“Must Be a Tuesday”: Affect, Attribution, and Geographic Variability in Equity-Oriented Visualizations of Population Health Disparities

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ABSTRACT

This study examines the impacts of public health communications visualizing risk disparities between racial and other social groups. It compares the effects of traditional bar charts to an alternative design emphasizing geographic variability with differing annotations and jitter plots. Whereas both visualization designs increased perceived vulnerability, behavioral intent, and policy support, the geo-emphasized charts were significantly more effective in reducing personal attribution biases. The findings also reveal emotionally taxing experiences for chart viewers from marginalized communities. This work suggests a need for strategic reevaluation of visual communication tools in public health to enhance understanding and engagement without reinforcing stereotypes or emotional distress.

Index Terms: Health Equity, Public Health Communication

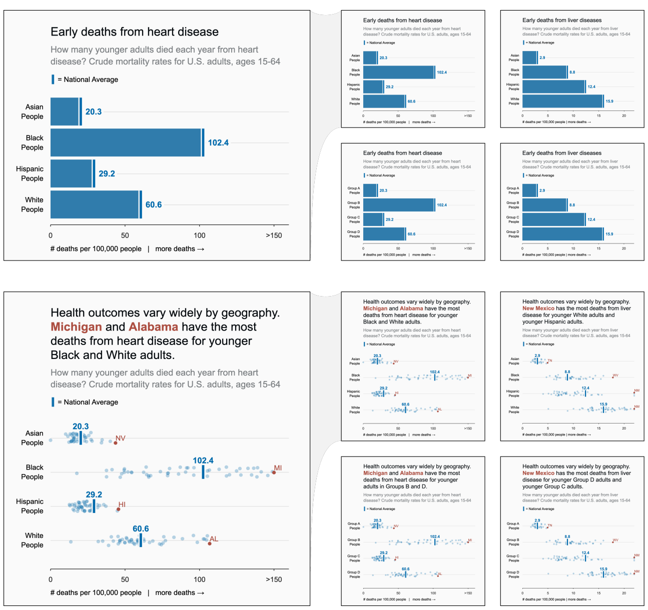

Figure 1: Right two columns: The eight stimuli charts, as either **bars** or **geo-emph** charts, showing crude mortality rates for heart or liver disease, for either race or letters groups.

1 INTRODUCTION

Tracking and improving health outcomes for marginalized communities is a top priority for public health in the United States [51]. However, effectively communicating health equity issues may not be as intuitive as simply plotting group-level outcome disparities [40, 31]. For example, consider this participant's response to a stimuli chart (Figure 1), showing younger Black adults' disproportionate risk for heart disease:

“I'm a Black man with high blood pressure, whose father died of a stroke. My niece has been on blood pressure medication since she was EIGHT. I look at this chart and think, ‘Must be Tuesday.’”

His comment reveals not only a sharp sense of humor but also a striking sense of fatalism. Affective responses like these are a complicated side effect of the chart, reflecting the underlying data seen through viewers' lenses of lived experience and prior beliefs. Viewers' *causal attributions* (i.e., how they ascribe causes to health disparities) are another side effect that may be difficult to anticipate. For example, viewers may (unconsciously) attribute unsupported underlying causes to the outcomes shown in Figure 1, despite the charts offering no such causal information.

Although public health communication often centers on conventional objectives such as risk calibration, behavior change, and policy support, affective responses and attributions present unique challenges for public health and health equity [52, 40]. For example, fatalistic feelings may inhibit health protective behavior [33, 27] while attributing health outcomes to personal choices or genetics is associated with decreased support [49, 44, 19].

In this study, we compare two approaches for visualizing health disparities. The traditional bar chart (**bars**) shows overall mortality rates for four groups. The geography-emphasized chart (**geo-emph**), an extension of prior work [23], includes the same overall mortality rates but uses annotations and jitter dots of U.S. states to emphasize within-group differences (and between-group overlap). We find that these two approaches have similar effects on conventional health communication goals (i.e., risk assessment, behavioral intent, and policy support) but significantly different effects on health equity goals (i.e., reducing misattribution of causes).

1.1 Contributions

For public health practitioners, we demonstrate that visualization design choices can influence the public's causal attributions of health disparities, finding that the **geo-emph** approach can move participants' attributions from personal toward external explanations. Further, our findings suggest that adopting the **geo-emph** approach would not require sacrificing conventional communication goals. We also demonstrate the method's external validity and generalizability across diseases (varying which participant group is most vulnerable to either disease) and group types (race or letters).

We also contribute to the visualization literature by offering further evidence of visualizations' influence on viewers' attitudes, emotions, and beliefs, beyond what is strictly entailed by the underlying data, as well as the need for carefully considered communication goals [26, 30, 55, 23, 24, 2, 10]. In particular, we demonstrate the importance of social psychology and other biases in understanding how viewers make sense of data visualizations that reach diverse audiences or highlight social identities such as race, gender, class, or politics [23, 24, 8, 29, 20, 57, 15]. Our findings emphasize that commonly used visualizations can lead to unexpected consequences when not designed with minoritized communities in mind.

2 BACKGROUND

Communicating Health Disparities. Health disparities are “differences in health that are systematically associated with being socially disadvantaged” [6]. Institutions track and communicate group-specific health outcomes for accountability, policy support, agenda setting, intervention tailoring, risk calibration, and promoting healthy behaviors [6, 44, 19, 52, 21, 42, 18, 2, 52]. Educating the public on the social determinants of health is a related goal, critical for contextualizing health equity issues [35, 6, 31, 42, 51].

Social Comparison Frames. Communicating health disparities can adversely impact population health when highlighting between-group differences [40, 31]. Contrast effects can distort risk perceptions [18, 4, 31, 43]. Comparisons to groups with worse outcomes may undermine policy support [46, 31, 40] and negate otherwise effective behavior change interventions [34] while comparisons to groups with better outcomes may invoke fear, despair, resentment, and fatalism, undermining behavioral intent or information acceptance [14, 47, 27, 31, 40]. Further, stigmatized groups' risk of ostracization may undermine seeking testing or treatment [40].

Attribution. Visualization viewers' unsupported causal attributions may undermine policy support and promote harmful stereotypes. Individuals more readily support policies when they perceive the beneficiaries to lack agency, such as when social determinants of health drive health outcomes rather than personal choices [49, 35, 36]. Attributions may also influence perceived policy efficacy. For example, outcomes attributed to genetics may receive less support for policy interventions because they are perceived as immutable [44, 19]. Attribution biases also underly issues with framing outcomes for minoritized communities in terms of their deficits relative to more dominant social groups (i.e. "gap gazing" or "deficit thinking") [21, 9]. Deficit thinking is characterized by "blaming the victim," or misplaced personal attributions, where viewers misattribute outcome disparities to more personal, intrinsic differences between groups of people [48, 23, 9]. Thus, deficit-framed messages can perpetuate harmful social stereotypes and lead policymakers to misdiagnose systemic issues as those of personal responsibility [41, 9, 25].

Health & Social Visualizations. Improving risk calibration during health decision-making is a crucial achievement for data visualization [13, 3]. For example, icon arrays or waffle charts can improve risk judgments of treatment efficacy [17], even for low-numeracy viewers [16]. Similar approaches can contextualize marginal risks of side effects [58] and reduce vaccine hesitancy [12]. Recent work also offers epidemiologists tools to more accurately convey pandemic forecasts, calibrate risk perceptions [38, 39], and address misperceptions of COVID-19 as an urban problem [11].

Visualization design may help mitigate risks in communicating health disparities. Viewers' tendencies to underestimate within-group variability, exaggerate between-group differences, and read spurious cues as signs of causality [22, 28, 53, 55] suggest a pathway for misattributing differences between social groups, which can be mitigated by highlighting within-group outcome variability [23]. More respectful, humanistic group representations [8] and trust-conscious designs may offer insights into managing negative affect and information resistance [10, 14]. Understanding how viewers' prior beliefs affect information interpretations may help manage pre-existing stereotypes and prejudices [56, 44]. Visualizations' social normative influences also suggest opportunities for improving group-specific policy support, behavior change, and adherence to public health guidelines [29, 20, 24, 1, 37, 52]. This body of prior work provides a foundation for our prediction that **visualizations highlighting overlapping within-group *geographic* variability in health outcomes can mitigate the attribution biases underpinning harmful health stereotypes.**

3 Study Design

Population. We aimed to recruit 50 Black and 50 White participants from the United States for each of our eight between-subject dimensions, totaling 800 participants, crowd-sourced through Prolific. To ensure consistent racial identification, we excluded 20 participants whose self-reported race on our survey differed from their Prolific profile and recruited 20 replacements (n = 820). Additionally, we removed 37 participants over 65 years old who were not represented in our stimuli. After these adjustments, our final sample size was 763 people, identifying as 368 women, 379 men, and 16 individuals of nonbinary/third/no genders, with an average age of 38.5 years (SD = 11.1).

Experiment Design. The experiment was a mixed within- and between-subjects design, with four between-subjects dimensions: 2 (race: Black and White) x 2 (disease: heart and liver) x 2 (chart condition: **bars** and **geo-emph**) x 2 (group label: race and letters). This design created 16 between-subject groups, with each participant viewing only one chart. The within-subject measures included repeated questions that participants answered at the start of the survey and again after viewing the visualization (complete questions in the supplement and overviewed in Sec. 3). The goal of this design was to examine *changes* in participants' responses from before to after viewing the visualization.

Stimuli. The stimuli (Figure 1) showed crude mortality rates for U.S. adults aged 15-64 across four race/ethnicity groups based on 2018—2021 CDC WONDER data [50]. We generated eight variants of the chart for each between-subject condition. For the **group label** condition, we labeled the stimuli rows with racial groups (Asian, Black, Hispanic, and White) or ambiguous letter groups (Group A-D, respectively). We designed the letter group condition to be consistent with prior work, accounting for social desirability biases where participants might suppress personal attributions for racial groups to conform to social expectations from experimenters or themselves [23]. This approach also enhances generality, as outcomes like public support can be sensitive to the types of groups being compared [44, 19]. For **disease**, the stimuli showed either heart or liver disease. For both diseases, outcome distributions overlap substantially between White and Black people, however these two diseases differ in which group is most vulnerable, enabling us to counterbalance such that half of participants viewed their group as the most vulnerable, while the other half saw their group as either the second or third most vulnerable.

Finally, the stimuli varied by chart condition (**chart cond**). The **bars** chart was a conventional bar chart, commonly used in public health communication, where the bar length represents the average mortality rates for each group. The **geo-emph** chart also showed average mortality rates for each group, but used jitter dots (with each dot representing the rate of a single U.S. state) and chart text to emphasize within-group geographic variability and between-group outcome overlap. We note several differences between the charts, including title, mark type, and annotations. We allowed the charts to vary to a large degree because this work aimed not to pinpoint the specific visual element that produces effects but to demonstrate a redesign that considers the impact on minoritized groups.

Procedure. Participants first provided informed consent from the Institutional Review Board and read instructions outlining the experiment's procedures. They then answered initial questions, including demographics, to establish their baseline responses before being exposed to the stimuli. Next, participants viewed their assigned visualization and text identifying the group each participant self-identified with (e.g., for Black participants in the letters **group label** condition, they saw "Based on your earlier responses, you are part of Group B shown below"). Participants were required to view the stimuli for at least 90 seconds before proceeding. During this time, they also provided a brief text description of the visualization to facilitate engagement. Finally, they revisited the same set of questions, answering them a second time to assess the visualization's influence on their responses.

3.1 Measures

We selected the measures to capture key public health communication goals, using 0-100 scales with textual anchors. See the supplement for full question text.

Conventional Measures. These measures represent essential communication goals for health disparity charts [52, 31]. We captured these as composites of multiple questions.

- **Perceived Vulnerability:** Two questions covered probability beliefs of being affected [52, 18], including *"How likely do you think you are to develop [disease] in your lifetime?"*
- **Behavioral Intent:** Six questions covered self-reported willingness to take action toward more favorable outcomes [52], including *"I would consider changing my lifestyle to reduce my chance of getting [disease]."*
- **Policy Support:** Three questions covered support for related policy interventions [32], including *"The government should cover medical expenses for [disease] screening for everyone."*

Attributional Measures. These captured four explanations, each with a single question based on prior work [44], framed as *"People who die most often from [disease] do so because of differences in [explanation]' Do you disagree or agree?"* These included two external-leaning and two personal-leaning attributions:

- **Environment**: *"...environment (e.g., air / water quality)"*
- **Insurance**: *"...health insurance coverage"*
- **Genetics**: *"...genes inherited from parents"*
- **Health Habits**: *"...health habits such as eating healthy food, getting exercise, smoking, or managing stress"*

We also asked a fifth question, choosing between external and personal attributions on the same scale.

Affective Response. A follow-up, open-ended question asked for emotional responses, which we coded for fatalism, surprise, non-surprise, fear, positive emotions, and negative emotions. We established codes with open thematic coding, reviewing and generating codes independently for the first 50 responses. After reconciling these codes, we created a codebook using the converging codes then independently coded the 800 responses. We concluded by refining our codes through discussion, ensuring consistency and accuracy.

4 Analysis

We report each measure using separate, similarly specified linear mixed-effects models for ease of interpretation. The models were specified in R using the *lme4* v. 1.1-35.2 package as follows:

$$\begin{aligned} \text{response} \sim\ & \text{before/after} \times \text{chart type} \\ & + \text{before/after} \times \text{race} \times \text{disease} \\ & + \text{before/after} \times \text{group label} \\ & + \text{question} + \text{politics} + \text{age} + (1|\text{ID}) \end{aligned} \tag{1}$$

The dependent **response** is the participant's response to a question. **Before/after** represents whether the response was before or after seeing the stimuli. **Chart type** is either **bars** or **geo-emph**. **Race** is the participant's reported race, either Black or White. **Disease** is the disease in the stimuli, either heart or liver disease. **Group label** is whether the stimuli showed either racial groups or letter groups. **Question** codes each question. **Politics** represents participants' political alignment, accounting for ideological differences in attribution biases [36], and **age** captures their age. **ID** is the participant's unique identifier, included as a random effect.

We were primarily interested in two chart-related effects. The first involved chart-specific **before/after** main effects, indicating significant impacts for either chart type. The second concerned differential effects between chart types, marked by significant interactions in the **before/after** × **chart type** comparison.

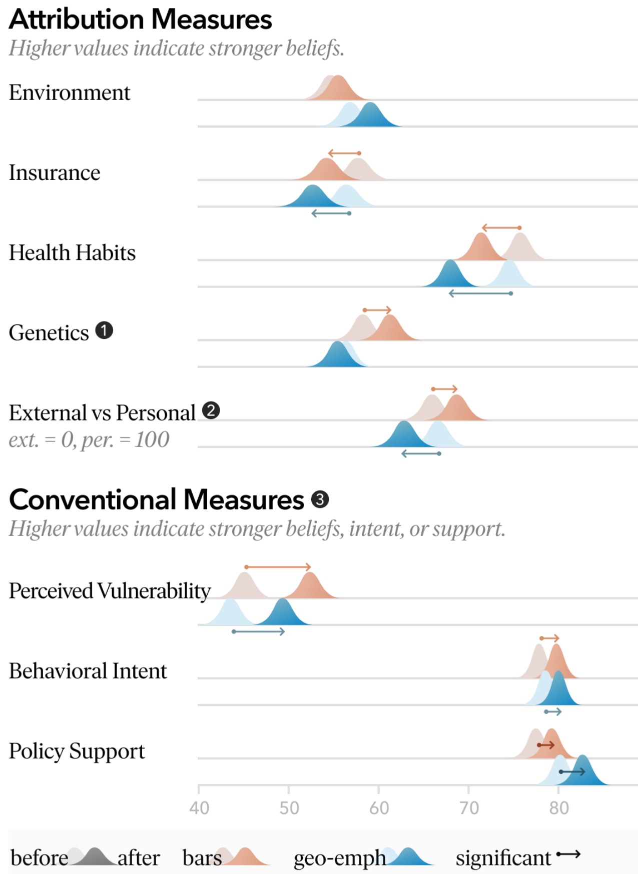

Figure 2: Responses before (lighter) and after (darker) seeing **bars** or **geo-emph** stimuli, broken down by measure category. The chart conditions had similar effects, with the exception of genetic attributions and the external-vs-personal attribution scale. The distributions are based on the 95th confidence interval for the estimated mean. Arrows indicate significant before/after changes.

model	bars	geo-emph	diff-in-diff
Attrib.: Environment	-	+2.3 †	-
Attrib.: Insurance	-3.5 *	-3.8 **	-
Attrib.: Habits	-4.3 ***	-6.5 ***	-
Attrib.: Genetics	+2.9 *	-	-3.8 *
Attrib.: Ext. vs Per.	+2.7 *	-3.7 ***	-6.5 ***
Perceived Vulnerability	+7.2 ***	+5.8 ***	-
Behavioral Intent	+1.9 ***	+1.5 ***	-
Policy Support	+1.7 **	+2.5 ***	-

Table 1: Significant differences in estimated marginal means for the post hoc comparisons (shown in Figure 2). Values for **bars** and **geo-emph** show the differences in participants' responses before and after seeing either stimulus. The diff-in-diff column shows the significant interaction coefficients for **before/after × chart type**. Stars indicate p-values where $* \leq 0.05$, $** \leq 0.01$, $*** \leq 0.001$.

5 Results

Table 1 summarizes the results, detailing significant differences for either chart and significant interactions (labeled as diff-in-diff) between charts. See sections 2.2—2.3 in the supplement for full model results. Figure 2 plots these same results on the original response scale. As Table 1 and Figure 2 show, **bars** and **geo-emph** had similar effects for six of eight measures: Both charts increased perceived vulnerability, behavioral intent, and policy support (Fig. 2 ❸). There were two significant differences between charts (**before/after** × **chart type**). First, for genetic attributions ($\chi^2(1) = 5.05$, $p = .025$), **bars** increased genetic attributions by 3.8 points relative to **geo-emph** ($MD = 3.81$, $SE = 1.7$, $p = .025$, Fig. 2 ❶). The second was for the combined external-vs-personal attributions ($\chi^2(1) = 17.96$, $p \leq .0001$), where, relative to **bars**, **geo-emph** moved responses 6.5 points away from personal attributions toward external attributions ($MD = 6.47$, $SE = 1.53$, $p \leq .0001$, Fig. 2 ❷).

We also found significant effects for **before/after** × **disease** × **race** and **before/after** × **group label**, as well as a number of significant effects related to individual differences (e.g., age and political alignment). Although these effects may corroborate others' prior work [54, 18, 43, 4, 31, 44, 19], since they are incidental to the chart effects, we describe them in the supplement for reference.

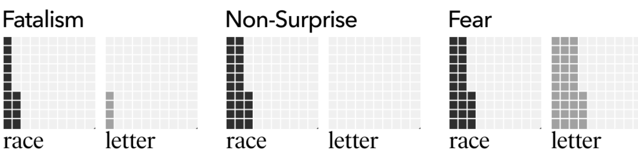

Figure 3: Percentages of Black participants' emotional responses to heart disease charts across the group labels.

Exploratory analysis of the coded affective responses suggests that the "must be a Tuesday" style of fatalism was not unique to the participant in the introduction. Of the 97 Black participants who viewed heart disease in the racial group condition, 12% (12/97) expressed similar fatalism, 22% (21/97) were *not* surprised, 24% (23/97) reported fear, and 55% (53/97) expressed some negative emotion. For comparison, see Figure 3, which shows that of the 97 Black participants who viewed heart disease in the letter group condition, only 4% (4/97) expressed fatalism, 0% were not surprised, 34% (33/97) reported fear, and 54% (52/97) had negative emotions.

Chart condition had little impact on fatalism, nonsurprise, or negative emotions. However, for Black participants in the racial group, heart disease was reported as scarier by those who saw **bars** (29%, 14/48) than **geo-emph** (18%, 9/49).

6 Discussion, Limitations, Conclusions

This study investigates the effects of two distinct approaches to visualizing public health disparities in mortality risk. It compares **bars**, a conventional bar chart, to **geo-emph**, a chart using annotations and jitter plots to emphasize geographic variability. Both **geo-emph** and **bars** show similar, significant impacts for three conventional health communication measures: perceived vulnerability, behavioral intent, and policy support. Both charts also evoke negative affective responses. However, **bars** significantly increased personal, genetic attributions, blaming outcome differences on intrinsic characteristics of the people being visualized, while **geo-emph** moved participants' attributions from personal toward external explanations. These findings suggest that equity-related communication goals (e.g., highlighting social determinants of health) may be better supported by charts like **geo-emph**, which emphasize within-group geographic variability and between-group outcome overlap, and that these approaches could be adopted without sacrificing other essential health communication goals, such as risk calibration, behavior change, or public support.

The increased genetic attribution for **bars** deserves consideration. These findings echo prior work showing that people unjustifiably attribute racial health disparities to genetics [19, 44]. Genetic attributions were also unjustified in our study because the stimuli did not show the causes of disparities, suggesting that **bars** may exacerbate misperceptions of race as a biological rather than a social construct [7]. These inappropriate genetic attributions not only reinforce harmful stereotypes but may also impact downstream goals, such as policy support from less vulnerable majority groups [19, 44]. Considering this, our findings support prior work suggesting that conventional ways of communicating social outcomes (e.g., **bars**) may undermine racial equity [9, 5, 41, 45, 23].

Prior work suggests that social comparison framing often fails or backfires [31, 4, 18, 40]. Our results are not necessarily contradictory, but they suggest other factors are involved, possibly related to differences in our experiment design. Our experiment design differs from previous work in a few key ways, including using stimuli showing four groups instead of binary Black / White comparisons, using visualizations instead of text or tables, and that none of our participants saw themselves as the *least* vulnerable groups in the stimuli. These design differences could have muted the underlying mechanisms (e.g., contrast effects, upward comparisons, etc). Despite these differences, as discussed in the supplement, we still found distortions consistent with contrast effects, where White participants' perceived risk increased disproportionately for liver disease (where they are ranked most vulnerable) compared to heart disease (where their absolute risk is much higher than liver disease). We also found that both charts evoked negative emotional reactions, particularly fatalism for Black participants. Given the nuances described above, we still advocate for Liu et al.'s assertion that social comparison framing is not as straightforwardly beneficial as it may seem and should be approached cautiously by public health communication professionals [31].

Limitations. As a short, exploratory study, there are a few limitations to consider. In the **geo-emph** condition, the annotations and plot type both differed from **bars**; while these two elements both emphasize geographic variability, we cannot determine their unique contributions to the observed effects, or whether they're jointly required (e.g., prior work found similar effects with only plot type differences [23]). Additionally, Black participants were unexpectedly older and more conservative than White participants, which is associated with increased personal attribution [36]; our models account for this by including age and political orientation. The charts are also limited in scope. While testing concrete racial groups *and* abstract letter groups suggests generalizability, other specific groups (e.g. Native Hawaiian, Pacific Islander, American Indian, Alaska Native people), or group types (e.g. age, gender), may evoke different prior beliefs or prejudices, potentially impacting the observed effects. State-level aggregates of heart and liver disease mortality show overlapping distributions between groups, which may not be the case for other topics (e.g. education outcomes), group types, or aggregation levels and may impact the observed effects for **geo-emph**. Finally, even though **geo-emph** showed improvement over conventional charts, other (noncomparative) designs may show further improvements.

Conclusions, Design Implications. When visualizing public health outcomes, our design choices matter. Our findings, reaffirming prior work, suggest that visualizations emphasizing between-group differences (e.g. conventional bar charts), can reinforce harmful stereotypes and are insufficient for responsibly depicting group health outcomes, particularly racial risk disparities. On the other hand, the **geo-emph** approach, emphasizing within-group geographic variability with a jitter plot and annotations, can offset these social-cognitive biases while achieving similar performance on key health communication goals. When visualizing group health outcomes, conventional design choices should not be taken for granted. In similar contexts, alternatives such as emphasizing geographic variability, may offer a promising step forward for promoting public health, without undermining health equity.

Acknowledgments

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