Annals of Behavioral Medicine, 2023, **XX**, 1–11
https://doi.org/10.1093/abm/kaad055
Advance access publication XX XX XXXX
Regular Article

Contrasting Objective and Perceived Risk: Predicting COVID-19 Health Behaviors in a Nationally Representative U.S. Sample

Rebecca R. Thompson, PhD[1] · Nickolas M. Jones, PhD[1] · Dana Rose Garfin, PhD[2] · E. Alison Holman, FNP, PhD[1,3] · Roxane Cohen Silver, PhD[1,4]

[1]Department of Psychological Science, University of California, Irvine, USA
[2]Community Health Sciences, University of California, Los Angeles, USA
[3]Sue & Bill Gross School of Nursing, University of California, Irvine, USA
[4]Program in Public Health and School of Medicine, University of California, Irvine, USA

Roxane Cohen Silver
rsilver@uci.edu

Abstract

Background Individuals confronting health threats may display an optimistic bias such that judgments of their risk for illness or death are unrealistically positive given their objective circumstances.

Purpose We explored optimistic bias for health risks using k-means clustering in the context of COVID-19. We identified risk profiles using subjective and objective indicators of severity and susceptibility risk for COVID-19.

Methods Between 3/18/2020-4/18/2020, a national probability sample of 6,514 U.S. residents reported both their subjective risk perceptions (e.g., perceived likelihood of illness or death) and objective risk indices (e.g., age, weight, pre-existing conditions) of COVID-19-related susceptibility and severity, alongside other pandemic-related experiences. Six months later, a subsample (*N* = 5,661) completed a follow-up survey with questions about their frequency of engagement in recommended health protective behaviors (social distancing, mask wearing, risk behaviors, vaccination intentions).

Results The k-means clustering procedure identified five risk profiles in the Wave 1 sample, two of which demonstrated aspects of optimistic bias, representing almost 44% of the sample. In OLS regression models predicting health protective behavior adoption at Wave 2, clusters representing individuals with high perceived severity risk were most likely to report engagement in social distancing, but many individuals who were objectively at high risk for illness and death did not report engaging in self-protective behaviors.

Conclusions Objective risk of disease severity only inconsistently predicted health protective behavior. Risk profiles may help identify groups that need more targeted interventions to increase their support for public health policy and health enhancing recommendations more broadly.

Lay summary

As we move into an endemic stage of the COVID-19 pandemic, understanding engagement in health behaviors to curb the spread of disease remains critically important to manage COVID-19 and other health threats. However, peoples' perceptions about their risk of getting sick and having severe outcomes if they do fall ill are subject to bias. We studied a nationally representative probability sample of over 6,500 U.S. residents who completed surveys immediately after the COVID-19 pandemic began and approximately 6 months later. We used a computer processing (i.e., machine learning) approach to categorize participants based on both their actual risk factors for COVID-19 and their subjective understanding of that risk. Our analysis identified groups of individuals whose subjective perceptions of risk did not align with their actual risk characteristics. Specifically, almost 44% of our sample demonstrated an optimistic bias: they did not report higher risk of death from COVID-19 despite having one or more well-known risk factors for poor disease outcomes (e.g., older age, obesity). Six months later, membership in these risk groups prospectively predicted engagement in health protective and risky behaviors, as well as vaccine intentions, demonstrating how early risk perceptions may influence health behaviors over time.

Keywords: Risk perceptions · COVID-19 · k-means clustering · Optimistic bias

Introduction

The COVID-19 outbreak in the USA has been an acute example of how objective disease risk and subjective perceptions of risk do not always map on to individual's decisions to engage in health protective behavior. Indeed, in February and March 2020 and through the continued emergence of multiple COVID-19 variants, individuals' perceptions of COVID's severity and willingness to adopt protective health behaviors varied widely. At the same time, communication about who is most at risk rapidly evolved; as the scientific community learned more about the novel Coronavirus (SARS-CoV-2), how it spreads, and how to treat the disease it causes, information was disseminated to the public with mixed success in terms of the public's understanding of the crisis [1]. As a result, individual beliefs about the risks posed by COVID-19 differed widely across groups with varying levels of objective risk, with some who may have been most at risk for severe outcomes (e.g., older people with pre-existing conditions) perceiving themselves invulnerable [2]. By the time the novel Coronavirus evolved into the Omicron variant, the U.S. National Academies for Science, Engineering, and Medicine advocated for a person-centered approach to health behaviors, highlighting that individuals should assess their own risk and that of others around them when making decisions about whether to take protective actions such as wearing a mask in public [3]. This approach prioritizes and exemplifies personal decision making that is commonly implemented to combat other prevalent diseases in the USA, such as the decision to vaccinate against other viral threats, to engage in physical activity to combat cardiovascular disease [4], or to consume a healthier diet as part of diabetes management [5].

Of course, this personal approach to risk mitigation assumes that people are making accurate and objective decisions about their own levels of risk and the benefits of taking protective action. Research suggests that people are able to perceive their risk accurately, especially when provided accurate and straightforward information [6]. However, in an era "infodemics" and misinformation where high-quality and trustworthy facts are not always easy to come by [7], this may not be the case. The widespread prevalence of COVID-19 provides an opportunity to assess subjective risk perceptions and responses to an exogenous threat to which many were susceptible but with varying objective risk of severe outcomes; this is critical given the link between risk perceptions and decisions to engage in health protective behaviors in response to viral threats and disease more generally [8].

While people believe their risk perceptions are accurate and well-reasoned, these judgments are often biased in predictable ways [9]. An example of this in the healthcare context is optimistic bias [10–13], or the belief that one is less likely to experience negative outcomes when compared to others. A similar cognitive bias is the "Better-than-Average Effect" [14, 15], wherein majorities of individuals will indicate themselves as being better than "the average person" on a variety of metrics (a mathematical impossibility). There have been many previous studies examining optimistic bias in the context of health risks. For example, people think they are less likely to have a heart attack [16], develop cancer [17] or an acute gastrointestinal illness [18], or experience negative consequences from smoking [19] compared to others. There is also some evidence for an optimistic bias among individuals at high clinical risk for COVID-19 [20], though there is also evidence for shifting perceptions of vulnerability to COVID-19 over the course of the pandemic as more information became available [21].

Though there is some evidence that optimistic bias is associated with health benefits [22], multiple theories of health behavior suggest that unrealistically low perceptions of risk are associated with a reduced likelihood of engaging in protective action against health risks (e.g., Theory of Planned Behavior [23]; Health Belief Model [24]). Prior work in illness contexts suggests that lower risk perceptions are associated with reductions in a variety of health protective behaviors, including lower vaccine uptake [8] and lower likelihood of changing sunbathing behavior [25]. Studies across multiple countries have also indicated that reduced perceptions of risk related to COVID-19 were associated with worse adherence to precautionary measures [20, 26–28]. As such, it is likely that an optimistic bias in subjective risk perceptions surrounding the COVID-19 pandemic would be associated with fewer health protective behaviors, even among individuals who were at greater risk of severe consequences to COVID-19 infection.

Risk and the COVID-19 Pandemic

One challenge to characterizing risk during the COVID-19 pandemic is that some individuals, by nature of their age, weight, or pre-pandemic health, are objectively at greater risk than others from health complications from contracting COVID-19—that is, their risk for severe outcomes is higher than others. In other words, some people may have reason to be optimistic about their potential health outcomes if infected with COVID-19, while others might have several compounding risk factors that color their perceptions of vulnerability. In fact, research has revealed several vulnerabilities to COVID-19, including advanced age (65 and older), excessive weight, as well as the presence of underlying conditions (e.g., other chronic illnesses) [29]. Individuals who do not fall into any of these categories may believe that their risk for severe illness is sufficiently low such that they may not feel a great need to take precautionary measures to prevent themselves from getting sick.

In addition, individuals may have differing perceptions of their susceptibility to contracting COVID-19. Some individuals may believe themselves to be more or less susceptible because of their health status (i.e., better or worse immune response). Similarly, some individuals were more or less likely to catch COVID-19 based on their work conditions (e.g., public-facing compared to working from home) [30] or geographic location (including population density and current outbreak status). During the early days of the pandemic in March and April, 2020, with few exceptions most outbreaks of COVID-19 in the USA were primarily localized and on the East Coast, indicating a different degree of objective risk for those living in different parts of the country. Additionally, communities across the country experienced various secondary stressors related to the pandemic (e.g., shortages of goods in stores) and implemented disparate strategies for stopping the spread of the virus (e.g., closing schools, stay-at-home orders, etc.), thus impacting an individual's susceptibility of contraction.

Individuals' understanding of their risk was likely associated with other factors as well. Even as early as April 2020, responses to the pandemic had become politicized in the USA by the White House and other Republican elected officials such that conservatives were more likely to downplay the risks posed by COVID-19, suggesting that it was no more serious than a cold or flu and that people should continue about their daily lives with no interruptions [31]. As a result, significant differences in perceptions of the threat from COVID-19 have emerged between individuals who identify as politically conservative or liberal [32–34]. At the same time, in parts of the country with differing levels of viral spread, individuals experienced differing levels of exposure to the virus itself, with many individuals experiencing a great deal of loss and others knowing very few people who had been sick at all [28]. Individuals also spent their time gathering information about the virus from the news and via social media [35, 36], which likely affected their risk perceptions.

Thus, objective risk and subjective risk perceptions—both of susceptibility and severity—likely interact with each other and may be associated with important outcomes, including acting to protect one's health (e.g., social distancing, mask wearing, getting vaccinated) during COVID-19. For example, older age has been associated with increased perceptions of COVID-19 severity risk but lower perceptions of susceptibility risk [37], perhaps because some older adults took more precautions (lowering their risk). Although it is possible to examine how each is uniquely associated with such outcomes on average, this obscures the fact that any collection of individuals will vary in terms of their *objective* risk factors and their *subjective* risk perceptions. A standard clustering approach via machine learning may offer a way to categorize individuals based on these varied patterns of objective and subjective risk to fully understand any incongruencies across both types of risk and the behavioral outcomes differentially associated with the potential patterns. Given the high risk of contracting COVID-19 throughout the population, examining these issues in the context of COVID-19 provides a unique opportunity to examine population-based responses to a widespread health threat.

The Present Study

The present study aimed to identify latent clusters of COVID-19-related susceptibility and severity risk across objective and subjective indicators to characterize responses to the beginning of the pandemic among a large probability-based representative sample of U.S. residents drawn from the NORC AmeriSpeak panel (https://amerispeak.norc.org/). Across two waves of data collection, respondents completed surveys of their experiences during the COVID-19 pandemic. We assessed a series of variables to examine individuals' subjective risk perceptions and their levels of objective risk as defined by the U.S. Centers for Disease Control and Prevention (CDC). A k-means clustering approach was employed to cluster respondents by their objective and subjective risks. Characterizing groups of individuals with similar risk profiles can demonstrate whether and for whom there is likely to be a mismatch in objective (e.g., age, prior health conditions) and subjective (i.e., beliefs about personal susceptibility and severity) risk variables. This approach has been used to generate profiles of risk in physical [38] and mental [39, 40] health contexts in previous studies, though not among large probability-based nationally representative samples. Once risk clusters were identified, we then sought to examine whether individuals within these clusters differentially engaged in health protective behaviors over time. Such an approach can enable a more thorough understanding of how people with disparate profiles of subjective/objective risk and pandemic-related experiences understand a novel threat to their health.

Methods

Study Design and Participants

The participants for the present study were drawn from the NORC AmeriSpeak panel, which uses probability methods to recruit and maintain a national representative panel of approximately 35,000 U.S. households. Unlike other online panels, AmeriSpeak uses random door-to-door interviewing to select households for participation, who then complete surveys via the Internet or telephone. No one can volunteer to join the AmeriSpeak panel. These recruitment procedures result in a higher average response rate relative to other representative panels [41]. Upon entry into the panel, participants' demographic data were collected, including age, gender, race/ethnicity, education, income, geographic region of residence, and residential area (e.g., urban, rural). AmeriSpeak panelists also provided informed consent upon joining the panel, and their identities are kept confidential.

The sample for the present study was drawn from the AmeriSpeak panel using a stratified random sampling technique based on age, race/Hispanic ethnicity, education, and gender (48 sampling strata in total). 11,139 Panelists were selected to be sampled for the study and were randomly assigned to one of three cohorts (Cohort 1: March 18–March 28, 2020; Cohort 2: March 29–April 7, 2020; Cohort 3: April 8–April 18, 2020); this design enabled us to capture responses to the pandemic as the first wave of infection was unfolding across the USA [42]. Precautions were taken by AmeriSpeak to ensure that panelists in our study were not administered any other COVID-19-related surveys prior to their participation in our Wave 1, providing an unbiased baseline assessment. In addition, our respondents were prioritized to receive little content about COVID-19 from other surveys over time. Eligible panelists (those who had completed an AmeriSpeak profile assessment prior to January 2020) were sent a link to the survey via email; surveys were available online for the duration of the participants' randomly assigned fielding periods and were self-administered via computer (44%), tablet (2%), or smartphone (54%). Surveys took approximately 20 min to complete. Survey respondents who completed the survey in under 1/3 the median duration (6.5 min) or who failed to respond to more than half of the survey questions (n = 84) were removed from the study and were not counted in the final sample. In total, 6,514 interviews were completed across the three cohorts (58.5% completion rate based on AAPOR guidelines). All respondents received the cash equivalent of \$4 USD as compensation for completing the survey. AQ10

Approximately 6 months later (September 26, 2020–October 16, 2020), all eligible panelists from Wave 1 (N = 6,501) were approached for a follow-up survey regarding their ongoing experiences with the COVID-19 pandemic. This Wave 2 survey yielded a total of N = 5,661 responses (87.1% completion rate, 86.9% Wave 1 retention; n = 61 responses removed for quality control using the same criteria as Wave 1). Wave 2 respondents spent approximately 24 min completing the survey and received the cash equivalent of \$6–\$10 USD in exchange for their participation. All research activities were reviewed and approved by the University of California, Irvine Institutional Review Board for Human Subjects research.

Measures

COVID-19 risk factors

The following variables were used to classify participants based on subjective assessments of COVID-19 susceptibility and severity risk and their levels of objective severity risk as defined by the U.S. Centers for Disease Control and Prevention (CDC) in 2020.

Age. Participant age was collected as part of participants' profile assessments upon joining the AmeriSpeak panel. Age was dichotomized (under 60 vs. 60 or older) based on the CDC guidelines for COVID-19 risk severity at the beginning of the study [43].

Body Mass Index (BMI). Participant weight (pounds) and height (inches) were collected as part of the AmeriSpeak profile assessment. These values were converted to kilograms (kg) and meters (m), respectively, and then used to calculate each participant's BMI (kg/m^2). BMI was also dichotomized for analyses (under 30 vs. 30 or above) based on CDC guidelines for individuals most at risk for severe COVID-19.

Pre-Existing Health Risk. Pre-pandemic physical health conditions were assessed as part of the AmeriSpeak profile assessment. Participants were asked to report whether a physician had ever diagnosed them with a series of physical health ailments, including high blood pressure or hypertension, heart attack or other heart disease, stroke, diabetes, lung disease, and cancer, among others. CDC guidelines indicate that individuals suffering from these ailments are at higher risk for severe illness from COVID-19; responses to these items were coded as 0 (no pre-existing health risks) or 1 (at least one pre-existing health risk). (While a cancer diagnosis itself is not a risk factor for COVID-19, this was included in the count of pre-existing health conditions due to the immunosuppressing effects of many cancer treatments.)

High-Risk Status. At Wave 1, participants responded 0 (no) or 1 (yes) to the following item as an indicator of their self-reported high-severity risk status: "I am at high risk for complications should I become infected with Coronavirus."

Perceived Risk. This measure was adapted from items used in prior studies of global disease outbreaks [44]. A prior report presented descriptive correlates of these risk judgments at Wave 1 [28]. *Susceptibility* was assessed with the question "What is the percent chance that you will get sick with Coronavirus in the next 3 months?." Participants reported their risk assessment ranging from 0% chance to 100% chance of getting sick. *Severity* was assessed with the question "What is the percent chance that you will die if you get sick with Coronavirus?." Participants reported their risk assessment ranging from 0% chance to 100% chance of dying.

Covariates

Political Party Affiliation. Political party affiliation was assessed during the AmeriSpeak profile survey using a 1-item Likert-type scale (1 "Strong Democrat" to 7 "Strong Republican").

COVID-19 Exposures. Participants completed a checklist to assess exposure to the COVID-19 outbreak [42]. Personal exposures were assessed using ten items reflecting direct or indirect disease exposure (e.g., I/someone close to me was diagnosed with Coronavirus). Responses were dichotomized due to low rates of exposure at the time of data collection.

Essential Worker Status. Two survey items assessed whether an individual was continuing to work in a face-to-face setting in the early days of the pandemic. Participants responded 0 (no) or 1 (yes) to the following items: "My job requires in-person interaction and I am still working" and "I work in an essential service (e.g., grocery store, healthcare) and am working extra hours." Participants were coded as 1 if they answered "yes" to either of these two items and 0 if they answered "no" to both. This measure was used in a prior report [30].

COVID-19 Media. Participants were asked to report the average number of hours (0–11+) of pandemic-related media coverage they had consumed in the previous week across three sources (television, radio, and print media; online news; and social media). Responses were summed to create a composite media coverage score; responses could sum to greater than 24 h per day due to the possibility of individuals engaging with multiple media sources at once (range: 0–33). This measure was based on similar assessments that have been used in previous research [45, 46].

Dependent variables

Health Protective Behaviors. At Wave 2, participants reported the frequency with which they had engaged in each of a list of six health protective behaviors on a 1 (never) to 5 (all the time) Likert-type scale. These behaviors included: "Washed my hands for at least 20 seconds," "Wore a face mask when in public," and four social distancing behaviors (e.g., "Avoided socializing with people outside my household"). A mean social distancing score was calculated for the four social distancing items [range: 1–5; (α = .81)]. (At the time of Wave 2 data collection, which was prior to the availability of a vaccine, these were the recommended behaviors for preventing the spread of COVID-19.) This measure has been used in prior reports [28, 47].

Risk Behaviors. At Wave 2, frequency of engaging in risky behaviors was assessed. Participants were asked to report whether they had they engaged in a series of eight behaviors that might put them at risk for exposure to COVID-19 since the relaxation of restrictions in their communities. These behaviors included: "Flown on an airplane," "Eaten at a restaurant indoors," and "Gone to a social gathering of more than 10 people (e.g., party, wedding, funeral)." Participants could report engaging in these behaviors not at all (0), just once (1), or more than once (2). Responses to these items were summed (range: 0–16).

Intent to Vaccinate. At Wave 2, participants' intention to receive the COVID-19 vaccine (which was still undergoing testing and was not yet available at the time of the survey) was assessed with one item. Participants were asked to report the percent chance that they would "…get the COVID-19 vaccine when it is made widely available" (range: 0%–100% chance).

Analytic Strategy

A k-means clustering approach using R (R Core Team, 2021) was employed to cluster respondents on six survey items: three objective risk items (i.e., age, BMI, physical health ailments) and three subjective risk items (i.e., self-reported perceived high-risk status, perceived risk of COVID-19 sickness, and risk of death should they get sick). This data-driven (unsupervised) technique aims to identify an underlying structure of the data; specifically, a number of clusters is specified and the algorithm iterates cluster starting points in a vectorized space (based on the number of variables at play) until it arrives at a solution in which the centroids are placed optimally, such that the sum of distance scores between cases and centroids is minimized. A test of the optimal number of clusters was conducted via the NbClust package [48] in R, which uses 30 different cluster estimation indices to generate an overall best number of clusters for a given dataset. The results of this procedure indicated that five was the best number of clusters. Thus, five clusters were requested in the k-means analysis and respondents were categorized into one of the five clusters.

Next, Wave 2 health and risk behavior adoption was regressed on the following Wave 1 variables in a multiple OLS regression using Stata 16.1 (StataCorp, College Station, TX): cluster assignment, demographics (gender, ethnicity, income, bachelor's degree vs. not, Urban area vs. not, region), political party affiliation, COVID-19-related media exposure, personal exposure to COVID-19, and essential worker status. Regression models were weighted to account for differential probabilities of inclusion into the AmeriSpeak panel, differences between the sample and U.S. Census benchmarks, and for attrition over time using probability weights. Multiple imputation was used to account for missing items at each wave; a total of 20 imputations were used due to low missingness on all variables by wave (less than 1% missing for all study variables).

Results

The final weighted sample demographics closely aligned with U.S. Census benchmarks [42]. The final weighted Wave 1 sample (N = 6,514) ranged in age from 18 to 97 years (M = 47.51 years; SD = 17.45); 29.5% of the sample was age 60 or older. Approximately half the sample was female (51.9%); 63.6% of the sample identified as white (non-Hispanic), 11.8% as Black (non-Hispanic), 16.0% as Hispanic, and 8.7% identified as multiracial or other ethnicities. Almost 10% had not finished high school, 28.5% had earned a high school diploma, 28.0% had attended some college, and 33.6% had earned a bachelor's degree or higher. The median annual income for the sample was between $40,000 and $49,999.

The patterning within each of the five clusters revealed differential subjective risk perceptions and objective risk factors for disease severity and susceptibility (see Fig. 1; subjective risk in green; objective risk in blue). The first cluster represented a group of individuals whose subjective perceptions of both types of risk were low, and in which few respondents indicated objective risk factors for severe illness. In other words, this group was made up of relatively healthy individuals (low objective risk of severity) who reported low perceived risk of susceptibility or severity for COVID-19. The second cluster was comprised of relatively younger individuals with BMIs above 30 and with some pre-existing conditions. Although these individuals were objectively more vulnerable than the first cluster, their perceptions of subjective risk of susceptibility to infection and severity of illness were nearly identical to the first cluster. The third cluster exhibited an incongruence such that this older group, with objective risk factors that made them more vulnerable to severe illness, did not perceive risk of sickness and death in a corresponding way. Instead, their levels of perceived susceptibility and severity risk were similar to the first two clusters. The fourth cluster was comprised of relatively healthy individuals who subjectively perceived more COVID-19-related susceptibility and severity risk than the previous groups, and were likely to report a 50/50 chance of getting sick with COVID-19 (indicating uncertainty about their susceptibility risk [49]). The fifth cluster exhibited a congruent pattern such that individuals in this group had more objective risk factors and also perceived higher risk of sickness (susceptibility) and dying (severity) from the coronavirus. Figure 2a and b present the distributions of the perceived risk of susceptibility and severity to COVID-19 variables across cluster assignment. These violin plots demonstrate low overall risk perceptions for clusters 1, 2, and 3 and greater variability in clusters 4 and 5.

Table 1 presents a breakdown of demographic and COVID-19 related variables by cluster assignment. Notably, self-reported engagement in health-protective behaviors was high at Wave 2; participants reported a mean frequency of mask wearing of 4.51 (SD = 0.85; between often and all the time) and an overall mean frequency of engaging in social distancing of 3.42 (SD = 1.04; between sometimes and often). Mean frequency of engagement in risk behaviors was relatively low (M = 3.90; SD = 3.17), indicating that most participants were continuing to take precautions to prevent the spread of COVID-19, even as many community restrictions had been lifted. Mean levels of intention to vaccinate at Wave 2 were moderate (M = 43.16; SD = 40.34), though the distribution was trimodal: 30.6% of the Wave 2 sample (n =

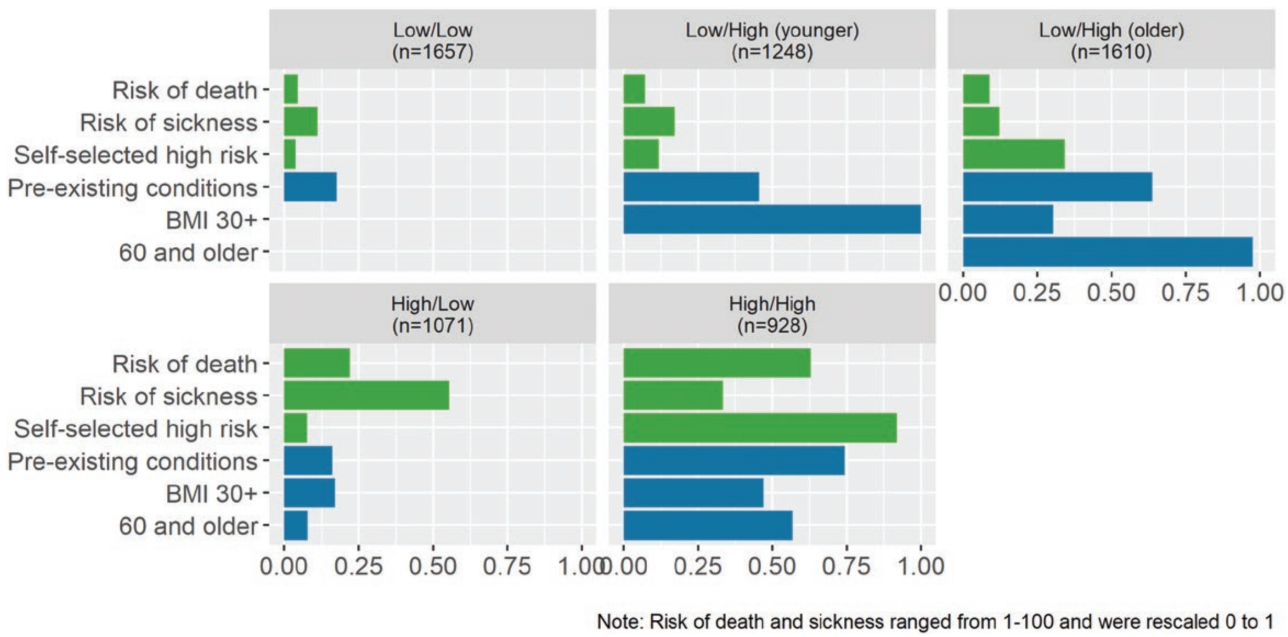

Fig. 1. Mean values of subjective (green) vs. objective risk (blue) factors by cluster (N = 6,514)

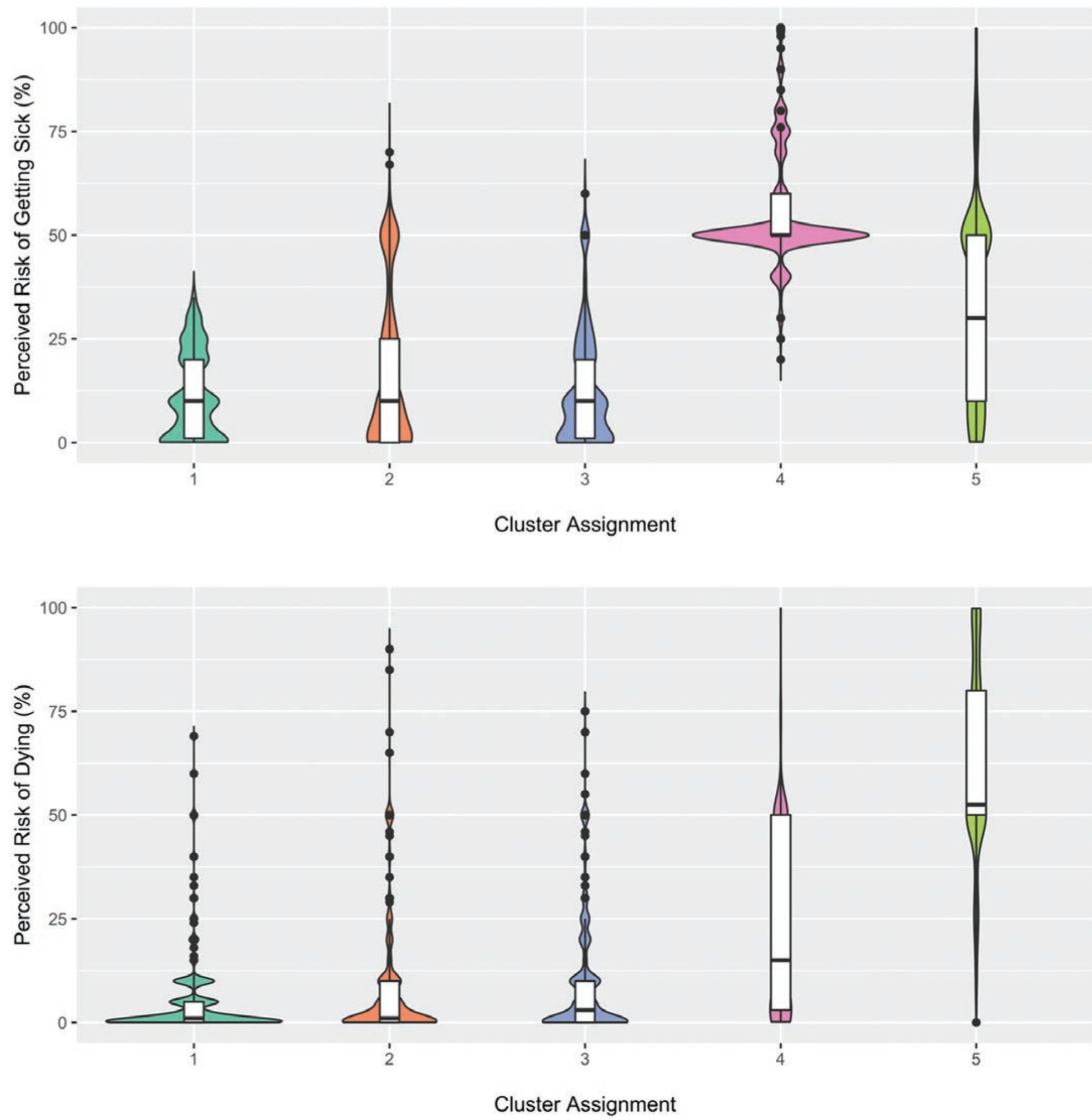

Fig. 2. Violin plots of personal risk assessments (sick and dying from COVID-19) across cluster assignment (N = 6,514)

1,706) reported a 0% chance of getting the vaccine, 14.6% reported a 50% chance (i.e., uncertainty about whether they will vaccinate; n = 818), and 20.4% reported a 100% chance of getting the vaccine (n = 1,139).

Table 2 presents the prospective predictors of health and risk behavior adoption 6 months into the pandemic (prior to vaccine availability). Relative to Cluster 1 (Low/Low), only clusters with elevated subjective susceptibility and severity risk assessments (Clusters 4 and 5) reported increased frequency of engaging in social distancing behaviors. In contrast, only Clusters 3 and 5 (two groups who reported increased objective severity risk and included higher concentrations of individuals aged 60+) reported more frequent mask wearing, less frequent risk behaviors, and intent to receive the COVID-19 vaccine. Cluster 2 (Low/High, Younger) reported similar health protective and risk behaviors as those in the Low/Low cluster. Other covariates in the models were also prospectively associated with outcomes. Variables positively associated with social distancing included female gender, other/2+ races, non-Hispanic ethnicity, having a bachelor's degree, living in an urban area, and media exposure to COVID-19-related media content. Republican political party affiliation and essential worker status were negatively associated with social distancing. Variables positively associated with mask wearing included female gender, other/2+ races, non-Hispanic ethnicity, higher income, having a bachelor's degree, and living in an urban area. Republican political party affiliation and essential worker status were negatively associated with mask wearing. Variables positively associated with risky behaviors included higher income, having a bachelor's degree, living in the Midwest, Republican political party affiliation, and essential worker status. Black, non-Hispanic ethnicity, other/2+ races, non-Hispanic ethnicity were both negatively associated with engaging in risky behaviors. Variables positively associated with intent to vaccinate included higher income and having a bachelor's degree. Female gender, Black,

Table 1 Weighted Descriptive Statistics by Cluster Assignment (*N* = 6,514)

Variables	Cluster 1: Low/Low (*n* = 1,657)	Cluster 2: Low/High (younger) (*n* = 1,248)	Cluster 3: Low/High (older) (*n* = 1,610)	Cluster 4: High/Low (*n* = 1,071)	Cluster 5: High/High (*n* = 928)
Age: *M* (*SD*)	37.29 (11.45)	39.87 (11.03)	68.03 (7.97)	38.40 (13.69)	57.62 (16.53)
Female gender (%)	45.7%	58.3%	46.6%	58.3%	56.0%
Race/ethnicity					
White (%)	56.1%	54.5%	76.7%	65.4%	69.6%
Black (%)	11.1%	19.7%	9.2%	7.1%	10.3%
Hispanic (%)	19.9%	20.1%	8.7%	17.8%	11.3%
Other (%)	12.9%	5.7%	5.4%	9.7%	8.9%
Income (median)	$40,000–$49,999	$35,000–$39,999	$50,000–$59,999	$40,000–$49,999	$35,000–$39,999
Education					
Less than HS (%)	11.7%	11.2%	7.6%	6.6%	11.4%
HS Diploma (%)	26.5%	35.3%	23.6%	29.7%	28.2%
Some college (%)	25.5%	30.2%	27.5%	28.2%	30.5%
Bachelor's degree + (%)	36.3%	23.3%	41.3%	35.3%	29.9%
Metropolitan area					
Urban (%)	71.7%	63.0%	63.5%	68.3%	60.2%
Suburban (%)	8.3%	12.3%	11.5%	9.1%	11.9%
Town (%)	12.3%	12.6%	13.7%	12.5%	14.0%
Rural (%)	7.7%	12.2%	11.3%	10.0%	13.9%
Region					
Northeast (%)	16.9%	16.0%	16.9%	20.6%	17.0%
Midwest (%)	18.9%	23.6%	19.7%	21.5%	22.6%
South (%)	36.1%	41.8%	38.8%	34.1%	36.8%
West (%)	28.2%	18.6%	24.7%	23.8%	23.5%
Political party identification *M* (*SD*)[a]	3.97 (1.78)	3.64 (1.81)	4.17 (2.23)	3.58 (1.94)	3.59 (1.99)
COVID-19 related media exposure: *M* (*SD*)	7.08 (6.89)	8.03 (7.09)	5.82 (6.33)	7.44 (6.97)	7.69 (7.34)
Personal COVID-19 exposure (% yes)	22.3%	24.6%	15.2%	32.8%	26.9%
Essential/in-person worker (%)	36.2%	39.0%	12.9%	40.2%	17.9%
W2 social distancing *M* (*SD*)	3.32 (1.03)	3.29 (1.02)	3.39 (1.08)	3.55 (0.99)	3.75 (0.94)
W2 mask wearing *M* (*SD*)	4.42 (0.84)	4.43 (0.86)	4.57 (0.89)	4.56 (0.82)	4.66 (0.78)
W2 risk behaviors *M* (*SD*)	4.36 (3.31)	4.11 (2.96)	3.76 (3.13)	3.99 (3.16)	2.79 (2.86)
W2 intent to vaccinate *M* (*SD*)	39.80 (37.96)	33.31 (36.59)	52.70 (43.78)	42.67 (40.10)	49.90 (40.78)

[a]1 = "Strong Democrat," 7 = "Strong Republican".

non-Hispanic ethnicity, Republican political party affiliation, and essential worker status were negatively associated with intent to vaccinate.

Discussion

Using a cluster-based analytic approach, we explored optimistic bias for disease susceptibility and severity during the early phase of COVID-19 by examining subjective and objective indicators of risk (susceptibility and severity) for COVID-19 to identify patterns of response among similar individuals. Five clusters were identified with distinct patterns of subjective risk perceptions and objective risk factors, which then prospectively predicted differential adoption of health and risk behaviors over the following 6 months. In particular, the two clusters with elevated subjective perceptions of risk severity-dying from COVID-19—performed health protective behaviors more frequently and risky behaviors less frequently than their counterparts who perceived near-zero levels of risk. Although adoption of health behaviors in our sample was high overall, our cluster-based approach was nonetheless able to predict variability in behavior across our nationally representative sample. These risk clusters represent a snapshot of the complex ways in which the population understood their own risk of COVID-19 disease contraction and its consequences in the context of their personal circumstances. They also function as early predictors of long-term behavior and can inform policy makers as to potential points of intervention during future pandemics.

We found evidence of optimistic bias in our sample wherein individuals' subjective perceptions of risk (susceptibility and severity) did not align with their objective risk characteristics. Furthermore, this mismatch was in some cases associated with no better adoption of health protective behaviors than seen in individuals for whom both objective and subjective risk were lower. In particular, Clusters 2 and 3, representing almost 44% of our sample, were characterized by near-zero perceptions of risk of getting sick or dying from COVID-19, despite increasing community transmission of the disease and high proportions of individuals in these clusters also reporting one or more objective risk factor. This finding fits within a growing body of evidence suggesting that optimistic bias was prevalent during the early stages of the COVID-19 pandemic

Table 2 Multiple OLS Regression Models Predicting Health and Risk Behavior Adoption at Wave 2 (*N* = 5,661)

Variables	Social distancing	Mask wearing	Risk behaviors	Intent to vaccinate
Cluster membership				
Cluster 2: Low/High (Younger)	−0.04 (−0.16, 0.07)	0.02 (−0.10, 0.13)	−0.06 (−0.18, 0.07)	−0.04 (−0.14, 0.07)
Cluster 3: Low/High (Older)	0.07 (−0.03, 0.17)	0.18 (0.08, 0.29)[b]	−0.18 (−0.28, −0.07)[c]	0.31 (0.21, 0.40)[c]
Cluster 4: High/Low	0.14 (0.03, 0.26)[a]	0.11 (−0.02, 0.24)	−0.10 (−0.22, 0.02)	0.06 (−0.05, 0.17)
Cluster 5: High/High	0.33 (0.23, 0.44)[c]	0.24 (0.13, 0.35)[c]	−0.42 (−0.53, −0.30)[c]	0.27 (0.17, 0.38)[c]
Female gender	0.19 (0.12, 0.26)[c]	0.23 (0.15, 0.30)[c]	0.06 (−0.02, 0.13)	−0.23 (−0.30, −0.16)[c]
Ethnicity				
Black, non-Hispanic	0.01 (−0.13, 0.14)	0.09 (−0.05, 0.24)	−0.16 (−0.30, −0.01)[a]	−0.54 (−0.66, −0.43)[c]
Other/2+ races, non-Hispanic	0.17 (0.05, 0.28)[b]	0.11 (0.004, 0.22)[a]	−0.28 (−0.40, −0.16)[c]	−0.02 (−0.15, 0.11)
Hispanic	0.05 (−0.07, 0.18)	0.09 (−0.05, 0.22)	−0.08 (−0.21, 0.06)	−0.11 (−0.24, 0.02)
Income	0.004 (−0.03, 0.04)	0.07 (0.03, 0.11)[c]	0.10 (0.06, 0.14)[c]	0.10 (0.06, 0.13)[c]
Bachelor's degree +	0.22 (0.16, 0.29)[c]	0.12 (0.05, 0.18)[c]	0.09 (0.02, 0.16)[a]	0.23 (0.15, 0.30)[c]
Urban residential area	0.11 (0.03, 0.19)[a]	0.24 (0.15, 0.32)[c]	−0.06 (−0.14, 0.02)	0.06 (−0.01, 0.13)
Region				
Midwest	−0.09 (−0.20, 0.02)	−0.03 (−0.17, 0.10)	0.14 (0.03, 0.26)[a]	0.01 (−0.10, 0.12)
South	−0.01 (−0.12, 0.11)	0.10 (−0.02, 0.23)	0.05 (−0.07, 0.16)	0.02 (−0.09, 0.13)
West	0.04 (−0.07, 0.16)	0.04 (−0.09, 0.17)	−0.07 (−0.19, 0.05)	0.07 (−0.05, 0.18)
Political party identification	−0.30 (−0.33, −0.26)[c]	−0.27 (−0.31, −0.24)[c]	0.20 (0.16, 0.24)[c]	−0.17 (−0.21, −0.14)[c]
COVID-19 media exposure	0.06 (0.02, 0.10)[b]	−0.0001 (−0.04, 0.04)	0.04 (−0.01, 0.08)	0.004 (−0.03, 0.04)
Personal COVID-19 exposure	0.01 (−0.07, 0.09)	0.03 (−0.05, 0.12)	0.02 (−0.07, 0.12)	−0.02 (−0.10, 0.07)
Essential worker	−0.16 (−0.24, −0.08)[c]	−0.12 (−0.21, −0.04)[b]	0.26 (0.17, 0.35)[c]	−0.13 (−0.21, −0.05)[b]
Constant	−0.34 (−0.47, −0.20)[c]	−0.48 (−0.64, −0.32)[c]	0.02 (−0.12, 0.17)[a]	−0.07 (−0.20, 0.05)
Model statistics	$F(18, 5654.7) = 36.82$[c]	$F(18, 5648.1) = 26.25$[c]	$F(18, 5657.4) = 22.25$[c]	$F(18, 5631.3) = 33.04$[c]

Reference group for model is Cluster 1: Low/Low. Reference group for gender is male; reference group for ethnicity is white (non-Hispanic); reference group for education is less than bachelor's degree; reference group for residential area is non-urban; reference group for region is Northeast. Political party identification: 1 = "Strong Democrat," 7 = "Strong Republican."
[a] $p < .05$;
[b] $p < .01$;
[c] $p < .001$.

and that it was associated with less engagement in health protective action in the population [50–52].

These findings have important implications for personal and public health in the population, including vaccine uptake for COVID-19 (now endemic with expected stabilized, ongoing prevalence [53]) and related viral threats such as seasonal influenza and Respiratory Syncytial Virus (RSV). For example, the Food and Drug Administration recently approved the first vaccine for RSV, which has some similar risk factors for disease severity to COVID-19 such as older age and underlying health conditions [54]. Yet this vaccine will only be effective at mitigating RSV risk if people opt to get it. Targeted communications and conversations from healthcare providers aimed at those reticent to take it yet at risk will be critical for reducing this threat. Indeed, our findings extend prior risk research by showing that effective risk communications must target several disparate audiences with different beliefs, attitudes, and perspectives. Considering these audiences separately provides critical information about how their risk contexts differ and why their subsequent behaviors may differ as well. As such, any messaging about health protective behaviors must recognize that a one size fits all approach is not appropriate; simple risk communication is likely to miss people who need to hear it while possibly adding unnecessary stress for others. Moreover, the more we rely on people's risk perceptions for disease policy, the more we risk conflating these perceptions with objective truth. Of course, nuance is difficult to communicate in the context of an evolving public health crisis [55]. Clear communication with people from different risk profiles about their specific risks is imperative [56–58].

With respect to COVID-19 specifically, now that it is endemic, public policy has shifted towards relying on individuals' particular levels of risk and their individual decision to engage in protective action. Some will need to wear masks during outbreaks, whereas others may not. Current guidance on vaccine boosters also varies based on individuals' objective risk [59]. Whether or not people take up these behaviors will depend on whether their objective risk aligns with their own perceptions of their susceptibility and severity risk. Yet as we demonstrate, this alignment is not to be universally expected. The present findings also have important implications for risk communications outside of the current COVID-19 context. Scholars have indicated that, despite the past several years of a pandemic, the world is vulnerable to future infectious disease outbreaks [60, 61], which have an increasing likelihood of recurrence [62]. In addition, similar gaps between people's subjective and objective risk for influenza have been demonstrated in prior research, suggesting that these findings may have application for this seasonal disease risk as well [63–65]. Moreover, these findings may be applicable outside of the disease context as well. For example, understanding perceptions of objective vs. subjective risks, and the role they play in preparation for natural disasters, may also encourage mitigation behaviors among both individuals and communities threatened by repeated exposure to hurricanes, wildfires, or earthquakes.

Limitations

This study is not without weaknesses. First, as it was exploratory in nature, future studies may seek to replicate these findings in other samples and consider its relevance to other threats (e.g., natural disaster response). Additionally, when the Wave 1 survey was launched, the range of ways that people might be affected by the COVID-19 pandemic was still unclear. Thus, additional or different questions may have been asked of survey respondents had we understood the full extent of impacts the pandemic would have over the course of months and years of extended exposure to disease and mitigation measures. Findings should be replicated with other endemic threats such as seasonal influenza and RSV as well as other chronic health threats such as cardiovascular disease and diabetes.

Finally, given high levels of uncertainty regarding community spread and rapidly changing circumstances, we were unable to measure objective indicators of susceptibility in our study. This was ultimately not possible because of how quickly the situation evolved over the weeks of data collection. Furthermore, in the context of our Wave 1 data collection, susceptibility may be considered a constant due to the lack of immunity at the time—the virus was novel and no vaccines were yet available. Thus, on balance, susceptibility was relatively equal in the context of a rapidly spreading virus for which people in the population had no prior immunity.

Despite these limitations, this study also has methodological strengths, including a prospective longitudinal design and, importantly, the use of a large, high-quality probability-based nationally representative sample that enables us to draw population-based conclusions from these findings. The AmeriSpeak panel was established using gold-standard survey methods, including the use of address-based sampling and prohibition of opt-ins. Additionally, protections were in place to ensure that participants were not exposed to COVID-19 related surveys prior to their participation in the present study. Furthermore, while such factors as geographical region, urban vs. rural residence, political party affiliation, and media use likely were associated with both subjective and objective risk, our large sample size and analytic approach enabled us to account for these factors through the use of statistical controls. The novel analytic strategy also enabled us to tease apart heterogeneous patterns of response that would not have been visible using a more traditional approach.

Future Directions and Conclusions

Understanding risk perceptions for a variety of threats in the context of objective and subjective factors at a population scale is vital. Our findings demonstrate that early understandings of one's own risk—based on both objective and subjective factors—play a role in predicting long-term behavior. Though these data were collected relatively early in the pandemic, we may reasonably expect that the high-risk clusters we identified in the present study may also be most likely to accept a COVID-19 vaccine once it was offered to them. As a result, perceptions of risk within these clusters may have shifted over the course of the pandemic as additional protections became available and the pandemic changed. The degree to which the pandemic context influenced individuals' understanding of their risk over time is another question that may be explored in future research. Expanding these findings to other contexts in which risks are repetitious in nature, as in other disease contexts (i.e., seasonal flu, chronic disease) or natural disasters is also important.

In addition, these findings may be used to help tailor messaging to individuals likely to demonstrate optimistic bias. To map intervention communications on to individuals' understanding of their risk, we must find out from people how they are perceiving their personal risk in the context of their experiences. As we contend with ongoing infectious disease outbreaks, with guidance often based on individuals' own risk perceptions, and action based on individual decision making, assessing the ways in which risk perceptions may be inaccurate or biased must play a role in risk communications. In this way, we may come closer to a more educated and healthier public that is more responsive to public health recommendations.

Acknowledgements

Project support provided by U.S. National Science Foundation grants SES 2026337 and SES 2049932. Dana Rose Garfin was funded by National Institute of Health K01 MD013910. Authors would like to thank the NORC AmeriSpeak team of J. Michael Dennis and David Reisner for their survey research and sampling guidance, for preparation of the online surveys, and for preparation of the data files. We also thank Emma Grisham, Kayley Estes, and Daniel Relihan for their contributions to the larger project from which these data were drawn.

Compliance with Ethical Standards

Authors' Statement of Conflict of Interest and Adherence to Ethical Standards The authors declare no conflicts of interest. All research activities were reviewed and approved by the [REMOVED FOR MASKED REVIEW] Institutional Review Board for Human Subjects research. Participants provided informed consent upon entry to panel and at each wave of data collection. AQ12

Authors' Contributions Rebecca R Thompson (Conceptualization: Lead; Formal analysis: Lead; Methodology: Equal; Visualization: Equal; Writing – original draft: Lead; Writing – review & editing: Equal), Nickolas M. Jones (Conceptualization: Supporting; Formal analysis: Supporting; Methodology: Equal; Visualization: Equal; Writing – review & editing: Equal), Dana Rose Garfin (Conceptualization: Supporting; Funding acquisition: Equal; Investigation: Equal; Methodology: Equal; Supervision: Supporting; Writing – review & editing: Equal), E. Alison Holman (Conceptualization: Supporting; Funding acquisition: Equal; Investigation: Equal; Methodology: Equal; Supervision: Supporting; Writing – review & editing: Equal), and Roxane Cohen Silver, PhD (Conceptualization: Supporting; Funding acquisition: Equal; Investigation: Equal; Methodology: Equal; Supervision: Lead; Writing – review & editing: Equal)

Transparency Statements (1) The overall program of research from which this report is drawn was registered on the Open Science Framework (OSF) after the study began at https://osf.io/b48dz/?view_only=d529b34cbaca4f228d39d7cc5fa4bc60. (2) The analysis plan was not formally pre-registered. (3) De-identified data from this study will be made available upon publication on the OSF at https://osf.io/b48dz/?view_only=d529b34cbaca4f228d39d7cc5fa4bc60. (4) Analytic code used to conduct the analyses presented in this study will be made available upon publication on the OSF at https://osf.io/b48dz/?view_only=d529b34cbaca4f228d39d7cc5fa4bc60. (5) All materials relevant to the data reported in this manuscript will be made available upon publication on the OSF at https://osf.io/b48dz/?view_only=d529b34cbaca4f228d39d7cc5fa4bc60.

References AQ13

1. Geldsetzer P. Knowledge and perceptions of COVID-19 among the general public in the United States and the United Kingdom: a cross-sectional online survey. *Ann Intern Med*. 2020; 173: 157–160. AQ14
2. Cipolletta S, Andreghetti GR, Mioni G. Risk perception towards COVID-19: a systematic review and qualitative synthesis. *Int J Environ Res Public Health*. 2022; 19: 4649. AQ15
3. National Academies of Science Engineering and Medicine. Supporting individual risk assessment during COVID-19. 2022. Available at https://nap.nationalacademies.org/catalog/26629/supporting-individual-risk-assessment-during-covid-19. Accessibility verified August 19, 2023.
4. Lavie CJ, Ozemek C, Carbone S, Katzmarzyk PT, Blair SN. Sedentary behavior, exercise, and cardiovascular health. *Circ Res*. 2019; 124: 799–815. AQ16
5. Fisher EB, Walker EA, Bostrom A, Fischhoff B, Haire-Joshu D, Johnson SB. Behavioral science research in the prevention of diabetes: status and opportunities. *Diabetes Care*. 2002; 25: 599–606. AQ17
6. Fischhoff B. The sciences of science communication. *Proc Natl Acad Sci USA*. 2013; 110: 14033–14039. AQ18
7. World Health Organization: Novel Coronavirus (2019-nCoV). Situation Report 13, 2 February. 2020. Available at https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200202-sitrep-13-ncov-v3.pdf. Accessibility verified August 19, 2023.
8. Brewer NT, Chapman GB, Gibbons FX, Gerrard M, McCaul KD, Weinstein ND. Meta-analysis of the relationship between risk perception and health behavior: the example of vaccination. *Health Psychol*. 2007; 26: 136–145. AQ19
9. Tversky A, Kahneman D. Judgment under uncertainty: heuristics and biases. *Science*. 1974; 185: 1124–1131. AQ20
10. Perloff LS. Social comparison and illusion of invulnerability to negative life events. In: Snyder CR, Ford C, eds. *Coping with Negative Life Events: Clinical and Psychological Perspectives*. New York: Plenum; 1987:217–242.
11. Weinstein ND. Optimistic biases about personal risks. *Science*. 1989; 246: 1232–1233. AQ21
12. Weinstein ND. Unrealistic optimism about susceptibility to health problems: conclusions from a community-wide sample. *J Behav Med*. 1987; 10: 481–500. AQ22
13. Weinstein ND. Unrealistic optimism about susceptibility to health problems. *J Behav Med*. 1982; 5: 441–460. AQ23
14. Taylor SE, Brown JD, Brown JD. Illusion and well-being: a social psychological perspective on mental health. *Psychol Bull*. 1988; 103: 193–210. AQ24
15. Sedikides C, Gregg AP. Portraits of the self. In: Hogg MA, Cooper J, eds. *Sage Handbook of Social Psychology*. London: Sage; 2003.
16. Perloff LS, Fetzer Barbara K, Fetzer BK. Self-other judgments and perceived vulnerability to victimization. *J Pers Soc Psychol*. 1986; 50: 502–510. AQ25
17. Fontaine KR, Smith S, Smith S. Optimistic bias in cancer risk perception: a cross-national study. *Psychol Rep*. 1995; 77: 143–146. AQ26
18. Sargeant JM, Majowicz SE, Sheth U, Edge VL. Perceptions of risk and optimistic bias for acute gastrointestinal Illness: a population survey. *Zoonoses Public Health*. 2010; 57: 177–183. AQ27
19. Segerstrom SC, Mcarthy WJ, Caskey NH, Gross TM, Jarvik ME. Optimistic bias among cigarette smokers. *J Appl Soc Psychol*. 1993; 23: 1606–1618. AQ28
20. Gassen J, Nowak TJ, Henderson AD, Weaver SP, Baker EJ, Muehlenbein MP. Unrealistic optimism and risk for COVID-19 disease. *Front Psychol*. 2021; 12: 647461. AQ29
21. Attema AE, L'Haridon O, Raude J, Seror V; The COCONEL Group. Beliefs and risk perceptions about COVID-19: evidence from two successive French representative surveys during lockdown. *Front Psychol*. 2021; 12: 619145. AQ30
22. Taylor SE. *Positive Illusions: Creative Self-deception and the Healthy Mind*. New York: Basic Books, 1989.
23. Icek A. The theory of planned behavior. *Organ Behav Hum Decis Process*. 1991; 50: 179–211. AQ31
24. Maiman LA, Becker MH. The Health Belief Model: origins and correlates in psychological theory. *Heal Educ Behav*. 1977; 2: 336–353. AQ32
25. Bränström R, Kristjansson S, Ullén H. Risk perception, optimistic bias, and readiness to change sun related behaviour. *Eur J Public Health*. 2006; 16: 492–497. AQ33
26. Chong YY, Chien WT, Cheng HY, et al. The role of illness perceptions, coping, and self-efficacy on adherence to precautionary measures for COVID-19. *Int J Environ Res Public Health*. 2020; 17: 6540. AQ34
27. Bruine de Bruin W, Bennett D. Relationships between initial COVID-19 risk perceptions and protective health behaviors: a national survey. *Am J Prev Med*. 2020; 59: 157–167. AQ35
28. Garfin DR, Fischhoff B, Holman EA, Silver RC. Risk perceptions and health behaviors as COVID-19 emerged in the United States: results from a probability-based nationally representative sample. *J Exp Psychol Appl*. 2021; 27: 584–598. AQ36
29. Centers for Disease Control and Prevention. Underlying medical conditions associated with higher risk for severe COVID-19: information for healthcare professionals. 2022. Available at https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-care/underlyingconditions.html. Accessibility verified August 19, 2023.
30. Garfin DR, Djokovic L, Silver RC, Holman EA. Acute stress, worry, and impairment in health care and non-health care essential workers during the COVID-19 pandemic. *Psychol Trauma Theory Res Pract Policy*. 2022; 14: 1304–1313. AQ37
31. Woodward C. AP FACT CHECK: Trump's faulty claims on flu and coronavirus. AP News. 2020. Available at https://apnews.com/article/virus-outbreak-donald-trump-ap-fact-check-anthony-fauci-flu-fe474f0c15f76adf324791a2cfc1e2bb. Accessibility verified August 19, 2023.
32. Calvillo DP, Ross BJ, Garcia RJB, Smelter TJ, Rutchick AM. Political ideology predicts perceptions of the threat of COVID-19 (and susceptibility to fake news about it). *Soc Psychol Personal Sci*. 2020; 11: 1119–1128. AQ38
33. Bruine de Bruin W, Saw H-W, Goldman DP. Political polarization in US residents' COVID-19 risk perceptions, policy preferences, and protective behaviors. *J Risk Uncertain*. 2020; 61: 177–194. AQ39
34. Relihan DP, Holman EA, Garfin DR, Ditto PH, Silver RC. Politicization of a pathogen: a prospective longitudinal study of COVID-19 responses in a nationally representative U.S. sample. *Polit Psychol*. 2023. AQ40
35. Kim S, Capasso A, Cook SH, et al. Impact of COVID-19-related knowledge on protective behaviors: the moderating role of primary sources of information. *PLoS One*. 2021; 16: e0260643. AQ41
36. Entradas M. In science we trust: the effects of information sources on COVID-19 risk perceptions. *Health Commun*. 2021; 37: 1715–1723. AQ42
37. Bruine de Bruin W. Age differences in COVID-19 risk perceptions and mental health: evidence from a national U.S. survey conducted in March 2020. *J Gerontol Ser B Psychol Sci Soc Sci*. 2021; 76: e24–e29. AQ43
38. Grant RW, McCloskey J, Hatfield M, et al. Use of latent class analysis and k-means clustering to identify complex patient profiles. *JAMA Netw Open*. 2020; 3: e2029068. AQ44
39. Liu F, Yang D, Liu Y, et al. Use of latent profile analysis and k-means clustering to identify student anxiety profiles. *BMC Psychiatry*. 2022; 22: 12. AQ45
40. Boersma K, Linton SJ, Linton SJ. Screening to identify patients at risk: profiles of psychological risk factors for early intervention. *Clin J Pain*. 2005; 21: 38–43; discussion 69. AQ46

41. Dennis JM. Technical overview of the AmeriSpeak panel: NORC's probability-based household panel. 2019. Available at https://amerispeak.norc.org/research/. Accessibility verified August 19, 2023. AQ47
42. Holman EA, Thompson RR, Garfin DR, Silver RC. The unfolding COVID-19 pandemic: a probability-based, nationally representative study of mental health in the U.S. *Sci Adv.* 2020; 6: eabd5390. AQ48
43. Koma W, Neuman T, Claxton G, Rae M, Kates J, Michaud J: How many adults are at serious risk of serious illness if infected with Coronavirus? KFFOrg. 2020. Available at https://www.kff.org/coronavirus-covid-19/issue-brief/how-many-adults-are-at-risk-of-serious-illness-if-infected-with-coronavirus/. Accessibility verified August 19, 2023. AQ49
44. Fischhoff B, Wong-Parodi G, Garfin DR, Holman EA, Silver RC. Public understanding of Ebola risks: mastering an unfamiliar threat. *Risk Anal.* 2018; 38: 71–83. AQ50
45. Holman EA, Garfin DR, Silver RC. Media's role in broadcasting acute stress following the Boston Marathon bombings. *Proc Natl Acad Sci USA.* 2014; 111: 93–98. AQ51
46. Garfin DR, Thompson RR, Holman EA, Wong-Parodi G, Silver RC. Association between repeated exposure to hurricanes and mental health in a representative sample of Florida residents. *JAMA Netw Open.* 2022; 5: e2217251. AQ52
47. Garfin DR, Thompson RR, Wong-Parodi G. Media exposure, threat processing, and mitigation behaviors in Gulf Coast residents facing the co-occurring threats of COVID-19 and hurricanes. *Risk Anal.* 2023; 43: 1370–1386. AQ53
48. Charrad M, Ghazzali N, Boiteau V, Niknafs A. NbClust: an R Package for determining the relevant number of clusters in a data set. *J Stat Softw.* 2014; 61: 1–36. AQ54
49. Fischhoff B, Bruine De Bruin W. Fifty–Fifty = 50%? *J Behav Decis Mak.* 1999; 12: 149–163. AQ55
50. McColl K, Debin M, Souty C, et al. Are people optimistically biased about the risk of COVID-19 infection? Lessons from the first wave of the pandemic in Europe. *Int J Environ Res Public Health.* 2022; 19: 436. AQ56
51. Fragkaki I, Maciejewski DF, Weijman EL, Feltes J, Cima M. Human responses to COVID-19: the role of optimism bias, perceived severity, and anxiety. *Pers Individ Dif.* 2021; 176: 110781. AQ57
52. Kuper-Smith BJ, Doppelhofer LM, Oganian Y, Rosenblau G, Korn CW. Risk perception and optimism during the early stages of the COVID-19 pandemic. *R Soc Open Sci.* 2021; 8: 210904. AQ58
53. Katzourakis A. COVID-19: endemic doesn't mean harmless. *Nature.* 2022; 601: 485. AQ59
54. U.S. Food and Drug Administration. FDA approves first Respiratory Syncytial Virus (RSV) vaccine. 2023. Available at https://www.fda.gov/news-events/press-announcements/fda-approves-first-respiratory-syncytial-virus-rsv-vaccine. Accessibility verified August 19, 2023.
55. Peters HP, Sharon D, Dunwoody S. Scientific uncertainty in media content: introduction to this special issue. *Public Underst Sci.* 2016; 25: 893–908. AQ60
56. Morgan MG, Fischhoff B, Bostrom A, Atman CJ. *Risk Communication: A Mental Models Approach*. Cambridge, UK: Cambridge University Press; 2002.
57. Bruine De Bruin W, Bostrom A. Assessing what to address in science communication. *Proc Natl Acad Sci USA.* 2013; 110: 14062–14068. AQ61
58. Bostrom A, Fischhoff B, Morgan MG. Characterizing mental models of hazardous processes: a methodology and an application to Radon. *J Soc Issues.* 1992; 48: 85–100. AQ62
59. Centers for Disease Control and Prevention. Stay up to date with COVID-19 vaccines including boosters. CDCGov. 2022. Available at https://www.cdc.gov/coronavirus/2019-ncov/vaccines/stay-up-to-date.html?s_cid=11737:covid. Accessibility verified August 19, 2023.
60. Galea S. *The Contagion Next Time*. New York, NY: Oxford University Press, 2021.
61. Haldane V, Jung AS, Neill R, et al. From response to transformation: how countries can strengthen national pandemic preparedness and response systems. *BMJ.* 2021; 375: e067507. AQ63
62. Marani M, Katul GG, Pan WK, Parolari AJ. Intensity and frequency of extreme novel epidemics. *Proc Natl Acad Sci USA.* 2021; 118: e2105482118. AQ64
63. Harris K, Maurer J, Uscher-Pines L, Kellermann A, Lurie N. Seasonal flu vaccination: why don't more Americans get it? Rand.org. 2011. Available at https://www.rand.org/pubs/research_briefs/RB9572.html. Accessibility verified August 19, 2023.
64. Brewer NT, Hallman William K, Hallman WK. Subjective and objective risk as predictors of influenza vaccination during the vaccine shortage of 2004–2005. *Clin Infect Dis.* 2006; 43: 1379–1386. AQ65
65. Weinstein ND, Kwitel A, McCaul KD, Magnan RE, Gerrard M, Gibbons FX. Risk perceptions: assessment and relationship to influenza vaccination. *Health Psychol.* 2007; 26: 146–151. AQ66