participants used the strategy the most with the BUBBLE CHART, investigating how different options changed over time using the interactive *time axis*. Participants also used *permutation* interactions to try different combinations of *regions* and *sources*.

5.7 $ES_{leverage}$: Leveraging the Familiar (👁️, 🗑️, 💬)

When using the $ES_{leverage}$, participants used their understanding of one view to learn about another view. We saw two variations of $ES_{leverage}$ in our study. Sometimes participants would switch to a new view, then quickly revisit the previous view in order to understand the differences

between the two views. In other cases, participants would realize that something in their current view was different from what they had seen in a prior view and would return to that view to compare it with the current view. Figure 16 shows how a participant moved back and forth between the STACKED BAR CHART and STACKED AREA CHART in order to compare them. Using $ES_{leverage}$, participants were able to begin to understand the functionality of a new view by leveraging what they knew about the views they had already visited. Overall, 10 participants used $ES_{leverage}$ at least once for a total of 60 occurrences.

6 EXPLORATION STRATEGIES IN CONTEXT

Throughout our study, we found that the exploration strategies participants preferred differed from view to view. Figure 17 shows the number of participants who used a given exploration strategy for each view. This suggests that the design of a view can evoke certain exploration strategies.

6.1 Exploration Strategies by Views

On three of the four views (STACKED BAR CHART, STACKED AREA CHART, LINE CHART), participants focused more on the *controls* than on the *chart* (see also Section 4 and Figure 11). Although the chart takes up most of the space in each view and communicates the most information, the controls serve as interactive legends and participants frequently returned to them to verify the current selection and compare color encodings. The sole exception to this was the BUBBLE CHART, in which more participants focused on the chart than on the controls. This is almost certainly due to the fact that the BUBBLE CHART was the only view in which the chart itself was interactive. In this view, it was possible to access data values for different *regions* or *sources* by mousing over the corresponding bubbles in the chart. Participants also focused more on *numbers* when using the BUBBLE CHART than they did on the other three views. This may be due to the fact that the timeline for this view was interactive and participants often focused on it when triggering those interactions. Overall, however, focusing on the *numbers* remained the least-used of the three $ES_{eyes\ only}$ sub-strategies.

ES_{text} was also used frequently, with 20 of our participants employing it at some point. Participants used this strategy across all views, with the most use on the BUBBLE CHART. Heavy use of the help may be a sign that some functionality was not easily discoverable. However, participants seemed to benefit from the localized help available for each control group, as it allowed them to quickly obtain explanations and information about those particular controls. Participants also used ES_{text} extensively on the START PAGE. While we expected participants to only briefly look at this page and quickly select a view, 22 participants read the entire introductory paragraph before proceeding. The attention map in Figure 5 highlights this common behavior pattern, in which participants focused more on the text than on the images on the START PAGE. However, this may be an effect of the social pressure implicit in a controlled lab study.

Participants used $ES_{opportunistic}$ and $ES_{structure}$ frequently across all views, as Figure 17 shows. $ES_{opportunistic}$ is the

	FOCUS ON CHART	FOCUS ON CONTROLS	FOCUS ON NUMBERS	READING TEXT	OPPORTUNISTIC INTERACTIONS	ENTRY POINTS	STRUCTURAL INTERACTIONS	PERMUTATIONS INTERACTIONS	LEVERAGING THE FAMILIAR
STACKED BAR CHART	21	23	2	13	21	3	23	2	8
STACKED AREA CHART	20	23	2	13	21	5	23	1	4
BUBBLE CHART	24	23	10	16	20	7	20	3	8
LINE CHART	20	24	4	13	19	9	23	0	3
ALL	24	24	13	19	24	13	24	6	10

Fig. 17. Number of participants who used each exploration strategy, per view and overall. The *all* counts reflect the number of unique participants who applied the given strategy at least once regardless of which view.

simplest exploration strategy and helps participants start to assess what an option or a group of options does. $ES_{structure}$ is more organized and suggests that participants are trying to understand what the different options in one control group represent and how they compare to each other. The $ES_{permutations}$ strategy is more advanced and participants who apply it are most likely trying to understand the relationships and dependencies between multiple groups of controls. Participants in our study used this advanced interaction approach the least.

6.2 Oscillating Behavior

From our eye movement data and from comments participants made directly, we could observe that they spent much of their time oscillating between the controls and the chart to understand what the effect of their interaction with the controls had on the chart. For example, one participant (P05) observed that “[...] having to go back and forth between the icons and the circles would kind of drive you nuts after a while [...]”. The oscillating behavior can also be seen in the scanpath visualizations (Figure 6) and is shown in the AOI timelines (Figure 7), where it is characterized by near-vertical lines connecting small horizontal fixation points.

6.3 Discovering Unusual Functionality

Even though both the STACKED BAR CHART and STACKED AREA CHART included a sliding rail control (Figure 3), only 4 participants (P01, P09, P10, P21) successfully discovered how to use these sliding rails. From the video and audio recordings, we observed that all four of these participants discovered this functionality by using $ES_{opportunistic}$. For example, P10 exclaimed “[...] just looking at Alberta. I can reorder these, oh thats cool, that’s really cool [...]”. It is likely that the presence of a rail between the items in the control group did not clearly suggest that the sliding interaction was possible, and neither simple visual scanning nor most of the common exploration strategies supported its discovery.

7 DESIGNING FOR DISCOVERY

Based on our observations and the exploration strategies we identified, we now review how our exploration strategies

reveal design opportunities that may lead to the creation of more discoverable interactive visualizations. In this discussion, we connect our empirical findings to previous work in visualization and human-computer interaction.

7.1 Inviting Interaction

Participants all took their time before starting to interact with any of the views (see also Section 4 and Figure 12). This initial pause might reflect a lack of obvious available interactions. One approach for increasing the discoverability of possible interactions is to hint at their existence using *feedforward*. Feedforward [24] can suggest potential interactions by using animation or emphasis to preview the change that would happen if those interactions were carried out. Recent work by Boy et al. [6] suggests that feedforward can be used to suggest possible interactions in a manner that entices people to interact more with a visualization.

Another possible explanation for the delay before participants' initial interactions may be that they were passively interacting [11] with the view. This behaviour remains difficult to confirm based on the eye movement and interaction data alone and would require retrospectively asking participants what they were doing or thinking, which would have interrupted their exploration process.

7.2 Providing Entry Points

There are several examples of visualizations where the use of entry points (ES_{entry}) has successfully been applied to engage people and encourage them to interact. For example, the NameVoyager [19] visualization has a direct personal entry point — a person's own name. In the NC-DRisc Height Map [8], people typically start investigating the visualization by selecting their home country or the country they live in. The Bohemian Bookshelf offers multiple entry points to the same system in order to encourage playful exploration and serendipitous discovery [45].

7.3 Using Spatial Organization

In addition to known exploration methods like opportunistic interaction [12] and entry points [14], our participants also used two exploration approaches, $ES_{\text{structure}}$ and $ES_{\text{permutations}}$, that each made use of the spatial organization of the controls. $ES_{\text{structure}}$ used the spatial organization to step through grouped sets of interactive controls. $ES_{\text{permutations}}$ used the spatial organization of at least two sets of grouped controls to explore the possible permutations. This suggests that designers need to think deeply about the organization of controls. For instance, graphic design guidelines such as Kidd's [46] are simple but effective: 1) left to right; 2) top to bottom; 3) front to back; and 4) dark to light. The attention that participants paid to the spatial organization of controls also suggests that careful placement can be used to guide a person through a specific sequence.

7.4 Combating Oscillation

We observed that participants spent much of their time oscillating back and forth between controls and the chart. They also explicitly told us that they found this irritating

(see Section 6.2). This is evidence for the importance of *embedded interactions*. Research in both InfoVis [47]–[50] and human-computer interaction [51]–[53] has called for greater use of direct interaction. Interaction can be direct in terms of temporal immediacy, when there is no lag between an interaction and the data update. An interaction can also be direct in terms of spatial immediacy, when the interaction is co-located with the data. Temporal immediacy is now common and the visualizations we studied did not exhibit time lag between interactions and data updates. However, spatial immediacy remains challenging. The tendency in the visualization community is to place the controls adjacent to a visualization to minimize possible visual interference caused by having the controls too near or on-top of a visualization. Our study provides additional evidence that this spatial separation is problematic and can cause oscillation which participants found irritating. Integrating interactions into the data representation could limit attention switching, but may make them more difficult to discover.

Consequently, there is a trade-off between interaction familiarity and spatial immediacy. Despite the fact that more direct interaction is a recognized design goal [51], most interactive visualizations, including those we studied, are still commonly implemented using the WIMP paradigm [50], [51]. Similarly, The visualizations we studied exhibited a clear separation between control panels and the visualization. This preference for familiar layouts may be due in part to the fact that the general public lacks visualization literacy [54] and that people have difficulty discovering embedded interactions, because these interactions lack established metaphors and clear signifiers [55]. For example, in comparison to familiar controls like buttons and sliders, the bars or marks in a chart provide little information to suggest that they might be interactive [6].

7.5 Supporting Transitions

During our study, we observed that participants often compared different views in order to find out what had changed or see how the data was represented differently in another view (ES_{leverage}). These comparisons happened mostly at the interface level, with participants comparing differences between interface elements (visualization-to-visualization [13]) rather than changes in the data. To allow people to compare views at both the interface and data level, interactive visualizations could provide support for smoother transitions between views and between datasets, for example, through *seamless transitions*. Seamless transitions between views, paired with techniques for emphasizing changes, could make the process of switching views less disorienting. Transitions between pairs of interactive visualizations could be designed to help mitigate change blindness [56] and preserve participants' mental map of both views [57], [58]. Using consistent layouts for multiple views may make this process easier by reducing the number of changes that need to be included in a transition, thereby reducing the transition cost [13]. Supporting cross-filtering between views [59] or adding phosphor traces and afterglow effects to transitions [60] may also help limit cumbersome transitions between views.

Another way to address this problem is to use multiple-coordinated views [61], in which changes in one view can

cause updates in others. Such views are common in visual analytics and many systems use techniques like brushing and linking [62] or graphical overlay methods [63] to connect many different interactive visualizations together.

7.6 Scaffolding Complex Interactions

When using the STACKED BAR CHART and the LINE CHART, only four participants discovered the sliding rail functionality and used it to reorder *regions* or *sources*. Given that the use of more advanced interactions can lead to more efficient investigation, helping people learn how to use more complex interactions is important. Here, task-based *tutorials* and *information scent* cues may be useful tools to help people transition to more complex interactions. This important challenge has been discussed both in the InfoVis [64] and human-computer interaction [26], [27] literature.

One possible approach is to highlight new functionality directly when a viewer first visits a visualization, using techniques such as stencil-based tutorials [65]. Human-computer interaction researchers have also explored more game-like approaches, including using integrated and engaging *tacit tutorials* [66]–[69].

The use of information scent cues — providing embedded navigation hints that encourage people to navigate to nearby views that may contain relevant content — were first introduced by Pirolli and Card [70] as part of a broader model of information foraging. This principle has since been applied to a variety of visual search and browsing tasks [71]–[74]. Related techniques like *scented widgets* [75] embed social and data-driven scent cues directly into existing interface controls. These kinds of embedded visual hints could be used to encourage novices to investigate new views or examine areas of an interface they have previously ignored, explicitly encouraging them to discover new functionality.

8 LIMITATIONS AND SCOPE

While providing less realism and potentially lower ecological validity, a controlled lab study has the benefit of providing more precision [76]. In a lab setting we were able to collect data from a range of sources, triangulating eye movement data, interactions, and observations from video and audio to isolate and pinpoint specific strategies that participants applied. Although our methodology allowed us to utilize a variety of data sources, we still cannot infer whether participants applied the exploration strategies purposefully or unintentionally. Given our initial set of strategies, future studies could use Freeman’s [77] triggered think-aloud method (in which moderators can intervene in participants’ exploration to ask for clarification) to try to assess participants’ intent. We did not use this process for this initial study because such interruptions would disrupt participants’ process of discovery and risk corrupting the eye movement data and interaction logs.

Our study does not intend to provide an exhaustive list of strategies people use when interacting with visualizations in general. We focused specifically on visualizations designed for public use and public engagement with open data, therefore guidelines such as scaffolding complex interactions and providing entry points may not apply to

visualizations used in professional data analysis contexts, where explicit training is more common. We studied discovery in the context of one set of web-based visualizations of open energy data. While the set of exploration strategies we identified is broad, other strategies likely remain. We hope that the research community will build on this work by further exploring how people interact with new visualizations, thereby helping to build a more holistic understanding of the discovery of interactivity in visualizations.

9 CONCLUSIONS

In this paper, we investigated how people discover functionality of an interactive visualization designed for public consumption. Unlike prior studies of interactive visualization use, our analysis incorporates not only interaction logs and audio/video recordings, but also includes detailed analyses of eye movement data. Combining these data streams allowed us to enumerate several exploration strategies — $ES_{\text{eyes only}}$, ES_{text} , $ES_{\text{opportunistic}}$, ES_{entry} , $ES_{\text{structure}}$, $ES_{\text{permutations}}$, and ES_{leverage} — that our participants used when trying to understand a new interactive visualization. While $ES_{\text{eyes only}}$, ES_{text} , $ES_{\text{opportunistic}}$, ES_{entry} and $ES_{\text{permutations}}$ are known exploration strategies, $ES_{\text{structure}}$ and ES_{leverage} are interesting as they offer possible design directions for improving the discoverability of interactive visualizations.

Understanding these exploration strategies led to several promising suggestions that may make functionality more discoverable in interactive visualizations. These include:

- Inviting Interaction
- Providing Entry Points
- Leveraging Spatial Organization
- Combating Oscillation
- Supporting Transitions
- Scaffolding Complex Interactions

Ultimately, we hope that by understanding how people approach interactive visualizations, we can empower an even broader range of people to experience, interact with, and gain insight from open data.

ACKNOWLEDGMENTS

Supported in part by: the National Energy Board (NEB) of Canada; Alberta Innovates - Technology Futures (AITF); the Natural Sciences and Engineering Research Council of Canada (NSERC); SMART Technologies; and the German Research Foundation (DFG) within SFB/Transregio 161.

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