Enthusiastic and Grounded, Avoidant and Cautious: Understanding Public Receptivity to Data and Visualizations

Helen Ai He, Jagoda Walny, Sonja Thoma, Sheelagh Carpendale, and Wesley Willett

Abstract—Despite an abundance of open data initiatives aimed to inform and empower "general" audiences, we still know little about the ways people outside of traditional data analysis communities experience and engage with public data and visualizations. To investigate this gap, we present results from an in-depth qualitative interview study with 19 participants from diverse ethnic, occupational, and demographic backgrounds. Our findings characterize a set of lived experiences with open data and visualizations in the domain of energy consumption, production, and transmission. This work exposes *information receptivity* — an individual's transient state of willingness or openness to receive information — as a blind spot for the data visualization community, complementary to but distinct from previous notions of data visualization literacy and engagement. We observed four clusters of receptivity responses to data- and visualization-based rhetoric: Information-Avoidant, Data-Cautious, Data-Enthusiastic, and Domain-Grounded. Based on our findings, we highlight research opportunities for the visualization community. This exploratory work identifies the existence of diverse receptivity responses, highlighting the need to consider audiences with varying levels of openness to new information. Our findings also suggest new approaches for improving the accessibility and inclusivity of open data and visualization initiatives targeted at broad audiences. A free copy of this paper and all supplemental materials are available at https://OSF.IO/MPQ32.

Index Terms—Diverse audiences, Information receptivity, Information visualization, Open data

1 Introduction

Phrases such as "data-driven decision making" and "evidence-based policy" are common across governments and civic institutions at all levels. Increasingly, an essential part of being an informed individual involves having access to and understanding the data that underlies public decisions and policies. To ground data-driven discourse around topics of public interest, institutions and governments around the world are embracing open data initiatives, making public data available online in freely accessible formats. Broadly, these initiatives seek to improve institutional accountability and transparency, allowing individuals to play a larger part in collaborative policy and decision-making processes [4].

Over the past several decades, organizations have also increasingly used interactive web-based visualizations to surface open data. For example, the OECD's Better Life Index provides a simple interface for accessing indicators of well-being in various countries [52]. Similarly, the Gapminder Foundation provides visualizations of global indicators of well-being using bubble charts [24]. Such visualizations allow audiences to explore and ask questions of open data in visually appealing and dynamic ways. The aim is to improve public engagement through open data and data visualizations [41, 81]. At present however, open data initiatives most directly support professional data analysts. They emphasize making open data available in machine-readable formats such as spreadsheets, CSV, JSON, or text files [7]; ensuring that data is complete, traceable, timely, documented and otherwise high quality [80]; as well as ensuring ease of download and open licensing [4, 85]. Using and analyzing this data requires domain expertise, data wrangling skills, and knowledge of statistical and quantitative analysis methods. Consequently, these initiatives often exclude audiences who lack the expertise to make use of unprocessed data. As political, economic and environmental decisions become increasingly data-driven, individuals who are not professional analysts are excluded from participating in data-driven discourse in public spheres.

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Meanwhile, the information visualization research community has begun to investigate visualizations for more diverse types of audiences who may not have professional data analysis, statistics, domain, or visualization expertise. To date, this research has focused on data visualization literacy [9, 10, 45], visualization authoring tools for novices [26, 35, 65], personal visualization [31] and narrative visualization [33, 61, 67]. Meanwhile, the growing prevalence of visualizations and data-driven reporting in news media, particularly online, has increased the visibility of these approaches.

Despite the large number of visualizations that are ostensibly targeted towards broader audiences, we still know little about the realistic barriers, needs, and experiences of the potential users of open data and visualizations. In this paper, we examine this gap via an exploratory interview study with 19 diverse participants. We characterize their lived experiences with open data and data visualizations in the domain of energy production, transmission, and demand. Our results reveal an information receptivity space with four clusters of receptivity responses to energy information. Some responses were **Information-Avoidant**, where individuals exhibited an active and intentional resistance to consuming new information. Some were **Data-Cautious**, where individuals were highly receptive to consuming new information, but expressed notable concerns around trust, bias, and agenda. Other responses were **Data-Enthusiastic**, with individuals bringing an intrinsic interest in data and seeking both underlying datasets *and* help from external sources to interrogate and interpret that data. A final set of responses were **Domain-Grounded**. These individuals were domain-experts and tended to respond to energy topics by interrogating datasets to draw their own conclusions, but were wary of external interpretations.

Overall, our findings highlight the need to consider *information receptivity* — individuals' willingness to receive new information — alongside existing notions of data engagement and data visualization literacy. Based on our findings, we identify ten research opportunities for the open data and visualization communities. Ultimately, our contributions highlight the limitations of a "one-size-fits-all" approach to visual and data-driven communication, understanding that individuals can hold vastly different willingness and openness to receive new information. This work aims to broaden the inclusivity and accessibility of open data and visualizations for a wider range of audiences.

2 Background: Visualization for General Audiences

Our examination of individuals' experiences with open data and visualizations builds on a range of prior work examining visualization for broad audiences. Historically, non-interactive data graphics have targeted a wide range of readers. As early as the 19th century, Minard created map visualizations with detailed explanatory reading instructions. As Rendgen highlights [60], these were spread to a relatively broad audience for the time, including administrative officials, researchers, and business people. In the early 20th century, Neurath and collaborators developed ISOTYPE, a picture language for communicating data to multilingual audiences [83]. More recently, information design — which is closely related to data visualization — has become an active field with wide appeal, with information graphics frequently appearing in print and online publications (see Rendgen's compendium [59]).

Vis for Non-Analysts. Interactive visualizations for non-analysts have also gained considerable attention from visualization researchers. ManyEyes [81] introduced an online platform that allowed communities on the web to both create and discuss visualizations. Pousman et al. used the term *casual information visualizations* [57] to describe non-analytic visualizations for use in everyday contexts, such as ambient visualizations in public spaces, visualizations of social networks, and data-driven artistic works. *Personal visualizations* [31] are now commonplace for tracking personal data, such as budgets, fitness habits, or food intake. Meanwhile, *narrative visualization* [67] and *data-driven storytelling* [61] approaches are frequently used to communicate data-driven news stories or to explain concepts to less-technical audiences.

Vis Authoring. Other work has also begun to support independent data exploration and visualization authoring for non-analysts. Dedicated visual analytics tools such as Tableau [74] and Power BI [49] have made visualization creation more accessible to business audiences through simple GUIs. Meanwhile, the visualization research community has developed a wide range of graphical visualization authoring interfaces (including systems like Charticulator [58], Data Illustrator [46], Lyra [64], and StructGraphics [77]) aimed at non-programmers. Other related research has investigated non-analysts' experiences authoring visualizations [26] including via accessible physical construction approaches that use tangible tokens [35]. Overall, these efforts reflect a growing interest by the visualization community to make data and data visualizations easier for people to understand, explore, and create.

Data Visualization Literacy. Much of this existing work is grounded in broader notions of *data visualization literacy* [9, 10, 45], which Lee et al. define as "the ability and skill to read and interpret visually represented data and to extract information from data visualizations" [45]. One strategy to increase literacy has been to address gaps in data visualization education [1, 15], for example, through interactive literacy workshops, such as VisKit [34]. D'Ignazio further defines *creative data literacy*, which proposes alternatives to traditional quantitative techniques to empower non-technical learners to work with data [19].

Moving Beyond a Monolithic "Public". Nearly all of the community's efforts to date are complicated by the lack of consensus around what characterizes visualization "novices" or who constitutes the "general public". As Burns et al. highlight, the majority of visualization research that discusses "novices", "non-experts", or members of the "public" fails to define these terms [11]. As a result, much of the existing work on visualization outside of traditional analytic contexts still presupposes a monolithic "public" and relies on notions of access, ability, and literacy that are often grounded in stereotypes and caricatures, rather than understandings of real, diverse individuals. Accordingly, the literature contains relatively little examination of real-world audiences' experiences with public visualizations and data, and whether such efforts are effective. Previous notions of "effectiveness" in the visualization community have been characterized as the accurate perception of quantitative information [12, 50], the speed of comprehension, cognitive load, or efficient task completion [3, 8, 32]. Scholars have since argued this definition may be too narrow — it targets professional analysts [22, 37, 38] but may be inappropriate for general audiences. Many visualization studies also examine participant reactions to visualization prompts as isolated events that are disconnected from external political or cultural influences [33, 38]. Yet, Kennedy and colleagues argue, "people are not lab rats, and their engagement with designed artefacts does not occur in situations free of cultural or social values and contexts" [38]. Indeed, Peck and colleagues' study revealed that educational background, political affiliation, and personal experience all played an important role in how visualizations were perceived by rural Pennsylvanians [55], further supporting the argument that engagement with data and visualization occurs within a socio-cultural context.

To explore these kinds of richer socio-cultural themes and examine a wider range of experiences with open data and visualizations, we follow an emerging trend of visualization research that employs qualitative methods to understand individuals' lived experiences. We present findings from a preliminary interview study with 19 individuals from diverse demographic backgrounds to explore their barriers and needs with regards to open data and visualizations in the domain of energy. Our work builds on qualitative insights from Kennedy et al. [37, 38] and Peck et al. [55], where our goal is to broaden understanding of how best to reach new kinds of audiences with data and visualizations.

3 Method

As part of a trend towards qualitative methods in visualization research [17, 48], we conducted an exploratory interview study with 19 participants from the Canadian public to investigate their relationships to open data and visualizations. To ground our interviews in a concrete theme, we focused on Canadian energy production, transmission, and demand — all highly contentious and public issues in Canada at the time of the study. We investigated three research questions:

- *RQ1*. How do individuals with diverse backgrounds and interests understand and relate to open energy data and visualizations?
- *RQ2*. How can open data and visualizations inform or change public discourse around energy?
- *RQ3*. What barriers (if any) exist to public engagement and empowerment with open energy data and visualizations?

Context and Funding. Canada is a resource-rich nation and ranks in the top ten countries worldwide for crude oil, methane, hydroelectricity production, and wind power capacity [51]. Consequently, topics surrounding energy production, transmission, and demand have become of increasing importance to the Canadian public and politicians alike. In 2019 when the study took place, energy, sustainability, climate, and Indigenous rights consistently appeared as headlines in Canadian news. Topics included polarizing issues such as the federal government's purchase of the controversial Trans Mountain pipeline [71], a government overhaul of energy regulations [20, 75], anti-pipeline protests [87], reconciliation with Indigenous communities [39], and carbon tax policies [6]. The high visibility of these articles at the time of the study indicate that information about energy was perceived by the Canadian public as highly salient. Meanwhile, the Canadian government has committed to open government practices [76] that require that Canadian energy data is freely accessible. This study was funded by a research grant from the National Energy Board (NEB) — the Government of Canada's previous federal energy regulator [1]. The NEB was aware that a study was planned, but agreed to remain at arm's length and not have any knowledge of or access to the study. Participants were informed of the funding connection to the NEB during recruitment, consent, and before the interview began. This study was independently planned and conducted by the authors without input from the NEB at any point during the research or writing process[2].

Recruitment and Sampling. To maximize issue salience around the topic of Canadian energy, we limited recruitment to residents of Canada. Over a period of four months (February to May 2019), three interviewers physically traveled to and recruited from three Canadian provinces (two Western, one Eastern), which have diverse prevailing opinions and perspectives towards energy. To decrease barriers to participation and attract individuals who may not typically sign up for these kinds of studies, our team emphasized recruiting from public spaces (such as bulletin boards at public cafes and public libraries), in addition to recruiting

[1] A new regulatory body, the Canada Energy Regulator (CER) replaced the National Energy Board (NEB) on August 28, 2019.

[2] The second author has since been employed by the CER. However, the views expressed in this paper are solely those of the authors and do not reflect the opinions or endorsement of the CER.

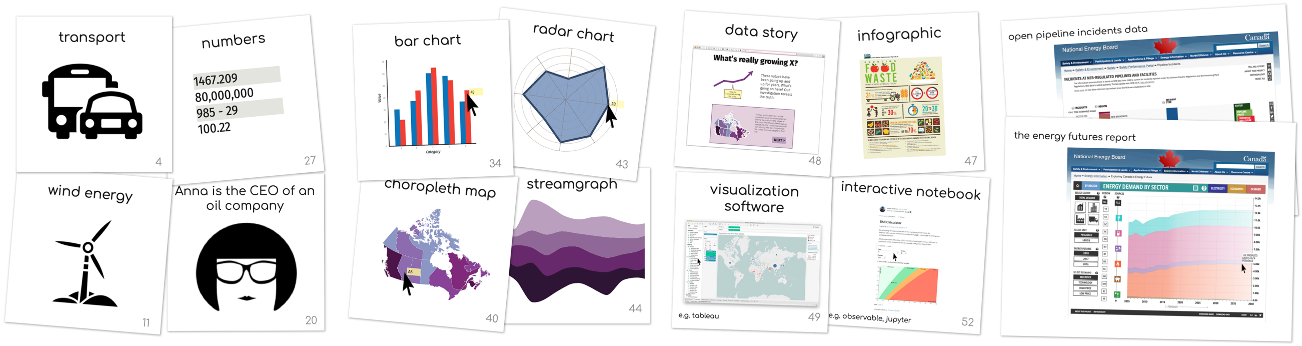


Fig. 1: A sample of the visual card prompts shown to interview participants. See supplemental materials for the complete set.

via email, social media, and snowball sampling. In alignment with a qualitative methodology, our intent was not to gather a comprehensive sample to systematically cover all demographic dimensions, but rather to seek a rich, reality-based understanding of the lived experiences from a small but diverse sample of individuals. Interested people were directed to fill out an online screening questionnaire, which received 74 responses. From this, we selected as diverse a set of participants as possible based on demographic information and scheduling constraints. Recruitment in British Columbia was particularly challenging; we speculate that attitudes of distrust towards the federal government and/or our funding agency may have been a contributing factor.

Participants. Our 19 participants (anonymized as P1-P19) include individuals from 15 different occupational backgrounds, 14 different ethnicities, and 3 Canadian provinces (British Columbia, Alberta, Ontario), with a nearly even split of gender identities (9 male, 10 female). To maintain gender neutrality and anonymity for participants, we adhere to a policy of using singular 'they' pronouns when referring to participants. This approach is in line with APA guidelines [2] and with recent discussions in the Human-Computer Interaction community [13]. Figure 2 summarizes additional participant demographics.

Participants' self-described occupations included accounting, architecture and urban planning, biology and climate science, business, computer science (2), farming and music, information science and music, geography, healthcare (2), information technology, natural resource analysis (2), political science and customer service, psychology (2), science communication, and telecommunications. Four were retired or semi-retired. Participants' self-identified ethnicity included Ashkenazim Jewish, Black-Asian, Caucasian (5), Caucasian-Jewish, Central Asian, Chinese, Chinese-Caucasian, Francophone, German (2), Gujurati, Igala, Korean, Polish-Canadian, and Polish-Russian-German.

Interview Protocol. Three interviewers conducted in-person, one-on-one interviews from March to May of 2019. To support a high level of consistency between the three interviewers, we employed a carefully planned, semi-structured interview protocol. Our protocol was built on a backdrop of energy topics — where "energy" referred to production, transmission, and use. Interviews lasted approximately 90 minutes. Questions explored participants': 1) knowledge of and relationship to energy information, 2) reactions to data and visualizations, and 3) perceptions of personas related to energy discussions in Canada (including the CEO of an oil company, a First Nations Elder, a journalist, a pipeline welder, and an anti-pipeline activist).

Visual Card Prompts. We expected that energy, data, or data visualization may not be areas of expertise for most participants. Thus, our protocol included a set of visual card prompts [62] that made a range of vocabulary available for discussion. The prompts (Figure 1) included: activities, people, and sources related to energy (22 cards — including "cooking", "solar", and "Anna the oil company CEO"); structured and unstructured data types (5 cards — "numbers", "text", "images", "locations", and "connections"); visualization types and tools (20 cards — including "bar charts", "streamgraphs", "infographics", and "interactive notebooks"); and four images of open energy data visualizations from the NEB website. This breadth was intended to minimize fixation on any particular set of topics. During the interview, participants were invited to freely manipulate and reorganize the cards (Figure 3), where discussion of the cards was voluntary and optional. At predetermined stages of the interview, we introduced new subsets of card prompts to guide discussion. We used a printed version of Plutchik's Emotion Wheel [56] to ask participants about their reactions to data and visualization types. Our protocol and full set of card prompts can be found in the supplemental materials.

Data Collection. To reduce the chance of interviewer bias, we divided our interviews between three interviewers (the first three authors of this paper). Interviews took place at a location of convenience for our participants — in meeting rooms in public libraries or in the participants' home. Each participant received a $20 gift card, given after consent and before the interview began. All interviews were audio- and video-recorded, using a front-facing camera to capture participants' facial expressions and an additional overhead camera to capture participants' interactions with the card prompts. All audio was fully transcribed for analysis purposes. Approximately 1,710 minutes of interview data was collected, with a total of 225,845 transcribed words.

Data Analysis. Our data analysis process took place in several rounds over the course of four years, with several pauses due to extenuating circumstances (including the COVID-19 pandemic, institution changes for four of the five authors, and two extended parental leaves). The first round of analysis took place between March (after the first interview was conducted) and September 2019. We employed an inductive, open-coding method [16] to analyze interview transcripts and corresponding

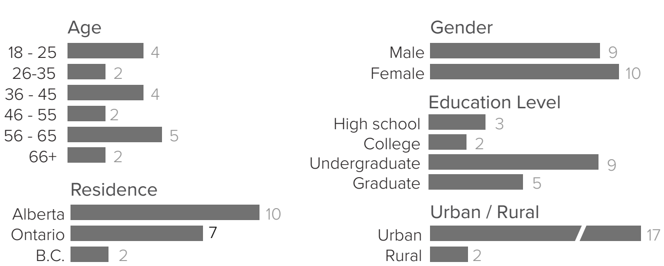


Fig. 2: Summary of participant demographics. Note: Canadian colleges offer diploma and certificate programs with a focus on trades, while Canadian universities grant undergraduate and graduate degrees with a focus on academic and professional programs.

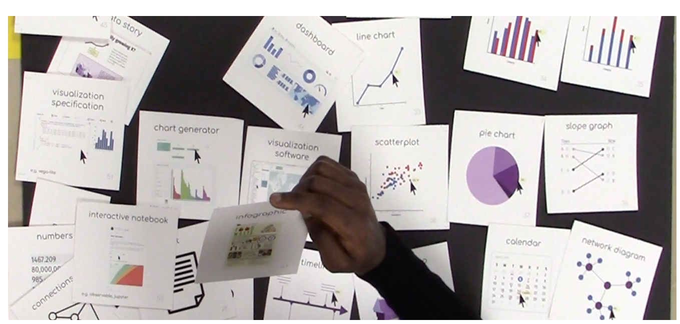


Fig. 3: During their interview, participants were free to organize, examine, and use the visual card prompts to guide conversation.

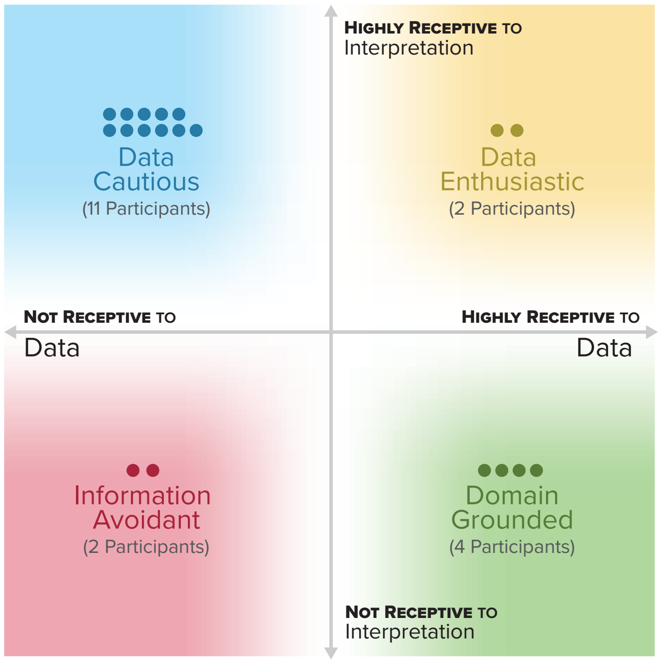


Fig. 4: Our information receptivity space characterizes individuals' responses to both data and interpretation.

videos. First, three researchers individually coded and analyzed all interviews using the process of affinity diagramming [27, 66, 73]. We began this process using paper post-it notes on a whiteboard, and later transferred to collaborative virtual whiteboards. Each coder generated initial ad-hoc tags for thematic categories, and then hierarchically reorganized and merged the tags to identify similarities between themes. Next, the three coders met on a weekly basis to discuss and refine the affinity clustering using a shared virtual whiteboard. Following this, all five members of the research team gathered for an intensive two-day workshop to further discuss, integrate, and refine themes. We published a whitepaper describing our process in late 2019 [29] and submitted a manuscript discussing our findings for peer-review in early 2021. In response to reviewer feedback to the (rejected) 2021 submission, we conducted an additional round of analysis in January-March of 2022. During this phase, we iteratively revised the coding scheme, refined terminology, reconsidered the contextual nature of receptivity, and more clearly articulated implications for visualization research.

4 An Information Receptivity Space

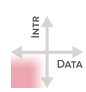
In analyzing our interviewees' experiences with open data and visualizations in the energy domain, four clusters of participants' receptivity responses to information emerged. Throughout this paper, we define an individual's **information receptivity** *as a transient state of willingness or openness to receive information*. Importantly, we characterize information receptivity not as an enduring trait of a person, but rather a temporary, situated *response* to information within a given socio-cultural context, at a given time, for a specific topic domain. As our interview questions and card prompts centered specifically around public experiences with energy information (production, transmission, and demand), our findings are oriented to the energy domain and do not represent participants' receptivity to information in general.

From our analysis, four clusters of information receptivity responses emerged from our 19 participants: **Information-Avoidant** (2), **Data-Cautious** (11), **Data-Enthusiastic** (2), and **Domain-Grounded** (4). As illustrated in Figure 4, we organize these clusters within an information receptivity space along two axes: 1) receptivity to *data*, and 2) receptivity to external *interpretations* of data. We use the term *data* to refer to primarily quantitative and numerical content in spreadsheets or other unprocessed formats. Meanwhile, we use *interpretation* to refer to meaning derived from data, as interpreted by an external source outside the individual. We consider data visualizations as a form of external interpretation. We have intentionally chosen to define the terms *data* and *interpretation* from the perceptual and cognitive perspective *of our participants* (as delineated by Chen et al. [14]), as opposed to their more technical definitions in systems or information theory.

Participants who exhibited Information-Avoidant receptivity responses (2 of 19) were actively resistant to consuming new energy information, regardless of whether information was in the form of data or interpretation. These participants held a deep concern for issues of climate change and sustainability and experienced emotional and practical barriers that contributed to low information receptivity. Notably, these individuals were highly receptive to the *topic domain* of energy, but adamantly unreceptive to consuming new information (whether data *or* interpretations) from that domain. Another cluster of participants exhibited Data-Cautious receptivity responses (11 of 19). These individuals were highly motivated to stay updated on new energy information, but held considerable concerns about data quality and accuracy. They were not interested in accessing data and were most receptive when information was presented in an already interpreted form by an external trusted source. Finally, individuals exhibiting Data-Enthusiastic (2 of 19) and Domain-Grounded (4 of 19) responses were most receptive to energy information when it was directly and visibly grounded in data. Individuals with Data-Enthusiastic responses enjoyed accessing datasets in unfamiliar domains and sought out external resources to help them navigate interpretations of that data. Participants exhibiting Domain-Grounded responses possessed the domain knowledge to confidently interrogate energy-related datasets, and consequently were wary of external interpretations and preferred to draw their own conclusions.

Our qualitative approach contributes preliminary evidence of four clusters of diverse receptivity responses to data and visualizations. These clusters are neither exhaustive nor complete — rather, they provide a starting point for identifying the existence of varied public responses to energy information. Additionally, while our participant pool contained 19 demographically diverse individuals, it by no means represents their distribution in the broader population. Instead, this work describes rich variations in the experiences of a small number of individuals who exhibited Information-Avoidant, Data-Cautious, Data-Enthusiastic, and Domain-Grounded responses. The distribution of our participants' responses across the clusters is extremely unlikely to be indicative of the clusters' true distribution. For example, we expect that a majority of Canadians might fall into the Information-Avoidant cluster for this topic, but — as a result of that avoidance — would be unlikely to volunteer for this type of study. Similarly, our emphasis on the energy domain likely drew a higher number of individuals with Domain-Grounded receptivity responses who have a strong interest in energy data. Later, in our Conclusion, we discuss how future work may further refine and expand upon these preliminary clusters.

4.1 Information-Avoidant (I-A): I Don't Need to See That Information



Two out of nineteen participants (P5, P19) exhibited receptivity responses that we characterize as Information-Avoidant. Both participants were resistant to consuming new energy information, regardless of whether it was in the form of data or interpretations of data (including visualizations). Most strikingly, both of these individuals held a deep concern for energy topics such as climate change and sustainability, and engaged in daily actions that aligned with their concern. For example, P19 is a member of a forestry organization who is *"always thinking of ways we can move to cleaner energy in our business"*. Similarly, P5 stated that *"Human beings destroyed our own land. I'm really worried about global pollution and am very careful of how I consume"*. At the same time, both participants were adamantly resistant to consuming new energy information. Below, we discuss their emotional and practical barriers to these topics, contrasting this with their reactions to data and visualizations in general.

4.1.1 I-A: Powerlessness to Impact Change

P5 and P19 were intentional (even adamant) about avoiding energy information. For both, despair and powerlessness to impact change emerged as recurring themes in their interviews. P5 expressed a complete lack of interest in energy data, assuming that looking at data would not lead to environmental impact but only negative emotions: *"I'm so little, so tiny. I can't change the world. I'm just feeling powerless. I appreciate that you have [data], but it's not going to change anything, right? I'm worried [about climate change] but I don't need to see data. It only adds more sadness. You don't have to see [data]. You sense that, you feel that."* It is noteworthy that P5 describes themselves as *"really good with numbers"* and as someone who finds spreadsheets *"easy"*. Nonetheless, at multiple points in their interview, P5 described the futility of looking at energy data to impact environmental change: *"It doesn't matter if the government has open energy data, I still take the same actions regardless. Like I know I can't change anything."* P19 expressed similar sentiments of powerlessness and futility. With visible emotion during their interview, P19 stated: *"My personal feeling is that things aren't going to change that fast or fast enough. I'm skeptical of our efforts to change the world. Living up north the way we did, growing our own food, having a farm, my childhood was so idyllic. I don't see it as being recoverable in any way, shape, or form. That, to me, is just sad. Just sad... I don't think it's ever coming back."*

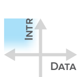
4.1.2 I-A: Personal Factors, Cognitive Effort, and Trust

While themes of powerlessness and despair recurred multiple times in P5's and P19's interviews, both participants also briefly noted cognitive effort and personal factors as barriers. For P19, health issues contributed to information avoidance: *"I had a severe stroke in 2015. Since then, I have an aversion to over-information."* Additionally, P19 briefly commented on the quality of available energy information: *"You can find information about anything, but where is it coming from? Who's doing this? Why are they doing it? It questions my trust. Does somebody want to gain renown or fame? Or is it scientifically-backed information? There's no way of knowing for sure."* P5 did not express concerns about data quality, but instead discussed the barriers of effort and interest: *"Every day I'm busy, busy. I rarely have time. [Even if I did], I'd want to watch something relaxing, I wouldn't look at data."*

4.1.3 I-A: Receptivity to Visualizations

Our two Information-Avoidant participants were unwavering when it came to rejecting consumption of new energy information. Yet they were split in terms of their receptivity to data visualizations in general. When prompted with the visual card prompts for bar chart, stacked bar chart and line chart, P19 found them to be "familiar' and "attractive", due to previous experience working with these charts in their business. When prompted with card prompts showing more complex visualizations, P19 stated *"Basically I'd just want to avoid them"*. P5 was receptive to the idea of visualizations more broadly, highlighting positive personal associations with certain visualization types — for example, associating streamgraphs with mountains, radar charts with the army and scatterplots with freedom: *"Streamgraphs remind me of mountains. I used to hike a lot. I just love mountains. Every time I see mountains, I feel stress free. I like radar charts because I'm interested in army stuff. It was my dream to be a soldier. Scatterplots, they're scattered here and there. It feels like freedom."* Most strikingly, P5 stated with enthusiasm that if data were visualized in a "playful and entertaining" way, they would be motivated to look at it due to their "childlike" nature. Unlike P19 who expressed trust concerns regarding the underlying data, P5 focused instead on the *form of data representation* to attract their interest: *"I have a little child inside me who wants fun, not just boring work. If I could make all kinds of shapes, maybe animals I love [in interactive visualizations]...Only if I'm interested [in a visualization], would I put in the time to learn."*

4.2 Data-Cautious (D-C): Tell Me an Interpretation I can Trust



The majority of our participants (11 out of 19) expressed receptivity responses that we characterize as Data-Cautious. Unlike participants in the Information-Avoidant cluster who actively resisted consuming new energy information, these individuals were highly motivated to seek out and stay current on energy information. Both inside and outside the energy domain, they perceived themselves as lacking the statistical and data wrangling skills to effectively evaluate information sources and expressed no desire to access any underlying datasets. For example, P7 noted: *"I don't like spreadsheets, too much information. Unless you're really familiar with it, it does nothing to further your understanding."* P14 was one exception. Despite perceiving themselves to be skilled at data wrangling, they lacked motivation, stating: *"I don't imagine anybody, even me, would say, 'I'm going to look at the raw data.' I tend not to be very data-driven these days."*

Concerns about "trust", "bias", and "agendas" in general information were a recurring theme for participants in the Data-Cautious cluster. This is noteworthy as our interview questions did not explicitly probe themes of trust in information consumption. To cope, these participants actively sought out external interpretations of data from sources they trusted, whether a news media source or a person with whom they shared values. Their preferred data visualizations varied, ranging from those providing a high amount of interpretation to those that allowed them to ask questions of the data and seek alternative explanations. Overall, these participants were most receptive to external interpretations of information from trusted sources that contained implied, rather than direct, references to data.

4.2.1 D-C: Concerns about Trust, Bias, and Agenda

Concerns about trust in data (or interpretations of data) emerged consistently in the interviews of all 11 participants (P1, P2, P3, P7, P9, P11, P12, P13, P14, P15, P18). Participants characterized trust issues in different ways. One set (P1, P2, P3, P9, P11, P18) discussed trust in high-level terms, phrasing concerns around "facts", "bias", "agenda" or "not getting the full story". For example, P1 noted : *"I rely very much on journalistic fact-checking. But right now, it's hard to even know the origin of so-called 'facts'."* Similarly, P18 expressed: *"I have to feel confident that the source is good. I do my best but everyone has an agenda. At this point, I don't trust anyone because I don't know who is going to actually give me the real answer...if there is a real answer."*

Another set of participants (P7, P12, P13, P14, P15) expressed specific trust concerns, often around methodology such as how data was collected, funding sources, and whether the appropriate statistical methods or data visualizations were applied. For example, P15 noted: *"A lot of times, [articles] say, 'Studies show this' but it doesn't tell you who wrote it, from what school, where's funding coming from, or conflicts of interest. They don't mention demographics or the types of statistical analysis used."* P14 described their process of evaluating trustworthiness of the visual card prompt of pipeline incidents from the NEB website: *"I'd click on the links for 'Methodology' and 'Disclaimers'. Anytime there's any sort of disclaimer you want to see what they're disclaiming. Just what constitutes a pipeline 'incident'? How reliable is the data? [Do] people have vested interests?"* Similarly, P12 summarized their concern as: *"We can all come up with examples of data being massaged and manipulated to serve a particular goal."*

4.2.2 D-C: Seeking Trusted Interpretations and Interpreters

To cope with the challenge of evaluating the trustworthiness of new energy information, participants in the Data-Cautious cluster looked for interpretations from sources they deemed trustworthy. One subset of participants (P1, P7, P9, P12, P13, P14, P15) actively sought out information that was interpreted by known source(s), such as news media. These participants noted that a single news source may not be *"100% correct"*, and thus pursued diverse sources (from different languages or countries) to obtain multiple perspectives. Some participants (P7, P12, P13, P14, P15) further felt that current sources lacked an in-depth critical analysis. They wished to know not only what happened, but why. For example, P7 stated: *"[The news] is all reactionary but they don't give a critical analysis. As an average Canadian, you don't have the time or ability to do that research yourself. I want the news media to do that."* P15 was another example, turning to academic articles when news sources did not fulfill their requirements. For example: *"A year ago, I tried to look up more about nuclear energy. I googled it, then Wikipedia, then ended up on Google Scholar. I abandoned that* *really quickly. [Academic] papers are obviously meant for people in that field. I didn't find anything [else] that was more palatable for me."*

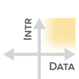
Another subset of participants (P2, P3, P11, P18) actively sought out trusted interpreters — individuals who could translate or explain information to them. For these participants, *value alignment with the interpreter* seemed to be a prerequisite to information receptivity. P2 and P3 were the most notable examples. For P2, who described themselves as coming from a "low-income family", themes of power and wealth consistently emerged. When prompted on what information they would ask different energy personas (reflected in our card prompts), P2 stated: *"I would not ask [Anna the CEO and Ryan the administrator of an oil company] anything. CEOs and administrators have a lot of power. I don't matter to them, so they don't matter to me. Whatever I say, suggestions, opinions, most definitely will not change the decisions they make, unless I too, had a lot of power."* P3 was another striking example, making frequent statements throughout their interview evaluating the *person* conveying the information (rather the information itself). P3 expressed that they were less receptive to information when value alignment was not present: *"I struggle when someone sits in a very different position that opposes what I stand for. I'd like to say I'm open to hearing things but I do struggle with that. Sometimes I hear opinions where, my God, like, I cannot even have a conversation with you."*

4.2.3 **D-C:** Receptivity to Visualizations

When presented with the card prompts showing various visualizations types, most participants in the Data-Cautious cluster did not react. Only a handful of participants (P7, P13, P14) exhibited varying degrees of receptivity towards standard or more complex visualizations. P7 was on one end of the spectrum, being most receptive to visualizations that offered a clear interpretation or conclusion: *"I like [Infographics] because it's the highlights, the important things."* P13 and P14 were along the other end, being most receptive to visualizations that allowed them to ask questions and draw their own conclusions. P13 said: *"I like 'visualization specification'. I could control the flow of info at my pace. It's not whatever the researcher decided to focus on."* P14 noted: *"Something that says, 'Here's the conclusion,' I might be suspicious. For chart generator [and] data story, they're both valuable in the sense that I can ask my own questions and sometimes get surprised."*

However, P7 and P14 also indicated that the cognitive investment required to understand NEB open energy visualizations in the card prompts can be futile, since their efforts would not directly impact high-level policy change. For example, P14 said: *"It's not clear how anything I learn will make any difference to anybody [in government] making decisions. You've got access to data but not the levers of power."* Similarly, P7 reacted to a card prompt depicting energy futures, saying: *"Oh God, I would have a hard time understanding this. I'd only make the effort if I know it will impact my behaviour or somebody else's."*

4.3 **Data-Enthusiastic (D-E)**: Show Me the Data and Help Me Interpret It



Two participants (P6, P17) exhibited receptivity responses that we characterize as Data-Enthusiastic. Unlike individuals with Information-Avoidant and Data-Cautious responses, these participants were *innately curious and intrinsically interested in data*, in the energy domain or elsewhere. In their professional work, P6 and P17 interact regularly with data and exhibited confidence in their ability to understand, wrangle, and analyze data in the form of spreadsheets, CSV, or XML files. In the energy domain, they desired access to underlying datasets but acknowledged limitations in their ability to evaluate this data due to a lack of domain expertise. To cope, these participants sought out external interpretations to assist them in understanding complex data from unfamiliar domains. What distinguishes these participants from those in the Data-Cautious cluster is a higher level of familiarity and comfort in working with data. While those in the Data-Cautious cluster relied exclusively on trusted external interpretations or interpreters (with little to no receptivity to data), individuals with Data-Enthusiastic responses actively sought the presence of data, almost as a prerequisite to information receptivity.

4.3.1 **D-E:** Data as a Prerequisite to Receptivity

In various domains, P6 and P17 expressed a desire to view and access underlying datasets. P17, a renewable energy hobbyist, described themselves as *"very interested in anything relating to energy"*. When prompted by the card prompts of NEB energy visualizations, P17 indicated that they would *"save [these online spreadsheets] to my desktop. To look at, maybe arrange it a bit, just play around with it"*. In comparison, P6 described themselves as *"not really into energy"*. Despite this, they tended to stayed informed about energy-related news. Considering themselves a *"a scientist at heart"*, P6 noted the necessity of data, in order to evaluate external claims. For example, when discussing a recent article about energy, they stated: *"[U.S.] democratic candidates are saying stuff like 'By 2030, half of our cars will be electric if I'm elected.' I don't know how to evaluate that claim. It'd be nice if there was some data to see what goals are realistic."*

4.3.2 **D-E:** Data Trust and Mistrust

Like participants in the Data-Cautious cluster, P6 and P17 expressed concerns around bias and trust, with P6 being the more skeptical. In contrast to individuals in the Data-Cautious cluster who expressed trust concerns about external *interpretations* of data, P6 and P17 expressed trust concerns *in the data* itself. P17 expressed wariness about the data source: *"If it comes from reputable sites, I would trust that the data is correct. If it's from the oil industry, for example, talking about renewable energy or electric cars, I will probably not believe it because they have ulterior motives"*. P6 was even more skeptical of data quality, regardless of its source: *"I know just enough statistics to know that if [data] is interpreted incorrectly or used in incorrect ways, it could lead to wildly false conclusions. I think the truth is one of the most important things, so it annoys me when people play with it like that."*

4.3.3 **D-E:** Assistance in Interpreting Data

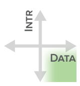
To cope with trust concerns in data, P6 and P17 relied on different strategies to assist them with interpreting data and assessing its credibility. P6 accessed online communities (such as Reddit — an online news aggregator and community) to crowdsource critical analysis. If an article on Reddit had comments that pointed out potential issues in data, analysis, or interpretation, P6 would find themselves immediately more skeptical of that information: *"I'll read comments [on Reddit]. If someone knows the data is being used incorrectly, they'll point it out. If I see at least one negative thing [about an article], I'll look at it with a more skeptical eye."* P6 went further to *"try to be conscious of my bias"* and *"not get stuck in an echo chamber."* To challenge their own perspectives, P6 would seek out diverse viewpoints and *"communities that have very different politics from me"*. P17 also sought assistance in interpretations of data by seeking out varied sources. For example: *"I look at the Ottawa Sun, Ottawa Citizen, National Post, CTV, Global, and CBC. I'm also on Facebook. You start on Facebook, they bring you to one site, then another, and you keep going, going, going, and I have 20 tabs open. Sometimes I also use a VPN and go to the French version of Google. I look at Le Monde or different newspapers there."* Overall, while P17 did not seem deterred by the effort of these deep dives into information seeking, P6 was, stating: *"Sometimes I'll see a headline that resonates, but I don't feel like looking into it right now. Like, I don't have time to confirm this, I'm going to pretend I never saw it 'cause I don't feel like dealing with that right now."*

4.3.4 **D-E:** Receptivity to Visualizations

P6 and P17 differed in their receptivity towards visualizations, with P17 the more trusting of the two. P17 stated a general preference for consuming and using traditional visualizations including bar, pie, and line charts in their professional work. They responded positively to the card prompts for dashboards (due to the ability to *"look at data in different ways"*), infographics (since *"they provide a lot of good information quickly"*), data stories and visualization specification (*"due to the ability to drill down and look at data all at once"*). When presented with unfamiliar visualization types, P17 responded with an excited curiosity and desire to learn. For example, when discussing radar charts and chart generators, P17 stated playfully: *"I don't understand them* *well. When I get back home, I'm going to go onto Google, YouTube, and see how to make one using Excel. Chart generator, I haven't done anything with that either. Darn, more things to learn!"*. Overall, P17 expressed an innate trust in visualizations, calling it "proper": *"[Topic-specific websites] show pie or bar charts, but I don't see such a thing in news online. It's mostly people that are enthused about it that put information in a proper format."* P17 voiced mild concern about how visualizations can be manipulated to convey a certain viewpoint, but did not express significant apprehension about this.

In comparison, P6 was less trusting of visualizations and distinguished between "high" vs "low-effort" visualizations. P6 indicated they would invest more time in consuming visualizations when it appeared that they had been designed with high effort: *"I usually won't see so much effort put into [visualizations] of simple or uncontroversial topics. [But], a long article that takes 20 minutes to read, has animated visualizations and different parameters you can play with, it's high-effort content. It makes me feel like 'I should look at this'. It's much easier to ignore a line graph. Even though they might be essentially the same data."* At the same time, "high-effort" visualizations triggered P6 to be more skeptical of the presented conclusions or interpretations. Here, they refer to the card prompt of a pipeline visualization from the NEB website: *"If the [visualization] showed a clear conclusion, I'd question the validity of the data. Right now, the way [it] looks, I'm not really suspicious of it. But if it was showing comparisons to other methods of transport and it led to a certain conclusion, like 'This mode of transport is clearly the safest when you look at the data', then I'd start viewing it more suspiciously. I guess the high-effort visualization I see almost exclusively as trying to convince me of something."*

4.4 Domain-Grounded (D-G): Let Me Interrogate Data and Draw My Own Conclusions



Four participants exhibited receptivity responses we characterize as Domain-Grounded (P4, P8, P10, P16). All were professional energy analysts or energy domain experts. Unlike individuals in the Data-Enthusiastic cluster who were receptive to energy data *and* interpretations of that data, those with Domain-Grounded responses were wary of external interpretations. They preferred reaching their own conclusions by directly interrogating datasets. We distinguish these individuals from those in the Data-Enthusiastic cluster by their extensive domain knowledge, domain-specific analysis experience, and access to other professional energy analysts.

4.4.1 D-G: Need for High-Quality Data

All participants in this cluster were less favourable on information that is already curated by others. They preferred to have access to the underlying data to perform their own analyses. For example, P16 said: *"It's not easy to get data in the format I want, or combine data in the way I'd like to analyze it. The way [dashboards] are displayed is already prepared. It doesn't tell the whole story. We're forced into seeing it in one way or another."* P10 expressed: *"What really adds credibility is an ability to dive below that data. To see where it came from."* These individuals discussed needs around centralized data sources, data quality, consistency, transparency, credibility, and timeliness. These themes echo many of the efforts that open data initiatives already target with regards to providing quality data to professional analysts.

4.4.2 D-G: Visualizations for Interpretation + Communication

Professional analysts in the Domain-Grounded cluster often found themselves acting in the role of interpreters of energy data for outside audiences in both professional and casual capacities. A common challenge was how best to improve public energy literacy, something they felt was *"definitely lacking"* (P8). To do this, these analysts used and even authored visualizations to interpret energy data for other audiences, with a preference for standard rather than complex visualizations. For example, P10 noted: *"Slope graph and radar chart, they just confuse people. You can use it if you're an analyst, but for conveying energy information to the public, no."* P8 had a similar view: *"We try to stick with something that's easy to explain, like line, bar, pie charts, that type of thing."* Likewise, P16 stated: *"Scatterplots — as a scientist, I'm quite comfortable with them, but I'm never very convinced they're a good visualization for the public."*

One exception was P4, a professional analyst who out of our 19 participants, was most closely involved in communicating energy information to outside audiences. For P4, utilizing non-standard visualizations with a higher engagement factor was key: *"I can give the most mind-blowing piece of data to somebody and present it in a very unengaging way, like if I printed out a spreadsheet. Versus communicate data engagingly. Pie, bar, line chart, scatterplot, slope graph — they serve a purpose, absolutely, but they just aren't exciting. I'm always curious about new ways of representing information."* P4 was particularly interested in visualizations that communicated "the qualitative human story" to provide context to data: *"If you put a graph in front of somebody with no context, that graph will mean something different than if you tell a story about how the [data] was collected, why it's important, who this affects. In telling a story, you're introducing bias, but from my perspective, story is what makes things engaging."*

4.4.3 D-G: Barriers for Visualization Authoring

Individuals in the Domain-Grounded cluster felt limited in their ability to author non-standard visualizations (such as visualization specification languages, chart generators, interactive notebooks) in their professional work due to a lack of programming skills. These analysts relied on basic visualizations (such as bar charts, line charts, and scatterplots) as their "go-to" in professional contexts. Despite having an interest in programming, participants were held back by a lack of time and ability. For example, P4 said: *"The way you described [interactive notebooks] as the ability to manipulate and play with data is automatically more interesting to me. I'd be really curious. I'd love to [code], but no. I've got no training in it and no capacity or time to learn it."* P16 stated: *"I'm an amateur when it comes to data vis. If coding was a core part of my job, it'd be great, but when you don't use it for months and try to go back, it's time-consuming and off-putting."*

5 Research Opportunities for Visualization

Our findings from this preliminary interview study highlight the key role of information receptivity for understanding public experiences with open energy data and visualizations. In this section, we highlight information receptivity as a blind spot for the visualization community more broadly and identify opportunities for future research. We contextualize each opportunity based on our findings and related literature from economics, psychology, and social science.

5.1 Untangling Literacy, Engagement, and Persuasion

To understand how to make visualizations that effectively transmit information, we must understand the interplay between visualization and reader. In introducing the notion of *information receptivity* — an individual's transient state of willingness or openness to receiving information — we add a new layer to the body of work that seeks to understand the various human factors (including literacy, engagement, persuasion) that govern information transmission and consumption.

Visualization research often emphasizes *data visualization literacy* — "the ability and skill to read and interpret visually represented data and to extract information from data visualizations" [45]. As discussed in Section 2, these efforts aim to improve data literacy of students and media consumers, typically by measuring and teaching the mechanical acts of visualization authoring and consumption. Yet, improving individuals' *ability* to read, create, and interpret visual representations of data, with little consideration of their *receptivity or willingness* to do so reflects a serious blind spot in visualization research — that individuals' capacity for understanding and connecting with data reflects more than just the ability to read it. Our observations of Information-Avoidant and Data-Cautious responses suggests that it may be unlikely that such audiences would invest the time or effort to join data literacy initiatives.

Meanwhile, work on *engagement* (as defined by Kennedy et al.) examines "the processes of looking, reading, interpreting and thinking that takes place when people cast their eyes on data visualizations and try to make sense of them" [38]. Implicit in this definition is a viewer's intrinsic willingness to spend time with, look at, and interpret visualizations — that is, their receptivity. Indeed, the structure of many visualization studies (including more ecologically valid studies like Peck et al.'s [55]), explicitly ask audiences to *look at* visualizations for evaluation, bypassing the potential barrier of reader receptivity.

Yet research into *persuasive visualization* has highlighted how challenging it is to shift people's attitudes [47]. It suggests that a reader's initial attitude affects persuasiveness [54], underscoring the human-visualization interplay. The reasons that Pandey et al. [54] found for persuasion success and failure echo themes relating to receptivity, such as skepticism, reluctance to parse complex visualizations, and openness to new data. This suggests links between receptivity and persuasion.

In fact, the notion of information receptivity may be a more foundational concept that underpins literacy, engagement, and openness to persuasion. The lived experiences that our interviewees shared suggest an intricate relationship between these concepts that deserves further study. For example, P14 (Data-Cautious) was data-literate, yet still avoided engaging with data directly. Similarly, feeling engaged by a visualization does not necessarily imply receptivity to the underlying data or interpretations (such as P5's (Information-Avoidant) response when discussing "fun" visualizations). Overall, our findings highlight the importance of understanding the nuanced relationships between data visualization literacy, engagement, persuasion, and information receptivity, and call for a deeper consideration of receptivity as a related and crucial area for visualization research. These issues pose a clear research opportunity (RO) for the visualization community:

RO1 Deepening our understanding of the interactions between data visualization literacy, engagement, persuasion, and information receptivity and how they manifest for different audiences.

5.2 Examining Information Avoidance

To date, the phenomenon of information avoidance has been largely unacknowledged by the visualization community. Our findings underscore the need for research that characterizes and measures the phenomenon of active information avoidance and how it impacts receptivity. Beyond simply encouraging data visualization literacy or presenting information in clearer or more engaging ways, our findings highlight a deeper challenge — *that the presence of data and visualizations themselves may lead individuals to disregard or retreat from information, particularly if the information and its implications are overwhelming, intimidating, or emotionally fraught*.

This phenomenon of intentional resistance to information is widely documented as "information avoidance" in the psychology and economics literature. Outside of visualization research, information avoidance is a commonly-reported behavior that can manifest as physical avoidance, inattention, biased interpretation of information, or self-handicapping [25]. Most commonly, people steer clear of information to avoid distressing emotions, even when that information may benefit decision-making. For example, investors check their portfolios frequently when markets are performing well, but not when the market is down — a phenomenon known as the "ostrich effect" [68]. Individuals at risk for health conditions often evade medical tests, even for serious genetic conditions or STDs [53]. During the COVID-19 pandemic, distress about COVID-19 and information overload was linked with a tendency to avoid pandemic-related information [69, 72]. Information avoidance is associated with lower compliance with preventative health behaviors [21] and can interfere with effective crisis management [69].

In the visualization community, most data literacy studies do not consider audiences' emotional response or willingness to receive data, focusing instead on systematizing the definition [9], evaluation [10, 45] and the teaching [15,34] of core visualization skills. While a few studies (like Lee et al.'s exploration of novice sensemaking [44]) have revealed point examples of Information-Avoidant behavior, visualization research has provided little insight into the broader impact of receptivity on diverse audiences' experiences with data and visualization.

Our participants' reflections and the considerable body of work on information avoidance in psychology and economics emphasize the importance of considering information receptivity in tandem with more pedagogical literacy strategies. Work emphasizing the effect of emotion [28, 37] and framing [42] on visualization interpretation also hints at emotional and social undercurrents that are at odds with strictly positivist notions of visualization perception and cognition. As Peck et al. note in their examination of rural Pennsylvanians' attitudes towards visualization, individuals' experiences with data graphics can depend heavily on their personal relationships to the topic and their political and social identities [55]. Moreover, as Lee et al. highlight in their analysis of "data-driven" rhetoric in online anti-mask communities, even literate communicators and readers can use visualizations in unorthodox or deceptive ways [43]. As such, characterizing and enhancing people's ability to make sense of data likely requires a deeper understanding of *literacy*, *receptivity*, and *intent*.

Some initial evidence suggests that it may be possible to mitigate information avoidance with visualizations whose form or mode of interaction intentionally evoke positive associations or emotions. In our study, P5 reacted positively to the idea of playful visualization formats and indicated positive personal associations with certain visualization types, despite their adamant avoidance of new energy information. Previous work has also identified associations between visualizations and emotions. Kennedy and Hill [37] showed that people's emotional responses can be deeply entangled with visualizations' subject matter and context and their own sense-making approaches. Peck et al. [55] found that a personal connection or experience with data can drive engagement with visualizations. As a result, there may be value in examining how playful or social visualization mechanics (e.g. game-like visualizations [18] or physicalization workshops [34]) can influence Information-Avoidant responses. The absence of work examining information avoidance in visualization suggests further research opportunities:

RO2 Expanding our understanding of the phenomenon of information avoidance and the role it plays in people's experiences with data and visualizations.

RO3 Engaging directly with audiences who exhibit Information-Avoidant responses to examine the potential for new approaches to mitigate or overcome barriers to information consumption.

5.3 Countering Data-Cautiousness through Trust

In the psychology literature, trust in information sources is often characterized as an exercise in risk management [79] governed by two dimensions: *competence* (ability, expertise) and *motives* (integrity, honesty) [78]. Perhaps because participants in the Data-Cautious cluster perceived themselves as lacking the data wrangling skills or the motivation to evaluate the *competence* of external interpretations, they largely questioned the *motives* of interpretations instead — raising concerns around bias, agenda, and data provenance.

Trust is also linked to the perception of individual values. When perceived value similarity exists between oneself and an information provider, trust increases [70]. This phenomenon aligns with observations from P2, P3, P11 and P18, who sought *individual interpreters based on shared value systems* before evaluating the trustworthiness of the information (or interpretations) being presented. This can be problematic when interpreters convey biased interpretations in domains where audiences do not have the skills to assess those claims. Individuals in the Data-Cautious cluster may be particularly vulnerable to possible deception by those sources because cognitive resistance to false or illegitimate sources is a finite, depletable resource, particularly when people are mentally fatigued [40, 63].

A key barrier to building visualization tools for audiences who feel Data-Cautious is a better understanding of the signals of information trustworthiness. The gap between information sources and the data behind their claims suggests a need for new visualization approaches that can surface those signals without overburdening viewers with data. Our preliminary research suggests such audiences may be receptive to approaches that surface information about data, analysis, and authorship more visibly within existing news articles, or to data-light adaptations of data-driven storytelling techniques [61]. These audiences may also be receptive to new presentation formats such as data comics [5], which can combine data and interpretation in a way that demands fewer cognitive resources. These findings suggest new research opportunities:

RO4 Building a deeper understanding of the signals of information trustworthiness that people who feel Data-Cautious use to assess the validity (competence) and trustworthiness (motives) of external interpretations of information.

RO5 Developing visualization approaches that more clearly and legibly surface signals of information trustworthiness, including information about data and analytic provenance, and authorship.

5.4 Deepening Data-Enthusiastic Discussions

Individuals in the Data-Enthusiastic cluster saw access to data as a prerequisite to information receptivity. They were driven by an innate curiosity and desire to learn, often interrogating data from unfamiliar domains, with the help of external sources. These individuals represent an ideal audience for the data visualization community and there remain opportunities to better support their data exploration. In particular, the experiences of our participants highlight the roles that visualizations can play in broader systems of public discourse and the need for tools to better support individuals and communities as they collectively evaluate the validity of data representations. Many audiences' exposure to data increasingly occurs via social media and online communities (as highlighted by P6's experience on Reddit and P17's experience on Facebook), rather than conventional journalistic, corporate, or government channels. Yet social media platforms generally integrate poorly with visualization and analysis tools, resulting in discussions grounded in screenshots and external links rather than more malleable representations. This means that most readers lack the ability to annotate, modify, or contextualize presentations of data on social media. While the visualization literature contains many examples of social data analysis systems [30, 81, 84, 86], these tools have generally been isolated — with systems like Many Eyes seeing their greatest uptake only when surfaced within existing social networks [82]. Deepening Data-Enthusiastic discussions in these social spaces may call for new tools focused specifically on supporting data-driven public discourse within prevailing online communities, and particularly on social media. Building on these observations, we identify two research opportunities:

RO6 Providing individuals who feel Data-Enthusiastic with increased guidance, context, and discourse surrounding the interpretation and interrogation of complex data in unfamiliar domains.

RO7 Exploring new annotation, discussion, sharing, and provenance mechanisms to support more nuanced discourse around data and visualizations on social media and help online communities collectively evaluate their validity.

5.5 Supporting Domain-Grounded Communication

Individuals in the Domain-Grounded cluster were the only participants in our sample who perceived open energy data as accessible and empowering. The needs of these individuals align most with current work in the open data and visualization communities that seek to improve data quality, consistency, and accuracy [23, 36, 85], or software to support the interpretation of complex datasets (for example, Tableau [74] or PowerBI [49]). As indicated in our findings, such efforts are essential to address the data needs of audiences with Domain-Grounded responses.

Our findings also reveal two additional opportunities. First, professional analysts in the Domain-Grounded cluster emerged as interpreters of energy data in professional and casual conversations with other audiences, including people who feel Data-Cautious or Data-Enthusiastic. Yet we know little about their outgoing communication needs. Second, analysts in the Domain-Grounded cluster expressed a desire to expand their visualization authoring repertoire, but lacked the time and technical skillsets to use visualization authoring tools, interactive notebooks, or publishing platforms. This presents opportunities to develop lower-effort approaches to help domain experts to employ visualizations to more effectively analyze and communicate their work, including:

RO8 Characterizing the outgoing communication needs of Domain-Grounded practitioners who can serve as interpreters and communicators of complex data to diverse audiences, particularly those with Data-Cautious or Data-Enthusiastic responses.

RO9 Developing new visualization tools that help Domain-Grounded scientists and practitioners (particularly those with limited technical and design skills) communicate data to broader audiences.

5.6 Understanding Evolving Receptivity Responses

Our grouping of Information-Avoidant, Data-Cautious, Data-Enthusiastic, and Domain-Grounded receptivity responses are not meant to reflect a permanent state of participants' receptivity to energy information, or information more generally. Rather, the clusters characterize participants' transitory reactions to energy information, captured at a specific point in time, within the context of participants' lives and the sociopolitical factors around them. In fact, findings from this exploratory work already suggest a fluidity in participants' receptivity responses, influenced by the topic domain or life circumstances. For example, P6 (Data-Enthusiastic) indicated that their scrutinizing mindset when consuming information would not be possible for all topics, due to the high cognitive effort required. Given this, P6 sometimes actively avoided consuming new information, suggesting that they — and perhaps others with Data-Enthusiastic inclinations — might feel Information-Avoidant in certain domains. Another example is P19 (Information-Avoidant), who indicated that after having a stroke, they found more information more overwhelming. P14 (Data-Cautious) is another example — despite a previous comfort with wrangling and analyzing data, P14 indicated that they were *"not very data-driven these days"*, suggesting that P14 may have transitioned from a Data-Enthusiastic to a Data-Cautious response at some point in their life. Overall, these examples emphasize the fluidity and transient nature of the four clusters in our information receptivity space. Examining what might encourage a person to shift from one receptivity response to another represents an interesting opportunity for future study.

RO10 Building a deeper understanding of the contexts and situations in which individuals shift from one receptivity cluster to another, and how to help facilitate those shifts.

6 Conclusion

Information-Avoidant, Data-Cautious, Data-Enthusiastic, and Domain-Grounded audiences are receptive to different forms of information, whether data, external interpretations or both. Visualizations designed with one receptivity response in mind may not be effective for others. The presence of diverse audiences with differing levels of receptivity presents a fundamental challenge for visualization and open data communities. It raises questions about the effectiveness of approaches focused solely on improving data literacy or engagement. Instead, researchers need to contend with the fact that — with regards to public information consumption and communication — one size does not fit all in terms of individuals' willingness and openness to receive new information. Going forward, it is important that visualization researchers develop a better understanding of the personal, emotional, social, cultural, and socioeconomic barriers that drive public information receptivity, and how, when, and why people transition between receptivity responses. Findings in this study are highly dependent on the topic of energy and our participant sample. Future work should explore different topic domains and cross-sections of the population to further refine, modify, or expand upon these clusters. Larger-scale surveys and studies could help to quantify the distribution of these receptivity responses within the broader public. Ultimately, a deeper consideration of information receptivity will contribute to more inclusive and accessible approaches to open data systems and visualizations that target a wider and more diverse range of audiences.

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