A Case Study on COVID-19 Intervention Visualizations: The Role of Trust, Beliefs, and Interpretations

Priyam Mohanty, Murtaza Ali, Aditya Parameswaran, B. Aditya Prakash, and Niloufar Salehi

Abstract—Visualizations have been widely employed to convey important information regarding COVID-19 to the public, regarding cases, deaths, and intervention effectiveness. However, the way the general public reacts to these visualizations, given their preexisting biases and beliefs, is understudied. Specifically, for visualizations that highlight interventions, it is unclear if and how the visualizations help shape user understanding, and how, if any, they change user's beliefs. Early on in the pandemic, we collected intervention information manually and developed a visualization interface, COVIDVIS, that overlaid intervention information on case and death counts as a case study. Employing an extended version of this interface as an exemplar intervention visualization, we conducted a user study to collect the priors and posteriors of participants' opinions of COVID-19 intervention effectiveness before and after interacting with such visualizations. Analysis of the participants' reactions to our visualizations allowed us to group participants into three distinct personas: COVID-Cautious, New Believers, and Skeptics. By gauging each group's level of institutional trust and societal (interpersonal) trust, we uncover trends that help explain how the role of each form of trust changes the way people interpret and react to COVID-19 visualizations. Our findings have ramifications for anyone developing visualizations that are part of the public eye.

Index Terms—COVID-19 visualizations, intervention visualizations, qualitative study, trust, Bayesian prior elicitation

1 Introduction

Data visualization has witnessed a renewed interest and significance during the COVID-19 pandemic. Visualizations, such as those of Burn-Murdoch, have played a crucial role in conveying the status, risk level, and trajectory of the pandemic [26]—with a proliferation of dashboards across health departments at all levels, as well as news organizations and non-profits. Shneiderman calls this period data visualization's "breakthrough moment" [56], while others have called 2019 the year visualization "hit the mainstream" [46]. Visualization has also been weaponized by COVID skeptics to craft alternative narratives [42].

Many of these COVID-19 visualizations also displayed information about interventions [66]. As a response to the pandemic, governments at various levels, from federal to local, enacted intervention measures in an attempt to stop the spread. Interventions, such as mask wearing, social distancing, and closing schools, universities, and high-exposure businesses, had a huge impact in slowing transmission of the coronavirus [13, 16]. In many cases, interventions have also been met with polarization [37].

In this work, we conduct a case study on how people interpret and make sense of visualizations that display disease trajectories, overlaid with intervention information in the United States, primarily establishment closures. Establishment closures are regarded as one of the most effective forms of interventions, with clear-cut start and stop dates [13]. At the same time, such drastic interventions often come at a cost to personal freedom, leading to negative reactions from certain segments of society. Therefore, visualizations that show the effects of interventions can both be incredibly important for affecting public opinion, while also eliciting the strongest response—and therefore well worth investigating further.

Overall, understanding what drives the interpretations of such visualizations can influence the design of more informative visualizations in the future—especially those that can help interventions be more effective. In the face of large incentives and detractions, depending on one's personal perspective and risk belief of COVID-19, the views and the strength of such views that one holds can often be a matter of life or death [6]. We also seek to understand what priors, such as personal trust in institutions or preexisting opinions on COVID-19, may possibly drive or influence interpretations of visualizations. Our study aims to provide actionable takeaways of better visualization design for the various personas that characterize the viewer of COVID-19 visualizations. These insights are most useful for journalists, public health scientists, and academics that find themselves in the public eye.

In the early days of the pandemic, pandemic intervention data was hard to find and very decentralized. We developed methods to extract them via a manual process. Our challenges and process may be of independent interest for future work on pandemic data collection. Data was collected from various verified sources into a coherent CSV-style format. We then use this data to develop a visualization platform that displays the impacts of interventions in the context of the case load. To the best of our knowledge, visualizations that displayed these interventions in-situ were not available at the time of development—though many have emerged since [42, 66]. Our visualizations were deployed on `covidvis.berkeley.edu` and garnered visits from around 5500 individuals—most visits were in April and May 2020, when centralized, clear pandemic intervention data was hard to come by.

Finally, we conduct a user study using our intervention visualizations to demonstrate how deliberate use of visualizations can update people's existing beliefs about the effectiveness of intervention measures compared to their prior beliefs. We designed the study this way to not only evaluate how visualizations may change one's opinion about intervention measures and how, but also study how priors come into play regarding visualization interpretations. Our design was inspired by prior work on Bayesian cognition for visualization [40]. During the study we collected participants' prior and posterior beliefs. In the middle of collecting both, participants interact with visualizations of COVID-19 case data in various states in relation to establishment closures. In collection priors and posteriors, we ask participants' to rate interventions' effectiveness in the "ideal case" (everyone follows interventions) and in the "reality case" (interventions as currently implemented). We find that, on average, the visualizations caused a shift towards a positive view of COVID-19 interventions. We also find that, on average, people commonly believed interventions as effective ideas, but not in practice. We found a natural grouping of participants into three personas: COVID-Cautious, New Believers, and Skeptics. These personas, described in detail later on, allow us to delve into the themes of institutional and societal trust as driving factors of people's interpretations of visualizations. We find that levels of trust, inferred from the

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Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

quantitative and qualitative data, can be predictive of one's reaction to the COVID-19 visualizations we demonstrate.

2 Related Work

2.1 Data Visualization Literacy

Visual literacy is defined as a "group of skills that enable an individual to understand and use visuals for intentionally communicating with others" [8]. Today, in the information age, being able to make sense of data visualizations is as important as reading and writing text. There is considerable research on assessing visual literacy and determining how people understand visualizations [12, 30, 43, 51]. Relevant recent work points out data is personal, and that educational, political, and personal contexts all play a role in one's understanding of data visualization [51].

As we focus on information uptake with respect to personal context for visualizations, we find that visualizations, especially for the COVID-19 pandemic, have the power to both persuade [50, 66] and misinform [17, 42]. There have been many examples of COVID-19 pandemic data misrepresented by both the media and governmental agencies [23]. This is partly a result of the lack of statistical literacy among the general public as well as with organizations sharing this data. Some visualizations are also intentionally misleading in order to promote a certain narrative [42]. Such misleading visualizations sometimes are shared on social media extensively, permeating the public consciousness with incorrect data. However, recent work has shown that digital media literacy intervention does increase discernment between mainstream and false news [30].

In our work, we study how participants interpret COVID-19 intervention visualizations shown. For some participants, such visualizations are unfamiliar. We collect data on participants' impressions of the visualizations themselves to understand how people make sense of potentially unfamiliar visualizations in the same vein as recent research [43]. There has also been reasonable discourse around visualization science and effectiveness. For example, recent research sets guidelines for effective visualizations [27]. However, we acknowledge that data visualizations within the pandemic are inherently an "arena of political struggle" and not neutral [42]. Everyone has also had different individual experiences with the pandemic, while visualizations show a collective averaged experience [11]. As a result, participants will nonetheless impose their political and personal insights onto visualizations if they are so inclined.

2.2 Institutional and Societal Trust

Trust is the bedrock of a functioning society. We focus on two types of trust: *institutional trust* towards large institutions (e.g., public institutions, media corporations) and *societal trust* towards other people. Generalized societal trust, i.e., the belief that unknown people around us don't mean us any harm, is an important factor in the makeup of government and state of a society [21]. Declining or low levels of trust are often associated with a potential reluctance to comply with laws [19, 44, 45] and higher possibility of social unrest [7]. Furthermore, trust reduction is associated with lower levels of health, happiness, and wellbeing among people [4, 32, 36]. Bollyky et al. show that higher interpersonal trust would have led to more positive outcomes during the pandemic [10].

According to a recent RAND study, trust in many institutions, such as government and media, has declined significantly in the past 20 years [35]. The study showed that trust in media and the US Congress, in particular, registered as having the lowest levels of trust among respondents. Using the study's scale of trust, only two institutions, local newspapers and the military, were considered relatively trustworthy by the public. According to respondents, the primary drivers of trust for institutions were competence, integrity, performance, accuracy, and relevance of information provided. For example, competence mattered the most for respondents to trust the US Congress, while accuracy mattered the most for media trustworthiness. Regardless, a loss of institutional trust where the institution has let down the individual in some way can cause institutional trust to never heal [60].

The COVID-19 pandemic has spurred new research into the effects of institutional and societal trust on various subjects. Woelfert and Kunst found a positive correlation between social distancing intentions and societal trust [64]. Other early research spoke of the difficulties of policy-making and getting societal buy-in in low-trust society-state relationships, such as Hong Kong [31]. Finally, some research tries to get to the bottom of what affects trust in COVID-19 specifically, with some reasons pointing to a positive correlation between government transparency and government decision making [24].

Research has also found that in times of crisis, institutional trust goes down, while societal trust stays stable [25]. We want to emphasize that institutional and societal trust are different factors and are not necessarily correlated [59]. Both can affect behavior and perspective in different ways. In our study, we learn how both institutional and societal trust play key factors in how our visualizations are interpreted. We even find that our visualizations are able to affect societal trust levels within our participants.

2.3 Pandemic Preparation and Response

Pandemic preparation has been in the news for at least a decade, with epidemiologists repeatedly predicting that one would occur in the future. Just prior to the COVID-19 pandemic, researchers attempted to assess global preparedness for the next pandemic by developing and applying an Epidemic Preparedness Index for each country [48]. The study found that the most prepared countries were in Europe and North America while the least prepared countries were in Africa and Southeast Asia. The countries were assessed based on reporting speeds of disease outbreaks and vaccination proportion of the public during the 2009 pandemic.

Furthermore, there are various other aspects that are important for dealing with pandemics. For example, institutional capacities are necessary to coordinate, plan, manage, allocate resources, and formulate policy. Furthermore, while such institutional capacities are crucial in dealing with a pandemic, they are difficult to build, slow to develop, and prone to quick degradation by political instability [52]. The resulting conclusion is that countries with stable institutional structures generally should respond better to pandemics. Economic resources are also important to both detect and invest in resources against infectious epidemic diseases. Evidence shows that there is a direct link between health financing and an effective response with better health outcomes [41]. This link is due to various reasons, including better access to healthcare equipment, more access to treatment, and higher investment in prevention, such as vaccine development.

Lastly, public health communication plays an important role in pandemic preparedness and response. Sharing effectively can lead to reduced risk for the public by providing actionable guidance quickly [54, 62]. Furthermore, related to our work in this paper, we see that there are various factors that can influence public understanding and acceptance of such communications, such as the level of public education and the public's trust in authorities that disseminate such information [10, 49, 62]. Some qualitative responses within our study specifically comment on the pandemic response by the US government.

2.4 Visualizations as a Pandemic Response

Visualizations themselves are also a part of the pandemic response, as they convey information to the public. The calls to "flatten the curve", a direct reference to visualization, has spurred new forms of visual knowledge to talk to the public [14]. Other papers have called the pandemic a "breakthrough moment" for data visualization research due to the popularity and importance of COVID-19 charts, such as those of John Burn-Murdoch [56]. Burn-Murdoch's charts helped millions of people understand the scale of the pandemic within the United States [26]. Others have cited the year before, 2019, as when data visualization started gaining momentum in the "mainstream" [46].

There is also debate about the value of producing COVID-19 visualizations since it's easy to create misleading ones by mistake [1]. Concerns raised have lead to the creation of visualization design guidelines and principles for the pandemic, in order to aid in proper knowledge transfer [18, 63]. However, many visualizations that have gone viral are also deliberately misleading, created by actors with malicious or misguided motives [42].

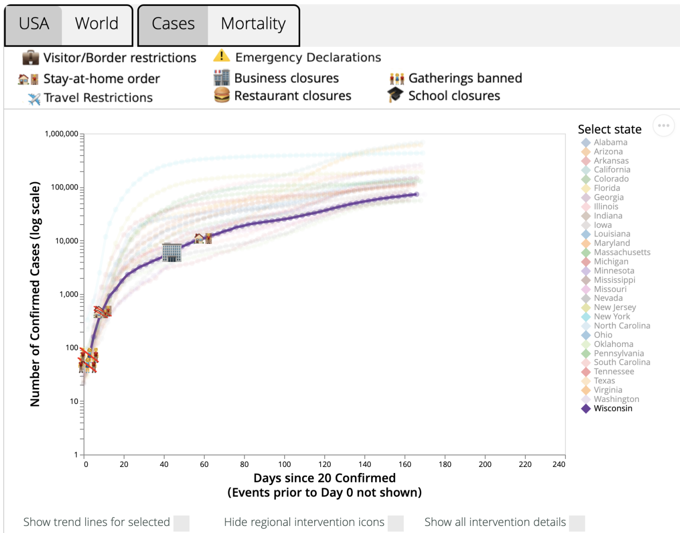

Fig. 1: Example of an interactive graph shown on the COVIDVIS website as it stands today: the charts stopped being manually revised after late May 2020.

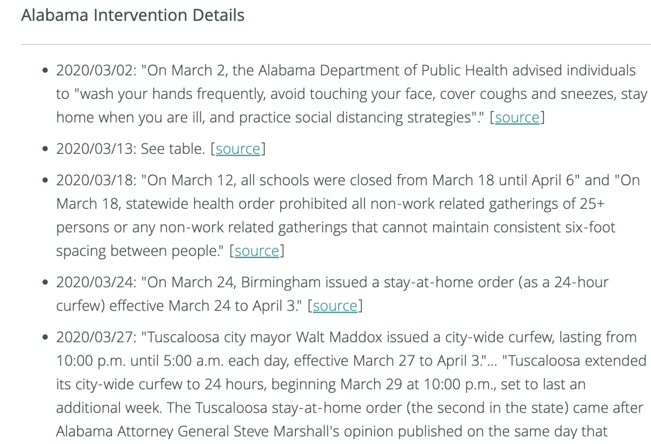

Fig. 2: Example of intervention details and sources shown on the COVIDVIS website.

2.5 Bayesian Cognition for Visualization Perception

The format of our study, wherein we collect visualization priors and posteriors after exposure to intervention visualizations, is inspired by prior work on Bayesian cognition for visualization [40]. While our visualizations have interactive aspects, research shows that interactivity is not always beneficial in improving Bayesian reasoning with visualization [47]. Regardless, we felt that our visualizations' user experience was improved through interaction, and our participants confirmed that the interactivity was beneficial for their understanding. Subsequent research confirms themes that we also discover in our study, such as the fact that the effectiveness of Bayesian assistance can depend on the participant's trust of the data, whether due to the source of the data [38] or how representative the data is [65]. Since our data sources are all institutional, we can map the trust of the source of our data as institutional trust. Other Bayesian cognition approaches focus on belief updating through uncertainty visualizations [34], which we did not incorporate into our study for simplicity.

3 Methods

After collecting, curating, and analyzing COVID-19 case and intervention data, we developed various visualizations to display the effects of interventions in the US. Our goal was to see how priors, such as institutional trust, may influence visualization interpretation and vice versa. This effort would allow us to learn more about developing effective visualizations for future public health events or times of crisis, since information exposure can influence people's behavior and thus the direction of the pandemic or a similar crisis [66].

3.1 Data Collection and Sources

Since this project was started near the beginning of the pandemic, we (including one author who is a public health data mining expert) were initially motivated by determining and visualizing trends in the data based on interventions to gauge intervention effectiveness on initial COVID-19 case and death trends. There wasn't a centralized, trustworthy source of intervention data, such as start and stop points for various intervention orders. As a result, we took it upon ourselves to collect data from various trustworthy sources, organize it into useful formats, and then develop visualizations.

The data collection is based on events from 1/1/2020 to 6/19/2020, including both countries and 50 states and Puerto Rico in the United States. The entire data collection included two types of data: intervention, and reopening records. Intervention data recorded governmental policies that had been announced to respond to the spreading of COVID-19. Examples included "State of Emergency declared", "Travel Restrictions", "Shelter-in-place Order", "K-12 School Closure", "Gathering Limitations", "Bar and Dine-in Restaurant Closure", and "Non-essential Businesses Closure". The full intervention records included 607 US state-level and 283 world intervention policies. Reopening data contained governmental policies to reopen cities. Examples included "State of Emergency lifted", "Travel restrictions lifted", "Shelter-in-place order lifted", "School opened", and "Banning gatherings lifted". As mentioned earlier, data was collected from various sources, such as government websites and verified news articles.

The use of wordings was different in different US states. For example, states enacted different orders to force people to stay indoors. Maryland enforced a stay-at-home order; Georgia announced a shelter-in-place order; Alabama enacted a safer-at-home order to slow the pandemic. Although these orders had similar content, the use of different wordings made it hard to identify and categorize them quickly.

Administrative orders were also inconsistent across different government levels. US counties often announced individual orders in addition to state-level orders. For example, Dallas County imposed a stay-at-home order effective on March 23 [58]. Over a week later, a statewide stay-at-home order went into effect on April 2 [57]. Thus, we needed to record information of various granularities to address these conflicts.

To overcome the challenges discussed above, we formulated a coding scheme to capture intervention policies, and captured three categories of information: 1. Location and Effective Date; 2. Intervention Policy; 3. Details and References. Location and Effective Date include the state/effective date/coverage information of an intervention policy, helping define the range of an intervention policy. The Intervention Policy section refers to the responses enacted by the government. We defined nine policy types ranging from the State of Emergency Declaration to Non-essential Businesses Closure.

Records were extracted from Wikipedia, NBC News, U.S. News, Bloomberg, and other publicly available sources. Four coders manually excerpted records from the above sources, and cross-checked every entry to ensure the quality of the data. The collected data can be found in our GitHub, located under Supplemental Materials.

3.2 Visualization Design and Deployment

Using the aforementioned intervention data, we aimed to provide a public visualization platform of US states' COVID-19 cases and deaths overlaid with points in time representing various intervention measures. The visualizations on the website are built with Altair and depict interventions overlaid as stamps onto log-scale graphs of COVID-19 cumulative cases and deaths, such as in Figure 1. Each intervention stamp is mapped in the legend below the visualization. The visualizations on the site covered the 50 states in the US along with various countries around the world. Under the visualizations are the sources of the intervention data collected for the corresponding graph, with an example shown in Figure 2.

The data, sources, and visualizations were deployed onto `covidvis.berkeley.edu`. The website had around 5500 visitors, with the majority of visits between April 6 and May 20, when other sources of information were hard to come by. The site was deemed to be useful by medical experts such as Bob Wachter, Chair of the Dept. of Medicine at UCSF who said on Twitter "Amazing to see more on-line dataviz tools to help understand the pandemic. Two great new ones show impact of policy changes on cases/deaths: 1) .. 2) COVIDVIS"[1]. The site is still live, but stopped automatically updating in Fall 2020.

We took inspiration from this initial visualization project to conduct a subsequent user study on perception. The initial visualizations share similarities to those of the subsequent study, such as having intervention stamps. However, our new visualizations included additional interactive features that the initial visualizations did not have, for reasons that we describe below.

4 Study Design

Our research goal is two-fold:

- Display COVID-19 case data overlaid with intervention data
- Collect and understand the priors and posteriors of participants' opinions of effectiveness of six different interventions, both in the ideal case and in practice, before and after interacting with such visualizations

We designed a between-subjects user study with 500 participants. We recruited participants from Prolific, rewarding their participation with $2.0 [3]. The average time to complete the study was 7.3 minutes (SD=5). The study was conducted from February 11, 2021 to April 4, 2021.

Our study design explores intervention visualizations. The interventions we focus on include restaurant and bar closures and opening dates, marked onto daily, averaged COVID-19 case graphs. We focus only on establishment closures for three reasons. First, they usually had a clear start and end date. Second, they were common—most states enacted these interventions. Finally, mixing in more categories of interventions, especially those without clear start or end dates, cluttered the visualizations, added confusion, and led to information overload during early runs of the study.

The study consists of three "phases." "Phase 1" and "Phase 3" were very similar in order to measure participants' prior and posterior elicitations. To elicit participants' prior and posterior distributions, we gather opinions of COVID-19 interventions from participants using Likert scales. These questions ask the participant for their opinions on the effectiveness of various COVID-19 interventions: mandatory lockdown orders, restaurant/bar closures, mask orders, school closures, restricting indoor gathering orders, and social distancing orders. We also have two sets of Likert scales for this question, one for where the interventions are followed by everyone, and one for if these interventions were implemented locally in the participant's area today. We also add a visual component by letting participants mark a blank, unlabeled graph of daily, averaged COVID-19 cases with their belief regarding start/end dates of the intervention. These questions are in "Phase 1" and repeated again in "Phase 3." "Phase 3" also contains some extra questions inquiring what the participant thought of "Phase 2."

"Phase 2" contains an interactive module, allowing participants to see visualizations of restaurant and bar closures and openings in various states, marked onto daily, averaged COVID-19 case graphs of US states. Participants would need to examine at least three visualizations and answer some attention check questions to move on to Phase 3.

Our study is designed by keeping in mind that data visualization interpretation is a social, narrative-driven experience, as research shows [22, 33, 42, 51]. However, we also realize that observing the world and quantifying it is inherently a political act and therefore deserves ethical consideration [9, 17]. As a result, we acknowledge that our study may not be fully free of bias since both visualization and COVID-19 have politics embedded within them [42].

[1] `https://twitter.com/Bob_Wachter/status/1256406721821503488`

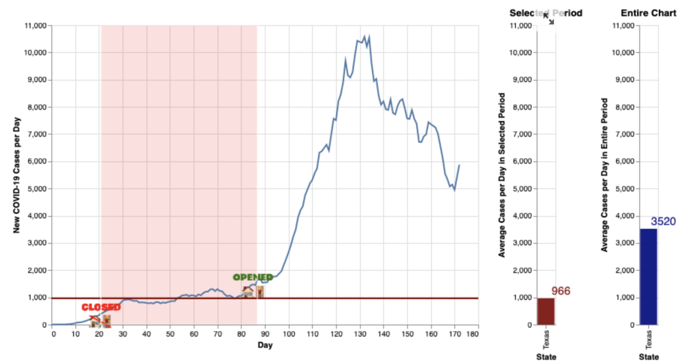

Fig. 3: The graph is interactive, allowing users to highlight parts of the graph to see the average number of cases per day for that highlight. Users can click and drag the red box from one point to another to select a period of time on the graph. The red horizontal line on the graph and the red box on the right of the graph represent the average number of daily COVID-19 cases for the selection area. As the box is dragged, both the line and the box update automatically. There is also a static blue bar on the right that shows the average number of cases per day for the entire chart, for comparison purposes. This allows users to compare the average cases per day in a selected period to the average amount of daily cases for the entire chart.

4.1 Pre-Study Questions

Before participants could officially start the phases of the study, we first displayed a confidentiality statement and study details. Participants were asked to consent in order to participate in the study. Subsequently, we asked them for the following demographic information: Age, State, Gender, Political Party, Race, Education Level, Citizenship Status, and Occupation.

4.2 Phase 1

Phase 1 consists of two main questions:

1. For each of the following orders, how effective are they to you if implemented properly and everyone follows them?
2. For each of the following orders, how effective have they been in practice as implemented in the US?

The first question is meant to capture the "ideal" case for interventions, if everyone followed them. This first question is potentially revealing of how people view interventions themselves by taking human behavior out of the equation. The second question is meant to capture the "reality" case for interventions, or how people viewed interventions as currently implemented. This second question is potentially more revealing on how people see society around them by focusing more on human behavior. Both questions are synergistic as they give us details about two different contexts of intervention perspectives.

Both questions are answered by rating the following interventions on a Likert Scale: Lockdown order (mandatory stay-at-home), Social distancing, Mandatory masks in public, Closing bars/restaurants, Closing schools, Restricting Indoor Gatherings. The Likert scale used for each intervention is: Strongly Ineffective, Slightly Ineffective, Neutral, Somewhat Effective, and Strongly Effective.

We also asked participants to visualize their beliefs on establishment closures by giving a blank graph with a line representing daily COVID-19 cases and allowing them to mark a start and end point of such interventions. This was to encourage visualizing one's own predictions to improve recall and comfort with the visualization platform [39].

4.3 Phase 2

Participants interact with visualizations in Phase 2. We allow users to pick from several states, such as California and Florida, and see restaurant and bar closure dates (start, end) overlaid on a daily case graph of COVID-19 in that state. The visualizations are interactive case trajectory visualizations, overlaid with restaurant and bar closure intervention points. We chose restaurant and bar closures as they had the clearest start and stop points, and thus were consistent to visualize. The graphs shown in Phase 2 are depicted in Figure 3. In contrast to our visualizations on `covidvis.berkeley.edu`, we made our graphs interactive by allowing users to compare average cases in a selected graph region versus the entire graph. Our interactivity was added after receiving feedback from piloting initial versions of our study—wherein participants wanted to quantitatively understand the difference in average number of cases in during different intervention periods—and from receiving positive responses from pilot users after it was added. We also realize that participants have an incentive to complete the study as fast as possible. As a result, we hoped the interactivity exercises would help participants retain information better.

In order for participants to move forward to Phase 3, they must complete three simple questions for three different graphs. Participants are required to view visualizations from states where interventions worked immediately on the graph, and others where they didn't work on the graph at all, in order to reduce bias. This was to not only combat anyone skimming over these visualizations, but also to enforce seeing a variety of charts so that users could at the minimum see how things played out in multiple locations. As mentioned before, this also was to help with retention and encouraged users to actually look at the visualizations themselves [28].

4.4 Phase 3

Phase 3's main purpose was to collect the participants' posteriors following the visualizations interactions in Phase 2. We first asked participants the same main questions as in Phase 1. Then, we asked users three further questions to try to understand their thought process throughout the study. This allowed us to collect valuable qualitative data that could be potentially valuable to understand the quantitative data. The three questions were:

- How did Phase 2 affect your opinion about COVID-19 interventions? (Possible answers: Reinforced my views, Changed my views, Convinced me to seek more information, Didn't change my views)
- Why did you pick the above answer?
- In Phase 2, were there any specific aspects of the visualizations you found particularly helpful in understanding the data?

4.5 Iterations within Study Design

The study design was a lengthy process and went through multiple iterations. We built the study using Streamlit, which allowed for easy prototyping of the study. The visualizations themselves went through multiple iterations, some of which can be found in the supplementary materials.

5 Data Analysis

In order to understand participants' opinions about COVID-19 and their interpretations of the visualizations, we conduct both qualitative analysis of the responses to questions in Phase 3, along with quantitative data analysis of Likert scale data.

5.1 Qualitative Analysis

Our qualitative dataset was made of up the three short-form responses to questions posed in Phase 3. We began by putting together some common codes that we extracted from discussing themes we saw within the responses. Two of the authors conducted open coding on a line-by-line basis separately using the same code book, then compared code results in order to compare any differences. Any differences were discussed and then narrowed down to a chosen code. We also came up with "sub-codes" in which some codes had some extra details that we thought might be relevant. This was especially helpful for some high-level codes which were descriptive but also left room for interpretation. For example, we had a code called "New Realization", but there were sub-codes within this such as "Lockdowns Helpful" and "Lockdowns Unhelpful" which described the direction of the new realization that occurred. An example of a "New Realization" with the "Lockdowns Helpful" subcode is "Because after going through this pandemic, it seemed that no matter what was put into place, nothing was working. But after taking this survey and looking at the numbers, I see now that there is a method to what our state governments do" (P20).

In general, we found that these codes generally described various responses pretty well. They also were helpful when paired with quantitative analysis, as we were able to see changes from Phase 1 to Phase 3 within certain codes. The codes were also assignable to certain personas identified, described in Section 6.2.

Intervention Order	Phase 1 (mean)	Phase 3 (mean)	Shift
Stay-at-Home Effectiveness	2.85	3.88	+1.03
Social Distancing	2.99	3.85	+0.87
Mask Mandates	3.33	4.03	+0.70
Establishment Closures	3.08	3.97	+0.88
School Closures	3.20	3.73	+0.53
Indoor Gathering Restrictions	2.98	3.89	+0.91
Average	3.07	3.89	+0.82

Table 1: Phase 1, Phase 3, and Shift averages for COVID interventions assessed in the "reality" case, where participants were asked about effectiveness of such interventions in practice

Intervention Order	Phase 1 (mean)	Phase 3 (mean)	Shift
Stay-at-Home Effectiveness	4.54	4.48	−0.07
Social Distancing	4.37	4.26	−0.11
Mask Mandates	4.43	4.35	−0.08
Establishment Closures	4.22	4.38	+0.16
School Closures	4.11	4.19	+0.08
Indoor Gathering Restrictions	4.35	4.33	−0.02
Average	4.34	4.33	−0.01

Table 2: Phase 1, Phase 3, and Shift averages for COVID interventions assessed in the "ideal" case, where participants were asked about effectiveness of interventions if everyone followed them

5.2 Quantitative Analysis

Within the quantitative analysis, we started off by converting the Likert scale answers in Phase 1 and Phase 3 into numerical data. We used the following mapping: Strongly Ineffective (1), Slightly Ineffective (2), Neutral (3), Somewhat Effective (4), and Strongly Effective (5).

Quantifying the Likert scales allowed us to compare priors and posteriors easily, as they could be averaged and split across various scales, such as different interventions and/or demographical factors. To verify that the results were was statistically significant, we used the Wilcoxon signed-rank test to compare between two averages. The Wilcoxon signed-rank test is like a t-test, in that it tests the statistical significance of two comparative samples, except that unlike the t-test, the Wilcoxon signed-rank test doesn't assume a normal distribution. Any analysis and interpretation performed below is only with statistically significant comparisons.

Afterwards, we used the Likert scale conversions in Phase 1 and Phase 3 and compared them. These served as our priors and posteriors that we aimed to acquire, using Kim et al. as a model [40].

6 Results

We found that intervention visualizations generally caused a shift towards a more positive view of COVID-19 interventions, however, people often thought of them as good ideas that are difficult to implement in practice. The overall shift from Phase 1 to Phase 3 for interventions support was $+0.82$, shown in Table 1.We performed a Wilcox-On test on Likert scale data (1=strongly ineffective and 5=strongly effective), since data was not normally distributed, and found that the shift was statistically significant (p-value range: $[1.32 \times 10^{-33}, 1.75 \times 10^{-15}]$. In general, people were neutral (3.07) on interventions on average during Phase 1. After presenting the visualizations, we found that the average shifted to 3.89, or a shift of $+0.82$. However, this average belies the fact that different individuals shifted by both different amounts and different directions as we will see later.

We found many people changed their opinions on COVID interventions based on the graph towards a positive direction. One participant said: "I see that they did in fact help more than I had originally thought." (P8). Some other participants recognized the complexity of understanding the effects of the interventions: "Phase 2 helped me to realize that it can be difficult to evaluate the effectiveness of each of these measures in the real world when many may be occurring at one time." (P54)

People commonly believed that interventions were good ideas, but not in practice. We explored the difference in shifts from the "ideal" case and the "reality" case. "Ideal" in this sense meant that everyone would follow interventions that were put in place, while "reality" meant the way interventions were put into place now. We can see the difference in Table 1 versus Table 2. This difference is also evident in our qualitative data, such as this response: "I thought certain mandates were only somewhat effective in practice, but I think they were strongly effective in practice given these charts." (P119)

We found that people interpret the same visualization differently based on their priors. Since priors are relative, this means that a visualizations has different effects on different people. Some people had high expectations for intervention effectiveness and as a result, their quantitative shift was negative.

> "It changed my views slightly (unfortunately for the worse), as there seemed to be a lot of new cases based on the numbers, despite these interventions taking place." (P383)

Other people had low expectations for intervention effectiveness and therefore had a positive quantitative shift.

> "I didn't think closing restaurants had as much effect as it did, but seeing the numbers changed my mind." (P267)

Given the wide range of reactions to the visualizations, we sought to study what factors may predict how someone's perceptions of the interventions change after seeing the visualizations.

6.1 The Key Factors of Institutional & Societal Trust

We hypothesize that the key concept that governs and also allows us to potentially predict a person's reaction to an intervention visualization and vice versa is trust. We found that participants relied on two key levels of trust in their responses. As a result, we break down trust into 2 types: institutional and societal trust [62].

Institutional Trust. Trust in large, prominent institutions, such as the government, various organizations like the media, universities, and more. Generally, these have been the main sources of information throughout the pandemic in regards to pandemic data and updates.

Societal Trust. One's trust in those around them. This is not limited to people in the real world but also applies to one's interactions with others online, which is important to note since COVID essentially forced most people online, increasing information flow through peer sources dramatically.

The pre-Phase 2 questions can essentially be mapped to these two types of trust, with institutional trust impacting the "ideal" case and societal trust impacting the "reality" case. By measuring these two trust factors beforehand, we may be able to predict how someone will react to a visualization of pandemic interventions. To understand how trust plays a role within participants, we divided participants into distinct personas based on quantitative criteria detailed in Table 3, described next.

Persona	Quantitative Criteria
COVID-Cautious	Phase 1 (reality) mean ≥ 3.75
New Believer	Reality shift ≥ 0.50 OR Phase 3 (reality) mean ≥ 3.75
Skeptic	Reality shift < 0.50 AND Phase 3 (reality) mean < 3.75

Table 3: Criteria for Persona Categorization.
COVID-Cautious: Believe in intervention effectiveness before and after Phase 2.
New Believers: Convinced that interventions were effective in practice after Phase 2.
Skeptics: Unconvinced by visualizations. Neutral or negative support of interventions before and after Phase 2.

	COVID-Cautious	New Believers	Skeptics
Count	133	193	97
Reality Shift	$+0.20$ (4.20 to 4.40)	$+1.41$ (2.73 to 4.14)	-0.16 (2.42 to 2.26)
Ideal Shift	$+0.00$ (4.60 to 4.60)	$+0.06$ (4.35 to 4.41)	-0.10 (3.60 to 3.50)

Table 4: Shifts in Opinion Regarding Interventions per Persona. Each shift is listed as *Shift* (*Phase 1 average* to *Phase 3 average*).

6.2 Trust Levels of Personas Map to Post-Visualization Shifts and Responses

In order to better understand the role of trust in people's perceptions of the visualizations, we distinguish our participants by creating three distinct role-based personas, described in Table 3. While personas are generally used in design research and product development, we find that role-based personas are useful in our case to understand what role our participants play in society in relation to the COVID-19 pandemic [20]. We decided to develop personas because they were a quantitative way of distinguishing between different personalities within the data. Furthermore, they helped formalize the process of creating qualitative codes and contextualizing the quantitative data [15]. Personas help us empathize with each viewpoint represented by participants and to better understand them [2].

We introduce three personas, each divided and categorized using quantitative parameters, described in Table 3. The quantitative characteristics of each are organized in Table 4. The "COVID-Cautious" are supportive of interventions in both the "ideal" and "reality" case, before and after Phase 2. "New Believers" are those who scored high in "ideal" before and after Phase 2, but had a big positive shift in "reality" after Phase 2. "Skeptics" had low impressions in both cases and had neutral or negative shifts after Phase 2. While we defined each persona through quantitative characteristics, we found that each groups' qualitative characteristics added rich explanations about the behaviors of each participant. The qualitative responses provide us with insights into how certain people react to COVID-19 visualizations and how their priors come into play regarding their reactions.

We found that while the majority of participants experienced a positive shift in their views of intervention effectiveness; there was a subset that actually shifted much lower than the average, with around 18.4% of the study population actually experiencing a negative shift in "reality" intervention effectiveness. Personas help us uncover the story of this group: the Skeptics.

Lastly, we also categorize personas using Institutional and Societal Trust levels in Table 5. For each, we map Institutional Trust to the average Phase 1 "ideal" intervention opinion and Societal Trust to the average Phase 1 "reality" intervention opinion. Trust is considered High if the respective average for the persona in Phase 1 is greater than 3 and Low if that average is lower than 3. In the next few subsections, we discuss each persona in detail, delving into their qualitative responses to understand how visualizations affect their impressions of COVID-19 interventions.

	COVID-Cautious	New Believer	Skeptic
Institutional Trust	High	High	Low
Societal Trust	High	Low	Low

Table 5: Institutional and Societal Trust Levels per Persona. Institutional Trust refers to Phase 1 intervention effectiveness beliefs in the "ideal" case, while Societal Trust refers to such beliefs in the "reality" case. "High" trust is when the respective average of such beliefs is greater than 3, while "Low" is if that average is below 3.

6.2.1 "COVID-Cautious" - High Institutional and Societal Trust

COVID-Cautious people are people who generally had a positive view on interventions both in the ideal and reality case, both before and after Phase 2. As a result, their opinions didn't change much as a result of Phase 2, but their qualitative responses still give us an insight into their impressions.

As seen in Table 4, the COVID-Cautious made up about 31.4% of participants and did not display any change in Phase 3 regarding interventions in the "ideal" case. In the "reality" case, this group displayed a slight positive shift. This is backed up by themes within their qualitative data, explained below.

Reinforced views and new realizations. For example, some noted that the visualizations reinforced their views "about the measures taken to prevent the spread and how effective they are" (P63). Others had new realizations, such as being surprised that "closing restaurants much more effective than [I] previously realized" (P251). Both these shifts were visible in the slight positive shift in the "reality" case.

Lockdowns deemed helpful. Others commented on the data and noted that lockdowns were helpful if people listen: "There is strong evidence of effectiveness in the aforementioned efforts. The actions of whether people follow these orders are key to their success, regardless" (P296). A number of COVID-Cautious people expressed support for interventions and felt that they were necessary in order to keep the pandemic under control.

Visualizations deemed helpful. Lastly, COVID-Cautious people also felt like our visualizations were a helpful tool for understanding, with many praising their interactivity and clarity: "I found the interactive aspects of the graph useful in seeking the average cases within a specific timeframe useful as well as understanding when restaurants closed and opened." (P352)

We can see evidence of both high institutional trust and societal trust within the COVID-Cautious persona group. In this case, the government is the official source of interventions applied.

- High Institutional Trust: "I am strongly in favor of government restrictions to stop the spread of a pandemic." (P50)
- High Societal Trust: "Because I believed these measures were effective before if enforced, the charts show this to be true." (P126)

6.2.2 "New Believers" - High Institutional Trust, Low Societal Trust

New Believers are people who generally had a positive view on interventions in the ideal case, both before and after Phase 2. However, they were negative on interventions working in reality in Phase 1, but they became convinced that they were effective in Phase 3, as seen in Table 4. We see how this shift occurs through their qualitative data, explained below.

New realizations of effectiveness and reinforced views. Many New Believers felt that Phase 2 reinforced their views, though this wasn't as obvious in their Phase 1 answers compared to the COVID-Cautious group. This group generally had positive views of interventions, but not of them in "reality," which means they didn't think they were being followed correctly or that they were effective in practice. As a result, the data not only reinforced their "ideal" case views, but also led them to realize that the interventions were more effective than previously believed: "I already thought closing restaurants/bars was effective, but the graphs showed me that it was more effective than I thought in curbing COVID infections" (P100). Many admitted that they were "wrong in [their] perception of COVID-19 intervention" (P387), realizing that their belief about COVID-19 interventions working in an "ideal" case carried over to reality too.

Lockdowns deemed helpful—even if their experience indicated hesitancy in following directives. Like the COVID-Cautious, many New Believers noted that lockdowns were helpful if people listen: "I think people before in the US did follow measures more, but now they would follow them less if stipulated. Either way, I think these interventions are effective to some degree" (P201). While this group admitted that the interventions worked better than they believed, there was still some hesitancy about them being fully followed by people over time.

Visualizations deemed helpful in changing beliefs. New Believers also believed visualizations were a helpful tool to intake and understand the data shown: "The structure of the graph itself was very helpful. It clearly denoted when bars/restaurants were closed and especially when they were open (as evidenced by the dramatic spike(s) in cases).... I loved the interactive design of the graphs and enjoyed using them" (P305). Interactivity and the comparison bars were mentioned often as an useful aid for understanding.

Overall, this persona group showed the same traits as the COVID-Cautious but were more pessimistic about society's ability to take part in interventions.

Within the New Believer group, we see clear evidence of high institutional trust and low societal trust:

- High Institutional Trust, Low Societal Trust: "I believe in prevention measures, but the trick is how effective they can be without any mandatory orders or enforcement. Many remain ineffective because there are a lot of selfish idiots out there." (P307)
- Low Societal Trust: "there are so many unknowns with covid, and we really don't know who many people are listening to the stay at home orders, mask wearing etc. I work at a hotel and see alot of people coming to a hotel just to 'get away', not wearing a mask and have no business being out." (P294)
- Low Societal Trust: "I still believe that if everybody followed cautions laid out by the government, we wouldn't still be in a lockdown." (P176)
- Low Societal Trust: "I know they are helpful if people actually do what they are supposed to do, the problem is those that don't follow the guidelines." (P49)

The results of the New Believers fall in line with the same shift that Padilla et al. saw in their risk score assessments from incident COVID-19 visualization exposure [50]. Our participants found that interventions were more effective than initially expected after visualization exposure, while Padilla et al. also found the same after participants with very high risk scores slightly lowered their risk assessment of the pandemic.

6.2.3 "Skeptics" - Low Institutional and Societal Trust

Skeptics were around neutral on interventions in the ideal case, both before and after Phase 2. However, unlike the above two personas, Skeptics actually had a slight shift downward in the reality case as a result of Phase 2 (see Table 4. Their qualitative responses were also notably different, which allowed us to categorize these personas in the frame of trust. Here were the qualitative themes that emerged:

The visualizations need more context. Many participants were under the impression that the data is incomplete or obscured the true picture. For example, one participant said: "I do not necessarily think the data shown reflects the entire story" (P9). Many wanted more information and context around both the data and visualizations.

Steadfast in their priors. Skeptics stuck to their beliefs, even in the face of new information, seen both quantitatively and qualitatively. For example, one participant said: "I picked the answer because I'm sure I'm right about the facts on COVID" (P217). They did budge from their priors, some even moving slightly lower in their impression of intervention effectiveness in Phase 3.

Skeptical, suspicious, and untrusting. Many participants even questioned the nature of the pandemic and the pandemic data collection itself—poking holes at how cases are counted and how the data is collected, and speculating whether there was an underlying conspiracy. For example, one participant said: "The definition for a 'case' of COVID-19 is still nebulous" (P37).

There is a notable difference in the qualitative responses of the Skeptics versus those of the first two personas. Their responses are far more inquisitive, either questioning the data or asking for more information, and distrusting. For example, one participant said: "I stuck to my own answers and did not trust the data I was given" (P409). Unfortunately, we do not know why this participant specifically didn't trust the data given, but we can infer through the collective responses of the persona. For example, one participant cites political polarization and distrust in the government: "This issue is so politicized, and the government is so dishonest, that we have reasons to be skeptical of even 'official' data. And honestly, I'm so tired of hearing about COVID that it's hard to care anymore" (P332). As a result, when comparing the answers of the Skeptics to the first two personas, Skeptics trusted their own personal experience much more than the data presented to them.

Furthermore, this group rarely commented on the visualization itself. Instead, many requested more data, transparency, or other external sources before they felt they could trust the visualization shown.

The Skeptics showed a marked difference in their trust levels, such as evidence of distrust in institutions like the government and media. We also see additional examples of low societal trust:

- Low Institutional Trust: "Also, don't forget that our friends in the mainstream media chose to ignore the obvious cover-up of nursing home deaths by the governeor of New York (https://www.nytimes.com/2021/02/12/nyregion/new-york-nursing-homes-cuomo.html) until just recently, so that may change the number that were presented here." (P206)
- Low Societal Trust: "a bunch of people didn't follow the rules and then started going out. These measures didn't work in the U.S. because people kept doing the wrong thing." (P121)

While we do not have enough data to characterize Skeptics as anti-maskers, we note that research by Lee et al. into coronavirus skeptics has shown that "anti-maskers value unmediated access to information and privilege personal research and direct reading over 'expert' interpretations" [42], which are similar qualities shown in our Skeptics. Furthermore, the reasoning behind Skeptics' resistance of shifts in opinion are consistent with work by Peck et al. where people didn't change their opinions on data because they ranked other criteria higher (such as other sources) [51]. Some Skeptics also felt that the visualizations and data shown wasn't contextualized or transparent enough, possibly further eroding trust in the visualizations' validity. This may have played a factor as we know that transparency generally leads to an increase in trust [53].

6.3 People Trust Themselves First

We found that notably, many people across all groups trusted themselves first. They commonly used their own prior knowledge or personal experience as a guide [43]. This makes sense given that data can be personal and that those ties may supersede many other dimensions of design [43, 51]. In the case of the COVID-Cautious personas, this meant a reinforcement of their views: "Because I already thought that the COVID-19 interventions were highly effective" (P67). The New Believer personas also had the same reinforcement that interventions were effective, but needed a little nudge of data to have more conviction with it, as shown by the quantitative data: "I already think that, when followed properly, the given guidelines and mandates can be effective" (P182). The Believers believe that interventions work based on their own view of the world/society or are convinced that they have been working by the data visualizations presented, not by the word of public health officials. Both personas display traits of anti-conspiratorial thinking, convinced by "empirical evidence to validate truth." [55].

For Skeptics, we found that they generally had no change or were skeptical in their views due to their higher self-trust overall, regardless of contradictory data: "Because my personal experience is more accurate than some graph" (P379). The Skeptics believe that interventions don't work, believer their own personal experiences first, or believe that the data is manipulated, which is a common belief among COVID-19 skeptics [42]. Others fall into conspiratorial thinking, such as "I picked my answer by my opinion. Covid-19 is fake and is not real. The people who get sick just get told that so the government and health facilities profit from it" (P258). In the vein of self-trust, these people refuse to adjust their belief systems even when confronted with different information and "put more faith in their ability to use intuition to assess factual claims..." [55].

Even though we designed our study to reduce bias as much as possible, we realize that, in turn, the data loses some of its "narrative." Scheufelea et al. show that individuals are more likely to accept information that appears to follow a logical narrative and comes from a "credible" source [55]. However, states that locked down early didn't necessarily have better outcomes than those that locked down later. As a result, the story of intervention effectiveness is quite messy in reality and can reduce credibility in the data, even though the two are unrelated. Grossman et al. also show that COVID-19 responses have been affected by political partisanship by both governments and the public [29], so our visualizations will also inevitably be seen sometimes through a political lens [9, 42, 43].

It also would have been beneficial to know if our research team were seen as the institution. If we had posed as an individual researcher doing research for a blog or newsletter, would people's trust have been different? In general, we tried to be as transparent as possible in our communications with participants, noting that transparency increases trust [53]. It is definitely possible that the fact that the study and data was presented by an institution played a role. However, no qualitative comments explicitly mentioned us or our institution(s). Instead, if there were qualms, a comment on the data and the way it was presented would be made instead: "I had heard in the media that the changes in new cases are reflected two weeks after a closing/opening order. Your graphs seems to reflect the changes immediately. I don't know who's right or wrong here" (P253). This feedback, asking for more context and information, is useful for future work.

6.4 Data Visualizations Boosted Societal Trust Levels

While we inevitably focus on Skeptics due to their resistance, we do want to highlight the average shift of the entire participant population being positive—indicating that visualizations and communication matters. The quantitative and qualitative data of the COVID-Cautious and New Believers show us that the visualizations boosted societal trust slightly to the point where their view of intervention effectiveness in reality shifted positively. Though our visualization only displayed one intervention, these two groups gauged the multifaceted impacts of the crisis [66]. They extrapolated one intervention's effectiveness to other interventions. This finding is important, as Bollyky et al. show that if societies had increased societal (interpersonal) trust to the global 75th percentile (marked by Denmark), global infections might have been reduced by around 40.3% [10]. The visualizations themselves also garnered approval from participants, with comments on the:

- **Interactivity**: "Being able to highlight a region and see average cases per day was really useful!" (P71)
- **Clear Icons**: "I liked to have the little house so I could tell which date I selected for closing or opening." (P421)
- **Comparison Tools**: "Being able to have the 'Selected Period' and 'Entire Chart' bars on the right helped simplify what I was

looking at." (P225)

7 Discussion

Our finding that visualizations change the perception of intervention effectiveness is consistent with prior COVID-19 visualization studies that studied the effects of visualization exposure, such as risk perception [50]. Our findings on the role of trust in COVID-19 visualization reactions can help various stakeholders make better decisions about the creation and presentation of visualizations. Overall, participants valued the interactivity of the charts, consistent with prior work showing interactivity as a useful retention tool [28]. Usually, most charts in the public sphere employ static graphics, but based on responses, we found that allowing users to play around with charts both increased their understanding of the data and also enabled them to remember the "narrative" that they got out of it [17,42]. We note that developing effective visualizations for public health is still very much a work in progress. Hence we discuss needs for participants viewing visualizations and actionable takeaways for stakeholders in visualization creation next.

7.1 Audiences Want More Context Around Visualizations

Participants requested more context around visualizations. Some mentioned that our visualizations needed to have more data, such as all interventions simultaneously displayed on the graph, to tell the whole story. Others asked for more types of visualizations with different metrics measured, such as percentage of population infected instead of raw numbers. These comments also reveal a point about the "ethics" of visualizations, in which they can easily be manipulated in order to impose a certain narrative [1,9,17,42]. The COVID-19 visualizations we showed were clean, but reality isn't so clean—with multiple political, social, and other events happening constantly. The absence of such variables was noted by some participants. Determining mechanisms for simultaneously making a clear point, while also not appearing to obscure the data and conveying the complexity is a challenge.

With public health messaging changing rapidly (including contradictions), we propose, for future work, visualizations with more detailed timeline markers of certain events, along with more varieties of visualizations available to viewers. For example, a participant viewing a COVID-19 visualization of cases per day should be able to quickly switch to one of newly infected percentage of population per day. They should also be able to set the axis ranges, and whether they are log scale. The sources of data, how it was collected, how it was transformed, and how it made its way onto the screen is also crucial. In our case, describing how intervention data was collected could have helped persuade certain participants. We need transparent disclaimers or explanations acknowledging a lack of certain data when it comes to visualizations, e.g., if data is missing from certain locations or time periods.

7.2 More Transparency Needed from Public Health Officials and Institutional Stakeholders

In our results, we focus on the importance of trust. Visualization makers, such as journalists and scientists, should do their best to be a trustworthy source [38]. While sometimes this can be pre-determined by a viewer's priors, generally we found that viewers value context and transparency. Many viewers were convinced to seek more information as a result of our visualizations, letting us know that we could've done a better job with providing more context around the data in visualizations ("I feel the information I know has many gaps or conflicting points, so I need clarification"–P328). As Rawlins notes, transparency improves trust [53], including in institutions such as the government [5]. Since many visualization makers represent institutions, being transparent is a valuable way to build credibility with the audience regardless of their priors. Furthermore, people's priors are influenced by where they live and how they spend their time, some of which can be inferred through technology today. There is an opportunity for basic personalization of visualizations here based on readily available demographic data.

7.3 Towards Actionable Visualizations

Pandemic response in free societies critically depends on the ability of public health officials in persuading people to take required actions. We know today that low government or institutional trust has led to lower vaccine uptake, and thus, a slowed stopping of the spread of COVID-19 [61]. Our study also shows signs of this in our Skeptics, where low institutional trust has led some to denying the validity of COVID-19 data or existence. Our study also showcases some of the necessary ingredients in getting us towards more *actionable* visualizations. Building more trust in institutions and adding more context to visualizations can help us persuade audiences to take the right action to help combat a pandemic more effectively.

We believe that future studies can focus on seeing how the COVID-19 pandemic, governmental responses, media coverage, and people's anecdotal experiences has affected people's trust in institutions and society. Since trust is such an important factor in societal stability [52], such studies can also provide insight into building more effective visualizations in times of crisis.

7.4 Limitations and Future Work

While trust became a significant theme in our findings, we did not set out to study trust at the onset. Therefore, we did not collect any data about trust specifically. Future work can more directly study trust, for instance by asking participants what information sources they trust and why. Other data we collected, like our demographic data, yielded no particularly notable trends when analyzed.

Moreover, our participants don't represent the population of the US as a whole—we did not ensure representation from every single US state and county, nor did we ensure representation from individuals across ages, spoken languages, races, political affiliations, and educational backgrounds. Future studies can consider employing more fine-grained sampling of participants. As a result, our results may not speak for the entire US population, though the takeaways are consistent with similar lines of research regarding trust [59]. Furthermore, our analysis is US-centric as we only showed visualizations regarding US states. We also did not conduct a state or demographic-based breakdown since our participant pool was limited. Future work could focus on a more diverse, worldwide participant pool.

While our first two limitations are related to study's data collection, our last limitation is related to the platform we actually built the study on. We built our study using Streamlit (`streamlit.io`), which is not a traditional survey platform. Streamlit is used to build web apps to explore data, but we found it to be stable enough to build our study with and it fit well with our workflows. However, initial responses from some participants resulted in many drops and/or longer completion times because Streamlit and the server we hosted it on, Heroku, were not able to handle more than 5-10 participants at once. This was not something we had foreseen beforehand, so we had to make sure that only 3 participants could be taking the survey at a time.

8 Conclusion

In this paper, we conduct a study to measure people's priors (Phase 1) and posteriors (Phase 3) in relation to COVID-19 intervention visualizations (Phase 2), primarily focusing on establishment closures. We identified three primary personas that arise out of a model of binary trust: institutional and societal trust. Each trust combination maps to a persona. Someone with both high institutional and societal trust generally already has positive opinions regarding intervention effectiveness and therefore are considered COVID-Cautious. Someone with high institutional trust and low societal trust, initially, is what we called a New Believer—this person was most impacted by the intervention visualizations in Phase 2. Lastly, someone with low trust on both scales is a Skeptic. We go on to identify potential causes for such trust levels. We find that trust and personal experience has a significant impact on the reception and interpretation of interventions visualizations. Future visualization designers, especially targeted at the general public, should be mindful of making visualizations more transparent with their data and provide more relevant context. Furthermore, customizing the visualizations to the individual given their priors could also be important to influence people's behavior.

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