2022

The interplay between cognitive and affective risks in predicting COVID-19 precautions: a longitudinal representative study of Americans

Marie Helweg-Larsen
Dickinson college

Laurel M. Peterson
Bryn Mawr College, lmpeterson@brynmawr.edu

Sarah H. DiMuccio
New York University

Citation

Helweg-Larsen, M., Peterson L. M. & S. H. DiMuccio. 2022. "The interplay between cognitive and affective risks in predicting COVID-19 precautions: a longitudinal representative study of Americans." *Psychology & Health*.

The Interplay between Cognitive and Affective Risks in Predicting COVID-19 Precautions: A Longitudinal Representative Study of Americans

Marie Helweg-Larsen[1], Laurel M. Peterson[2], and Sarah H. DiMuccio[3]

[1]Dickinson College

[2]Bryn Mawr College

[3]New York University

Word count: 7707

Marie Helweg-Larsen https://orcid.org/0000-0002-5009-6288

Laurel M. Peterson https://orcid.org/0000-0002-6666-7874

Sarah H. DiMuccio https://orcid.org/0000-0002-7311-5787

Author Note

Sarah H. DiMuccio is now at Catalyst Inc. This work was supported by grants from Dickinson College and Bryn Mawr College. We have no conflicts of interest to disclose. We thank James Shepperd and Vera Hoorens for their comments on a draft of this article. This study was preregistered at Open Science Framework: https://osf.io/ufb2v.

Correspondence concerning this article should be addressed to Marie Helweg-Larsen, Department of Psychology, Dickinson College, P.O. Box 1773, Carlisle, PA 17013. E-mail: helwegm@dickinson.edu, https://orcid.org/0000-0002-5009-6288

Abstract

Objective: Cognitive risk figures prominently in models predicting health behaviors, but affective risk is also important. We examined the interplay between cognitive risk (personal likelihood of COVID-19 infection or death) and affective risk (worry about COVID-19) in predicting COVID-19 precautionary behaviors. We also examined how outbreak severity bias (overestimation of the severity of COVID-19 in one's community) predicted these outcomes.

Design: In a representative sample of U.S. adults ($N = 738$; $M_{age} = 46.8$; 52% women; 78% white), participants who had not had COVID-19 took two online surveys two weeks apart in April 2020.

Main Outcome Measures: We assessed cognitive risk, affective risk, and outbreak severity bias at baseline and at follow-up two precaution variables: prevention behaviors (e.g., social distancing) and behavioral willingness (e.g., vaccinations).

Results: Overall, affective risk better predicted precautions than cognitive risk. Moreover, overestimating the severity of the outbreak predicted more affective risk (but not cognitive risk) and in turn more precautions. Additional analyses showed that when affective risk was lower (as opposed to higher) greater cognitive risk and outbreak severity bias both predicted more precautions.

Conclusion: These findings illustrate the importance of affective risk and outbreak severity bias in understanding COVID-19 precautionary behavior.

Key words: risk perception, COVID-19, outbreak severity bias, behavioral precautions, pandemic mitigation

The Interplay between Cognitive and Affective Risks in Predicting COVID-19 Precautions: A Longitudinal Representative Study of Americans

The Centers for Disease Control (CDC) confirmed the first U.S. COVID-19 case on January 21, 2020 (CDC, 2020), the World Health Organization declared it a pandemic on March 11, 2020 (World Health Organization, 2020), and by mid-April nearly 95% of Americans were instructed to stay at home (Mervosh et al., 2020). During this early period of the pandemic, the CDC (Pearce, 2020) also recommended social distancing and handwashing, and although surgical masks were generally not available, the CDC eventually began recommending the use of cloth face masks (Geggel, 2020). Furthermore, public health interventions used in previous pandemics (such as contact tracing) received public attention (Frieden, 2020) and human clinical testing on vaccines began in March 2020 (Thanh Le, et al., 2020). The pandemic presented an unprecedented set of dynamics and behavior change was imperative to prevent contracting and spreading COVID-19. The psychological literature is particularly well suited for examining how to change people's behaviors (Bavel et al., 2020) and perceived risk is one extensively studied predictor of health behavior change (Ferrer & Klein, 2015).

Cognitive and Affective Risk Perceptions

Theories of health decision making such as the health belief model (Rosenstock, 1974) and the protection motivation theory (Rogers, 1975), propose that personal susceptibility to threat plays a causal role in motivating behavior change. This susceptibility to threat (assessed by for example asking "how likely are you to get COVID-19") is sometimes called deliberative risk (Ferrer, et al., 2016), personal risk perception (Helweg-Larsen & Shepperd, 2001), or cognitive risk (Sheeran et al., 2014) as we do here. Cognitive risk predicts behaviors varying from willingness of returning to a violent partner (Harding & Helweg-Larsen, 2009) to quitting smoking (Helweg-Larsen, 2014) to getting the flu vaccine (Brewer et al., 2007). A meta-analysis of experimental studies showed that heightened cognitive risk significantly predicted both health-related intentions and behaviors (Sheeran, et al., 2014). With respect to COVID-

19, several studies have found that cognitive risk predicted precautionary behaviors when examined cross-sectionally in the U.S. (Bruine de Bruin & Bennett, 2020; Niepel, et al., 2020), cross-sectionally worldwide (Dryhurst et al., 2020), and longitudinally in diverse geographic contexts (Gratz, et al., 2021; Wise et al., 2020). The more people personally estimated their risk for getting COVID-19 the more they engaged in COVID-19 precautions. However, at least one study found that cognitive risk did not predict COVID-19 precautions (Fullerton et al., 2021).

In addition to cognitive assessment, emotional reactions to personal susceptibility to threat (such as worry or anxiety) are important to fully capture how risk influences health behavior. This emotional reaction to threat (assessed by for example asking "how worried are you about getting COVID-19") is sometimes called anticipatory emotions (Loewenstein et al., 2001) or affective risk (Ferrer, et al., 2016) as we do here. Research on "risk-as-feelings" (Loewenstein et al., 2001) and the affect heuristic (Slovic et al., 2004) is consistent with a range of findings showing that the assessment of affective risk is important in determining prevention intentions and behaviors. For example, a meta-analysis found breast cancer worry predicted breast cancer screening (Hay, et al., 2006) and for flu vaccination, affective risk predicted vaccination uptake better than cognitive risk (Weinstein et al., 2007). In the context of COVID-19, fear of COVID-19 predicted precautionary behavior over-and-above a range of other variables including cognitive risk and political attitudes (Harper et al., 2020).

To date, most research that has included both cognitive and affective risk perceptions as predictors of health behavior has examined the two types of perceptions separately. However, understanding the *interplay* between cognitive and affective factors is important for several reasons. First, it moves the field beyond a "main effects" approach in which predictors simply compete against each other to see which best predicts outcomes. But cognitive and affective risk are dynamic, may influence one another, or change relations between risk and behavior. Disentangling possible dynamic relationships between the two requires that researchers explore mediation and moderation (Kiviniemi &

Kalsko-Foster, 2018). Second, research suggests that cognitive and affective risk can influence different precautionary behaviors. For example, affective risk can be more influential in short-term behavior change whereas cognitive risk can be more influential in long-term behavior change (Kiviniemi et al., 2018). Third, a greater understanding of the relationship between cognitive and affective risk is key to creating effective behavioral interventions. A meta-analysis examining the effects of health interventions on cognitive and affective risk found that interventions changed both cognitive risk and affective risk and that cognitive and affective risk were related yet distinct constructs (Portnoy, Ferrer, et al., 2014). It is not necessarily better to create interventions that increase both cognitive and affective risks and depending on the specific health risk it might be desirable to increase only cognitive risk or only affective risk (Portnoy, Ferrer, et al., 2014). No published research has to our knowledge examined the complex interplay between cognitive and affective risks for COVID-19 health behaviors.

Outbreak Severity Bias

One way that people's cognitive and affective risks are shaped are via their perceptions of the severity of the risk. From a risk perspective, the pandemic was unique in the amount of detailed and local information that was available about the severity of the outbreak. For most health-related risks people have relatively little information available about the real-time objective reality of a problem. For example, it would be difficult or impossible for a person to find out local information on daily prevalence of disease such as the flu, measles, or AIDS or death rates from car accidents or strokes. However, during the coronavirus pandemic people had unprecedented access to information about prevalence or severity from a variety of sources including local and national news as well as trackers such as from the New York Times (n.d.) and Johns Hopkins University Dashboard (n.d.). Thus, the pandemic provided a unique opportunity to examine outbreak severity bias (perceived severity of the outbreak in light of the actual objective severity) and how it affected precautionary behaviors.

Despite the widespread access to prevalence information, we found no research examining whether outbreak severity bias predicted COVID-19 precautions although in public discourse claims of unnecessary over and under panicking seemed to be prevalent with some arguing that one ought to panic (Bogost, 2020) or not panic (Harmon, 2020). For non-COVID events we found just one study that seemed related in that it examined the correspondence between objective severity (e.g., prevalence rates from public health statistics) of nine society health problems across several decades, and people's subjective perceptions (e.g., how much was written about it in national news articles) of the severity of the same nine problems. Subjective severity generally tracked well with objective severity for many of the events (e.g., unemployment, crime, and polio), but not for events that seem to invoke a moral panic (AIDS, herpes, teenage suicide, and teenage pregnancy) where periods of spikes in concern were unrelated to spikes in objectivity severity (Loewenstein & Mather, 1990). Such an analysis is not available for COVID-19. To fully elucidate the role of outbreak severity bias, we examined outbreak severity bias as a predictor of precautions and examined the role of cognitive and affective risk in that relationship.

The Present Study

In this U.S. representative sample, we examined predictors of two types of outcomes we collectively refer to as *precautions*: (1) prevention behaviors: behaviors that were possible and encouraged (such as social distancing, handwashing, and mask-wearing) and (2) behavioral willingness: openness to behaviors not yet available (such as contact tracing, public temperature-taking, and vaccinations). We followed Kiviniemi et al.'s (2018) recommendations and examined the complex relationships using both mediation and moderation. First, using mediation we tested the "cognition precedes affect" and the "affect precedes cognition" models in predicting outcomes. Consistent with previous research (Kiviniemi & Klasko-Foster, 2018), we expected cognitive risk to precede affective risk and affective risk to drive outcomes directly and indirectly. Second, using moderation we examined the interplay of cognitive and affective risk in predicting the outcomes. Given the paucity of research on this question in a pandemic context we made no prediction of the interactional pattern. Third, we examined the novel outbreak severity bias variable, namely the direct path from outbreak severity bias to the two outcomes as well as the mediating and moderating role of cognitive and affective risk in that path. Because overestimation of the outbreak severity seemed likely to be associated with worry, we tentatively expected a direct path from outbreak severity bias to precautions but given the novelty of this variable we did not make specific predictions for how cognitive and affective risk mediated or moderated the paths.

Our study was longitudinal which is important for several reasons. First, the design allowed us to ask people to recall at Time 2 their preventive behaviors (mask wearing, social distancing, etc.) the past two weeks. Thus, at Time 1 we predicted people's prevention behaviors for the following two weeks, as recalled at Time 2. Second, cross-sectional research can sometimes show an (atypical) negative relationship between cognitive risk and precautions (greater risk, fewer precautions) because people sometimes say what precautions they are intending to take (but not actually taking) and then report a contemporaneous low personal risk estimate overvaluing anticipated risk-reduction behavior (e.g., Ferrer et al., 2016; Magnan et al., 2021). Our longitudinal study avoided this problem.

Method

Power Analyses

Using G*Power (version 3.1.9.4), we selected the "A priori option for linear multiple regression" option, set the effect size at f=.10, power to .95, alpha to .05, and the number of predictors to 10. We found that we needed a total of 254 participants thus at N=738 our sample was adequately powered. We did not analyze our data until we were completed data collection at Time 2.

Participants

Participants were U.S. adults who had not had (or suspected that they might have had) coronavirus. They completed two surveys two weeks apart in April 2020. The Time 2 sample had 738 participants in which 51.8% were women and 48.1% were men; 38% said they felt they belonged to a vulnerable or at-risk group for coronavirus. Ages ranged from 18 – 82 (M= 46.79, SD= 15.93) with participants identifying as White (78.0%), Black (12.3%), Asian (7.0%), or other (2.6%); 5.7% indicated they were Hispanic. Participants reported their educational level such that 26.8% had obtained a high school education, 14.5% had received an associate's degree, 37.4% had completed a bachelor's education, and 20.7% had post college education.

Procedure

We obtained the U.S. sample using Prolific which is an online recruitment platform that uses the prescreen responses from potential participants to open recruitment slots based on age, gender, and race/ethnicity. Prolific continues to recruit participants until the sample is matched to the U.S. census by age, race/ethnicity, and gender (Prolific, 2021). Participants received the first Qualtrics survey on April 14, 2020 (Time 1), and the second 2 weeks later on April 28, 2020 (Time 2). The mean time between Time 1 and Time 2 completion was 13.25 days (SD = 0.92, range: 11-17 days). The surveys opened with an informed consent and concluded with a debriefing that provided links to resources about coronavirus and mental health. Participants were compensated $9.68/hr at Time 1 and $10.23/hr at Time 2. The study was approved by the Institutional Review Board at Dickinson College. The study was preregistered at https://osf.io/ufb2v. Hypothesis 5 in the preregistration included our main effects hypotheses of cognitive risk, affective risk, and severity predicting the outcomes. However, the specific moderation and mediation patterns we examined here were not preregistered.

A total of 1,049 people took the Time 1 survey. Respondents were excluded if they reported that they had (or suspected they might have had) coronavirus (N = 67), failed the attention check which required them to correctly respond to a question asking, "If you are reading this, select Strongly

Disagree" (*N* = 45), or did not provide valid Prolific IDs (*N* = 21). As such, 916 people were sent the survey link for Time 2 and 798 took that survey (87% response rate). Of those who took the survey at Time 2, respondents were excluded if they reported that they had (or suspected that they might have had) coronavirus (*N* = 37), failed the attention check (*N* = 21), or did not provide accurate Prolific IDs to match to Time 1 data (*N* = 2). This resulted in a sample size of 738 participants with complete responses on both surveys. Participants retained to Time 2 did not differ on gender, race, Hispanic ethnicity, or social class (*p*s ≥ .22), but were more likely to be older and more highly educated (*p*s < .01).

Control variables

We controlled for age, gender (coded 0=woman, 1=man), race (dummy coded African American: 0=no, 1=yes, Asian: 0=no, 1=yes, Other: 0=no, 1=yes; White was the reference group), Hispanic ethnicity (coded 0=no, 1=yes), highest education degree (coded 1=high school GED or less, 2=associates degree, 3=college degree, 4=more than college), self-reported social class (coded 1=poor, 2=working class, 3=middle class, 4=upper-middle class, 5=upper class), and political ideology (coded 1=extremely liberal to 7=extremely conservative). These variables have been found to predict COVID-19 precautions (e.g., Gratz, et al., 2021; Peterson et al., 2021).

Predictor Variables Time 1

Cognitive and Affective Risk Perceptions

Cognitive risk refers to rule-based logical component of risk and like Wise et al., (2020) we asked, "How likely do you think you are to become infected with the coronavirus?" and "How likely do you think you would be to die if you became infected with the coronavirus?" with a sliding scale in which the endpoints were labelled 0 = *Very unlikely* to 100 = *Very likely*. We prefaced the question by asking participants to consider only their own opinion and reminding them that it was not a test and we were not asking about percentages. The two items were correlated, $r(738)= .36$, $p<.001$ and averaged (M=24.84, SD=20.59, range 0-94.5). Next, we measured *affective* risk with three questions: worry about getting infected, worry about people you know getting infected, and worry about the coronavirus outbreak in general. Responses were on a 5-point scale from *Strongly disagree* to *Strongly agree*. The three questions were averaged (α = .88, *M*=3.04, *SD*=0.99, range 1-5). The two risk variables were coded such that higher numbers indicated greater perceptions of cognitive or affective risk.

Outbreak Severity Bias

We asked about perceived state severity ("How severe is the coronavirus outbreak in your state right now?") with answers on a 5-point scale from *Not severe* to *Extremely severe (M*=2.68, *SD*=1.05, range 1-5). To obtain a measure of bias (how much people over or underestimated the actual severity), we controlled for actual state severity which was determined from objective epidemiological infection/death rates independently obtained for the state in which each participant resided at the time of the survey. Specifically, participants reported their resident zip code, which was used to link to geographically based state infection/death counts collated by the Johns Hopkins University Center for Systems Science Dashboard (Dong et al., 2020). To create infection/death *rates*, we divided counts by census population estimates for the respective state and multiplied by 100,000, resulting in an infection/death count per 100,000 person rate. I.e., state infection rate = state infection count/state population * 100,000 and state death rate = state death count/state population * 100,000. Due to an extreme positive skew, raw values were log-transformed.

The state infection rate was correlated with the state death rate, $r(733)= .91$, $p<.001$. Perceived state severity was correlated with both the state infection rate, $r(730)=.54$, $p<.001$, and with the state death rate, $r(730)=.52$, $p<.001$, suggesting that people's perception of severity of outbreak in their state was related to the actual objective severity in their state.

All analyses using the perceived state severity variable statistically controlled for objective state severity variable (which was the average of the state infection rates and the state death rates). Thus, for outbreak severity bias higher number indicated greater overestimation.

Outcome Measures at Time 2

Prevention Behaviors

We adapted questions from prior studies examining prevention behaviors for infectious diseases (Miller, Yardley and Little, 2012) and COVID-19 (Wise et al., 2020) and selected behaviors that at the time of data collection were considered important health precautions. We asked participants at Time 2 to report their behaviors in the past two weeks related to their coronavirus prevention; thus, the measure is a report of their own actual future behavior relative to Time 1. We asked, "In the past two weeks, I have…. 1) taken all precautionary measures against the coronavirus, 2) avoided close contact with all people outside my home, 3) avoided meeting up with any people in person (friends, family, etc.), 4) stayed at home nearly all the time, 5) washed my hands a great deal more than normal, 6) worn a face mask or cover every time I've gone outside, 7) sanitized or wiped down all my groceries" on a 5-point scale from *Strongly disagree* to *Strongly agree*. The seven items were averaged to create a scale with higher numbers indicating a greater engagement in prevention behaviors ($\alpha = .77$, M=4.11, SD=0.77, range 1.0-5.0).

Behavioral Willingness

We selected three willingness scenarios which described future possible behaviors that were not generally available in the U.S. at the time of the survey (Peterson et al., 2021). First, we asked about being contacted by a public health worker doing contact-tracing and how willing they would be to (1) answer any questions the public health worker asked, (2) take a coronavirus test if the public health worker recommended it, and (3) self-isolate if the public health worker recommended it. Second, we asked about a coronavirus tracing app and participants indicated their willingness to (4) download the app, (5) report to the app if they tested positive for coronavirus, and (6) self-isolate for two weeks upon learning from the app that they had been in close contact with someone infected. Finally, participants were asked how willing they would be to (7) have their temperature taken so they could enter a restaurant and (8) get vaccinated when a coronavirus vaccination becomes available. Participants reported their willingness for these eight items on a 5-point scale labelled (for the first seven items) *Not at all willing* to *Completely willing* and for the last item *Extremely unlikely* to *Extremely likely.* Items were averaged into a scale where higher numbers represented greater behavioral willingness (α = .87, M=4.03, SD=0.90, range 1.0-5.0).

Data Availability Statement

The data that support the findings of this study are available from the first author, upon reasonable request.

Results

Analysis Strategy

For the regression analyses we used PROCESS v 3.5.3 macro in SPSS (Hayes, 2018). We set the regression parameters at 5000 bootstrap bias-corrected samples, 95% confidence intervals, and mean-centered products. We report unstandardized regression weights along with their *p* values and 95% confidence intervals. Figures 3 and 5 depict the variable on the x-axis as dichotomized at the 16^{th} and 84^{th} percentiles of the data, as recommended by Hayes (2018); in these analyses we also report the results of the Johnson-Neyman technique to show where the conditional effect of X on Y transitions between statistically significant and not significant. Regression analyses controlled for age, gender, race, ethnicity, education, social class, and political ideology. The supplemental materials show the results of the regressions depicted in Figures 1, 2, and 4.

How Are Cognitive and Affective Risks, Severity Bias, Prevention Behaviors, and Behavioral Willingness Related?

Table 1 shows the bivariate correlations among all variables. As expected, the cognitive and affective risks were positively related to each other and to severity bias (i.e., greater overestimation of outbreak severity was associated with higher cognitive and affective risk). Furthermore, greater severity bias as well as cognitive and affective risk were associated with greater prevention behaviors and behavioral willingness. The results are similar and all significant when we control for age, gender, race, ethnicity, education, social class, and political ideology (see table in the supplemental materials).

How do Cognitive and Affective Risks Mediate to Predict Prevention Behaviors and Behavioral Willingness?

We examined the mediational pattern of the two risks in predicting the two outcomes to find out whether cognitive risks preceded the affective risks or the reverse. Thus, we constructed two mediational models with each risk as the predictor. In PROCESS we used Model 4 and set the predictor as either cognitive or affective risk and the moderator as the second risk, and the outcome as either prevention behaviors or behavioral willingness, controlling for age, gender, race, ethnicity, education, social class, and political ideology. Results appear in Figure 1 (cognitive risk as the predictor) and Figure 2 (affective risk as the predictor). Overall, all mediation models significantly predicted both outcomes (total effects: ts>4.37, ps<.0001).First, using cognitive risk as the predictor we observed no direct effect to either prevention behaviors (b=-0.0001, t=-0.0435, p=.9654, CI [-0.0029, 0.0027]) or behavioral willingness (b=0.0007, t=0.4136, p=.6793, CI [-0.0026, -0.0040]). The indirect path (bolded on Figure 1) was significant for prevention behaviors (b=.0063, CI [0.0047, 0.0079]) and behavioral willingness (b=.0059, CI [0.0041, 0.0078]). That is, how personally at-risk people felt about getting or dying from COVID-19 predicted people's affective risk (worry) which in turn predicted precautions. Thus, as predicted cognition preceded affect to influence health behaviors (cf. Kiviniemi et al., 2018).

Second, we considered affective risk as the predictor and examined whether affect preceded cognition to influence health behaviors. As shown in Figure 2, there was a (bolded) direct path to prevention behaviors (b=0.2760, t=8.9329. p<.0001, CI [0.2153,0.3367]) and behavioral willingness (b=0.2579, t=7.1499, p<.0001, CI [0.1871, 0.3287]). That is, a one-point increase in affective risk was uniquely associated with a 0.28 point increase in prevention behaviors and a 0.26 point increase in behavioral willingness, both measured on a 5-point scale. The indirect path was not significant for prevention behaviors (*b*=-0.0007, CI [-0.0291, 0.0284]) or behavioral willingness (*b*=0.0073, CI [-0.0243, 0.0406]). Thus, affective risk directly predicted outcomes but did not operate through cognitive risk (cf. Kiviniemi et al., 2018). Said differently, people who were worried engaged in more precautionary behaviors, but being worried did not predict precautionary behaviors via increases in cognitive risk.

How Do Affective and Cognitive Risks Interact to Predict Prevention Behaviors and Behavioral Willingness?

To examine if the affective and cognitive risks moderated each other to predict the two outcomes we used PROCESS Model 4 (as described above) and examined the significance of the predictor by moderator interactions. If the interaction was significant, we followed up by using PROCESS Model 1 (results below are from Model 1) to examine the specific simple effects and graph the relevant interaction.

We found a Cognitive x Affective risks interaction for behavioral willingness, $F(1, 723) = 4.0319$, $p = .045$ but not prevention behaviors, $F(1, 723) = 0.0451$, $p = .8318$. As seen in Figure 3, the interaction revealed that when affective risk was low, higher cognitive risk (marginally) predicted behavioral willingness (*b*=0.0050, *t*=1.8434 *p*=.0657, CI [-0.0003, 0.0104]) whereas when affective risk was high (*b*=-0.0008, *t*=-0.4246, *p*=.6712, CI [-0.0043, 0.0028]), cognitive risk did not predict behavioral willingness. To further explore the nature of the interaction we examined the Johnson-Neyman regions of significance which showed that for participants with the lowest 6.25% of affective risk scores cognitive risk significantly predicted greater behavioral willingness whereas for participants with higher affective risk scores cognitive risk did not predict behavioral willingness. That is, when worry was low (but not high), thinking you were personally at risk predicted behavioral willingness.

Do Cognitive and Affective Risks Mediate the Relationship between Outbreak Severity Bias and Prevention Behaviors and Behavioral Willingness?

We examined if the two risk variables mediated the relationship between outbreak severity bias and outcomes. We used Model 4 for the mediation analyses and set the predictor as perceived severity (controlling for actual severity), the two mediators as cognitive and affective risk, and the outcome as either Prevention Behaviors or Behavioral Willingness, controlling for age, gender, race, ethnicity, education, social class, and political ideology. Overall, the mediation models significantly predicted both outcomes (total effects: *t*s>5.01, *p*s<.0001).

The mediation analysis examined whether the cognitive and affective risk mediated the relationship between outbreak severity bias and the two outcome variables. First, as seen in Figure 4, we observed no direct effect from outbreak severity bias to prevention behaviors (*b*=-0.0558, *t*=1.7951. *p*=.0731, CI [-0.0052, 0.1168]) but we observed a direct effect to behavioral willingness (*b*=0.0965, *t*=2.6685, *p*=.0078, CI [0.0255, 0.1676]).The indirect path was (1) not significant for cognitive risk (prevention behavior: *b*=-0.0030, CI [-0.0209, 0.0138]; behavioral willingness: *b*=-0.0005, CI [-0.0202, 0.0188]) but was (2) significant for affective risk (prevention behaviors: *b*=0.0981, CI [0.0698, 0.1300]; behavioral willingness: *b*=0.0901, CI [0.0571, 0.1276]).

In sum, the outbreak severity bias directly predicted behavioral willingness but not prevention behaviors. Furthermore, outbreak severity bias indirectly influenced both prevention behaviors and behavioral willingness via greater affective risk, but not cognitive risk. That is, the more people overestimated the severity of the outbreak (relative to objective severity) the more they worried, predicting both greater precautionary behavior and behavioral willingness.

Does Severity Bias Interact with Cognitive and Affective Risks to Predict Prevention Behaviors and Behavioral Willingness?

To examine if severity bias moderated cognitive or affective risk to predict the two outcomes, we used PROCESS Model 4 (as described above) and examined the significance of the predictor by first moderator and predictor by second moderator interactions. For significant interactions, we followed up by using PROCESS Model 1 (results below are from PROCESS Model 1 analyses) to examine the specific simple effects and graph the relevant interaction.

First, we found a Severity Bias x Affective Risk interaction for prevention behaviors, $F(1, 718) = 16.85$, $p < .0001$ (Figure 5, Panel A). When affective risk was low the effect between severity bias and prevention behaviors was significant (b=0.1498, t=3.9079, p=.0001, CI [0.0745, 0.2250), but there were no effects when affective risk was high (b=-0.0385, t=-1.0128, p=.3115, CI [-0.1132, 0.0362]). Johnson-Neyman regions of significance results showed a more nuanced picture in that the results suggested that affective risk moderated the outbreak severity bias effect on prevention behaviors both at the bottom and the top of the affective risk variable but in opposite directions (that is, a cross-over interaction). At the bottom of the affective risk distribution, results showed that for participants with the lowest 79.51% of affective risk scores severity bias significantly predicted greater prevention behaviors; when people were less worried, greater outbreak severity bias predicted prevention behaviors. At the top of the affective risk distribution the Johnson-Neyman regions of significance results showed that for participants with the highest 7.38% of affective risk scores severity bias significantly predicted greater prevention behaviors; when people were very worried, lower severity bias predicted prevention behaviors.

Second, we found a similar pattern for the Severity Bias x Affective Risk interaction for behavioral willingness, $F(1, 718) = 14.06$, $p = .0002$ (Figure 5, Panel B). When affective risk was low the effect between severity bias and behavioral willingness was significant (b=0.1977, t=4.4238, p<.0001, CI [0.1100, 0.2854]) but there were no effects when affective risk was high (b=-0.0029, t=-0.0645, p=.9486, CI [-0.0899, 0.0842]). Johnson-Neyman regions of significance results showed that for participants with the lowest 55.87% of affective risk scores severity bias significantly predicted greater behavioral willingness. That is, when people were less (rather than more) worried, greater severity bias predicted behavioral willingness.

Third, we found a Severity Bias x Cognitive Risk interaction for behavioral willingness, $F(1, 718) = 8.5053$, $p = .0037$ (Figure 5, Panel C) such that when cognitive risk was low the effect between severity bias and behavioral willingness was significant (b=0.2285, t=5.3308, p<.0001, CI [0.1443, 0.3126]) but there were no effects when cognitive risk was high (b=-0.0663, t=1.3966, p=.163, CI [-0.0269, 0.1595]). Johnson-Neyman regions of significance results showed that the for participants with the lowest 79.51% of cognitive risk scores severity bias significantly predicted greater behavioral willingness. That is, when people thought their personal risk was lower (as opposed to higher), greater severity bias predicted behavioral willingness. These variables did not interact for prevention behaviors, $F(1, 717) = 0.0650$, $p = .7988$.

Discussion

Understanding the complex relationship between affective and cognitive risks are important for understanding health behaviors as well as designing interventions. Cognitive-based predictors have traditionally figured prominently in models predicting health behavior outcomes, but research shows that affective risk is a crucial determinant of health behavior (e.g., Williams, Rhodes, & Conner, 2018). Overall, we found a more important role of affective risk than cognitive risk in predicting COVID-19 precautions.

Specifically, we found that affective risk (but not cognitive risk) directly predicted both precaution variables (preventive behaviors and behavioral willingness) and affective risk mediated the path between cognitive risk and these outcomes. Thus, the “cognition precedes affect” model (but not the “affect precedes cognition” model) explained COVID-19 precautionary uptake (cf. Kiviniemi et al, 2014). This finding is consistent with research on vaccination behaviors where affective risk is also a better predictor than cognitive risk and mediates the path from cognitive risk to vaccinations (Chapman & Coups, 2006; Renner & Reuter, 2012). The same pattern emerges for preventive behavior such as sunscreen use (Kiviniemi & Ellis, 2014) and colonoscopy screening (Klasko-Foster et al., 2020) where affective risk mediates the relationship between cognitive risk and the health behavior.

We also found that affective risk was important as a mediator of outbreak severity in that people who showed greater overestimation of outbreak severity were more willing to engage in behaviors (such as vaccinations) via affective risk but not cognitive risk. That is, exaggeration of the local outbreak was associated with worry and increases in thinking that one was personally at risk but only worry mediated the path to behavioral willingness. These mediational findings are consistent with previous research which shows that affect, rather than cognition, serves a signaling role and is a proximal driver of health behavior (Kiviniemi & Klasko-Foster, 2018). One might conclude from these findings that cognitive risk was not important. But cognitive risk did predict precautions via worry (in the mediational analyses, as described above) and cognitive risk also predicted outcomes (in the moderation analyses). Specifically, affective risk acted as a moderator of both cognitive risk and of outbreak severity bias in predicting precautionary behaviors such that when affective risk was low (as opposed to high), cognitive risk or outbreak severity bias generally predicted precautionary behaviors. Thus, when people worried less or thought the outbreak was less severe, their risk estimation (cognitive risk) predicted their precautionary behaviors. Additionally, cognitive risk influenced the relation between outbreak severity and precautionary outcomes. When cognitive risk was low (as opposed to high) outbreak severity bias was more likely to predict precautions. This finding suggests that even participants who are not worried about the pandemic or the severity of the outbreak will engage in prevention behaviors (such as vaccinations) if they believe their personal risk is high.

We used two different outcomes variables but generally there were few differences: the patterns of results were similar for prevention behaviors (such as handwashing) and behavioral willingness (such as vaccinations). Interestingly, the interaction between affective and cognitive risk was significant only for behavioral willingness and not prevention behaviors. This finding is consistent with a

COVID-19 study (Magnan et al., 2021) that found no interaction between affective and cognitive risks for behaviors such as handwashing. However, our results expand these findings through investigating willingness to participate in developing public health interventions. Research on other health behaviors have found interactions between affective and cognitive risk in predicting health behaviors but not the pattern we found. We found that cognitive risk mattered in predicting precautions when affective risk was low (as opposed to high) whereas research on diabetes (Portnoy, Kaufman, et al., 2014) and other health risks (Ferrer, et al., 2018) found that cognitive risk mattered when affective risk was high (as opposed to low). Thus, more research is needed to examine when and for which health behaviors affective and cognitive risk interact.

The strengths of this study included a large and representative sample and multiple data collection points with a high retention rate which allowed us to predict longitudinally which precautions people took and were willing to take. We also controlled for factors known to predict COVID-19 precautions such as age, gender, and political ideology thus demonstrating the role of cognitive and affective risk on COVID-19 precautions above and beyond these factors. Our study also has limitations. First, the findings capture only a snapshot of a 2-week period early in the pandemic although our findings are generally consistent with other research findings (e.g., Klasko-Foster, et al., 2020) as well as COVID-19 research findings from different time points (e.g., Gratz, et al., 2021). Second, although we explored a dynamic representation of both affective and cognitive risk, we did not measure experiential risk which is a gist-based risk belief based on gut-level reactions to vulnerability and a direction for future research (e.g., TRIRISK model; Ferrer et al., 2016; 2018). Third, examining outbreak severity bias, which is novel to this research, allowed us to examine the extent to which people might have exaggerated or minimized the outbreak but there is no way of knowing exactly who was “biased” or “panicked” – only that people fell on a continuum from under to overestimation of the severity of the outbreak. Outbreak severity bias (i.e., exaggeration of the outbreak relative to objective rates) could be a symptom of moral panic. Future research should examine if moral panic might fuel increases in risk overestimation and is related to prevention behaviors. In addition, it is possible that cognitive and affective risks contributed to outbreak severity bias but we did not examine this mediational direction. Finally, we measured precautionary behaviors related to virus containment and control (e.g., social distancing, vaccination intentions), but did not measure other potentially negative consequences. For example, people who worried about COVID-19 were more likely to stockpile supplies such as gold, guns, and toilet paper (Micalizzi et al., 2021). In addition, a large international COVID-19 study showed that greater perceived risk was associated with more negative emotions which in turn were associated with worse mental health (Han et al., 2021).

Future research should examine the antecedents of cognitive and affective risks and consider interventions. We do not know a lot about the source of people's COVID-19 information. Our results suggest that overestimation of the spread of the virus drove affective risk toward more precautions. The media was likely one important source of both cognitive and affective risk information, but it is not clear which types of media (social media, newspapers, public health institutions, etc.) or information (testimonial/anecdotal focus versus factual/prevalence versus pseudoscientific COVID-19 beliefs) might be associated with cognitive versus affective risk beliefs. COVID-19 research shows that the quantity of social media use (Wheaton et al., 2021) and obsessive online searching (Jungmann & Witthöft, 2020) predicted COVID-19 anxiety. In addition, greater reliance on the media for COVID-19 information was associated with both greater anxiety and perceived risk of getting COVID-19 (Curtis et al., 2021). Pseudoscientific COVID-19 beliefs (likely acquired via media exposure) also predicted less social distancing over time through lower cognitive risk beliefs (Gratz et al., 2021). Research on risks and media consumption would be an important area for future research. Knowing how and where people gather risk-related information can also aid researchers in deciding where to place interventions and which aspects to manipulate or communicate.

In conclusion, we found that COVID-19 affective risk predicted COVID-19 precautions and qualified the effects of cognitive risk and outbreak severity bias on precautions. As pandemics emerge, public health efforts could harness worry by aggressively promoting actionable prevention behaviors, many of which are easily performed and low cost (e.g., handwashing). However, cognitive risk still plays an important role. For those low in affective risk, cognitive risk tracks with adopting greater prevention behaviors and higher cognitive risk predicts prevention behaviors through increases in affective risk. Therefore, communicating clear, factual risk information without instigating panic would continue to contribute to prevention behavior adoption.

References

Bavel, J. J. V., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., Crockett, M. J., Crum, A. J., Douglas, K. M., Druckman, J. N., Drury, J., Dube, O., Ellemers, N., Finkel, E. J., Fowler, J. H., Gelfand, M., Han, S., Haslam, S. A., Jetten, J., … Willer, R. (2020). Using social and behavioural science to support COVID-19 pandemic response. *Nature Human Behaviour*, *4*(5), 460–471. https://doi.org/10.1038/s41562-020-0884-z

Bogost, I. (2020, March 16). Now is the time to overreact. The Atlantic. https://www.theatlantic.com/health/archive/2020/03/theres-no-shame-in-overreacting-to-the-coronavirus/608140/

Brewer, N., Chapman, G., Gibbons, F., Gerrard, M., McCaul, K., & Weinstein, N. (2007). Meta-analysis of the relationship between risk perception and health behavior: The Example of Vaccination. *Health Psychology*, *26*(2), 136–145. https://doi.org/10.1037/0278-6133.26.2.136

Bruine de Bruin, W., & Bennett, D. (2020). Relationships between initial COVID-19 risk perceptions and protective health behaviors: A national survey. *American Journal of Preventive Medicine*, *59*(2), 157–167. https://doi.org/10.1016/j.amepre.2020.05.001

Pearce, K. (2020, March 12). What is social distancing and how can it slow the spread of COVID-19? Johns Hopkins University. https://hub.jhu.edu/2020/03/13/what-is-social-distancing/

Centers for Disease Control (2020, January 21). First travel-related case of 2019 novel coronavirus detected in the United States. https://www.cdc.gov/media/releases/2020/p0121-novel-coronavirus-travel-case.html

Curtis, A. F., Rodgers, M., Miller, M. B., & McCrae, C. S. (2021). Impact of sex on COVID-19 media exposure, anxiety, perceived risk, and severity in middle-aged and older adults. *Journal of Aging and Health*, 89826432110253–8982643211025383. https://doi.org/10.1177/08982643211025383

Chapman, G., & Coups, E. (2006). Emotions and preventive health behavior: Worry, regret, and influenza vaccination. *Health Psychology*, *25*(1), 82–90. https://doi.org/10.1037/0278-6133.25.1.82

Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases*, *20*(5), 533–534. https://doi.org/10.1016/S1473-3099(20)30120-1

Dryhurst, S., Schneider, C., Kerr, J., Freeman, A., Recchia, G., van der Bles, A., Spiegelhalter, D., & van der Linden, S. (2020). Risk perceptions of COVID-19 around the world. *Journal of Risk Research*, *23*(7-8), 994–1006. https://doi.org/10.1080/08870446.2011.580846

Ferrer, R. A., & Klein, W. M. (2015). Risk perceptions and health behavior. *Current Opinion in Psychology*, *5*, 85–89. https://doi.org/10.1016/j.copsyc.2015.03.012

Ferrer, R., Klein, W., Avishai, A., Jones, K., Villegas, M., & Sheeran, P. (2018). When does risk perception predict protection motivation for health threats? A person-by-situation analysis. *PloS One*, *13*(3), e0191994–e0191994. https://doi.org/10.1371/journal.pone.0191994

Ferrer, R., Klein, W., Persoskie, A., Avishai-Yitshak, A., & Sheeran, P. (2016). The Tripartite Model of Risk Perception (TRIRISK): Distinguishing deliberative, affective, and experiential components of perceived risk. *Annals of Behavioral Medicine*, *50*(5), 653–663. https://doi.org/10.1007/s12160-016-9790-z

Frieden, T. (2020, April 12). I sued to run the C.D.C. Here's what it can do to slow this pandemic. New York Times. https://www.nytimes.com/2020/04/12/opinion/cdc-coronavirus.html

Fullerton, M. K., Rabb, N., Mamidipaka, S., Ungar, L., & Sloman, S. A. (2021). Evidence against risk as a motivating driver of COVID-19 preventive behaviors in the United States. *Journal of Health Psychology*. https://doi.org/10.1177/13591053211024726

Geggel, L. (2020, April 3). Everyone should wear face 'masks' in public, CDC now recommends. Live Science. https://www.livescience.com/cdc-recommends-face-masks-coronavirus.html

Gratz, K., Richmond, J., Woods, S., Dixon-Gordon, K., Scamaldo, K., Rose, J., & Tull, M. (2021). Adherence to social distancing guidelines throughout the COVID-19 pandemic: The roles of pseudoscientific beliefs, trust, political party affiliation, and risk perceptions. *Annals of Behavioral Medicine*.https://doi.org/10.1093/abm/kaab024

Han, Q., Zheng, B., Agostini, M., Bélanger, J. J., Gützkow, B., Kreienkamp, J., Reitsema, A. M., van Breen, J. A., Collaboration, P., & Leander, N. P. (2021). Associations of risk perception of COVID-19 with emotion and mental health during the pandemic. *Journal of Affective Disorders*, *284*, 247–255. https://doi.org/10.1016/j.jad.2021.01.049

Harding, H. G., & Helweg-Larsen, M. (2009). Perceived risk for future intimate partner violence among women in a domestic violence shelter. *Journal of Family Violence*, *24*(2), 75–85. https://doi.org/10.1007/s10896-008-9211-6

Harmon, A. (2020, March 18). Some ask a taboo question: Is America overreacting to coronavirus? New York Times. https://www.nytimes.com/2020/03/16/us/coronavirus-hype-overreaction-social-distancing.html

Harper, C., Satchell, L., Fido, D., & Latzman, R. (2020). Functional fear predicts public health compliance in the COVID-19 pandemic. *International Journal of Mental Health and Addiction*, 1–14. https://doi.org/10.1007/s11469-020-00281-5

Hay, J. L., McCaul, K. D., & Magnan, R. E. (2006). Does worry about breast cancer predict screening behaviors? A meta-analysis of the prospective evidence. *Preventive Medicine*, *42*(6), 401–408. https://doi.org/10.1016/j.ypmed.2006.03.002

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). Guilford Press.

Helweg-Larsen, M. (2014). Does moralization motivate smokers to quit? A longitudinal study of representative samples of smokers in the United States and Denmark. *Nicotine & Tobacco Research*, *16*(10), 1379–1386. https://doi.org/10.1093/ntr/ntu091

Helweg-Larsen, M., & Shepperd, J. A. (2001). Do moderators of the optimistic bias affect personal or target risk estimates? A review of the literature. *Personality and Social Psychology Review*, *5*(1), 74–95. https://doi.org/10.1207/S15327957PSPR0501_5

Johns Hopkins University Dashboard. (n.d.). Coronavirus Resource Center. FAQ. https://coronavirus.jhu.edu/map-faq

Jungmann, S. M., & Witthöft, M. (2020). Health anxiety, cyberchondria, and coping in the current COVID-19 pandemic: Which factors are related to coronavirus anxiety? *Journal of Anxiety Disorders*, *73*, 102239–102239. https://doi.org/10.1016/j.janxdis.2020.102239

Kiviniemi, M. T. & Klasko-Foster (2018). The behavioral affective associations model. In D.M. Williams, R.E. Rhodes, and M.T. Conner (Eds.), *Affective Determinants of Health Behaviors* (pp. 1-18). Oxford University Press. https://doi.org/10.1093/oso/9780190499037.001.0001

Kiviniemi, M. T., & Ellis, E. M. (2014). Worry about skin cancer mediates the relation of perceived cancer risk and sunscreen use. *Journal of Behavioral Medicine*, *37*(6), 1069–1074. https://doi.org/10.1007/s10865-013-9538-1

Kiviniemi, M., Ellis, E., Hall, M., Moss, J., Lillie, S., Brewer, N., & Klein, W. (2018). Mediation, moderation, and context: Understanding complex relations among cognition, affect, and health behaviour. *Psychology & Health*, *33*(1), 98–116. https://doi.org/10.1080/08870446.2017.1324973

Klasko-Foster, L., Kiviniemi, M., Jandorf, L., & Erwin, D. (2020). Affective components of perceived risk mediate the relation between cognitively-based perceived risk and colonoscopy screening. *Journal of Behavioral Medicine*, *43*(1), 121–130. https://doi.org/10.1007/s10865-019-00049-w

Loewenstein, G., & Mather, J. (1990). Dynamic processes in risk perception. *Journal of Risk and Uncertainty*, *3*(2), 155–175. https://doi.org/10.1007/BF00056370

Loewenstein, G., Weber, E., Hsee, C., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037//0033-2909.127.2.267

Magnan, R., Gibson, L., & Bryan, A. (2021). Cognitive and affective risk beliefs and their association with protective health behavior in response to the novel health threat of COVID-19. *Journal of Behavioral Medicine*, *44*(3), 285–295. https://doi.org/10.1007/s10865-021-00202-4

Mervosh, S., Lu, D., & Swales, V. (2020, April 20). See which states and cities have told residents to stay at home. New York Times, April 20, 2020. https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html

Micalizzi, L., Zambrotta, N. S., & Bernstein, M. H. (2021). Stockpiling in the time of COVID-19. *British Journal of Health Psychology*, *26*(2), 535–543. https://doi.org/10.1111/bjhp.12480

Miller, S., Yardley, L., & Little, P. (2012). Development of an intervention to reduce transmission of respiratory infections and pandemic flu: Measuring and predicting hand-washing intentions. *Psychology Health Medicine*. 17(1), 59-81. http://doi.org/10.1080/13548506.2011.564188

New York Times (n.d.). Coronavirus int eh U.S.: Latest Map and Case Count. https://www.nytimes.com/interactive/2021/us/covid-cases.html

Niepel, C., Kranz, D., Borgonovi, F., Emslander, V., & Greiff, S. (2020). The coronavirus (COVID-19) fatality risk perception of US adult residents in March and April 2020. *British Journal of Health Psychology, 25(4)*, 883–888. https://doi.org/10.1111/bjhp.12438

Peterson, L.M., Helweg-Larsen, M., & DiMuccio, S.H. (2021). Descriptive norms and prototypes predict coronavirus prevention cognitions and behaviors in the United States: Applying the prototype willingness model to pandemic mitigation. *Annals of Behavioral Medicine.* https://doi.org/10.1093/abm/kaab075

Portnoy, D. B., Kaufman, A. R., Klein, W. M., Doyle, T. A., & de Groot, M. (2014). Cognitive and affective perceptions of vulnerability as predictors of exercise intentions among people with type 2 diabetes. *Journal of Risk Research*, *17*(2), 177–193. https://doi.org/10.1080/13669877.2013.794153

Portnoy, D. B., Ferrer, R. A., Bergman, H. E., & Klein, W. M. (2014). Changing deliberative and affective responses to health risk: a meta-analysis. *Health Psychology Review, 8(3), 296–318.* https://doi.org/10.1080/17437199.2013.798829

Prolific (2001, July 24). Representative samples FAQ. https://researcher-help.prolific.co/hc/en-gb/articles/360019238413-Representative-Samples-FAQ.

Renner, B., & Reuter, T. (2012). Predicting vaccination using numerical and affective risk perceptions: The case of A/H1N1 influenza. *Vaccine*, *30*(49), 7019–7026. https://doi.org/10.1016/j.vaccine.2012.09.064

Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude change. *The Journal of Psychology*, *91*(1), 93–114.

Rosenstock, I. M. (1974). Historical origins of the Health Belief Model. *Health Education Monographs*, *2*(4), 328–335. https://doi.org/10.1177/109019817400200403

Sheeran, P., Harris, P. R., & Epton, T. (2014). Does heightening risk appraisals change people's intentions and behavior? A meta-analysis of experimental studies. *Psychological Bulletin*, *140*(2), 511–543. https://doi.org/10.1037/a0033065

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. Risk analysis, 24(2), 311-322. doi:10.1111/j.0272-4332.2004.00433.x

Thanh Le, T., Andreadakis, Z., Kumar, A., Gómez Román, R., Tollefsen, S., Saville, M., & Mayhew, S. (2020). The COVID-19 vaccine development landscape. *Nature Reviews. Drug Discovery*, *19*(5), 305–306. https://doi.org/10.1038/d41573-020-00073-5

Weinstein, N. D., Kwitel, A., McCaul, K. D., Magnan, R. E., Gerrard, M., & Gibbons, F. X. (2007). Risk perceptions: Assessment and relationship to influenza vaccination. *Health Psychology*, *26*(2), 146–151. https://doi.org/10.1037/0278-6133.26.2.146

Wheaton, M. G., Prikhidko, A., & Messner, G. R. (2021). Is fear of COVID-19 contagious? The effects of emotion contagion and social media use on anxiety in response to the coronavirus Pandemic. *Frontiers in Psychology*, *11*, 567379–567379. https://doi.org/10.3389/fpsyg.2020.567379

Williams, D.M., Rhodes, R.E., & Conner, M.T. (2018). Affective determinants of health behavior. Oxford University Press.

Wise, T., Zbozinek, T.D., Michelini, G., Hagan, C.C., & Mobbs, D. (2020). Changes in risk perception and self-reported protective behaviour during the first week of the COVID-19 pandemic in the United States. Royal Society Open Science. 7, 200742. http://dx.doi.org/10.1098/rsos.200742

World Health Organization (March 11, 2020). Coronavirus disease 2019 (COVID-19) Situation Report – 51. https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200311-sitrep-51-covid-19.pdf?sfvrsn=1ba62e57_10

Table 1

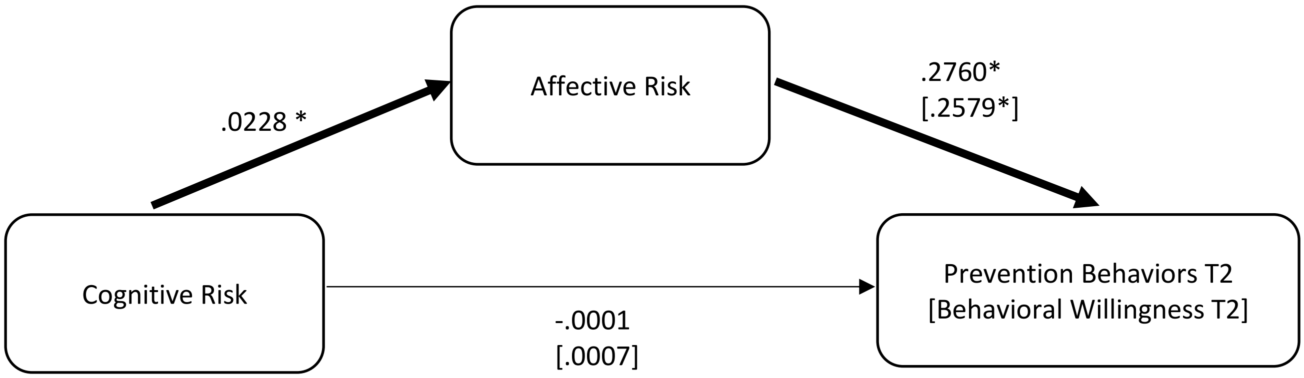
Bivariate Correlations among Study Variables

Measure	1	2	3	4	5
1. Outbreak Severity Bias	--				
2. Cognitive Risk	.25*	--			
3. Affective Risk	.37*	.51*	--		
4. Prevention Behaviors	.18*	.20*	.38*	--	
5. Behavioral Willingness	.19*	.18*	.37*	.41*	--
N	730	738	738	738	738
Measured at	Time 1	Time 1	Time 1	Time 2	Time 2

Note. *p < .001.

Figure 1

The Mediation Model of Cognitive Risk via Affective Risk to Prevention Behaviors and Behavioral Willingness

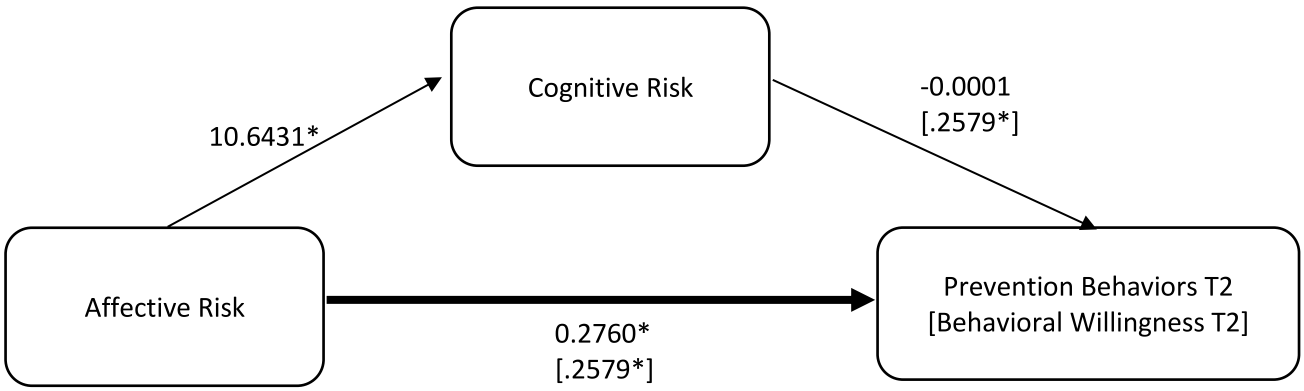


**p*<.0001

Note: The indirect paths were both significant and are bolded in the figure; the direct paths were not significant. Controls: age, gender, race, ethnicity, education, social class, and political ideology. Values reported as unstandardized effect sizes. The values in brackets are for behavioral willingness.

Figure 2

The Mediation Model of Affective Risk via Cognitive Risk to Prevention Behaviors and Behavioral Willingness

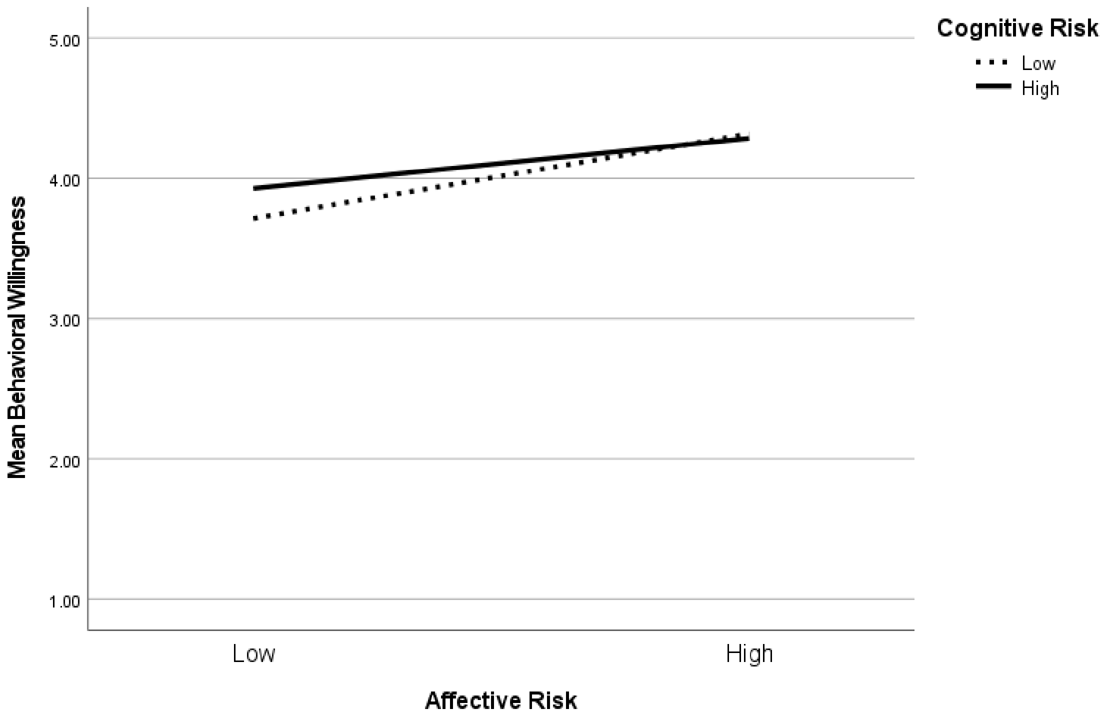


**p*<.0001.

Note: The significant direct paths is bolded in the figure; the indirect paths were not significant. Controls: age, gender, race, ethnicity, education, social class, and political ideology. Values reported as unstandardized effect sizes. The values in brackets are for behavioral willingness.

Figure 3

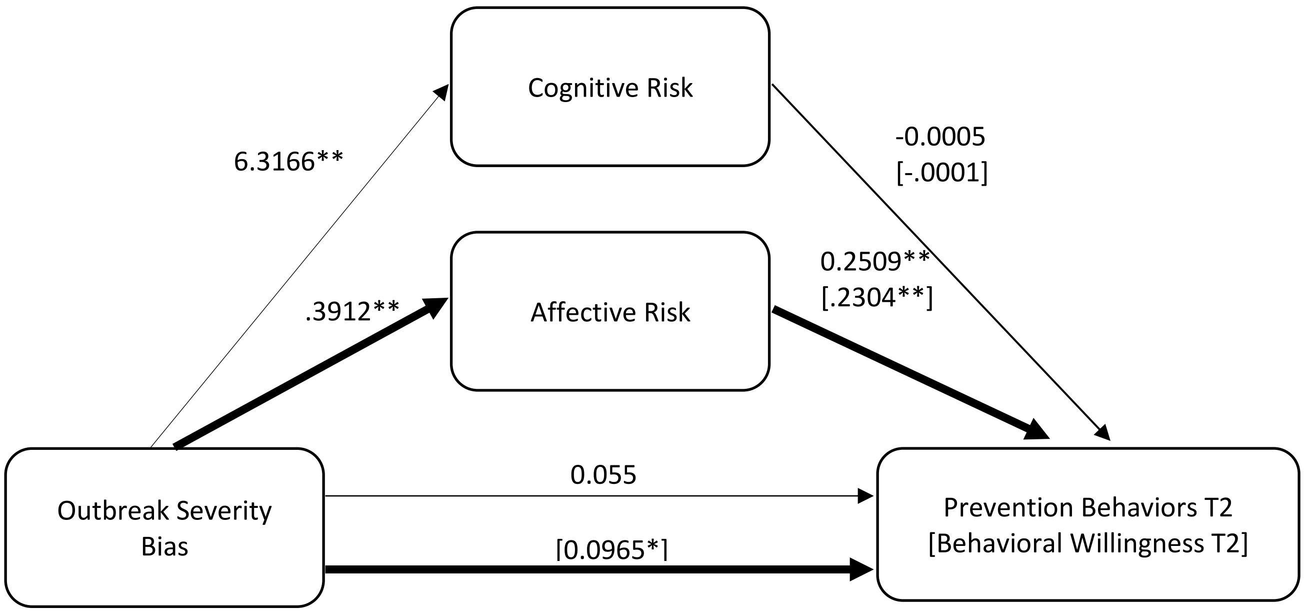
Interaction Between Cognitive and Affective Risk for Behavioral Willingness



Note: The variable on the x-axis is dichotomized at the 16th and 84th percentiles

Figure 4

The Mediation model of the Effect of Outbreak Severity Bias via Cognitive and Affective Risks on Prevention Behaviors and Behavioral Willingness

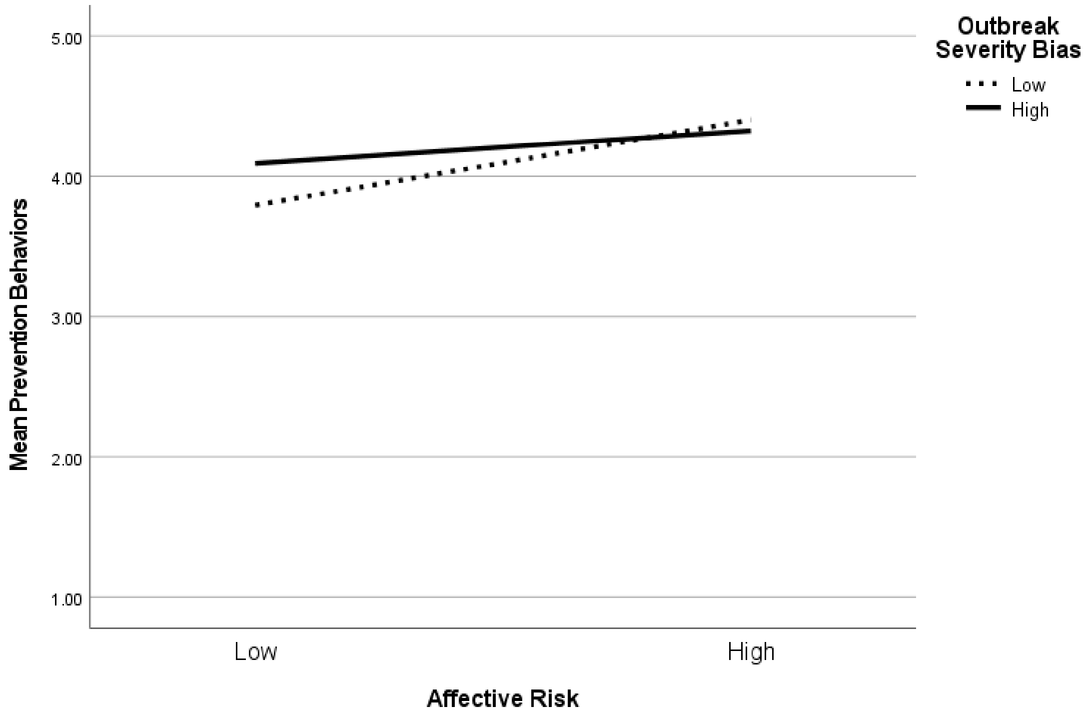


**p<.01. *p<.05

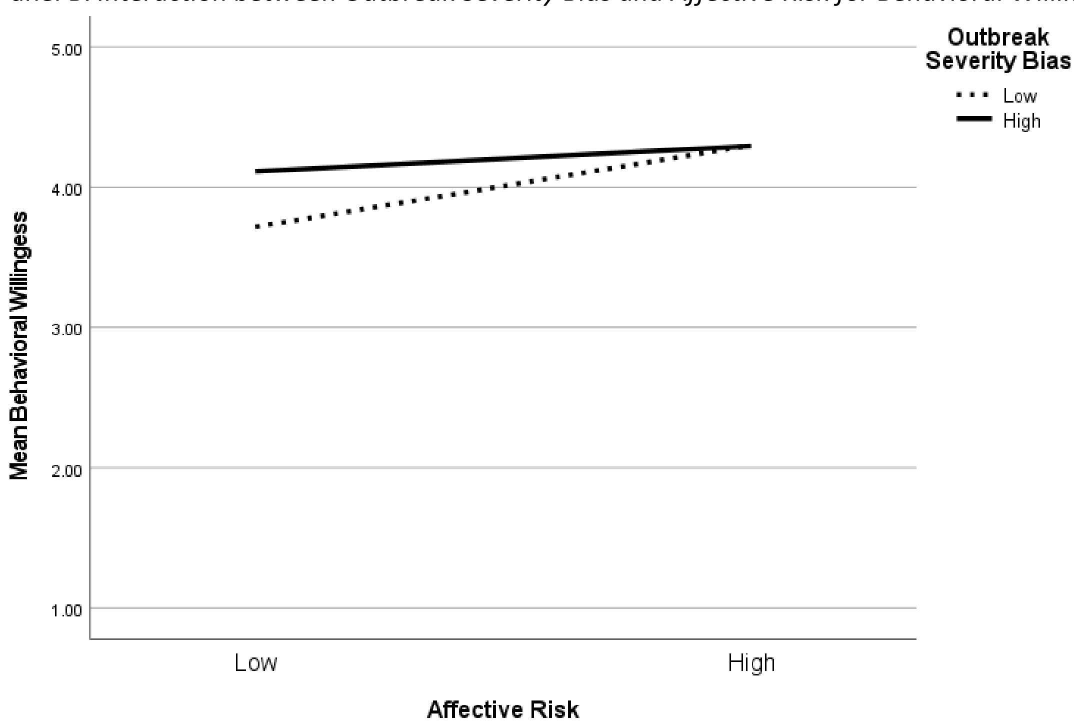
Note: The significant direct path and the indirect paths are bolded in the figure. Controls: age, gender, race, ethnicity, education, social class, and political ideology. Values reported as unstandardized effect sizes. The values in brackets are for behavioral willingness.

Figure 5

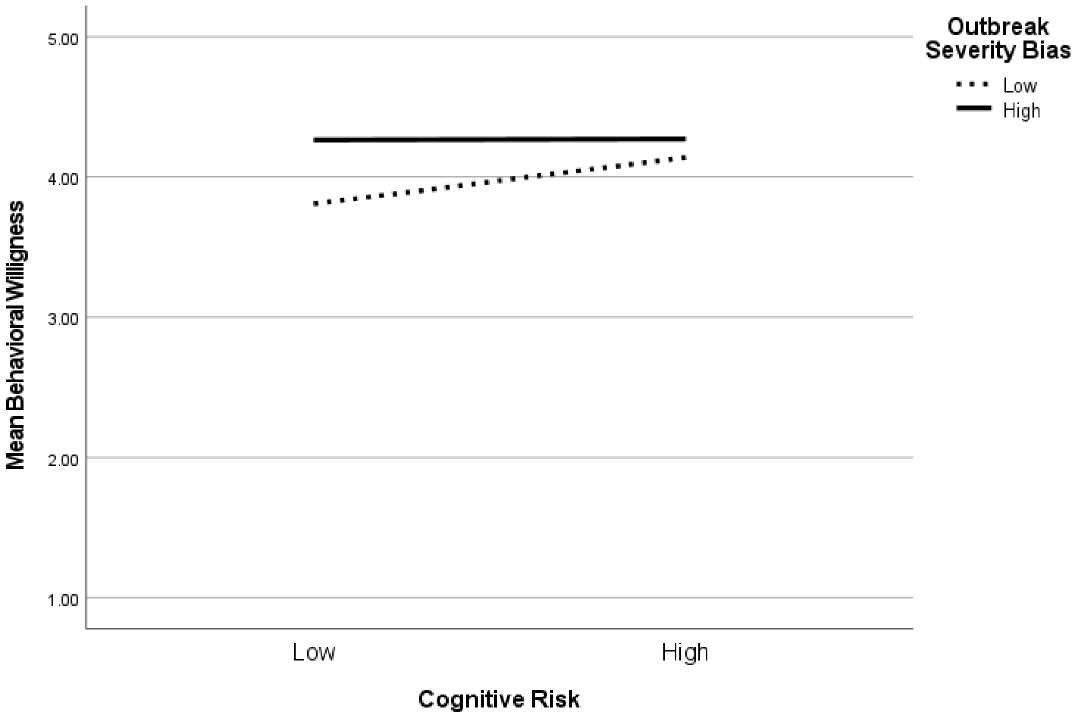
Panel A. *Interaction between Outbreak Severity Bias and Affective Risk for Prevention Behaviors*



Panel B. *Interaction between Outbreak Severity Bias and Affective Risk for Behavioral Willingness*



Panel C. *Interaction between Outbreak Severity Bias and Cognitive Risk for Behavioral Willingness*



Note: The variable on the x-axis is dichotomized at the 16th and 84th percentiles