Can Data Visualizations Change Minds? Identifying Mechanisms of Elaborative Thinking and Persuasion

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Abstract

Recent years have seen rapid growth in data-driven communication and the public availability of datasets on a broad set of social issues. Yet despite this unprecedented accessibility, the public often remains divided along partisan or ideological lines and to lack a common understanding of the issues at stake. In this paper we consider the role of data visualizations in communicating scientific evidence, and in particular, their power to persuade in the face of conflicting prior beliefs and attitudes. We describe a recent study showing that strong attitudes about politically polarized topics were associated with less belief change when interacting with statistical data visualizations. Moreover, there was little evidence for attitude change even when people updated their beliefs about specific empirical relationships. We then draw on research in cognitive science to identify elements of visualizations that may produce such attitude change because they encourage *elaborative thinking* when interacting with data. We argue for further research that considers how broader attitudes—which are tied to social identity, values, and worldviews—affect the power of data visualizations to persuade among communities with diverse ideological and cultural backgrounds.

Keywords: data visualization, persuasion, elaboration likelihood model, uncertainty visualization, belief elicitation

1 Motivation

A confounding gap between the accessibility and impact of public data has been starkly illustrated by the COVID-19 global pandemic. During this period the public struggled to interpret and synthesize uncertain, at times conflicting, recommendations related to the COVID-19 virus and mitigation strategies [31]. However, the inherent uncertainty of the pandemic alone can't account for the sharp divergence in public attitudes and behaviors surrounding measures such as masking and vaccination, particularly in later periods when a strong scientific consensus about those measures' effectiveness had emerged. Instead, the rapid politicization of public health responses became a defining factor in public opinion toward COVID-19 preventative behaviors [13]. Recent studies indicate this politicization has also influenced how people consume information about the pandemic: People interpret scientific evidence about mask-wearing in a way that is biased by their existing attitudes [15], view scientific sources as untrustworthy or partisan [40], and are susceptible to misinformation that undermines official public health messaging by reinforcing strongly held political or social identities [41]. These factors may have also influenced how people engaged with the panoply of "crisis visualizations" that emerged during the pandemic [42], with recent work suggesting that political leaning affects how people interpret visualizations related to COVID risks [10]. However, despite their prominence throughout this public health crisis, relatively little is known about how interactions with data visualizations affected people's attitudes or behaviors.

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What is the persuasive power of data visualizations? Do they mostly reinforce existing views and provide fodder for partisan attacks, or can they promote a common understanding of factual evidence among ideologically polarized audiences? While existing research has examined a multitude of factors that impact how people interact with and interpret visualizations, less work has considered how preexisting beliefs and attitudes impact what people learn from such interactions, particularly when the data conflicts with those existing views. As a result, little is known about the kinds of visualizations that not only inform but also spur broader shifts in attitudes and behavior. In this paper we highlight our recent work examining how preexisting attitudes affect belief updating about statistical relationships when interacting with data visualizations (scatterplots with different uncertainty representations). We then discuss what can be learned from psychological theories of persuasion in other communicative contexts, with a focus on the role of **elaborative thinking** in driving robust attitude change. Finally, we draw on research from cognitive science and visualization to identify mechanisms of elaborative processing that have been shown to enhance memory and learning in other contexts, and which might guide the design of interactive data visualizations that are persuasive.

2 Persuasive visualization: Changing beliefs vs. attitudes

Data visualizations are an increasingly vital tool for communicating scientific evidence to the public about important social issues such as public health (e.g., COVID-19 trends), democratic backsliding (e.g., polarization, gerrymandering), and extreme events (e.g., natural disasters and wars). For instance, in the growing field of data journalism visualizations are presented within news articles to show the empirical evidence for claims to readers. This has coincided with a rapid increase in the availability of public data sources and dashboards. These dashboards communicate the evidence guiding policy decisions, foster governmental transparency, and can support individual decision making based on fine-grained, localized data.

While such efforts have made it easier ever to disseminate scientific evidence to the public, their impact may be limited by failures to engage with, understand, and learn from data visualizations [28]. The uncertain impact of COVID-19 crisis visualizations illustrates a broader need to understand the persuasive power of visualizations when the data challenges people's existing views [35]. A wealth of research in psychology and cognitive science suggests that persuasion in these cases can be difficult due to confirmatory biases in cognitive processing that preserve existing views. People tend to interpret evidence in a biased manner [19] and to prefer information sources that are likely to reinforce existing beliefs and attitudes [20]. Similar confirmation biases have been shown to influence the interpretation of data visualizations [35].

Moreover, communicating a narrow set of data—even if deemed credible and interpreted correctly—may not be enough on its own to prompt shifts in attitudes and behavior [36]. Psychological theories distinguish between two levels of persuasion: changes in **beliefs** and changes in **attitudes** [2]. A belief represents a person's agreement with the truth or falsity of a claim, which can be represented as a proposition about the relationship between two entities or variables (e.g., *"Vaccines cause autism"*). Individuals might differ in their

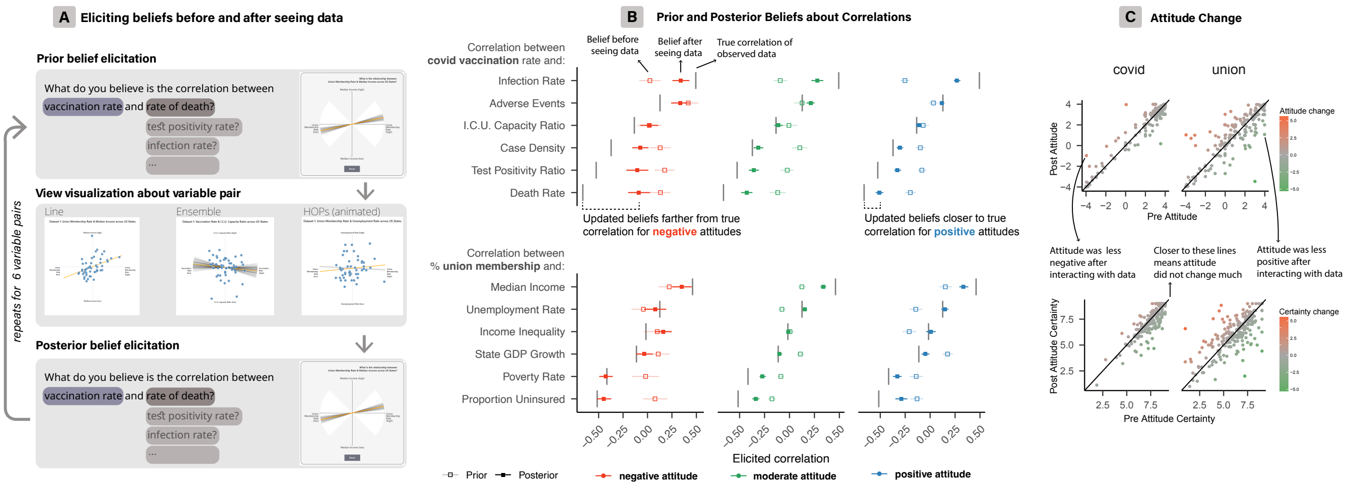


Figure 1: Study design and results from Markant et al. [26]. **A:** For each topic, participants interacted with a series of visualizations showing the correlation between a focal variable (e.g., COVID-19 vaccination rates by state) and other outcomes. Participants' beliefs about the correlation were elicited before and after they interacted with each visualization. **B:** Comparison of true sample correlations (vertical black lines), prior beliefs (open points), and posterior beliefs (filled points), separated by preexisting attitudes. Each row corresponds to a data visualization involving the focal variable and the variable listed at left. **C:** Comparison of global attitudes (top row) and attitude certainty (bottom row) before and after interacting with visualizations for each topic, revealing a decrease in attitude certainty for COVID-19 vaccination but no other changes in attitudes.

agreement with any given proposition, but beliefs about observable phenomena are typically subject to validation or falsification by empirical evidence. In this sense, the immediate goal of data visualizations in persuasive contexts like news articles and social media is to change beliefs about a narrow set of empirical patterns (e.g., to show that vaccination rates are unrelated to the incidence of autism).

In contrast, attitudes are overall evaluations of entities or issues (e.g., being pro-vaccination, anti-vaccination, or somewhere in between). Although attitudes are informed by specific beliefs about a topic, those beliefs are only one source of justification for a particular position. Attitudes are complex psychological constructs that are shaped by personal identities, social affiliations, and emotions [2]. They relate to ways of seeing the world and motives for coherence and social belonging. Strongly held attitudes can be difficult to change, both because they are rooted in ingrained ways of thinking and because they shape how people perceive and interpret information that contradicts existing views, leading counter-attitudinal evidence to be compartmentalized or rejected outright [22] when they threaten deeply held belief systems.

These interactions between broader attitudes and specific beliefs may help explain why public opinion toward COVID-19 preventive measures like vaccination and mask wearing have remained sharply polarized despite robust evidence for their effectiveness, as those measures became associated with partisan ideologies. This is consistent with past work showing that anti-vaccination attitudes are tied to religious beliefs and skepticism about science [39], and that correcting specific misconceptions (e.g., that vaccines are associated with greater incidence of autism) has little effect on anti-vaccination attitudes and behavioral intentions [32].

3 How do Attitudes Affect What People Learn from Data Visualizations?

Visualization researchers have considered a wide range of strategies for effectively communicating data [11], efforts which we broadly view as helping people to update their beliefs in an unbiased manner. Less work has examined how attitudes shape how people interact with and learn from data visualizations. Pandey et al. [35] found that persuasive messages with statistical evidence led to greater attitude change among people who did not have strong preexisting attitudes, and that among that group charts were more effective than tables. However, that study did not examine changes in beliefs about the message content, leaving it unclear whether existing attitudes had any influence on what people learned from the data.

In a recent study [26] we investigated how belief updating from visualizations is impacted by preexisting global attitudes, and whether attitudes change when people view data that conflicts with their prior expectations. We created visualizations about two politically charged topics: COVID-19 vaccination and labor union membership. For each topic we first measured global attitudes (i.e., the extent to which a person was for or against COVID-19 vaccination/labor union membership). As expected, global attitudes on both topics were related to participants' political leaning, with more liberal participants reporting more positive attitudes toward both COVID-19 vaccination and union membership. However, COVID-19 vaccination attitudes were more sharply polarized, with most participants either strongly in favor or against vaccination, while attitudes toward union membership were more ambivalent (Figure 1C).

Our first research question concerned whether these attitudes would impact what people learned from a set of data visualizations on each topic. Datasets were created from real-world data about each focal variable and its correlation with a health-related or economic outcome.[1] Each visualization included a scatterplot and a line depicting the sample correlation (Figure 1A). Participants in some conditions also saw uncertainty representations either in the form of a static ensemble of correlation lines or an animated hypothetical outcome plot [34]. We used a belief elicitation interface developed in [16] to measure prior and posterior beliefs about the relationship between each pair of variables before and after they observed the visualization, respectively. This allowed us to measure the degree to which beliefs about a given empirical relationship changed as a result of interacting with the dataset, and to relate those changes in beliefs across a set of related datasets to participants' global attitude.

The results showed that strong global attitudes were associated with smaller changes in beliefs after seeing the data visualizations (Figure 1B). This was predominantly seen for the COVID-19 topic

[1]Original data sources were the CDC (COVID-19 topic) and the U.S. Census (Union membership). Variables were state-level annual averages for 2021 (COVID-19) or 2019 (Union membership).

where people had stronger preexisting attitudes either in favor or against vaccination. Strongly anti-vaccination participants still shifted their beliefs to some extent, but their posterior beliefs were systematically biased further away from the true sample correlations compared to individuals with strongly pro-vaccination and more neutral attitudes. In contrast, people with both negative and positive attitudes toward union membership tended to show similar shifts in beliefs about specific empirical relationships between union membership and other outcomes (Figure 1B, bottom).

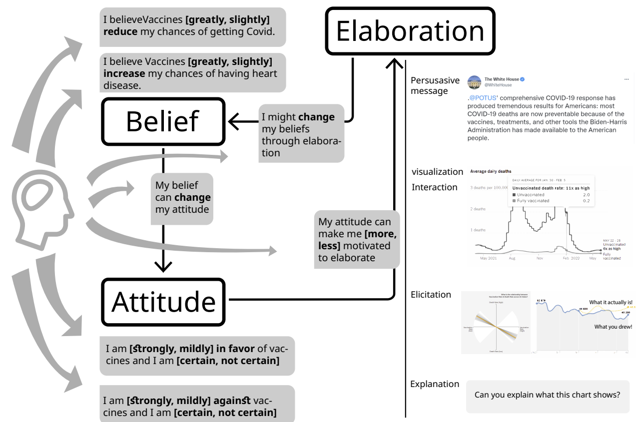
In addition to the effect of preexisting attitudes on belief change, we explored whether global attitudes would change as a result of interacting with the data. For instance, would anti-vaccination participants express a more favorable view after learning that vaccination rates are negatively correlated with a range of harmful outcomes? Although there was some indication of decreased confidence in COVID-19 attitudes, overall there was no evidence for shifts in global attitudes, as people expressed similar positions toward both COVID-19 vaccination and union membership before and after interacting with the associated datasets (Figure 1C).

These results cast some doubt on the power of data visualizations to persuade people with strongly held attitudes. This is especially notable for the COVID-19 topic where the evidence was relatively favorable across several datasets, including strong negative correlations between vaccination rates and fatalities, test positivity, and case density. As we noted above, prior work suggests this failure to persuade may not be surprising in the context of strongly held existing attitudes that are tied to other aspects of people's identities or worldviews. However, it's important to consider whether some aspects of the design for this initial study may have limited the persuasive potential of the visualizations. In the task we adopted a neutral stance in that we aimed to present data from credible sources in the absence of any overt persuasive messaging or framing. Participants were also generally passive viewers without any explicit incentives or prompts to explore or make sense of the data for themselves. In the remainder of the paper, we draw on previous work in social and cognitive psychology for insights on how to design more persuasive visualizations that promote deeper thinking about the data and integration with existing beliefs and attitudes.

4 Changing attitudes through elaborative thinking

Contemporary theories of attitude change resemble dual-process frameworks of other domains of cognition which distinguish between intuitive and deliberative forms of thinking. A prominent example is the Elaboration Likelihood Model [36] which proposes that attitude change is mediated by two processes: a *central route* which involves deliberative reasoning about the content of a message, and a *peripheral route* which entails heuristic or intuitive reactions to messages. **Elaborations** refer to the positive or negative thoughts that are generated while processing a message and which might bear on one's attitude. These include thinking about potential favorable or unfavorable implications of the message and their relative likelihood. For example, viewing a data visualization about melting ice caps due to climate change could prompt thinking about the negative impacts of rising sea levels on nearby coastal communities.

According to the Elaboration Likelihood Model, elaborations are more likely when people are motivated to think about the message content (e.g., due to personal involvement with the topic) and have the capacity to process it (i.e., they have the time, attention, and ability to comprehend the message). When people lack this motivation or ability, responses are more likely to occur through the peripheral route, such that they rely on simple cues or heuristics to make judgments about the message. This could include using source cues such as the perceived credibility of a news outlet to evaluate the message without close scrutiny of its content. Attitudes can still change via the peripheral route, but these changes tend to be short-lived and less likely to affect behavior compared to those that are driven by the central route [36].



There are several implications of this framework for persuasive data visualizations. Attitude change is more likely when people engage in elaborative thinking, reasoning about the content of a visualization and relating it their own experience or existing knowledge. Other contextual elements, like the message framing or source cues, may lead to heuristic (peripheral) evaluations that sidestep engagement with the visualization itself and are less likely to produce lasting attitude change. Thus it may be especially important when communicating about polarized topics to minimize overt partisan cues or framings that lead people to filter or reject the message outright [12]. If the audience chooses to engage with the message content, persuasion still depends on their ability to generate reasonable interpretations. Visualization design can be crucial for supporting accurate interpretations of the evidence and for highlighting features of the data that are central to the intended message [7].

Assuming that viewers have the motivation and ability to engage with a visualization, a key remaining question is what features lead to meaningful elaborative processing that connects interpretations of the data to their existing knowledge. In the remainder of this section we briefly consider three design elements that are likely to produce memorable and meaningful interactions with data, thereby creating the conditions for robust attitude change.

4.1 Belief elicitation

The first element involves eliciting users' beliefs before they view a dataset. In the study we described above, we used a visual belief elicitation method to measure changes in beliefs before and after participants interacted with each dataset related to a topic, which allowed us to identify cases where people with strongly held attitudes were more reluctant to follow the data. However, beyond this measurement purpose, belief elicitation itself may encourage elaborative processing of the evidence that is subsequently presented. Eliciting prior beliefs encourages the viewer to retrieve knowledge about a domain and to use their existing beliefs to generate predictions about observable outcomes. This process also produces a feedback signal that can drive belief change, as the viewer has already externalized a prediction that can be compared with the observed pattern in the data. Making specific predictions can also help participants gauge their own level of uncertainty and to guard against *hindsight bias*, or the feeling that one could have predicted the data even though it actually conflicts with prior expectations [38].

While a growing number of studies use belief elicitation to measure changes in beliefs, there is less work examining how belief elicitation itself changes how people subsequently process information and the consequences for persuasion. A study by Myers et al. found that estimating the level of scientific agreement about climate change before observing a consensus statement led to greater shifts in beliefs compared to when prior estimates were not made [30]. In the domain of visualization, Kim et al. found that making predictions before interacting with multivariate data visualizations led to better memory and comprehension of the observed data [18]. Belief elicitation has also begun to appear in the context of data journalism, with prominent examples coming from the New York Times [1,5,17]. One example is "You Draw It: Just How Bad Is the Drug Overdose Epidemic?" [17]. The article first elicits readers' beliefs about the rate of deaths in America over time due to a range of causes (car accidents, guns, HIV, and drug overdoses). The true trends are then revealed, allowing viewers to directly compare their predictions to the data. The final chart combines all 4 trends together to draw a contrast between the sharp rise in deaths from drug overdoses and (somewhat) downward trends of deaths from other causes.

More research is needed to understand the effects of this kind of belief elicitation on persuasion. This includes a need to develop belief elicitation methods that accurately capture people's beliefs while being intuitive and usable for a general audience. These techniques can be useful in a variety of contexts including interactive journalism, public decision making, and visual analytics. A promising direction for future work is to develop a unified design framework for eliciting beliefs about complex relationships through visual interactions. The design of such visual belief elicitation techniques requires understanding the users, the reasons we elicit beliefs, and how the beliefs are being elicited [24].

4.2 Agency

A second way to drive elaborative processing is creating a sense of agency in the viewer by giving them control over their interactions with a visualization. In the field of visualization, Dimara et al. defined interaction as a dialogue between a human user and the visualization system over data [8]. A central question in visualization research is how much freedom a user should have over how to interact with data. As with belief elicitation, greater interactivity can be a powerful measurement device, as indicated by research in visual analytics in which users' reasoning processes can be recovered from analyzing interaction sequences alone [9]. Interaction with visualization during sensemaking can be considered as a way to externalize cognitive processes involved in deliberating thinking [37].

A growing body of research in psychology suggests that a sense of agency also has broad benefits for learning and memory. The opportunity to actively explore allows people to ask questions that reflect their own uncertainty and hypotheses about a domain [25]. Other research has shown that the simple opportunity to make active choices over what information to see leads to enhanced memory compared to when those choices are predetermined. These effects have been linked to a number of mechanisms, including the ability to adjust the pacing and content of learning according to one's own understanding, and enriched encoding as incoming perceptual information is associated with internal representations related to action and decision making [27].

Of course, interactivity in visualizations can take many forms, and some kinds of control might be more conducive to elaborative thinking than others. For instance, controlling transitions between visualizations in a slideshow might allow people to modulate the pacing of new information, but may not on its own lead to closer scrutiny of the content of the visualization and its implications. Although it's likely that even minimal forms of control will enhance memory for visualizations, further work is needed to understand what forms of interactivity are most conducive to elaborative processing and how these might foster attitude change.

4.3 Self-explanation

Finally, a closely related form of elaborative processing is self-explanation, in which people generate explanations for observed data. Research in education and psychology has shown that prompting people to explain data leads to improvements in learning [3]. Self-explanation focuses attention on the causal structure of events [23] and encourages people to interpret evidence in terms of their own knowledge. When they have already generated predictions, people might try to make sense of discrepancies between their predictions and the observed data. Prompting viewers to explain a data pattern can naturally lead to elaborative processing about how the data was generated and its broader implications. In their study, Kim et al. found that self-explanation (either in conjunction with prior elicitation or without) led to better memory for the details of a data visualization, particularly in a less familiar domain [18].

Importantly, prompting viewers to engage in self-explanation isn't guaranteed to produce accurate interpretations of a visualization. People may differ in their willingness or ability to reason about data or may still favor biased interpretations due to their prior views. This further suggests the need to follow data visualizations with a persuasive message that reinforces the intended interpretation of the data [12]. We would expect that persuasive framings are most effective *after* viewers have already attempted to make sense of the data themselves, allowing them to focus on specific divergences from their own predictions or explanations. Creating opportunities to reconcile these conflicts between existing knowledge and the data visualization are likely to be essential for changing both specific beliefs and broader attitudes.

5 Ethical Considerations and Concluding Thoughts

The reliance of many governmental and mainstream media entities on data visualizations during the COVID-19 pandemic highlights the importance of such visualizations in achieving important societal outcomes (e.g., increasing vaccination rates). Notably, however, some purveyors of COVID-19 misinformation also used publicly available data and advanced visualization techniques to support misleading or false claims [21]. Through studying how anti mask groups leverage data visualization to communicate their viewpoint, Lee et al. concluded that "Data visualizations are not a neutral window onto an observer independent reality; during a pandemic, they are an arena of political struggle" [21]. This struggle is partially due to the fact that visualization design choices can shift the persuasive message, even for data from the same original source. For example, small additions to charts, such as highlights and annotations, can support perspectives from different political parties [4,11]. It is essential for designers of data visualizations to understand and acknowledge the political nature of their work in order to combat misinformation and to improve truthfulness of their art [6].

As communicators, we also have the responsibility to recognize that consumers of our work are humans with deep emotional, moral, social, and cultural connections to the information we produce and visualize. For example, some aspects of vaccine hesitancy in minoritized communities can be attributed to a deep mistrust towards governments and medical institutions due to legacies of colonialism, slavery, medical racism, abuse and malpractice [33], while individuals with emotional connections to crises (e.g., Boston marathon terrorist attacks) may be more receptive to misinformation about those topics [14]. Many visualization researchers and practitioners follow the nested design process introduced by Munzer [29] to produce effective data visualizations. But in light of how visualizations of real data have been used both for social good and to support false claims during the Covid-19 pandemic, visualization researchers and designers should be cognizant about how our work can potentially be leveraged to convey different (possibly unintended) messages during the design process. As data visualizations will continue to be vital to the public discourse over matters of urgent social concern, more research is needed to understand the dynamics of persuasion in visual communications among audiences of diverse backgrounds and motivations.

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