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# Vivifying Outbreaks: Investigating the Influence of a Forecast Visual on Risk Perceptions, Time-Urgency, and Behavioral Intentions

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**ABSTRACT**
Although visual depictions of epidemiological data are not new in public health, the US public saw more of them during the COVID-19 pandemic than ever before. In this study, we considered visualizations of forecasts (i.e. predictions of how a disaster will unfold over time) formatted as line charts. We investigated how two choices scientists make when creating a forecast visual – the outcome of focus (cases or deaths) and the amount of data provided (more or less data) about the past or the potential future – shape behavioral intentions via risk-related appraisals (e.g. threat and efficacy). In an online experiment, participants ($N = 236$) viewed a written health alert about a novel airborne virus, with one of the eight versions of a forecast visual or no visual (text only). The results of the experiment showed that exposing people to a health alert with a forecast visual in it may be less effective than anticipated. Reading a written health alert with a forecast visual was, at best, equal to outcomes from reading an alert without it, and sometimes it performed worse: participants appraised the novel virus as a less urgent threat and the recommended solutions as less efficacious. Implications of the findings for theories of risk and visual health communication and practical considerations for future health communicators were discussed.

In health crises, such as epidemics, scientists often use mathematical models to predict how an outbreak will unfold over time (i.e., *forecasts*) and to describe what may unfold if changes (e.g., interventions) are introduced into the system (i.e., *projections*; Massad et al., 2005). In a recent example, scientists offered forecasts of how many people could become infected with the COVID-19 virus over time (e.g., https://covid19forecasthub.org/) and projections of what might happen if we introduced an intervention, such as wearing masks, avoiding crowds, staying six feet apart, and getting vaccinated (e.g., https://covid19scenariomodelinghub.org/).

Scientists have choices in how to convey the forecast and projection results: they can verbally describe them (e.g., increasing) and/or they can depict them in a visual, such as a line chart of longitudinal data (Head et al., 2020). Although visual depictions of epidemiological data are not new in public health, the US public saw more line charts during the COVID-19 pandemic than ever before (Padilla et al., 2022). Indeed, forecast visuals (i.e., line charts) were so present that they made it into public discourse, such as discussing efforts to “flatten the [pandemic's] curve” (Head et al., 2020, p. 715). And yet, we know very little about whether and how exposure to such visuals shape the public's appraisals of risk or intentions to act (King & Lazard, 2020). Not knowing could impede effective risk communication, if we unintentionally employ visualization techniques that diminish people's perception of risk (Padilla et al., 2022).

Although the growing research into visual health communication (McWhirter & Hoffman-Goetz, 2014; Parrott et al., 2007; Parrott et al., 2005) offers many insights, existing research typically compares the absence and presence of visuals, instead of systematic variation in visual content, which limits theoretical advances in this work (King et al., 2014). Furthermore, even though “use of scientific evidence, which often resides in statistics, frequently forms a foundation for judgments and decision making relating to many domains, including health risk appraisals” (Parrott et al., 2005, p. 425), studies rarely focus on visualizations of data or statistical evidence (Parrott et al., 2005). To offer practical and theoretical insights, we focused on two choices scientists make when creating a forecast visual: a) which outcome to present (forecasting potential future cases vs. deaths) and b) how much data to share about the past or the potential future.

As a foundation for the study, in the next sections, we review theories and research on risk appraisals (perceived threat and efficacy) and their connection to behavioral intent. We then introduce a time-related emotion from organizational communication – time urgency – into the predictive rationale. Next, we considered reasons why two choices scientists make when designing a forecast visual might influence risk-related appraisals. We explored these predictions in an experiment in which participants read a written health alert that included information about a fictitious novel airborne virus, along with no forecast visual or one of the eight forms of a line chart. With this study, we aim to advance the study of data visualization in health communication (King & Lazard, 2020) and improve guidance for future outbreaks.

## Risk and recommended actions

Multiple theories of health communication (e.g., health belief model, Janz & Becker, 1984; protection motivation

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theory; Rogers, 1975; risk perception attitude framework; Rimal & Real, 2003) predict that people are more likely to engage in behaviors recommended by health experts or agencies when they perceive a problem as more threatening and the recommended behaviors as more efficacious. Threat perceptions are based on two components: perceived susceptibility to (i.e., likelihood of personally experiencing the problem) and perceived severity of a problem (e.g., pain and death; Janz & Becker, 1984; Rimal & Real, 2003). Efficacy perceptions can also include two components: perceived self-efficacy (i.e., one's ability to perform an act) and perceived response-efficacy of the action to succeed (i.e., effective, feasible, easy; Janz & Becker, 1984; Rimal & Real, 2003). Past behavior also matters: people are more likely to take actions in the future if they have taken them in the past (e.g., Fishbein & Yzer, 2003).

In the case of novel airborne infection, health agencies may recommend that people wear masks and avoid crowded social situations to reduce infection rates. People who perceive themselves at greater risk of infection, perceive infections as more serious, perceive actions (masks and distancing) as more effective in preventing infection, and perceive themselves as more capable of acting should have stronger intentions to enact recommended actions in the future. In addition, people who wore masks and distanced socially during the COVID-19 pandemic should be more likely to repeat these behaviors in the future. We predict:

**H1:** Stronger perceptions of threat and efficacy, and more instances of past behavior predict stronger intentions to (a) wear a mask and (b) social distance in a future epidemic.

Messages can influence perceptions of threat and efficacy, as well as related affective states (e.g., Rimal & Real, 2003; Witte, 1992). We explored the affective state of *time-urgency* (Ballard & Seibold, 2004), defined as "a felt need to initiate and complete an act in the immediate or near future" (Swain et al., 2006, p. 523) or feeling hurried (e.g., Landy et al., 1991). Feelings of time-urgency can be amplified through conversation, such as discussions around deadlines and "running out of time to complete a given task" (Ballard & Seibold, 2004, p. 145), which can influence intentions to act. For example, in an experiment, Swain et al. (2006) varied the amount of time participants had to act on a promotion (a free movie ticket): participants exposed to promotion messages with less time to act reported a stronger feeling of time-urgency, which predicted greater intentions to act on the promotion.

Indeed, organizational studies show that time-urgency is associated with multiple aspects of behavior. As people feel greater time-urgency, they procrastinate less (Milgram et al., 1988), work faster, work more efficiently, and conduct various forms of planning, scheduling, and progress checking (Chen & Nadkarni, 2017; Conte et al., 1998; Mohammed & Nadkarni, 2011; Waller et al., 2001). For health communication, time-urgency may be particularly useful: if people feel time-urgency about a problem, they should show greater intention to act. We predict:

**H2:** Stronger feelings of time-urgency predict stronger intentions to (a) wear a mask and (b) social distance in a future epidemic.

## Visualizing forecasts

Many scientific disciplines display quantitative information visually (Meloncon & Warner, 2017; Spiegelhalter et al., 2011). Increasingly, scientists and health professionals have used visuals to communicate risk information (e.g., disease prevalence and epidemic forecasts) to the public during emerging crises (Fansher et al., 2022; Zhang et al., 2021). This inclination may stem from the adage that a picture is worth a thousand words. Similarly, Tufte (2001) notes in his practical guide, "graphics reveal data … graphics can be more precise and more revealing than conventional statistical computations" (p. 13). Findings from forecast and projection models are often depicted visually, typically as line charts of longitudinal data that include shading or error bars to indicate uncertainty (Head et al., 2020). Due to the widespread distribution of forecast visuals on mass media and social media, the public's exposure to such visuals has grown (Zhang et al., 2021). In particular, the COVID-19 pandemic ushered in unprecedented growth in the use of line charts to inform the public of confirmed and potential rates of cases, hospitalizations, and deaths (Zhang et al., 2021).

The question remains whether and how exposure to data visualizations, like line charts, shape risk-related message effects (King & Lazard, 2020). Current opinions and results are mixed. On the one hand, forecast visuals have been associated with better comprehension of complex quantitative data (Hegarty, 2011), perceptions of risk to themselves and others (Padilla et al., 2022), and risk-related intentions to act (Zhang et al., 2021). On the other hand, there are concerns about forecast visuals (Lee et al., 2021; Padilla et al., 2023), such as causing public confusion and eroding confidence in data accuracy and medical interventions (Padilla et al., 2023). There is also a lack of theory development about why and how features of visual influence risk (King & Lazard, 2020), leaving communicators with weak guidance (Spiegelhalter et al., 2011).

In this study, we focused on line charts, a popular type of visual for epidemiological outcomes (Zhang et al., 2021; see Figure 1). Such visualizations depict time on the x-axis and the magnitude of a health issue or outcome on the y-axis. Most visuals depict one health issue at a time; thus, one critical decision is which health issue to depict on the y-axis (e.g., number of cases or deaths; Zhang et al., 2021), because the outcome, itself, may shape risk appraisals. A second important decision is how much data to present on the x-axis about the past and predicted future (forecasts). In visual terms, the decision can be thought of in terms of the length of time (i.e., duration): a longer x-axis represents more past data and/or forecasts.

## Forecast visuals and risk

In this study, we investigated whether including a forecast visual in health messages influences risk appraisals (perceived threat, perceived efficacy, and felt time-urgency) and considered why it might do so. We focused on two options for the forecast visual: the outcome (cases or deaths) and the amount of data provided (past and forecasts).

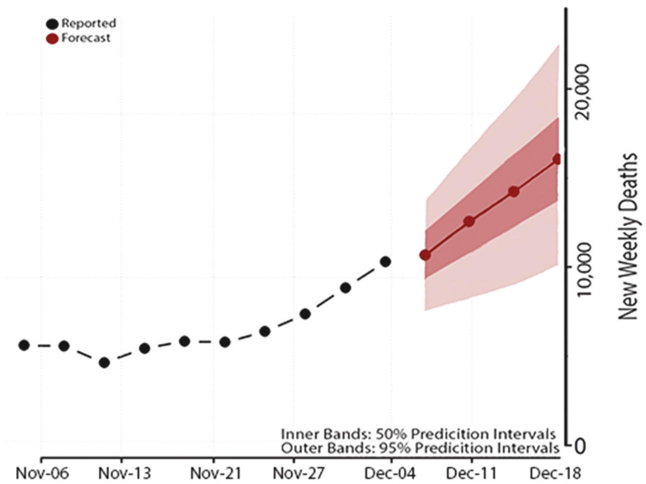


**Figure 1.** Example forecast visual of a fictitious new airborne virus. *Note*. This example forecast (one of the eight) represents the condition with death as the outcome of focus, more past data (long past), and more forecast (long future). Alternative visuals of the novel (fictitious) Guttula virus presented cases instead of deaths, and all possible combinations of more or less past data and forecasts.

Each outcome option offers a different kind of cost. Death is more serious than infection, thus forecasting deaths (vs. cases) may induce stronger perceived severity. On the other hand, the outcomes occur with different magnitudes: numbers of cases outpace deaths, often by a lot. At some points in an epidemic, the increasing slope of cases and of deaths across time (x-axis) could be the same, but the y-axis could vary dramatically. For example, in late 2020, the Centers for Disease Control and Prevention's (CDC, 2022) forecasts indicated that cases of COVID-19 infections were nearing 1 million, while deaths had only reached 10,000. Infections and deaths had similar slopes, but the y-axis for new weekly cases was about 50 times that of deaths. A large number of cases could signal a greater chance of getting infected, especially for infection with airborne transmission, which could induce stronger perceived susceptibility. Both more serious outcomes and higher magnitude could induce stronger feelings of time-urgency. We explored:

**RQ1:** Does showing more cases in a forecast visual influence perceived severity, perceived susceptibility, or time-urgency compared to fewer deaths or the control message without a visual?

The choice to provide more or less data about the past or future varies the amount of information people must process. Heuristically, just as offering more reasons (even flawed ones) increases credibility and persuasion (e.g., Petty & Cacioppo, 1984), providing more past or future information may result in stronger threat perceptions and heightened time-urgency.

Alternatively, forecast visuals with more past and future information may convey a greater temporal distance, which may weaken threat perceptions and lessen time-urgency. According to the construal level theory (Liberman & Trope, 1998; Trope et al., 2007), even though people can only experience the present, they are able to "make predictions about the future, remember the past, imagine other people's reactions, and speculate about what might have been" (Trope & Liberman, 2010, p. 440). As people mentally construct these moments in time, they subjectively experience them as more or less distant, anchoring them ego-centrically "from the self, here and now" (Trope & Liberman, 2010, p. 440). Depicting more information about the past or the future creates a longer time horizon, which could increase temporal distance. More temporal distance reduces personal involvement and concern (Trope & Liberman, 2010), which may lower perceived susceptibility to experiencing a threat, perceived severity of the threat, and feelings of time-urgency to address it. People react more strongly to events that are closer to them in time and space (Trope & Liberman, 2010); thus, shorter time frames (less data) may be associated with stronger threat perceptions and time-urgency. We explored:

**RQ2:** Does showing more data about a) the past or b) the potential future in a forecast visual influence perceived severity, perceived susceptibility, or time-urgency compared to less data or the message without a visual?

Forecast visuals display the magnitude of a problem, so it is reasonable to consider their influence on perceptions of threat and feelings of time-urgency – thoughts and feelings related to assessing the significance of a problem. It is also possible that the visual options will influence the perceived efficacy of recommended solutions. Efficacy perceptions, overall, reflect an assessment that a challenge can be overcome (Bandura, 1997; Rimal & Real, 2003; Skurka et al., 2022). Upon viewing a forecast visual, one may question whether the challenge has become insurmountable. Forecast visuals like those in Figure 1 show a problem with an increasing slope; this may reduce the perceived potential (response efficacy) of preventive actions (e.g., wearing a mask). Additionally, a forecast visual of an increasing case or death rate may implicitly convey that others have been unsuccessful in enacting recommended behaviors; such vicarious experience is an important source of perceived self-efficacy (Bandura, 1997). In contrast, people may process such visuals as depicting potential success – not everyone is infected or has died. Even with a rising slope, the visual offers potential hope for overcoming the problem. We explored:

**RQ3:** Does including a forecast visual or varying the visual (type of outcome [cases vs. deaths], amount of past data [short vs. long], or amount of potential future data [short vs. long]) influence perceived response-efficacy or self-efficacy of masking or social distancing?

## Methods

### *Participants and procedures*

An Institutional Review Board approved this study. Participants ($N = 273$) were recruited through Amazon's

Mechanical Turk. Based on best-practices (e.g., Zichar & Keith, 2022) participation was restricted to US residents, and closed- and open-ended questions were included as quality checks. The open-ended questions, in particular, allowed us to assess whether participants provided relevant answers versus nonsensical (e.g., a random set of characters) or off-topic answers. Of the 273 participants who completed the survey, 236 met quality-control standards and were included in the study; 37 were excluded.

Participants ($N = 236$), on average, were about 37 years old ($M = 36.67$, $SD = 10.00$, $Min = 21$, $Max = 69$). Participants self-identified as male (53%), female (40%), transgender male (3.4%), transgender female (2.6%), or did not answer (0.4%). Participants self-identified as heterosexual (71%), bisexual (25%), homosexual (2%), asexual (1%), or did not answer (1%). Participants self-identified, selecting as many choices as they wished, as Caucasian (92%), Asian (4%), African American (5%), American Indian or Alaska Native (2.5%), and Native Hawaiian or Pacific Islander (1%); 12% identified as Hispanic/Latinx. Participants' educational attainment ranged from some high school (.8%), a high school degree (7%), some college (10%), an associate's degree (6%), an undergraduate degree (62%), to graduate education (14%).

After providing consent, participants answered questions about their previous behaviors during the COVID-19 pandemic, and personality traits. Next, participants were randomly assigned to view one of nine health alerts ($n \sim 26$ per condition). The instructions explained that the information in the health alert was based on real, existing news stories about real diseases, but that there was not an outbreak of the virus currently in the US. Participants were asked to imagine that the health alert described a real situation as they completed multiple-item scales related to perceived threat, perceived efficacy, felt time-urgency, and intended non-pharmaceutical, behavioral responses (masking and social distancing). The survey ended with sociodemographic questions. Participants were paid $6 to complete the survey; most completed it in less than 30 minutes ($M = 20.41$, $SD = 15.49$).

### Design and stimulus

The study was a 2 (outcome: cases vs. deaths) × 2 (past data: short vs. long) × 2 (forecasts: short vs. long) between-subjects design with a nonvisual comparison group; participants were randomly assigned to one of the nine conditions. The dependent variables (perceived severity, perceived susceptibility, time-urgency, perceived response-efficacy, perceived self-efficacy, masking intentions, and social distancing intentions) were measured after exposure to the written health alert and visual, depending on condition.

All participants were shown a written health alert (see Appendix A); the wording was identical across all nine conditions. Drawing upon real health alerts shared by health agencies, the experimental alert described the symptoms, consequences, and treatment of a fictitious novel airborne virus, referred to as Guttula virus. It also included two ways to reduce the spread of Guttula recommended by health agencies: wearing masks and social distancing.

The graphical design of our forecast visual was based on an actual forecast visual of COVID-19 shared by the CDC in the late fall of 2020 (CDC, 2022). Modeling experts were consulted during the design process to ensure that our visuals were scientifically reasonable and biologically valid. The slope of the reported past and potential future forecasts was fixed to be consistent across the forecast visuals.

To vary *outcome*, which appears on the y-axis, the forecast visual showed either new weekly cases of infection (range: 0–1,000,000) or deaths (range: 0–20,000). To vary *amount of past data*, which appears on the left part of the x-axis, the visual showed either six past data points across three weeks (November 13 to December 4 2022; short past) or nine past data points across four weeks (November 6 to December 4 2022; long past). To vary *amount of forecast*, which appears on the right part of the x-axis and is visually distinct from past data (different colored data points and 50% and 95% prediction interval shading), the visual showed either two forecast points across one week (short future) or four forecast points across two weeks (long future). Figure 1 shows an example forecast visual that represents the condition with death as the outcome, more past data (i.e., long past), and a longer forecast (i.e., long future; all the visuals can be found in Appendix C).

### Measures

A confirmatory factor analysis of scales – virus severity (3 items), virus susceptibility (3 items), time-urgency (3 items), social distancing future intentions (5 items), social distancing self-efficacy (2 items), social distancing response-efficacy (2 items), masking future intentions (3 items), mask self-efficacy (2 items), mask response-efficacy (2 items), as well as past COVID-19 social distancing behavior (5 items) and past COVID-19 masking behavior (3 items) – was estimated with maximum likelihood in AMOS (version 27). The latent factors were treated as exogenous and were allowed to covary, but the error terms of the measured items were not. Before conducting the analysis, we evaluated any missing data: eight participants had 1 missing item. We replaced the missing data with mean imputation. The measurement model showed reasonable fit (Hu & Bentler, 1999): $\chi^2(441,\ N = 236) = 890.66$, $p < .001$, SRMR = .05, RMSEA = .07, 90% CI [.06, .07]. Descriptive statistics and intercorrelations appear in Table 1.

#### Perceived virus threat

Six items (adapted from Witte et al., 2001) were used to assess the perceived severity of (3 items, e.g., "the novel virus has serious health consequences") and perceived susceptibility to (3 items, e.g., "it is likely that I would get infected with the novel virus") infections caused by a (fictitious) novel Guttula airborne virus. Responses, marked on 5-point scales (1 = *strongly disagree* to 5 = *strongly agree*), were averaged into single scores ($\omega = .77$ for severity, and $\omega = .76$ for susceptibility).

#### Time urgency

Three items (adapted from Ballard & Seibold, 2004) were used to assess feelings of a pressing need to act (e.g., "urgent").

**Table 1.** Descriptive statistics and correlations among variables (N = 236).

| Variable | *M* | *SD* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Future intent: Social distancing | 3.85 | 0.81 | – | | | | | | | | | |
| 2. Past COVID-19: Social distancing | 3.60 | 0.77 | .66 | – | | | | | | | | |
| 3. Social distancing response-efficacy | 4.07 | 0.81 | .65 | .43 | – | | | | | | | |
| 4. Social distancing self-efficacy | 4.10 | 0.82 | .55 | .33 | .55 | – | | | | | | |
| 5. Future intent: Masking | 4.06 | 0.90 | .75 | .44 | .60 | .47 | – | | | | | |
| 6. Past COVID-19: Masking | 3.87 | 0.78 | .58 | .55 | .50 | .38 | .67 | – | | | | |
| 7. Masking response-efficacy | 4.04 | 0.88 | .64 | .42 | .67 | .47 | .75 | .58 | – | | | |
| 8. Masking self-efficacy | 4.21 | 0.79 | .58 | .34 | .54 | .55 | .69 | .53 | .59 | – | | |
| 9. Virus susceptibility | 3.66 | 0.82 | .31 | .25 | .38 | .32 | .31 | .26 | .32 | .33 | – | |
| 10. Virus severity | 4.06 | 0.74 | .48 | .30 | .56 | .38 | .54 | .40 | .52 | .51 | .42 | – |
| 11. Time-urgency | 4.02 | 0.76 | .61 | .44 | .49 | .34 | .57 | .45 | .59 | .46 | .44 | .48 |

*Note.* All correlations are statistically significant at $p$ <.05.

Responses, marked on 5-point scales (1 = *strongly disagree* to 5 = *strongly agree*), were averaged into one score (ω = .79).

### Perceived efficacy of social distancing

Four items (adapted from Witte et al., 2001) were used to assess the response-efficacy (2 items, e.g., "avoiding gatherings of 15 or more people is an effective way to reduce the risk of getting infected with the novel virus") and self-efficacy (2 items, e.g., "I find it easy to avoid in-person gatherings of 15 or more people") of social distancing. Responses, marked on 5-point scales (1 = *strongly disagree* to 5 = *strongly agree*), were averaged into single scores ($r$ = .60 for response-efficacy, and $r$ = .59 for self-efficacy).

### Social distancing intentions and past behavior

Ten items were used to assess participants' social distancing behavior during COVID-19 (5 items, e.g., "[during COVID-19, I] avoided gatherings of more than 15 people") and their future intentions to engage in these actions during a new outbreak (5 items, e.g., "[if the outbreak was real, I would] avoid gatherings of more than 15 people). Responses, marked on 5-point scales (1 = *never* to 5 = *all of the time*), were averaged into single scores (ω = .78 for past social distancing, and ω = .82 for future intentions).

### Perceived efficacy of masking

Four items (adapted from Witte et al., 2001) were used to assess response-efficacy (2 items, e.g., "Wearing a face mask around other people is an effective way to reduce the risk of getting infected with the novel virus") and self-efficacy (2 items, e.g., "I find it easy to wear a face mask") of wearing masks. Responses, marked on 5-point scales (1 = *strongly disagree* to 5 = *strongly agree*), were averaged into single scores ($r$ = .64 for response-efficacy, and $r$ = .48 for self-efficacy).

### Masking intentions and past behavior

Six items were used to assess participants' masking behavior during COVID-19 (3 items, e.g., "[during COVID-19, I] wore a face mask when out in public") and their future intentions to mask during a new outbreak (3 items, e.g., "[if the outbreak was real, I would] wear a face mask when out in public"). Responses, marked on 5-point scales (1 = *never* to 5 = *all of the time*), were averaged into single scores (ω = .72 for past, COVID-19 masking, and ω = .84 for future intentions).

## Results

As noted in Table 1, the correlations among perceived severity, perceived susceptibility, and felt time-urgency were large: $r(234) = .42$ for severity and susceptibility, $r(234) = .44$ for time-urgency and susceptibility, and $r(234) = .48$ for time-urgency and severity. In addition, the correlations between efficacy components (self-efficacy and response-efficacy) were also large: $r(234) = .55$ for social distancing response- and self-efficacy, and $r(234) = .55$ for masking response- and self-efficacy. These strong correlations are consistent with some theories of behavior change, such as protection motivation theory (PMT; Rogers, 1975), which argue that people make holistic appraisals of threat and coping. The holistic appraisal of threat is informed by perceived severity and susceptibility; the holistic coping appraisal is informed by response- and self-efficacy. In addition, later extensions of PMT (e.g., Maddux & Rogers, 1983) included affective states such as desperation in their conceptual descriptions of threat appraisal but never measured for the affective state, which we may have captured with time-urgency. Thus, based on theoretical support and the strength of the correlations, we combined perceived severity, perceived susceptibility, and felt time-urgency into one appraisal of *urgent threat*. We also combined the efficacy measures into one efficacy perception for each behavior. These appraisal scores were used in the rest of the analyses.

### Predicting future behavioral intentions

H1 and H2 stated that greater intentions to engage in the recommended behaviors (wearing a mask and social distancing) would be predicted by stronger threat perceptions, stronger feelings of time-urgency, stronger efficacy perceptions, and more engagement in those behaviors during the COVID-19 pandemic. To test H1 and H2, we conducted separate regressions for social distancing and masking. In each, the behavioral intention was regressed onto the urgent threat appraisal, perceived efficacy of that behavior, and self-reported enactment of the behavior during COVID-19 (see Table 2). Models for both behaviors were statistically significant, $F(3, 232) = 148.53$, $p < .001$, $R^2 = .66$ for social distancing and $F(3, 232) = 183.13$, $p < .001$, $R^2 = .70$ for mask wearing. As predicted, for both behaviors, greater intentions to engage in the recommended behaviors were predicted by

**Table 2.** Regressions of intentions to engage in recommended behaviors.

| | Social distancing | | | | Masking | | | |
|---|---|---|---|---|---|---|---|---|
| | *b* | *SE* | *β* | *t* | *b* | *SE* | *β* | *t* |
| Urgent threat | 0.29 | 0.06 | .23 | 4.65* | 0.15 | 0.07 | .10 | 2.16* |
| Efficacy | 0.43 | 0.05 | .38 | 7.89* | 0.71 | 0.06 | .58 | 10.90* |
| Past COVID-19 | 0.41 | 0.05 | .39 | 8.82* | 0.30 | 0.05 | .26 | 5.59* |
| $R^2$ | .66* | | | | .70* | | | |

*Note*. Efficacy is a combination of perceived self-efficacy and response-efficacy related to the specific recommended action. Past COVID-19 refers to the behavior referenced the relevant recommended action. The variable *urgent threat* (an appraisal combining felt time-urgency, perceived severity, and perceived susceptibility) was the same across the two recommended behaviors. Social distancing: $F(3, 232) = 148.53$, $p < .001$, $R^2 = .66$; Mask wearing: $F(3, 232) = 183.13$, $p < .001$, $R^2 = .70$.
*$p < .05$

stronger appraisal of an urgent threat, stronger perceptions of efficacy of the behavior, and more self-reported enactment of those behaviors during the previous COVID-19 pandemic. Thus, H1 and H2 were supported.

### Exploring the influence of forecast visuals

We offered a series of research questions (RQ 1–3) related to changes in the forecast visual: the outcome depicted (cases or deaths) and the amount of data shown (more or less past and future data). We conducted the analysis in phases. Before we started, the risk-related variables were mean-centered (i.e., the sample's average was subtracted from each observed value; Aiken & West, 1991; MacKinnon, 2008). Then, we assessed the differences in risk-related variables between the visual and no-visual conditions. Next, we separately assessed the two types of chart options (outcome and data) in comparison to the no-visual condition. Finally, we conducted a series of post-hoc tests, exploring for potential interactions among visual conditions, and for potential covariates, such as educational attainment.

### Visual vs. No-visual

To assess differences in risk-related variables between the visual and no-visual conditions, we conducted a series of independent sample $t$ tests. The results showed that urgent-threat appraisal was lower in the visual ($M = -0.04$, $SD = 0.62$) than the no-visual condition ($M = 0.20$, $SD = 0.61$), independent sample $t\ (234) = -2.14$, $p = .033$, Cohen's $d = -0.38$. In addition, masking-efficacy perceptions were lower in the visual ($M = -0.06$, $SD = 0.76$) than the no-visual condition ($M = 0.29$, $SD = 0.58$), independent sample $t\ (234) = -2.69$, $p < .008$, Cohen's $d = -0.48$. Social distancing efficacy perceptions also were lower in the visual ($M = -0.02$, $SD = 0.74$) than the no-visual condition ($M = 0.09$, $SD = 0.59$) but the difference was not statistically significant: independent sample $t\ (234) = -0.81$, $p = .419$, Cohen's $d = -0.14$. Overall, these results began to answer RQ1–3: the inclusion of a visual to depict the epidemiological forecast was associated with *lower* levels of the risk-related variables.

In the final test, we ran two separate path models in AMOS to assess urgent threat and efficacy as mediators of the effects of the forecast visual (effect coded as present or not) on masking or social-distancing intent. To assess mediation, we evaluated whether the indirect effects were statistically significant, with bias-corrected confidence intervals (Hayes & Scharkow, 2013) using bootstrapping procedures (2000 bootstrap samples). The standardized indirect effect between the forecast visual and masking intent was .15 (95% CI [.07, .23], $p = .005$). The standardized indirect effect between the forecast visual and social-distancing intent was .08 (95% CI [.01, .16], $p = .084$. The results showed that urgent threat and efficacy served as mediators for the effects of a forecast visual on masking intent, and a similar, albeit nonsignificant trend for social distancing intent.

### Differences by visual: presence, outcome, and amount of data

To gain further insight into these findings, in phase 2, we separately assessed the two types of visual options (outcome and data) in comparison to the no-visual condition. RQ1 and RQ3a asked whether the outcome (cases vs. deaths) in the visual influenced appraisal of the virus as an urgent threat (RQ1) or perceptions of masks or social distancing as efficacious (RQ3a). To assess RQ1 and RQ3a, we conducted a series of one-way ANOVAs with the risk-related variables as the dependent variable and the experimental condition (deaths, cases, or no visual) as the independent variable. The overall model was $F(2, 233) = 2.95$, $p = .055$, $R^2 = .03$ for urgent threat, $F(2, 233) = 2.60$, $p = .076$, $R^2 = .02$ for social distancing efficacy, and $F(2, 233) = 5.64$, $p = .004$, $R^2 = .05$ for masking efficacy. The comparisons between cells (see Table 3) showed that the risk-related variables were lower in deaths-as-outcome

**Table 3.** Differences in appraisal of urgency threat and perceived efficacy based on presence of a visual and its outcome.

| | Visualized forecast | | | | | |
|---|---|---|---|---|---|---|
| | Deaths ($n$ = 105) | | Cases ($n$ = 93) | | No visual ($n$ = 38) | |
| | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Urgent threat | $3.85_a$ | 0.70 | $3.96_{ab}$ | 0.51 | $4.14_b$ | 0.61 |
| Social efficacy | $3.97_a$ | 0.85 | $4.18_b$ | 0.57 | $4.17_{ab}$ | 0.59 |
| Masking efficacy | $3.97_a$ | 0.85 | $4.17_b$ | 0.63 | $4.41_c$ | 0.58 |

*Note*. Means with different subscripts differ at the $p < .05$ level. Urgent threat: $F(2, 233) = 2.95$, $p = .055$, $R^2 = .03$; Social efficacy: $F(2, 233) = 2.60$, $p = .076$, $R^2 = .02$. Masking efficacy: $F(2, 233) = 5.64$, $p = .004$, $R^2 = .05$.

conditions relative to cases-as-outcome, which, in turn, were sometimes lower than the no-visual condition. The strongest effects appeared for perceptions of masking efficacy, which was lower in the deaths-as-outcome condition ($M = 3.97$, $SD = 0.85$), relative to the cases-as-outcome condition ($M = 4.17$, $SD = 0.63$), $t(196) = 1.92$, $p = .056$, Cohen's $d = 0.27$, which was, in turn, lower than the no-visual condition ($M = 4.41$, $SD = 0.58$), $t(196) = 2.99$, $p = .003$, Cohen's $d = 0.57$. These results provided nuance in answering RQ1 and RQ3a: the choice of outcome influenced risk-related perceptions, with the deaths-as-outcome showing weaker levels of urgent threat and efficacy than cases-as-outcome or no-visual.

RQ2 and RQ3b asked whether the amount of past data and/or forecasts provided in a visual-influenced appraisal of the virus as an urgent threat (RQ2) or perceptions of masks or social distancing as efficacious (RQ3b). We conducted a series of one-way ANOVAs with the risk-related variables as the dependent variable and the experimental condition (variations in past and forecast data and the no-visual control). Results (see Table 4) differed by variable. Perceived efficacy of social distancing did not vary by condition, $F(4, 231) = 0.48$, $p = .752$, $R^2 = .01$. Appraised threat urgency and perceived mask efficacy varied by condition, $F(4, 231) = 2.20$, $p = .070$, $R^2 = .04$ and $F(4, 231) = 3.18$, $p = .014$, $R^2 = .05$, respectively. The means showed similar patterns: the lowest levels appeared in the short-future/long-past condition, followed by the other visual conditions, which were sometimes within sampling error of the no-visual condition. The differences between the short-future/long-past and no-visual condition were statistically significant with medium-to-large effect sizes (Cohen, 1988) for appraised threat urgency ($M = 3.77$, $SD = 0.77$ and $M = 4.14$, $SD = 0.61$, respectively), $t(77) = -2.35$, $p = .021$, Cohen's $d = -0.53$, and perceived mask efficacy ($M = 3.86$, $SD = 0.83$ and $M = 4.41$, $SD = 0.58$, respectively), $t(77) = -3.41$, $p < .001$, Cohen's $d = -0.77$. Thus, the answers to RQ2 and RQ3b were mixed.

### *Post-hoc analyses: interactions and education*

In the third phase, we completed a few post-hoc analyses to explore potential interactions between conditions, and potential covariates. To explore for interactions among the depicted outcome and the amount of data, we conducted a three-way, factorial ANOVA, with risk-related variables as the dependent variable, and the three conditions (outcome: cases or deaths, past data: short or long, and future data [forecast]: short or long) as independent variables. The pattern of results was consistent with a main effect for outcome, and an interaction between past data and forecast; no other main effects or interactions were statistically significant (details available from authors; see the Appendix B for the full table of conditions).

We also explored for potential influences of educational attainment. We re-ran the three-way, factorial ANOVA described above with education as a covariate (i.e., an ANCOVA). The covariate was not predictive (e.g., unstandardized $b = -.002$, $SE = .04$, $p = .958$ for urgent threat). The pattern of results was exactly the same. Education, then, did not provide its own influence on risk outcomes.

To explore its potential as a moderator, we categorized the sample into three groups (associate degree or less, bachelor's degree, or graduate education) and then assessed whether the relationships between exposure to a visual (or not; effect coded) and risk appraisals differed by group. Correlations for some appraisals varied by education category. The correlation between visual presence and social-distancing efficacy was extremely negative for the participants with a graduate education, $r(31) = -.50$, $p = .003$, slightly positive for those with a bachelor's degree, $r(144) = .02$, $p = .830$, and more positive for those with less education, $r(54) = .09$, $p = .497$. The sample size in the most extreme categories were small; these differences suggest that education may have moderate effects (see also Harsh et al., 2019), but additional research with more participants across the spectrum of educational attainment is needed.

## Discussion

In recent years, forecast visuals have gained popularity as a way to communicate risk to the general population, outpacing our understanding of how exposure to visualized forecasts influences the public's risk appraisals. In the context of a new, fictitious outbreak, this study investigated how two choices in forecast visuals – outcome of focus and amount of data (reported past or potential future) – shape people's appraisals of a novel virus as an urgent threat, and their perceptions of masking and social distancing as efficacious. Consistent with previous studies, stronger appraisal of the virus as an urgent threat, stronger efficacy perceptions of a recommended behavior, and more engagement in that behavior during the COVID-19 pandemic were all significant, sizable predictors of future intentions to engage in the recommended actions. That said, including a forecast visual in written health alerts may be less effective than anticipated. Results showed that health alerts with a visual included were, at best, equal to those without a visual, and sometimes those with forecast visuals were worse: participants appraised the novel virus as a less urgent threat and perceived the recommended solutions as less efficacious.

**Table 4.** Differences in appraisal of urgency threat and perceived efficacy based on amount of past and future data.

| | Short future | | | | Long future | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Short past | | Long past | | Short past | | Long past | | No visual | |
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Urgent threat | $3.98_{ab}$ | 0.47 | $3.77_{a}$ | 0.77 | $3.84_{a}$ | 0.57 | $3.98_{ab}$ | 0.66 | $4.14_{b}$ | 0.61 |
| Social efficacy | 4.03 | 0.65 | 3.99 | 0.78 | 4.13 | 0.67 | 4.12 | 0.86 | 4.17 | 0.59 |
| Mask efficacy | $4.20_{b}$ | 0.62 | $3.86_{a}$ | 0.83 | $4.06_{ab}$ | 0.65 | $4.08_{ab}$ | 0.90 | $4.41_{b}$ | 0.58 |

*Note*. Means with different subscripts differ at the $p < .05$ level. Urgent threat: $F(4, 231) = 2.20$, $p=.070$, $R^2 = .04$; Social efficacy: $F(4, 231) = 0.48$, $p = .752$, $R^2 = .01$; Mask efficacy: $F(4, 231) = 3.18$, $p = .014$, $R^2 = .05$.

### Urgent threats

We studied traditional cognitions associated with threat – susceptibility to and severity of experiencing the problem (e.g., Janz & Becker, 1984; Rimal & Real, 2003; Witte, 1992) – and extended this work to consider a time-oriented affective state: time-urgency (Ballard & Seibold, 2004). Time-urgency (i.e., feeling hurried; Ballard & Seibold, 2004; Landy et al., 1991; Swain et al., 2006) has received much attention in organizational communication, with scholars arguing that communication can shape feelings of time-urgency, which, in turn, leads not only to taking action but working quickly, efficiently, and strategically, and avoiding procrastination. We predicted that stronger feelings of time-urgency would predict intentions to engage in the recommended actions (wearing masks and social distancing). To our surprise, feelings of time-urgency were highly correlated with threat perceptions (severity and susceptibility). Based on this finding, we integrated the three reactions into a single variable representing an *urgent threat*, which strongly predicted future intentions to act. The combined variable was strongly predictive of behavioral intent. These results suggest that time-urgency may be a useful affective state to consider in health communication research.

Of note, the mean levels of perceived severity, perceived susceptibility, and time urgency were all above the mid-point of their scales (greater than 3 on a 5-point scale). It is possible that the recency of the COVID-19 pandemic produced strong reactions in all three components, simultaneously. Future research should try to replicate the findings in a year or so, when the pandemic begins to fade from public consciousness, or to replicate the tests with less familiar kinds of outbreaks to assess whether perceived threat and felt time urgency continue to synchronize.

Although scholars have argued for the role of time and timing in behaviors (e.g., Fishbein & Yzer, 2003) and campaign effects (e.g., Hornik, 2002), there is very little theorizing in health communication about the communication of time and time-related mechanisms involved in campaign outcomes. Time-urgency may offer a path for future research.

### Visualized risk

One goal of this study was to consider reasons why exposure to a forecast visual in a health alert may influence risk-related appraisals. The results showed that the no-visual (text-only) condition tended to be as good as – if not better than – conditions with a visual included within it. Overall, this lends support to those who have expressed caution and concern about forecast visuals and their potential to diminish trust in risk communication from health agencies (Padilla et al., 2023). Padilla et al. (2023) studied the effect of forecast visuals (line charts), varying shape, coloring, and number of forecast lines (without a no-visual control), and type of confidence interval, on trust. They found that participants expressed more trust in simpler charts (less visual information) and ones without visualized uncertainty (i.e., no confidence intervals). It is possible that text-only messages, inherently, have more simplicity and clarity than messages that include line charts, providing the text-only messages an advantage in producing stronger risk appraisals. This would be critical to know, because a study of stakeholders (VanDyke et al., 2021) identified perceived ease as a strong covariate of perceived usefulness and intent to use (weather) forecasts in decision-making about extreme weather events.

Alternatively, if the presence of a visual inherently raises a concern about trust, then people may engage in more questioning, skepticism, and counter-arguing, which could dampen risk appraisals. Indeed, a study conveying statistical evidence of genetic risk with or without data visuals showed that text-only outperformed messages with data visuals, and one reason was that messages with visuals were perceived as lower in evidence quality and less persuasive (Parrott et al., 2005). Future research is needed to identify which mechanisms explain why text-only messages outperform messages with visuals.

The most problematic versions of the visual included deaths (vs. cases) as the outcome and a long-past/short-future amount of information. Even though death is more serious than cases, cases necessarily both precede and exceed death, often by a sizable amount. In our forecast stimuli, we attempted to mimic the conditions of COVID-19 in the late fall of 2020. At that time, cases of COVID-19 infections were closing in on 1 million, while deaths had reached 10,000. Although scholars (e.g., Witte et al., 2001) have offered some guidance as to the intrinsic message features that generate stronger perceptions of threat (e.g., mortality) and efficacy (e.g., cues to social and geographic proximity), we still have much to learn about the types of message content that generate stronger effects. Based on the results of this study, the greater magnitude associated with cases was perceived as a more urgent threat (stronger perceptions of severity and susceptibility, as well as feelings of time-urgency) than the lower numbers associated with deaths.

Showing a higher rate of a less severe outcome may be more powerful than showing a smaller rate of a more severe outcome, but future research should separate the magnitude and severity of outcomes to identify which combinations engender the strongest responses. Our results provide an interesting counterpoint to research that uses narratives to influence health behaviors, finding that death narratives (i.e., storyteller dies) outperform survivor narratives (i.e., storyteller survives; e.g., Jensen et al., 2017; Lillie et al., 2021). It may be that death (vs. survival) provides compelling dramatic force in narrative persuasion focused on a single person, but mass infection among the larger population triggers appraisals of an urgent threat.

In addition, we may need to reconsider whether some content, such as death, influences only threat perceptions. As noted, exposure to a forecast visual of an increasing problem may convey that others have been unsuccessful in avoiding the problem, creating a vicarious experience that can be an important source of efficacy perceptions (Bandura, 1997; Skurka et al., 2022). Our findings support this; for example, exposure to a forecast visual of an increasing death rate (vs. case rate) resulted in weaker efficacy perceptions: self-efficacy to do and response-efficacy of the recommended actions.

Changing the amount of past data and/or forecasts also influenced risk-related appraisals, but the results were more complex. First, differences in data provision influenced threat urgency and mask efficacy, but not social-distancing efficacy. Second, the version that engendered the weakest reactions (long-past/short-future) showed more past data with fewer forecasts. Through the lens of construal level theory (Liberman & Trope, 1998; Trope & Liberman, 2010; Trope et al., 2007), a longer horizon of the past may induce more temporal distance from the past. One of the tenets of construal level theory is that as temporal distance from a time event (past or future) increases, people often use higher-level construal (i.e., higher levels of abstraction) as they think about that time and objects (goals, behaviors, and things) within that time (e.g., Trope & Liberman, 2010). More temporal distance weakens perceptions of a danger as threatening or urgent (i.e., not an imminent or present danger; Trope & Liberman, 2010). In addition, the shorter horizon for the future may induce temporal proximity to the future, and people tend to be less optimistic about proximal (vs. distal) future events (Trope & Liberman, 2010). Thus, it is possible that the long-past/short-future visual created a particularly salient visual stimulus of a distal past with a proximal future, generating lower concerns about the problem and weaker optimism about future efforts (at least for masks) to avoid it. This finding stands in contrast to studies showing that verbal risk appeals emphasizing benefits from recommended actions in the near (vs distant) future induce stronger efficacy and behavioral intent (e.g., Kim & Chon, 2023). Future research should consider how the presence of past and future information, conveyed verbally and nonverbally, shapes construals and risk appraisals.

The findings did provide clear doubt on one explanation. Counter to the prediction that more data, like more reasons (e.g., Petty & Cacioppo, 1984), could heuristically produce stronger threat and efficacy, the condition with the most information (long-past/long-future) produced similar levels of threat urgency and efficacy to the condition with the least information (short-past/short-future).

### *Limitations*

The findings of this research are limited by the sample, situation, visual format, format choices, and the forecast slope. Although the participants were diverse in many respects, this sample was not representative. Studies with nationally representative samples are needed to assess how well these findings generalize to the US population. In addition, the sample size limited our ability to detect small effects.

The situation described a fictitious outbreak, which may have influenced the findings. Our study investigated one type of visual format: line charts. Our results may not generalize to other formats, such as bar or area charts (Parrott et al., 2005; Zhang et al., 2021). In addition, we selected a line chart that used incidence, which may not generalize to other options. Padilla et al. (2022), for example, found that participants viewing forecast visuals with incident versus cumulative outcomes on the y-axis reported lower risk perceptions.

For consistency, the experimental visuals used the same slope: an increasing rate of the problem without a plateau or downward curve. Our results may not generalize to other slopes. Forecast visuals with increasing slopes may convey that it is too late or too hard to overcome the problem at this point. Future studies should consider forecast visuals that also vary by the functional form of the problem.

Last, we limited the scope of this study to forecast visuals: predictions of how a disaster is most expected to unfold over time ("*what will happen* . . . "). It is unclear whether our findings will generalize to scenario projections ("*what would happen if* . . . "), which consider what may unfold if alternative possible changes (e.g., different interventions) are introduced. Projection visuals may be a useful means by which to show the response-efficacy of an intervention. Depending on the intervention, projection visuals may provide nonverbal parallels to gain and loss frames (showing how many would be lost, or how many would be saved by an intervention); again, these are topics that should be considered in future research.

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