Pairing Facts with Imagined Consequences Improves Pandemic-Related Risk Perception

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Significance Statement

During the COVID-19 pandemic, individuals have been forced to balance conflicting needs: stay-at-home guidelines mitigate the spread of the disease but often at the expense of people's mental health and economic stability. To balance these needs, individuals should be mindful of actual virus transmission risk in their location. We found that pandemic-related risk perception is inaccurate, yet perceived risk closely predicts compliance with public health guidelines. Realigning perceived and actual risk is crucial for combating pandemic fatigue and slowing the spread of disease. Therefore, we developed a fast and effective intervention to improve the accuracy of risk perception. Our intervention improved risk perception accuracy and reduced willingness to engage in risky activities, both immediately and after a 1-3 week delay.

Abstract

The COVID-19 pandemic reached staggering new peaks during an ongoing global resurgence at the end of 2020. Although public health guidelines initially helped to slow the spread of disease, widespread pandemic fatigue and prolonged harm to financial stability and mental wellbeing have contributed to this resurgence. In this late stage of the pandemic, it is clear that new interventions are needed to support long-term behavior change. Here, we examined subjective perceived risk about COVID-19, and the relationship between perceived risk and engagement in risky behaviors. In Study 1 (N = 303), we found that subjective perceived risk is inaccurate but predicts compliance with public health guidelines. In Study 2 (N = 760), we developed a multi-faceted intervention designed to realign perceived risk with actual risk. Participants completed one of three variants of an episodic simulation task; we expected that imagining a COVID-related scenario would increase the salience of risk information and enhance behavior change. Immediately following the episodic simulation, participants completed a risk estimation task with personalized feedback about local risk levels. We found that information prediction error, a measure of surprise, drove beneficial change in perceived risk and willingness to engage in risky activities. Imagining a COVID-related scenario beforehand enhanced the effect of prediction error on learning. Importantly, our intervention produced lasting effects that persisted after a 1-3 week delay. Overall, we describe a fast and feasible online intervention that effectively changed beliefs and intentions about risky behaviors.

Pairing Facts with Imagined Consequences Improves Pandemic-Related Risk Perception

The COVID-19 pandemic has brought unprecedented global challenges, affecting both physical health and mental well-being (1–8). Public health experts have promoted restrictions to mitigate the spread of disease, including social distancing and closing non-essential businesses (7). Despite rapid progress in preventative and palliative care, widespread vaccination will require an extended period of time, and social distancing is recommended even after vaccination (9). Crucially, severe outbreaks will limit the success of vaccine implementation, underscoring the need for behavioral interventions that reduce the spread of disease (10). Given the exponential rate of virus transmission (9, 11), modifying even a single individual's compliance with public health guidelines could have significant and widespread downstream effects (12–16).

In this uncertain context, the cost-benefit analysis associated with any given choice has become more complex. To make adaptive decisions during the pandemic, individuals should balance conflicting needs, which might include limiting virus transmission, earning an income, supporting local businesses, or bolstering their own mental health (1–3, 5–7). Accurately assessing the risks associated with behavioral options is fundamental to adaptive decision making in any context (13–15), especially under chronic stress (20–22). Nonetheless, risk misestimation is common, especially for low-probability events (23–26), and low quantitative literacy is linked to poor health decision making and outcomes (27, 28). During the pandemic, risk *underestimation* could lead to risky behaviors that harm individuals and society at-large, but risk *overestimation* could increase distress and anxiety while reducing mental wellbeing (29, 30). The high-stakes context of a dangerous, fast-spreading virus underscores the potential effects of risk misestimation, suggesting a target for intervention.

Encouraging large-scale, long-term behavior change during the COVID-19 pandemic has proven difficult: widespread "pandemic fatigue" and prolonged economic hardship have contributed to a deadly resurgence of the virus (7, 9). Empowering individuals to accurately assess local risk levels can support more informed decision making, bolstering the efficacy of public health measures. Although recent studies have found that subjective risk perception relates to demographic variables, attitudes, and risky behaviors during the pandemic (3, 29, 31–36), past studies have not evaluated the accuracy of risk perception or intervened to change risk perception. Local risk levels can change rapidly over time (11, 37); an intervention that is fast, low-effort, and easy to administer could realign perceived and actual risk.

Prior interventions on risk estimation have shown some success, although effect sizes are typically small and weaken over time (38, 39). A separate line of research has demonstrated that episodic simulation of the downstream outcomes of choices can enhance decision making, including self-regulation (40–44). The rich, personalized mental imagery generated during episodic simulation may drive these effects by increasing the salience of an intervention (41, 45, 46). Furthermore, thinking concretely about outcomes increases perceived risk and estimation accuracy for common adverse events (47). Other studies have shown that increasing the salience of an intervention can enhance initial behavioral outcomes and also boost long-term effects (48, 49). Risk perception is influenced by the availability of information about outcomes (50–52); anecdotes tend to be more vivid and easily-recalled, and can exert greater influence on risk perception than statistics (53–55). Crucially, combining statistical information with an imagined narrative can create a synergistic effect that enhances learning (56).

Other studies have explored how individuals update beliefs and knowledge in response to feedback (57–60). *Information prediction error* (i.e., surprise) describes the discrepancy between expectation and reality; the valence (better or worse than expected) and magnitude of this surprise signal drives learning. Larger prediction errors lead to more successful belief revision (57–59). A prior study found that prediction error allowed beliefs about risk to be updated, but participants tended to resist using bad news to learn about future adverse events (61). However, this paradigm focused on adverse events that cannot be avoided by making adaptive decisions (e.g., cancer, burglary, dementia). Overall, presenting surprising risk information may change beliefs and improve the accuracy of risk perception. However, combining prediction error with another psychological intervention—such as an episodic simulation— could enhance learning, particularly if people tend to resist updating beliefs about adverse events.

Here, we report the results of an easy and accessible intervention designed to reduce risk misestimation and quickly realign individual behavior with public health guidelines. Using a large, nationally-representative sample of US residents, we first show that perceived risk is not aligned with actual risk (Study 1). To remedy this risk misestimation, we designed an intervention that combines an episodic simulation with a risk estimation exercise that includes accuracy feedback (Study 2). In this preregistered experiment, we found that a simple 10-minute intervention improved the accuracy of risk perception and reduced willingness to engage in risky activities. The magnitude of the information prediction error (surprise) during the risk estimation exercise drove change in perceived risk; this effect of surprise on learning was enhanced when the intervention included an episodic simulation about the possible outcomes of risky decisions.

Study 1

First, we sought to test whether subjective risk perception corresponded with actual local risk levels. We recruited a nationally-representative sample of 303 U.S. residents in May 2020. Participants completed an online survey that assessed *perceived risk* of engaging in six different activities in the participant's current location: going for a walk outside, shopping at a grocery store, eating inside a restaurant, meeting with a small group of friends, travelling within one's geographical state, and travelling beyond one's state. Participants also reported *willingness to engage in risky activities* during reopening, and past compliance with public health guidelines. We also measured *actual risk* in each participant's location by obtaining the number of active COVID-19 cases in their county of residence on the day that the study was completed. Actual risk was calculated as the probability (log-transformed) that at least one individual in a hypothetical gathering of ten people would be infected with SARS-CoV-2 (37).

If subjective perceived risk is aligned with the actual risk of COVID-19 prevalence in a given location, then perceived risk and actual risk should be positively correlated. Critically, we found that perceived risk was *not* correlated with actual risk, Pearson's $r(232) = 0.05$, $p = .472$, 95% CI [-0.08, 0.17] (Figure 1A). Moreover, actual risk was not correlated with willingness to engage in risky activities, $r(232) = -0.01$, $p = .854$, 95% CI [-0.14, 0.12]. This striking disconnect between actual and perceived risk indicates that subjective risk perception is highly inaccurate, and individuals do not have realistic understandings of risk levels in their given locations.

Although subjective risk perception was highly inaccurate, it was significantly related to behavior. Individuals who reported greater perceived risk tended to report lower willingness to engage in risky activities during reopening ($r(301) = -0.57$, $p < .001$, 95% CI [-0.64, -0.49], Figure 1B), greater adherence to hygiene and sanitation guidelines ($r(301) = 0.52$, $p < .001$, 95% CI [0.44, 0.60], Figure 1C), and more compliance with social distancing ($r(301) = 0.41$, $p < .001$, 95% CI [0.31, 0.50], Figure 1D). Overall, we found that subjective risk perception was inaccurate, yet predicted a variety of behaviors with crucial public health implications; we identified subjective risk perception as a critical target for interventions.

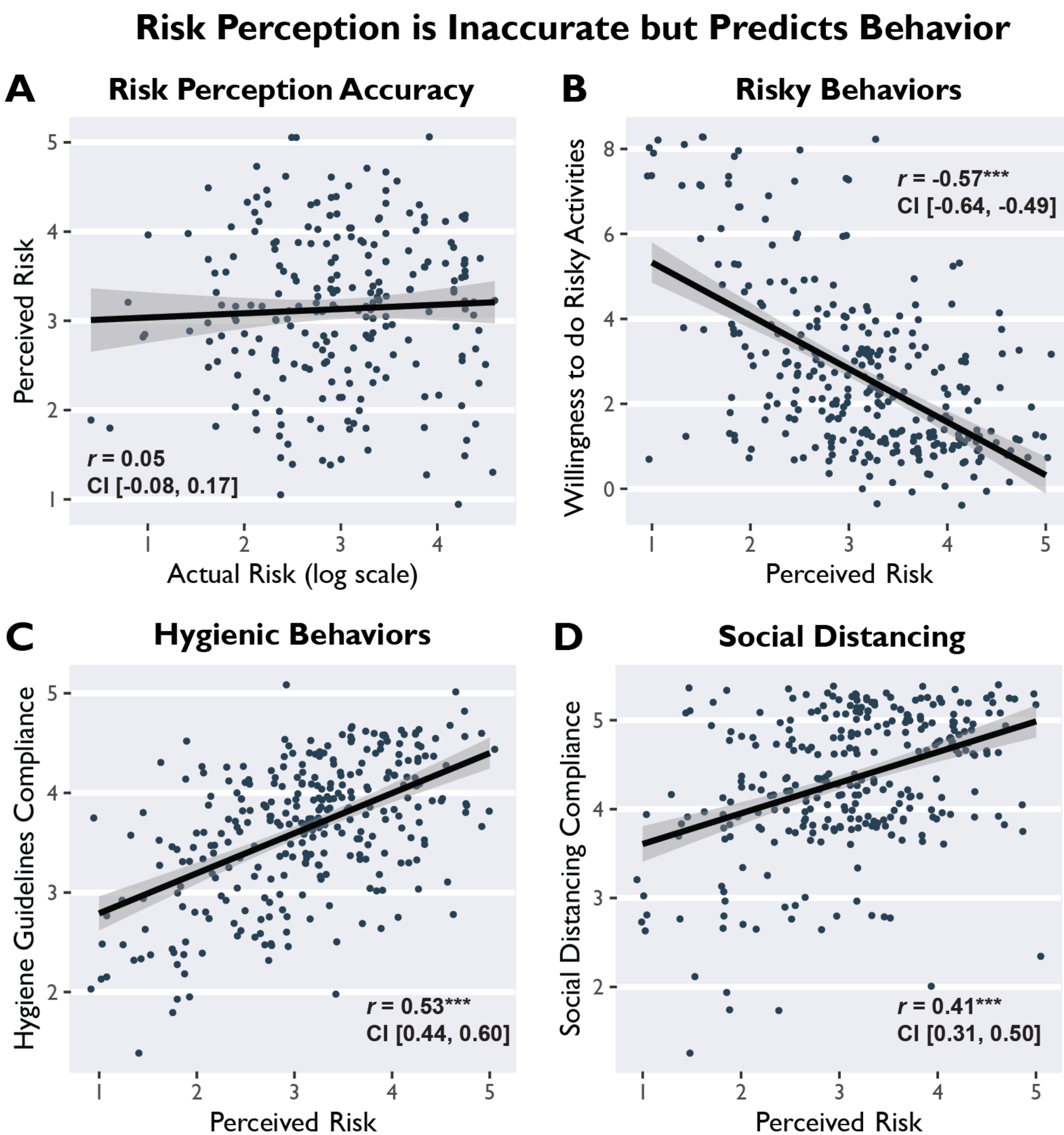

Figure 1. Risk perception is inaccurate, but predicts compliance with public health guidelines. In Study 1, we found the following: A) Perceived risk is not correlated with actual risk, B) Perceived risk is negatively associated with willingness to engage in risky activities, and positively associated with C) compliance with hygiene guidelines and D) social distancing guidelines. Points are jittered for visualization. Shaded bands indicate 95% confidence intervals around the line of best fit. * *p < .05, *** *p < .01, ****** *p < .001*

Study 2

In Study 2, we developed a new intervention designed to improve the accuracy of risk perception. We expected that, on average, improving risk perception accuracy would lead to better compliance with public health guidelines because people tend to underestimate risk of virus transmission. An online informational intervention could enable quick, broad dissemination of risk information. Numerous websites and tools have emerged to provide information about COVID-19 cases and deaths (11, 37, 62–64). Yet, the efficacy of these interventions has not been measured; to our knowledge, no past studies have tested whether exposure to information about the prevalence of COVID-19 cases influences risk perception or risky decision making. Our pre-registered (https://osf.io/6fjdy) intervention included two components: an **Episodic Simulation Task** (Figure 2B) and a **Risk Estimation Task** (Figure 2C, 2D). Participants completed the intervention during Session 1 and later returned for a follow-up survey during Session 2 (1-3 week delay) to evaluate the durability of the intervention over time.

We expected that imagining a pandemic-related scenario that demonstrated the potential consequences of risky decisions would increase the efficacy of our intervention, especially if the scenario included personalized elements. Therefore, we randomly assigned participants to receive one of three variants (Personal, Impersonal, Unrelated) of the Episodic Simulation task (i.e., guided imagination). In the **Personal Simulation**, participants imagined themselves hosting a dinner party with four guests (specific close others, such as friends or neighbors) invited to their home. As this scenario unfolds, one of the guests exhibits symptoms of COVID-19 and later confirms a diagnosis. The host must then contact the other guests to inform them of the exposure, and eventually also falls ill with the disease. Participants were asked to visualize sensory details of the episode and imagine the emotions that they would experience. In the

Impersonal Simulation, participants imagined a fictional character experiencing the same scenario. Lastly, in the **Unrelated Simulation**, participants imagined an episode that was neither pandemic-related nor personalized (a story about rabbits eating rotten vegetables).

Immediately following the Episodic Simulation, participants completed the Risk Estimation task, in which they attempted to estimate risk levels in their location. After receiving a brief tutorial on risk and probability, participants were asked to think about events of various sizes (5, 10, 25, 50, 100, 250, and 500 people) that could happen in their location. For each event size, participants predicted the probability (ranging from *0% - Impossible* to *100% - Definitely*) that at least one person attending the event was infected with COVID-19. After making predictions for all seven event sizes, participants received personalized, veridical feedback about the actual risk probabilities in their local community (37). We calculated *information prediction error* as the discrepancy between actual risk and perceived risk. This signed surprise metric was averaged across the seven event sizes to calculate an average prediction error score, reflecting each participant's overall risk misestimation. We hypothesized that change in risk perception would be driven by prediction error during the Risk Estimation task, but that this effect would be enhanced if preceded by a COVID-related imagination exercise (Personal and Impersonal simulation conditions). We expected that the Personal simulation would be most effective, the Impersonal simulation would be somewhat less effective, and the Unrelated simulation would be the least effective.

In addition to the three simulation conditions, we included an **Unguided Exploration** condition in which participants viewed an interactive nationwide risk assessment map (63) for a minimum of one minute, without specific instructions regarding how to engage with the information. Importantly, this condition used a well-advertised tool that reflects existing standards for disseminating risk information; this tool has been cited or promoted by the media over 2,500 times (63). Statistics about COVID-19 cases were presented without guidance or personalization, consistent with how individuals would encounter this information in a naturalistic setting. Participants in the Unguided Exploration condition did not complete the Episodic Simulation or Risk Estimation tasks.

We tested the four interventions across two sessions on a nationally-representative sample of 760 U.S. residents, after exclusions (see Methods) (Figure 2). Participants were randomly assigned to one of four conditions: **Personal Simulation** (Session 1: n = 181, Session 2: n = 158), **Impersonal Simulation** (Session 1: n = 180, Session 2: n = 166), **Unrelated Simulation** (Session 1: n = 185, Session 2: n = 173)**,** or **Unguided Exploration** (Session 1: n = 189, Session 2: n = 176). In all four conditions, participants completed an assessment of perceived risk and willingness to engage in the same risky activities pre-intervention (Session 1 baseline), immediately post-intervention (end of Session 1), and after a delay (Session 2). We defined subjective **perceived risk** as the average risk rating (on a 5-point Likert scale) for 15 activities, described in full under Methods (e.g., picking up takeout, dining indoors at a restaurant, going to a house party, flying on an airplane) (Figure 2A). Importantly, perceived risk was distinct from **risk estimation**, defined as the numerical estimates about the probability of virus exposure across various event sizes (Figure 2C). Risk estimation values were used to calculate information prediction errors (Figure 2F, 2G). We calculated within-subjects change scores (post-intervention – baseline) for each testing session, to determine whether the intervention influenced risk perception. Lastly, participants returned after a delay (1-3 weeks) to complete Session 2, which included a follow-up risk assessment and a version of the Risk Estimation task without feedback.

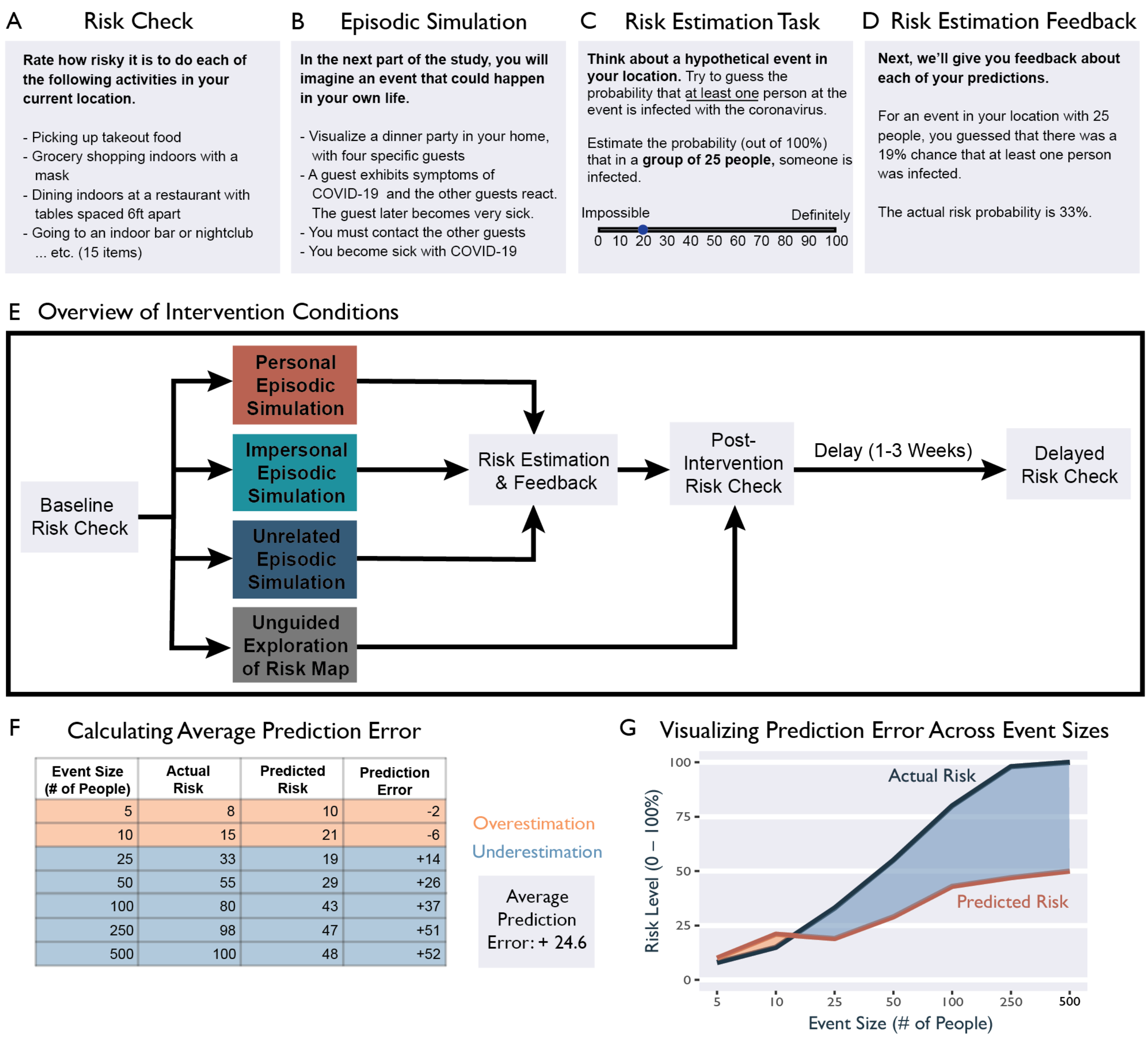

Figure 2. Overview of the intervention approach used in Study 2. A) Participants completed an assessment of perceived risk of 15 activities, and willingness to engage in those activities. The risk check was completed pre-intervention, immediately post-intervention, and 1-3 weeks post-intervention. B) During the episodic simulation task, participants were guided through an imagination exercise that involved visualizing sensory details of an event. C) During the risk estimation task, participants estimated risk probabilities in their location (based on the prevalence of COVID-19 cases). D) Following the risk estimation task, participants received feedback about the actual risk statistics. E) Overview of the four intervention conditions and the order in which participants completed tasks. F) Table depicting average prediction error calculation, using responses from the risk estimation task for an example participant. G) Visualization of the values provided in panel F.

Study 2, Session 1 Results

Overall Effects. Consistent with Study 1, we found that pre-intervention, perceived risk was unrelated to actual risk in each participant's location, $r(733) = -0.003$, $p = .94$, 95% CI [-0.08, 0.07]. Similarly, willingness to engage in risky activities was unrelated to actual risk at baseline, $r(733) = -0.05$, $p = .183$, 95% CI [-0.12, 0.02], but was strongly inversely related to perceived risk, $r(733) = -0.72$, $p < .001$, 95% CI [-0.75, -0.68]. Perceived risk at baseline was also moderately associated with social distancing compliance, $r(671) = 0.46$, $p < .001$, 95% CI [0.40, 0.52]. Overall, we replicated the associations between risk perception and risky behaviors that we observed in Study 1.

Across all intervention conditions, receiving risk information improved the accuracy of subjective risk perception. At the end of Session 1, perceived risk was weakly positively correlated with actual risk, $r(733) = 0.09$, $p = .019$, 95% CI [0.01, 0.16]. Next, we calculated within-subjects difference scores to assess post-intervention change in perceived risk and willingness to engage in risky activities. On average, there was a small-to-moderate increase in perceived risk after the intervention, $t(734) = 5.04$, $p < .001$, Cohen's $d = 0.19$, 95% CI [0.11, 0.26]. Likewise, there was a moderate decrease in willingness to engage in risky activities, $t(734) = -16.82$, $p < .001$, Cohen's $d = -0.62$, 95% CI = [-0.70, -0.54]. Changes in perceived risk were moderately negatively correlated with changes in willingness, $r(733) = -0.23$, $p < .001$, 95% CI [-0.30, -0.16].

We also investigated a potential backfire effect. Before implementing these interventions, it is important to determine whether any participants posed a *greater* risk to public health after the intervention. As previously discussed, the behavior of individuals during a pandemic can have widespread consequences. Therefore, we identified participants who had been underestimating risk prior to the intervention, but reported lower perceived risk and greater willingness to engage in risky activities after the intervention. We found that only a very small percentage of respondents showed a backfire effect (3.3%, 18 out of the 546 participants across the three simulation conditions). Further information about the proportion of responders and non-responders is provided in Supplemental Material (*Responders and Non-Responders*).

Comparing Simulation Conditions. Next, we tested the efficacy of each intervention. We hypothesized that the Risk Estimation portion of the intervention would bidirectionally improve the accuracy of risk perception, making perceived risk better aligned with actual risk. We expected that information prediction errors experienced during the Risk Estimation task would drive change in risk perception. Using multiple linear regression, we found that average prediction error was moderately positively related to change in risk perception, $\beta = 0.23$, $t = 5.32$, $p < .001$, 95% CI [0.14, 0.31] (Figure 3A, 3B). There was also a small-to-moderate interaction between prediction error and simulation condition predicting change in risk perception, such that the effect of prediction error was stronger in the Impersonal simulation condition than in the Unrelated simulation condition, $\beta = 0.16$, $t = 2.59$, $p = .0098$, 95% CI [0.04, 0.27] (Figure 4A, 4B). The effect of prediction error in the Impersonal simulation condition did not significantly differ from the Personal simulation condition, $\beta = 0.01$, $t = 0.20$, $p = .839$, 95% CI [-0.11, 0.13].

To examine this interaction further, we tested the relationship between prediction error and change in risk perception in each condition separately. Prediction error was moderately associated with change in risk perception in the Impersonal simulation condition ($r(175) = 0.37$, $p < .001$, 95% CI [0.24, 0.49]) and Personal simulation condition ($r(176) = 0.23$, $p = .002$, 95% CI [0.09, 0.37]), but not in the Unrelated simulation condition ($r(180) = 0.06$, $p = .429$, 95% CI [-0.09, 0.20]). These effects remained statistically significant even after controlling for relevant demographic and individual difference variables: political conservatism, age, episodic future thinking ability, subjective numeracy ability, and self-reported vividness and affect ratings from the simulation task (Supplemental Material, *Controlling for Individual Differences*).

Next, we conducted the same analysis for a different dependent variable: change in willingness to engage in risky activities pre- to post-intervention. Prediction error experienced during the Risk Estimation task was weakly-to-moderately related to change in willingness, $\beta = -0.14$, $t = -3.26$, $p = .001$, 95% CI [-0.23, -0.06] (Figure 3C, 3D). In other words, individuals who had been severely underestimating actual risk levels tended to show a greater decrease in willingness to engage in risky activities. This effect remained significant after controlling for potential covariates (Supplemental Material, *Controlling for Individual Differences*). However, the interaction between prediction error and simulation condition was not significantly related to change in willingness (Impersonal vs. Unrelated: $\beta = -0.03$, $t = -0.40$, $p = .690$, 95% CI [-0.15, 0.10]; Impersonal vs. Personal: $\beta = -0.01$, $t = -0.16$, $p = .872$, 95% CI [-0.13, 0.11]).

Overall, we found that prediction error elicited during the Risk Estimation task was a moderately strong and statistically robust predictor of change in both perceived risk and willingness to engage in risky activities. This finding demonstrates that receiving veridical information about local risk statistics can bidirectionally improve the accuracy of risk perception. Furthermore, imagining a COVID-related scenario (either Impersonal or Personal) enhanced the effect of prediction error on risk perception.

Simulation/Estimation Intervention vs. Unguided Exploration. Lastly, we pooled data from our three novel intervention conditions (Personal Simulation, Impersonal Simulation, and Unrelated Simulation) and compared effects with the Unguided Exploration condition. We found that the Simulation conditions produced a slightly greater decrease in willingness to engage in risky activities relative to the Unguided Exploration condition, $t(733) = -2.91$, $p = .004$, Cohen's $d = -0.25$, 95% CI [-0.41, -0.08]. However, there was no significant difference between conditions for change in perceived risk, $t(733) = 0.37$, $p = .711$, Cohen's $d = 0.03$, 95% CI [-0.13, 0.20]. Overall, these results suggest that all four intervention conditions had a beneficial impact on risk perception and willingness to engage in risky activities, but the Simulation conditions were modestly more effective than Unguided Exploration. However, it is important to note that participants in the Unguided Exploration condition did not complete the Risk Estimation task; therefore, we could not determine whether they were underestimating or overestimating actual risk before the intervention. Unlike the prediction error analysis reported above, the group average in the Unguided Exploration condition does not indicate whether participants showed an improvement in risk perception *accuracy*.

Study 2, Session 2 Results

Overall Effects. First, we tested whether the average changes in perceived risk and willingness to engage in risky activities persisted after a 1-3 week delay. We found that the average increase in perceived risk (relative to the pre-intervention baseline) was still evident at Session 2, $t(672) = 3.37$, $p < .001$, Cohen's $d = 0.13$, 95% CI [0.05, 0.21]. Within-subjects, change in risk perception from Session 1 was moderately-to-strongly correlated with lasting change in Session 2, $r(671) = 0.51$, $p < .001$, 95% CI [0.46, 0.57].

Likewise, the average decrease in willingness to engage in risky activities also persisted after a delay, $t(672) = -6.89$, $p < .001$, Cohen's $d = -0.27$, 95% CI [-0.34, -0.19]. Within-subjects, change in willingness from Session 1 was moderately-to-strongly correlated with lasting change in Session 2, $r(671) = 0.49$, $p < .001$, 95% CI [0.43, 0.54]. Consistent with Session 1, we also found that lasting changes in perceived risk were moderately negatively correlated with lasting changes in willingness, $r(733) = -0.27$, $p < .001$, 95% CI [-0.34, -0.20]. Overall, we found that across all four intervention conditions, participants reported lasting increases in perceived risk and decreases in willingness to engage in risky activities after a delay.

Comparing Simulation Conditions. Next, we tested whether prediction error during the Session 1 risk estimation task predicted lasting changes in risk perception. We accounted for variable delay lengths in all of the following models by including a covariate for the number of days between Session 1 and Session 2. We found that prediction error experienced during the Risk Estimation task in Session 1 continued to predict lasting changes in perceived risk in Session 2, $\beta = 0.18$, $t = 4.21$, $p < .001$, 95% CI [0.10, 0.27] (Figure 3E, 3F). The interaction between prediction error and simulation condition was no longer significant (Impersonal vs. Unrelated: $\beta = 0.08$, $t = 1.38$, $p = .168$, 95% CI [-0.04, 0.20]; Impersonal vs. Personal: $\beta = 0.01$, $t = 0.16$, $p = .870$, 95% CI [-0.11, 0.13]). However, numerically the results across conditions were consistent with Session 1 (Figure 4C, 4D), such that prediction error was weakly-to-moderately related to lasting change in perceived risk in both the Impersonal condition ($r(163) = 0.26$, $p < .001$, 95% CI [0.12, 0.40]) and the Personal condition ($r(153) = 0.19$, $p = .018$, 95% CI [0.03, 0.34]), but not in the Unrelated condition ($r(169) = 0.10$, $p = .194$, 95% CI [-0.05, 0.25]). Overall, prediction errors experienced during Session 1 were associated with lasting changes in risk perception, particularly in the Impersonal and Personal simulation conditions.

We then conducted the same analysis for lasting change in willingness to engage in risky activities (Figure 3G, 3H). Prediction error was not significantly related to willingness to engage in risky activities in Session 2, $\beta = -0.05$, $t = -1.08$, $p = .283$, 95% CI [-0.14, 0.04]. There was no significant interaction between prediction error and simulation condition predicting willingness (Impersonal vs. Unrelated: $\beta = 0.01$, $t = 0.22$, $p = .824$, 95% CI [-0.11, 0.14]; Impersonal vs.

Personal: β = -0.04, t = -0.56, p = .577, 95% CI [-0.16, 0.09]). As reported above (Overall Effects), we found that participants were less willing to engage in risky activities after the intervention, both immediately and after a delay. However, prediction error only described the magnitude of change in willingness immediately after the intervention. These results suggest that participants who were highly risk averse at baseline reverted to risk aversion after a delay, thus attenuating the parametric effect of prediction error on willingness to engage in risky activities.

Simulation/Estimation Intervention vs. Unguided Exploration. Lastly, we pooled Session 2 data from the three Simulation conditions and compared these interventions to the Unguided Exploration condition. Relative to the Unguided Exploration condition, the Simulation conditions produced a slightly larger lasting increase in perceived risk, β = 0.09, t = 2.00, p = .046, 95% CI [0.002, 0.17]. The difference between conditions for willingness to engage in risky activities was not significant, but the Simulation conditions tended to produce a slightly larger lasting decrease in willingness, β = -0.08, t = -1.87, p = .062, 95% CI [-0.17, 0.004]. Taken together, these results indicate that the interventions that involved the Episodic Simulation and Risk Estimation tasks were somewhat more effective at producing lasting increases in perceived risk and decreases in willingness to engage in risky activities.

We also asked participants to retrospectively report whether they had engaged in any of the risky activities during the delay period. The average number of risky activities reported did not differ between the Simulation and Unguided Exploration conditions, β = 0.06, t = 1.34, p = .180, 95% CI [-0.03, 0.15]. However, the duration of the delay between sessions was weakly positively related to the number of risky activities, β = 0.04, t = 2.05, p = .041, 95% CI [0.001, 0.07]. It is likely that the relatively short delay between sessions (M = 7.5 days) made it unlikely that participants would have the opportunity to complete many of the risky activities listed, regardless of their willingness (e.g., dining in a restaurant, going to the dentist, flying on an airplane).

Change in Risk Estimation Accuracy over Time. We also computed a model-free measure of estimation accuracy to evaluate risk estimation change over time. Note that only participants in the three simulation conditions completed the risk estimation task during Session 1, but all returning participants completed the risk estimation task during Session 2. We examined how each individual's risk estimation function related to actual risk across all group sizes by computing the area between the two curves, first at Session 1 and again at Session 2. This measure was highly correlated with the mean PE measure reported above in for Session 1 and the mean (unsigned) accuracy computed for Session 2 (Session 1: $r(536) = 0.99$, $p < 0.001$, 95% CI [0.992, 0.994]; Session 2: $r(660) = 0.99$, $p < 0.001$, 95% CI [0.992, 0.994]), but provides additional information – especially visually – about where (i.e., for which particular group sizes) individuals were most inaccurate or benefited most from the intervention. We found that overall misestimation decreased significantly from Session 1 to Session 2 (paired $t(481) = 9.84$, $p < 0.001$, Cohen's $d = 0.45$, 95% CI [0.35, 0.54]), reflecting mitigation of both over- and under-estimation.

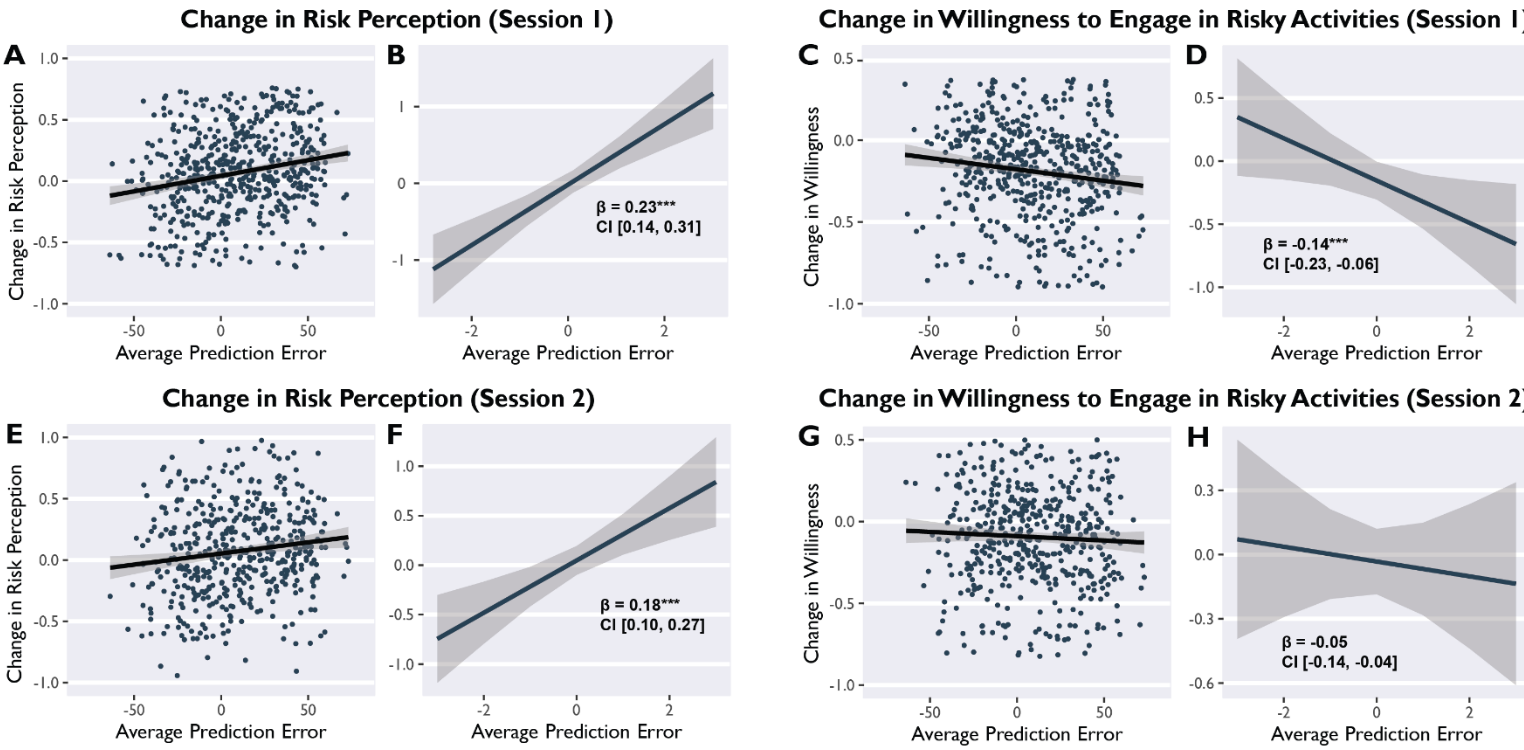

Figure 3. Main effects of prediction error on perceived risk and willingness to engage in risky activities. Panels A-D depict results for Session 1, and panels E-H depict corresponding results for Session 2 (after a 1-3 week delay). Panels A/C/E/G depict all raw data points. Panels B/D/F/H depict model-derived estimates for main effects (standardized variables), after controlling for the effects of simulation condition and delay period. Shaded bands indicate 95% confidence intervals around the regression line. ** $p < .05$, ** $p < .01$, *** $p < .001$*

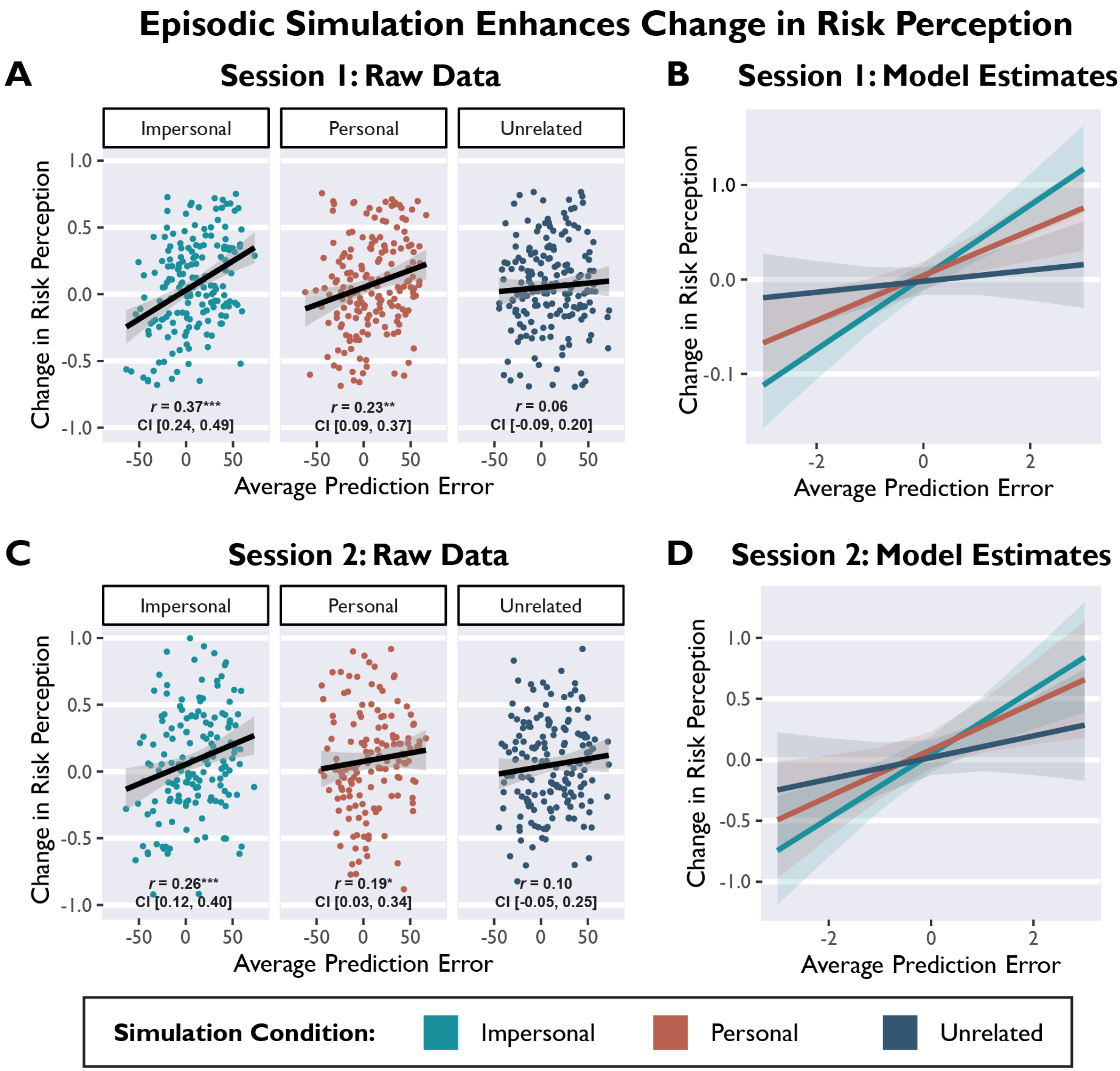

Figure 4. Simulation condition moderates the effect of prediction error on perceived risk. Prediction error from the risk estimation task was significantly related to change in risk perception in the Impersonal and Personal conditions (imagining a COVID-related scenario), but not the Unrelated condition. Panels A/B depict Session 1 results, and panels C/D depict Session 2 results. Panels A/C depict all raw data points, subset by simulation condition. Panels B/D depict model-derived estimates (standardized variables), after controlling for the effect of covariates (e.g., delay period). Shaded bands indicate 95% confidence intervals around the regression lines. * *p < .05,* ** *p < .01,* *** *p < .001*

General Discussion

During the COVID-19 pandemic, individuals have struggled to balance conflicting needs and make informed decisions in an environment characterized by high uncertainty. Although public health guidelines initially helped to slow the spread of disease, widespread pandemic fatigue (7) and the emergence of a new highly-transmissible viral variant have contributed to a catastrophic resurgence (65). New interventions are needed to sustain long-term behavior change, allowing individuals to comply with public health guidelines while also fulfilling other needs. Here, we report an informational intervention that provided individuals with accurate information about local risk levels; this information could improve decision-making to strike a balance between public health, personal, financial, and community needs. In Study 1, we found that subjective risk perception was inaccurate, yet predicted compliance with public health guidelines. In Study 2, we demonstrated that a brief online intervention changed beliefs and intentions about risk. Information prediction error, a measure of surprise, drove beneficial change in perceived risk and willingness to engage in risky activities. Furthermore, imagining a pandemic-related scenario prior to receiving risk information enhanced learning. Importantly, the benefits of our intervention persisted after a 1-3 week delay.

Our intervention leveraged insights from multiple disciplines to maximize the likelihood of realigning perceived risk with actual risk. We predicted that the efficacy of the intervention would be driven by both the risk information itself (information prediction error) and the context in which it was received (episodic simulation). Our results supported this hypothesis, demonstrating that the effect of prediction error on risk perception was enhanced by manipulating the salience of the interventional context through imagination of a COVID-related scenario. Interestingly, we found that the Personal and Impersonal simulations were equally effective. We had expected the Personal simulation to be most effective, but highly specific personal details could have detracted from the experience by making it seem less plausible (e.g., “My sister would never be willing to take her mask off.”). Overall, we found that the Impersonal simulation was sufficient to enhance the effect of prediction error, offering practical utility because impersonal elements are easy to implement in large-scale online interventions.

Post-intervention, participants who had previously underestimated risk reported greater perceived risk in a variety of everyday activities (e.g., dining indoors at a restaurant, grocery shopping with mask, exercising at a gym without a mask) and reduced willingness to engage in these behaviors. These changes reflect a realignment with public health guidelines both immediately and after a delay, with risk perception showing the most durable change. Although on average participants continued to be less willing to engage in risky activities 1-3 weeks post-intervention, the parametric effect of prediction error on willingness to engage in risky activities did not persist after a delay. More frequent, regular exposure to risk information may be critical for linking interventions on risk estimation to behavioral risk tolerance (66).

Prior interventions seeking to mitigate biases in risk perception have largely targeted numerical cognition, especially in individuals low in quantitative literacy (28, 67). Traditional informational interventions (e.g., pamphlets in clinical settings) have been widely used, especially in health decision making (27, 28). Such decision aids are easy to implement, but they lack features that engage attention, facilitate retention, and drive lasting changes in behavior (68). Importantly, there is little evidence of long-term efficacy for even the most effective interventions (28, 67). Recent work has highlighted the potential of using affect and gist-based thinking to shape the learning context, thereby making risk information more salient (69, 70).

To increase the likelihood of intervention success, we combined the most effective elements of past interventions, pairing surprising risk information with a novel interactive experience designed to contextualize and increase the salience of risk information. Past studies have shown that prediction error (i.e., surprise) drives belief and knowledge updating (58–61), and can influence risk perception (61). However, past research has not explored whether prediction error can change risk perception when individuals are capable of avoiding adverse outcomes by making better decisions. For the first time, we demonstrated that information prediction error improved the accuracy of risk perception and also influenced willingness to engage in risky activities. Crucially, we found that an episodic simulation *prior* to a learning experience enhanced the effect of prediction error on learning. Past studies have shown that episodic simulation can support decision making in other domains, improving both patience (44, 71) and prosociality (46). However, other studies have shown no effect of episodic simulation on risk perception (72, 73), perhaps because narratives are more powerful when they are paired with statistics (56). Importantly, our intervention is the first to combine an episodic simulation with prediction error. We propose that imagining a COVID-related episode may establish a link between risk estimation and the potential outcomes of risky decisions, thus enhancing the effect of prediction error (40, 42). Our findings bear broader theoretical implications: For example, prediction error can support revising common misconceptions (e.g., about vaccine safety), correcting misinformation in the media, and learning in educational settings. Providing an episodic simulation prior to a learning experience could enhance the effect of prediction error in these other domains.

Some of our results suggest important avenues for future research. Although on average our intervention helped participants align perceived risk with actual risk and reduce their willingness to engage in risky activities, there were still many participants who did not shift their beliefs and intentions (Supplemental Material, *Responders and Non-Responders*). Why did the intervention work as intended for some participants but not others? Emerging research suggests that the COVID-19 pandemic has created a breeding ground for conspiratorial thinking on social media (8, 74), with many Americans confidently dismissing the pandemic as a hoax (75–77). Conspiratorial thinking about the pandemic tracks the propensity for people to engage in anti-social and risky behaviors (78, 79). Alternative (or additional) methods may be necessary to successfully realign risk-related beliefs for people who dismiss the severity of the pandemic, perhaps through facilitating analytic thinking or through training to better discriminate between reputable vs. disreputable sources of information. In addition, our future work will explore how individual differences may influence receptivity to our intervention; recent studies have suggested that political partisanship (77, 80), age (14), gender (81), analytical thinking (75), and open-mindedness (82) may influence beliefs about risk during the pandemic.

In the present study, we assessed whether our effects persisted after a relatively short delay of 1-3 weeks. However, risk levels are constantly changing, so an effective intervention should be updated frequently and administered repeatedly. Our intervention is fast to complete and easy to disseminate online, making it well-suited to frequent updates. These features enhance feasibility for both participants and behavior designers. Future interventions could focus on cultivating a habit of information-seeking from reputable sources; these small behavioral nudges could be used to quickly realign perceived risk with actual risk.

Conclusion

In America and other countries globally, the outbreak has reached new levels of severity more than ten months after initial lockdowns. Viral transmission is following an exponential trajectory (7, 11, 63), and the World Health Organization has recommended a harm reduction approach to combat widespread pandemic fatigue (7). Importantly, severe outbreaks will limit the success of vaccination programs (10), highlighting the urgent need for behavior change to reduce viral transmission. Here, we report the results of new interventions that improved the accuracy of risk perception and reduced willingness to engage in risky activities. In this high-stakes context, increasing even a single individual's compliance with public health guidelines could have significant downstream effects and limit superspreading events (12, 15, 16). Furthermore, individuals repeatedly choose whether or not to engage in everyday risky activities; the impact of changing perceived risk would accumulate over many decisions.

Importantly, our intervention is simple to implement. Our findings suggest that existing risk assessment tools could be improved with simple changes. Existing websites that present COVID-19 statistics could be modified to enhance efficacy, such as by adding a brief impersonal episodic simulation or eliciting prediction error via a risk estimation game (e.g., "Imagine a restaurant with 10 people dining inside. Estimate the probability that at least one of the diners is infected.") Overall, we describe a fast and effective intervention to improve risk perception accuracy, and offer concrete recommendations for implementation. Effectively communicating local risk information could empower individuals to make better decisions during the pandemic by finding the optimal balance between personal and public health needs.

Methods

Study 1

Participants. We recruited 303 current U.S. residents to complete an online survey via Prolific, an online testing platform. However, 70 participants did not provide location data or resided in counties that were not reporting COVID-19 statistics; these participants were omitted from analyses that involved measures of actual risk. The sample was nationally-representative, stratified by age, sex, and race to approximate the demographic makeup of the U.S. Participants were paid $4.75 USD for completing a task that took approximately 30 minutes. The study was approved by the Duke University Health System IRB (Protocol #00101720). Data collection took place on May 18th and 19th, 2020.

Survey. The task was administered with Qualtrics survey software. Participants answered questions about perceived risk related to COVID-19, willingness to engage in risky activities, and compliance with public health guidelines. We measured *perceived risk* by asking participants to rate how risky they believed it was to engage in six different activities: Going for a walk outside, shopping at a grocery store, eating inside a restaurant, meeting with a small group of friends, travelling within one's state, or travelling beyond one's state. Participants rated perceived risk of these activities on a 5-point Likert scale (*not at all risky … extremely risky*). Risk perception scores were averaged across the six items. We measured willingness to engage in risky activities by asking participants if they would be willing to do the following activities, if all stay-at-home restrictions in their location were lifted: Going to a park or playground, going to the gym, eating inside a restaurant, meeting with up to 5 friends, meeting with up to 10 friends, meeting with over 10 friends, travelling within one's state, or travelling beyond one's state.

Participants were able to check all activities that they would be willing to do, and we summed the total number of activities endorsed.

Actual Risk Calculation. Additionally, we collected location information (U.S. state and county) from participants. We measured *actual risk* by obtaining measures of local outbreak severity by retrieving COVID-19 case data from each participant's county on the day that the study was completed. Data were sourced from the COVID Tracking Project (62). Population data were sourced from 2019 estimates based on the 2010 U.S. Census (83). To calculate an objective measure of actual risk, we used the formula employed by the COVID-19 Risk Assessment Planning Tool developed by researchers at the Georgia Institute of Technology (37). The risk assessment formula estimates the probability that at an event of a given size, there will be at least one individual who is infected with SARS-CoV-2 and may spread the disease to others. Risk estimates were calculated for hypothetical events with 10 attendees, on the basis of the current number of active cases in a participant's county and an ascertainment bias of 10 (accounting for additional cases that are unidentified because of insufficient testing). Note that the choice of event size for the actual risk measure is arbitrary; we were interested in the *correlation* between perceived and actual risk scores, despite the different measurement scales. The actual risk measure was log-transformed to normalize the distribution and meet assumptions for parametric statistical tests.

Study 2

Participants. We recruited a nationally-representative sample of 816 current U.S. residents via Prolific. After exclusions (see Exclusions section below), our final sample consisted of 760 participants who were randomly assigned to four different intervention conditions: Personal Simulation (n = 181), Impersonal Simulation (n = 180), Unrelated Simulation (n = 185), and Unguided Exploration (n = 189). Participants were paid $4.50 for a survey that took approximately 20-30 minutes to complete. The study was approved by the Duke University Health System IRB (Protocol #00101720). Data collection took place between September 14th and October 9th, 2020. The intervention study was pre-registered (https://osf.io/6fjdy).

Additionally, we recontacted our participants one week later for a follow-up survey. Of the 760 participants who successfully completed Session 1, 664 returned for Session 2 after a delay (Personal Simulation: n = 158, Impersonal Simulation: n = 166, Unrelated Simulation: n = 173, Unguided Exploration: n = 176). The average delay between Session 1 and Session 2 was 7.74 days (SD = 2.11, range [7, 25]). Participants were paid $1.25 for a survey that took approximately 5 minutes to complete.

Procedure. The assessment of perceived risk and willingness to engage in risky activities was expanded to include 15 activities sampled evenly across five levels of risk, ranging from low risk activities (e.g., picking up takeout) to very high risk activities (e.g., going to a crowded nightclub). Using 5-point Likert scales, participants rated perceived risk (*1 = Low risk … 5 = High risk*) and willingness to engage in these activities (*1 = Definitely would NOT do this … 5 = Definitely WOULD do this*). The full list of activities was as follows: Picking up takeout food, walking outside without a mask in an area without many people, having an outdoor picnic with friends 6+ feet apart, playing a group sport outside without a mask, grocery shopping indoors with a mask, retail shopping indoors with a mask, going to the dentist, taking a taxi/Uber/Lyft, dining outdoors at a restaurant, dining indoors at a restaurant, getting a haircut, exercising at a gym without a mask, flying on an airplane, going to an indoor bar or nightclub, or going to a large indoor house party. Actual risk was calculated in the same manner as in Study 1 (i.e., likelihood of 1+ COVID-19 cases in a group of 10 people), using updated COVID-19 case statistics for each participant's local community.

Participants were randomly assigned to one of four conditions: **Personal Simulation**, **Impersonal Simulation**, **Unrelated Simulation,** or **Unguided Exploration**. Across all four conditions, all participants completed an assessment of perceived risk and willingness to engage in risky activities pre-intervention and post-intervention. Between the intervention and the post-intervention survey, participants also completed a demographics questionnaire and several individual differences measures. The four conditions differed in terms of the intervention provided in the middle of the study session. Participants in the three simulation conditions completed two novel intervention tasks: the **Episodic Simulation** and the **Risk Estimation Task**. Participants in the **Unguided Exploration** condition did *not* complete the simulation or risk estimation tasks; instead, they viewed an interactive nationwide risk assessment map without specific instructions regarding how to engage with the information. Participants in this condition were required to view or interact with the map for at least 60 seconds before proceeding.

Episodic Simulation. The full text of all simulation conditions is provided in Supplemental Material (*Episodic Simulation Text*). In brief, the Personal and Impersonal simulation conditions involved imagining a pandemic-related scenario in which guests fall ill after virus exposure at a dinner party. In the Personal simulation, participants imagined themselves as the host of the dinner party, and identified specific close others (family members, friends, coworkers, or neighbors) as their guests. In the Impersonal simulation, participants imagined a fictional character named Martin experiencing the same scenario. The Unrelated simulation involved imagining a scenario that was neither pandemic-related nor personalized (rabbits getting sick after eating rotten vegetables). In all three simulation conditions, participants typed into a text box to describe the details they imagined before proceeding to the next step of the simulation.

Risk Estimation Task. Immediately after the episodic simulation, participants in the three simulation conditions completed a risk estimation task framed as a prediction game. Participants provided and confirmed their current location (county within state), then read a brief explanation of probability and risk that explained concepts with an example of selecting fruit from a bowl. Next, participants were asked to think about events of various sizes (5, 10, 25, 50, 100, 250, and 500 people) that could happen in their location. Participants predicted the probability (ranging from *0% - Impossible* to *100% - Definitely*) that at least one person in the group was infected with COVID-19. On each trial, participants also rated confidence in their prediction (ranging from *0% - Guessing* to *100% - Very Sure*). After making predictions about all seven event sizes, participants received veridical feedback about the actual risk probability for each event size, based on current risk statistics in their location. Participants also rated subjective surprise after receiving feedback for each event size (5-point Likert scale, ranging from *1 - Not at all surprised* to *5 - Extremely surprised*).

Statistical Analysis. Analyses were conducted with R v4.0. Data and code necessary to reproduce the results and figures are available in a public repository hosted by the Open Science Framework (https://osf.io/6fjdy). All continuous variables were standardized before submission to multiple linear regression. Factor variables for conditions were effect coded. Visual inspection of histograms indicated that several variables exhibited high kurtosis, with some extreme values at both tails of the distribution. As a result, residuals from fitted models were larger for values at the tails. To correct for high kurtosis and meet the assumption of normality, we winsorized extreme values to the 5th and 95th percentiles. Variables for change in perceived risk (Session 1) and change in willingness to engage in risky activities (Session 1 and Session 2) were winsorized. Winsorizing these variables improved model fits but did not change the statistical significance of any of our findings (Supplemental Material, *Results without Winsorizing*). Additionally, we corrected skewed distributions by applying log-transformations to the variables for actual risk, retrospective report of risky behaviors, and willingness to engage in risky activities (Session 1). Other variables were not transformed because distributions were approximately normal.

Exclusions. We excluded all data from 88 participants for the following preregistered reasons: lack of COVID-19 statistics for their location (27), failing an attention check (27), or providing irrelevant or excessively short responses to the Episodic Simulation task (34). We also excluded two extreme outlier observations for the retrospective report of risky behaviors between sessions (15/15 activities) because it was exceptionally unlikely that any participant could have completed the full list of activities over the course of a week (e.g., going to the dentist, getting a haircut, and flying on an airplane). Manual inspection of the data from these participants indicated that their other responses appeared legitimate, suggesting that they may have misread the instructions for this particular question. Therefore, we omitted their responses for this question, but did not exclude other data from these participants. Lastly, 35 participants failed to complete all questions for the Risk Estimation task during the Session 2 follow-up survey. These incomplete data points were excluded from the analysis of risk estimation accuracy.

Deviations from Preregistration. In addition to the demographic and individual difference measures that we tested as covariates (Supplemental Material, *Controlling for Individual Differences*), we also measured Actively Open-Minded Thinking and Social Value Orientation. These measures were listed under planned exploratory analyses, but we did not analyze these individual differences here for the sake of brevity. As described above, in Study 2 we excluded two data points from the variable for retrospectively reported risky activities between testing sessions. All other exclusion criteria were preregistered. Furthermore, we included a covariate for delay length (between testing sessions) in all Session 2 models. This covariate was not preregistered because we did not anticipate receiving survey responses over a long period of time. We also computed a model-free measure that resolved global changes in risk misestimation across the full set of group sizes, area between the curves. This single metric provided a more parsimonious alternative to testing change in misestimation separately for each group size (as planned).

Author Contributions: A.S., S.H., M.S., and G.SL designed the studies. A.S., S.H., and M.S. created stimulus and survey materials. A.S. performed data collection. A.S. and S.H. analyzed data with input from M.S., A.A., and G.SL. A.S. and S.H. drafted the paper, with input from M.S., A.A., and G.SL. All authors approved of the final version.

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Supplemental Material

Responders and Non-Responders

As described in the main text, we found that only a very small proportion of participants demonstrated a backfire effect in response to the intervention. We also identified participants who showed beneficial change after the intervention, based on their risk estimation bias at baseline (i.e., risk underestimators who reported greater perceived risk and lower willingness to engage in risky activities, or risk overestimators who reported lower perceived risk and greater willingness). The slight majority of participants showed beneficial change after the intervention: 52.2% of participants (285/546) reported more accurate risk perception and 56.8% of participants (310/546) reported willingness to engage in risky activities that was better aligned with actual risk levels. We could not determine the prevalence of beneficial and backfire effects for the Unguided Exploration condition because we did not test whether these participants were underestimating or overestimating risk at baseline. Overall, we found that the efficacy of our interventions was not undermined by a backfire effect; the vast majority of participants either benefitted from the intervention or showed no change.

Why was the intervention ineffective for some participants? We hypothesized that a subset of non-responders may have already held accurate beliefs about risk at baseline, rendering the intervention unnecessary. To test this idea, we conducted an exploratory analysis comparing the average unsigned prediction error scores between responders (participants who shifted risk perception in the appropriate direction) and non-responders (participants who did not). We found that non-responders were slightly more accurate than responders at baseline; non-responders reported lower unsigned prediction error scores, $t(535) = -2.05$, $p = .041$, Cohen's $d = -0.18$, 95% CI [-0.35, -0.01]. This effect was driven by a subset of non-responders (29.4%, 74/252) who were already highly accurate at risk estimation (average unsigned prediction error scores <= 15). Distributions of unsigned prediction error scores for responders and non-responders are provided in Figure S1.

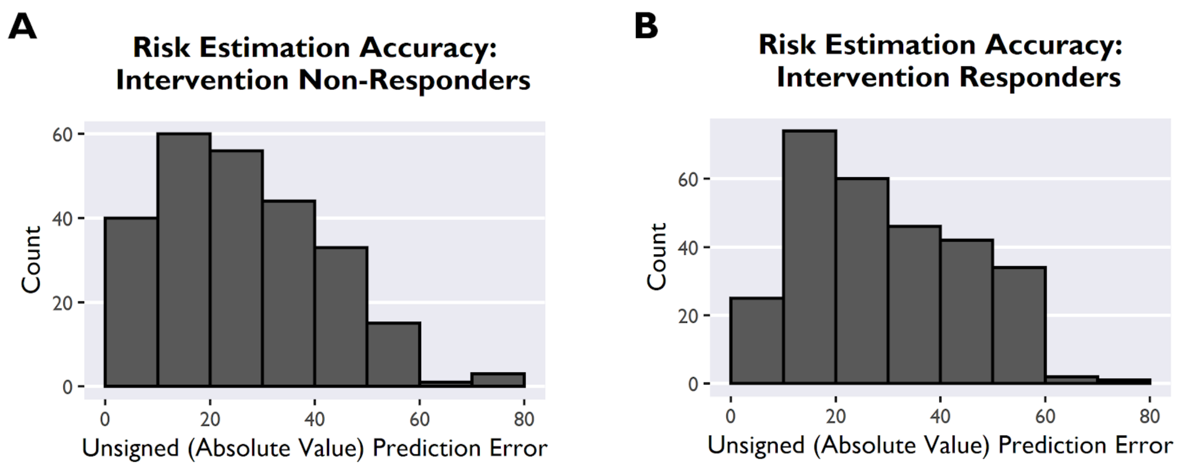

Figure S1. Distributions of average unsigned prediction error scores. A) Among participants who did not respond to the intervention (i.e., did not shift risk perception in the correct direction), a subset showed very high risk estimation accuracy before feedback (prediction error scores < 20), suggesting that the intervention was unnecessary. B) Among participants who did respond well to the intervention (i.e., shifted risk perception in the correct direction), fewer participants showed very high baseline risk estimation accuracy.

Results without Winsorizing

As described in the Methods section of the main text, we winsorized several variables in order to account for leptokurtic distributions. However, the significance of our results remained unchanged when variables were not winsorized. Below, we report alternate results with unaltered variables.

First, we tested for overall effects averaged across all intervention conditions. At the end of Session 1, there was a small average increase in perceived risk after the intervention, $t(734) = 3.85$, $p < .001$, Cohen's $d = 0.14$, 95% CI [0.07, 0.21]. This effect persisted to Session 2, $t(734) = 3.75$, $p < .001$, Cohen's $d = 0.13$, 95% CI [0.05, 0.21]. At the end of Session 1, there was also a moderate average decrease in willingness to engage in risky behaviors after the intervention, $t(734) = -13.37$, $p < .001$, Cohen's d = -0.49, 95% CI [-0.57, -0.42]. This effect persisted in Session 2, $t(672) = -5.39$, $p < .001$, Cohen's d = -0.21, 95% CI [-0.28, -0.13].

Next, we compared the effect of prediction error across the three simulation conditions. Using multiple linear regression, we found that average signed prediction error was weakly-to-moderately associated with change in risk perception, $\beta = 0.20$, $t = 4.91$, $p < .001$, 95% CI [0.12, 0.28]. There was also an interaction between prediction error and simulation condition predicting change in risk perception (Impersonal vs. Unrelated: $\beta = 0.14$, $t = 2.36$, $p = .019$, 95% CI [0.02, 0.25]; Impersonal vs. Personal: $\beta = -0.01$, $t = 0.58$, $p = .845$, 95% CI [-0.12, 0.10]). This interaction indicated that prediction error was significantly associated with change in risk perception in the Impersonal Simulation condition ($r(175) = 0.35$, $p < .001$, 95% CI [0.21, 0.47]) and Personal Simulation condition ($r(176) = 0.18$, $p = .015$, 95% CI [0.04, 0.32]), but not in the Unrelated Simulation condition ($r(180) = 0.09$, $p = .246$, 95% CI [-0.06, 0.23]). Note that the variable for change in perceived risk was not winsorized for Session 2, because the distribution was approximately normal.

Next, we conducted the same analysis for an additional dependent variable: Change in willingness to engage in risky behaviors. Prediction error experienced during the Risk Estimation task was weakly negatively related to change in willingness, $\beta = -0.10$, $t = 2.51$, $p = .012$, 95% CI [-0.18, -0.02]. However, the interaction between prediction error and simulation condition was not significantly related to change in willingness (Impersonal vs. Unrelated: $\beta = -0.05$, $t = -0.87$, $p = .383$, 95% CI [-0.16, 0.06]; Impersonal vs. Personal: $\beta = -0.04$, $t = 0.63$, $p = .528$, 95% CI [-0.15, 0.08]). In Session 2, prediction error was not significantly related to lasting change in willingness to engage in risky activities, $\beta = -0.03$, $t = -0.62$, $p = .538$, 95% CI [-0.12, 0.06].

Controlling for Individual Differences

We tested whether the effects of prediction error and simulation condition held after controlling for several possible covariates: political conservatism, age, subjective numeracy ability, episodic future thinking ability, self-reported vividness of the episodic simulation, and self-reported change in affect after the episodic simulation. In Session 1, the effect of prediction error on change in perceived risk ($\beta = 0.20$, $t = 4.57$, $p < .001$, 95% CI [0.12, 0.29]) and the interaction between prediction error and simulation condition (Impersonal vs. Unrelated: $\beta = 0.15$, $t = 2.48$, $p = .014$, 95% CI [0.03, 0.27]) remained significant after controlling for demographic and individual difference variables. Conservatism was significantly positively associated with change in perceived risk ($\beta = 0.09$, $t = 2.42$, $p = .016$, 95% CI [0.02, 0.17]), likely because conservatives were more likely to underestimate risk at baseline ($r(733) = -0.36$, $p < .001$, 95% CI [-0.43, -0.30]). No other covariates showed a significant association with change in perceived risk.

Episodic Simulation Text

Below, we have reproduced the text used to guide participants through the three episodic simulation conditions. The three simulation conditions were matched in length and format. Participants were instructed to imagine each step of the episode and then type out the details that they visualized to confirm participation in the task. To encourage vivid imagining and thorough responses, participants were not allowed to advance to the next stage of the simulation until a minimum of 10 seconds had passed at each stage. Each of the three simulation conditions took approximately 5 minutes to complete. After the simulation task, participants rated their change in affect ("Overall, how do you feel after imagining this scenario?" 1 = *Much worse* … 5 = *Much better*) and subjective vividness of the simulation ("Overall, how vivid (clear and detailed) was the scene that you imagined?" 1 = *Not vivid at all* … 5 = *Extremely vivid*).

Personal Simulation. "In the next part of the study, you will imagine an event that could happen in your own life. We will guide you through the imagination exercise on the following pages. First, please think about four people who you know personally who you might invite over to your home for dinner. Please type in the box below to indicate the five people you chose (e.g., "my friend Martin", "my sister", "my boss"). You may use first names if you want, but to protect privacy, please do not write full names." [text entry]

"Now, please try to imagine what each of the four people look like when they are in your home. Close your eyes and try to visualize what their faces look like, what clothes they are wearing, and how it makes you feel to see them. When you are done imagining, please briefly describe what each person looks like or what they are wearing (1 sentence per person)." [text entry]

"Next, imagine the part of your house where you would be serving dinner. Close your eyes and try to visualize what the scene looks like, where each of your guests would be sitting, and what you would serve for dinner. When you are done imagining, please briefly describe what the room looks like and what you are eating for dinner. (2-3 sentences)" [text entry]

"Next, choose one of your four guests (other than yourself). Type below to indicate which guest you chose:" [text entry] "Imagine that the guest you chose begins coughing during dinner. They say that it may just be allergies. Close your eyes again and imagine what this scene would look like and how your other guests might react. Imagine how you would feel. Please describe how you would feel or what you would do in the box below. (1-2 sentences)" [text entry]

"Now, imagine that three days later, the guest tells you that they have tested positive for COVID-19 and are going to the hospital because they feel very sick. Imagine that you have to contact each of your other guests and tell them that they may have been infected at your home. Think about what it would be like to talk to each of your guests, what you would say to them, and the emotions that you would feel. Please describe how you would feel in the box below. (1-2 sentences)" [text entry]

"Imagine that you also become sick with COVID-19 after your dinner party. You have a fever, feel dizzy, and have a cough that makes it hard to breathe. Close your eyes and try to imagine what these symptoms would feel like. Please describe how you would feel in the box below. (1-2 sentences)" [text entry]

Impersonal Simulation. "In the next part of the study, you will imagine an event that could happen in someone's life. We will guide you through the imagination exercise on the following pages. First, please think about a man named Martin and four people who he has invited to a dinner party at his house. Martin's other guests are his wife, coworker, and two of their friends. Please make up names for Martin's four guests, and type their names in the boxes below." [text entry]

"Now, please try to imagine what Martin and each of the other four people look like when they are at the dinner party. Close your eyes and try to visualize what their faces look like, what clothes they are wearing, and what they are feeling. When you are done imagining, please briefly describe what each person looks like or what they are wearing (1 sentence per person).” [text entry]

“Next, imagine the part of Martin’s house where the party guests are seated for dinner. Close your eyes and try to visualize what the scene looks like, where each of the people would be sitting, and what they are eating for dinner. When you are done imagining, please briefly describe what the room looks like and what the people are eating for dinner. (2-3 sentences)” [text entry]

“Next, choose one of the four party guests (other than Martin). Type below to indicate which person you chose:” [text entry] “Imagine that the guest you chose begins coughing during dinner. They say that it may just be allergies. Close your eyes again and imagine what this scene would look like and how the other guests might react. Imagine how they would feel. Please describe how the party guests would feel or what they would do in the box below. (1-2 sentences)” [text entry]

“Now, imagine that three days later, the guest tells Martin that they have tested positive for COVID-19 and are going to the hospital because they feel very sick. Imagine that Martin has to contact each of the other guests and tell them that they may have been infected at his home. Think about what it would be like for Martin to talk to each of the guests, what he would say to them, and the emotions that he would feel. Please describe how Martin would feel in the box below. (1-2 sentences)” [text entry]

“Imagine that Martin also becomes sick with COVID-19 after the dinner party. Martin has a fever, feels dizzy, and has a cough that makes it hard to breathe. Close your eyes and try to imagine Martin experiencing these symptoms. Please describe how Martin would feel in the box below. (1-2 sentences)” [text entry]

Unrelated Simulation. “In the next part of the study, you will imagine an event. We will guide you through the imagination exercise on the following pages. First, please imagine a rabbit named Martin, who lives together with four other rabbits. Please make up names for the four other rabbits who live with Martin, and type their names in the box below.” [text entry]

“Now, please try to imagine what Martin and the other four rabbits look like. Close your eyes and try to visualize what their bodies look like, what color fur they have, and what they are doing. When you are done imagining, please briefly describe what each rabbit looks like (1 sentence per rabbit).” [text entry]

“Next, imagine that Martin finds a vegetable garden in a backyard, and brings his friends there to find food. Close your eyes and try to visualize what the scene looks like, where each of the rabbits is sitting, and what vegetables are in the garden. When you are done imagining, please briefly describe what the garden looks like and what vegetables the rabbits are eating. (2-3 sentences)” [text entry]

“Next, choose one of the rabbits (other than Martin). Type below to indicate which rabbit you chose.” [text entry] “Imagine that the rabbit you chose discovers that the vegetables are rotten, and warns the other rabbits that the vegetables they have been eating might not be safe. Imagine what this scene would look like and how the other rabbits might react. Imagine how they would feel. Please describe how the rabbits would feel or what they would do in the box below. (1-2 sentences)" [text entry]

"Now, imagine that three days later, the rabbit you chose is feeling very sick after eating the rotten vegetables. Imagine that Martin has to tell the other rabbits that their friend is sick because the garden he found was full of bad vegetables. Think about what it would be like for the rabbits and what they would feel. Please describe how Martin would feel in the box below. (1-2 sentences)" [text entry]

"Imagine that Martin also becomes sick after eating the bad vegetables. Martin cannot eat and feels very weak. Close your eyes and try to imagine Martin experiencing these symptoms. Please describe how Martin would feel in the box below. (1-2 sentences)" [text entry]