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How People Use Information About Changes in Infections and Disease Prevalence

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Objective: To determine the influence of two representative metrics of epidemiological risk, changes in new infections, and disease prevalence, on people's risk judgments and disease-prevention behaviors. ***Method:*** Four experiments were conducted from August 2020 to May 2021. In Experiments 1 and 2, participants were exposed to information about different directions of change (upward and downward) and varying levels of prevalence of an infectious disease. In Experiments 3 and 4, participants were exposed to information about only one direction of change (upward or downward) and varying levels of prevalence. Participants reported risk judgments and intentions to engage in disease-prevention behaviors for each disease situation presented to them. ***Results:*** When both the direction of change and levels of prevalence varied, risk judgments and intentions were more influenced by change (vs. prevalence) information. Participants' reliance on prevalence information to guide risk judgments increased when they were presented with only an upward or downward change, particularly for situations with worsening infections. In all cases, the effects of epidemiological information on behavioral intentions were mediated by its effects on risk judgments. ***Conclusions:*** Information about changes in infections consistently influences people's risk judgments and drive subsequent behavioral response. The impact of prevalence information, however, is limited to situations in which changes in infections are stable, such that it affects risk judgments and behavior decisions only when changes in infections demonstrate a constant upward or downward direction. The results point to the need for public health interventions to increase the impact of prevalence information.

Keywords: health statistics, risk judgments, health behaviors, infectious disease prevention, communication

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Since the onset of the COVID-19 pandemic, health statistics has played a predominant role in communicating the risk of the novel coronavirus to the general public. Public health communications in the United States (e.g., CDC COVID Data Tracker, n.d.) and elsewhere (e.g., COVID-19 | European Centre for Disease Prevention and Control, n.d.; Korea Disease Control and Prevention Agency, n.d.) have delivered daily COVID-19 health statistics over the course of the pandemic. During this time, the media and private institutions have also communicated similar information, often through graphs depicting the progress of the coronavirus disease in the United States and the world. For example, *The New York Times* has closely tracked the coronavirus by publishing daily charts of new reported cases and changes in new cases, as well as total cases, tests, and vaccinations for every county and state in the United States and every country in the world (Coronavirus World Map, n.d.). Likewise, the Johns Hopkins University Center for Systems Science and Engineering regularly presented interactive visualizations of case counts and other metrics of the disease at the national, state, and county levels (COVID-19 Map—Johns Hopkins Coronavirus Resource Center, n.d.). The CDC has also established its own Center for Forecasting and Outbreak Analytics (CFA) to improve the national ability to respond to future disease threats through data analytics, modeling, visualizations, and communications (Center for Forecasting and Outbreak Analytics, n.d.).

Health statistics are presented to help the public grasp the pandemic's growth and to guide responses to rapidly changing threats. Surprisingly, however, how people respond to this information is not well understood. A number of important studies have examined how people respond to risk information presented in different formats (see Ancker et al., 2006; Büchter et al., 2014; Keller & Lehmann, 2008 for examples of meta-analyses), including those that vary in

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their graphical features (e.g., Fagerlin et al., 2017) and statistical versus narrative information (e.g., Bakker et al., 2019). Likewise, past research has examined how people understand the growth of infectious diseases (e.g., Lammers et al., 2020) and cumulative curves (e.g., Lalwani et al., 2020). However, no studies have yet investigated how people respond to information about change and number of infections, which are the most frequently provided public health information, as shown by public health communications in the area of COVID-19, and, more recently, Monkeypox Virus (MPV).

When people are exposed to epidemiological data such as changes in new cases and the number of total cases, do they use one type of information to judge risk more than the other? Or do they rely on both changes in cases and total cases? All else equal, increases in new cases communicate impending worsening and potentially numerous undiagnosed cases, whereas the absolute number of total cases signals the probability of infection quite directly. An empirical demonstration of the impact of change versus absolute data in this domain is thus necessary and may guide future communications about infections by, for example, deciding whether and when presenting a change in cases versus a number of cases might be most valuable.

Given this current gap in knowledge, this research investigated people's risk judgments and behavioral intentions in response to changes in infections, which convey whether new infections are increasing or decreasing during a specified time interval, and total cases or rates of infections at a specific time point or period formally known as *prevalence*. The selection of risk judgments and behavioral intentions as the outcomes of the investigation was based on the theoretical assumption that, given knowledge of efficacious behavioral measures, risk judgments can influence the disposition to respond to reduce the risk (Rogers & Prentice-Dunn, 1997; Rosenstock, 2000). Furthermore, we relied on a large literature on the impact of comparative and absolute risk judgments (P. R. Harris & Smith, 2005; W. M. Klein, 1997; W. M. P. Klein, 2010; Zajac et al., 2006) to make predictions about when the information would be more diagnostic as a basis for judgment (Albarracín, 2002; J. Wyer, 2003) and thus subsequently affect behavioral decisions.

Communicating Different Metrics of Epidemiological Risk

Information about changes in infections communicates whether new infections are increasing or decreasing during a time interval and serves as an important marker of fluctuations in disease risk during that time. Specifically, outbursts of new cases occurring at a particular time period typically signal the need for individuals and public health officials to implement appropriate preventive behaviors until the disease is controlled and new cases decline. During the course of the COVID-19 pandemic, the extent to which new infections demonstrate an upward or downward direction has often been cited to signal changes in disease threat in popular media (e.g., Scipioni, 2022) as well as used to advocate and/or make policy decisions about introducing or lifting restrictions such as travel bans, lockdowns, and curfews (e.g., LaFraniere & Stolberg, 2021; Stevenson & Wang, 2022). Changes in infections are commonly presented in the form of curves, those that depict an upward or downward direction, and have been an indispensable part of public health communications about COVID-19 (e.g., Coronavirus World Map, n.d.; COVID Live Update: 192,203,438 Cases and 4,123,976 Deaths from the Coronavirus, n.d.).

Prevalence is the number or proportion of people in a population who have a particular disease at a time point or period (Last et al., 2000) and thus includes both new and preexisting cases of the disease. In this sense, prevalence reflects the extent to which a particular disease is common in a population and signals the likelihood that one might contract the disease within a geographic area. Hence, disease prevalence has frequently been used to determine the level of community transmission and guide the evaluation of disease threat across regions (e.g., WHO Coronavirus (COVID-19) Dashboard | WHO Coronavirus (COVID-19) Dashboard With Vaccination Data, n.d.). Prevalence also helps to determine progress in accomplishing herd immunity, achieved when a high percentage of community residents become immune to a disease through previously contracting the disease or vaccinating against it (Randolph & Barreiro, 2020).[1]

Changes in infections and prevalence are related but nonetheless distinct. Specifically, if there is an upward change in new infections, this increase also contributes to higher disease prevalence because the total number or rate of cases includes both new and preexisting infections. However, a downward change does not always correspond to lower disease prevalence, as, even in this case, prevalence could still increase with the addition of new infections. In this regard, during an ongoing pandemic, prevalence rarely declines unless more individuals die or recover than new cases are added (Hunt & Kaloshin, 2010). Consequently, information about prevalence tends to be more constant and stable with little alterations in its pattern than information about changes in infections, which fluctuate frequently as an infection and its variants spread in the community.

When Changes in New Cases and Numbers of Cases are Likely to Matter

Information about risks as well as other events is diagnostic or relevant when it provides a useful signal to make a judgment (Albarracín, 2002; J. Wyer, 2003). Whereas some events, like the presence of a fire, may be quite diagnostic without much reference to a context or standard, epidemiological information is likely to be less informative for the general population (for a literature review about poor public understanding of health statistics, see Peters et al., 2007) unless a standard is provided. Therefore, changes in the number of cases, which provide a reference to make a comparative risk judgment, should be most diagnostic by default. At the same time, prevalence may become diagnostic under some conditions, such as when the direction of the changes becomes steady and thus ceases to provide a diagnostic basis for judgment.

Ample evidence about comparative risk judgments (Edmonds et al., 2021) supports the theoretical premise that epidemiological information that communicates changes should be more impactful than other information. Comparative risk represents contrasts or changes of status relative to important standards, which are particularly diagnostic because objective levels of risk are either ambiguous or vague (W. M. P. Klein, 2010; W. M. P. Klein & Rice, 2020). For example, when evaluating the risk of contracting a fictitious pancreatic disease, people who were told that their absolute risk was 30%, yet above average, were more concerned about the disease than were

[1] We note, however, there have been speculations as to whether herd immunity is attainable for COVID-19, due to the challenges associated with new viral variants coupled with substantial resistance to control the virus through vaccination and mask wearing (see Morens et al., 2022).

those who were told that their absolute risk was 60%, yet below average (P. Harris et al., 2002; W. M. Klein, 1997). Likewise, people's beliefs about how much they engage in health-relevant behaviors compared to a standard (e.g., an average person, peers, expert recommendations) have a greater effect on their health concerns than does their actual frequency of engaging in health-relevant behaviors (Miller et al., 2020). An online survey of COVID-19 risk judgments found that the perceived likelihood of developing COVID-19 in comparison to someone else of the same age and sex explained 54% of the variance of people's estimates of contracting the disease (Figueiras et al., 2022). Further, supporting the hypothesis that change information may matter more than prevalence information, perceived increases in personal risk for a disease (e.g., compared with yourself before, how would you rate your current risk of contracting the illness?) have a unique impact on people's risk judgments and willingness to engage in precautionary measures above and beyond their judgments of their objective risk (i.e., how would you rate your current risk of contracting the illness?; Edmonds et al., 2021).

We thus propose that people who receive public health statistics may be more able to use epidemiological information pertaining to changes in new cases than the total number of cases to the extent that these changes clearly communicate whether new cases have increased or decreased than before, and thus necessitates behavioral adjustments. Specifically, as shown in the top panel of Figure 1, exposure to information that varies in the direction of change will make these changes particularly diagnostic, which then should allow individuals to use changes more as a basis for risk judgments and respond accordingly than information about the total number of cases. In contrast, as shown in the bottom panel of Figure 1, exposure to changes in one constant direction (upward or downward) may undermine the diagnosticity of change information which then could increase people's use of other relevant information, such as the total number of cases. As a result, prevalence should be an important basis for judgment in this case. These propositions are summarized in the following hypotheses:

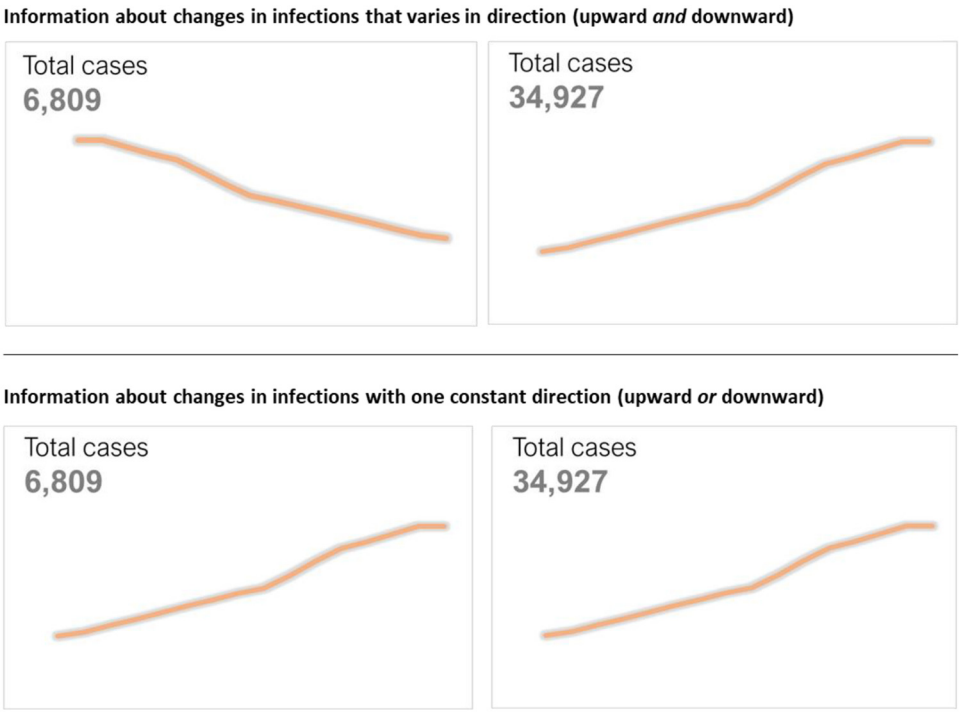
> *H1:* Information about changes in new infections (upward change and downward change) is likely to exert greater influence on people's risk judgments and disease prevention decisions than information about disease prevalence (lower and higher prevalence).

> *H2:* Information about disease prevalence may exert as much or more influence on people's risk judgments and disease-prevention decisions than information about changes in new infections when the direction of change is stable (upward *or* downward change).

The impact of prevalence information on risk judgments in the context of a constant upward or constant downward change is also worth examining because of its affective implications for judgments. Specifically, people may be more sensitive to epidemiological information as a signal of risk when the information has negative (vs. positive) implications, as doing so may help to prevent or control stressors (Baron et al., 1994; Slovic et al., 2013; R. S. Wyer et al., 1999). For example, the more people fear cancer, the more they seek and use relevant health information (Beckjord et al., 2008). Therefore, being solely presented with a constant upward (vs.

Figure 1

Information About Changes in Infections and Prevalence



Note. As shown in the top panel, information about changes in infections is more salient due to varying direction. As shown in the bottom panel, information about changes in infections is less salient due to constant direction. See the online article for the color version of this figure.

downward) change in new infections can heighten people's need to monitor the situation more carefully and therefore increase their use of prevalence information. This hypothesis is formally stated below.

> *H3:* Information about disease prevalence is likely to exert greater influence on people's risk judgments and disease-prevention decisions when new infections demonstrate a constant upward (vs. downward) change.

The Present Research

We conducted four experiments, three of them preregistered, to test our proposed hypotheses. Experiments 1 and 2 tested our first hypothesis, that, when changes abound, information about changes in new infections (upward *and* downward change) is likely to exert greater influence on people's risk judgments and disease-prevention decisions than is information about disease prevalence (lower and higher). Specifically, participants were presented with four graphs that varied in the direction of changes in new cases and levels of prevalence. In Experiment 1, the prevalence information was presented as raw counts (i.e., total number of cases), whereas in Experiment 2, the prevalence information was presented as rates (i.e., number of cases per 1 million people). Participants reported their risk judgments and willingness to engage in disease-prevention behaviors given the situation depicted in each graph they saw. We analyzed the impact of the different information on risk judgments and disease-prevention intentions and the degree to which the effects of the information on behavioral decisions are driven by judgmental processes, as proposed.

Experiments 3 and 4 tested our second hypothesis, that information about disease prevalence is likely to exert as much or more influence on people's risk judgments and disease-prevention efforts than information about changes in new infections when the direction of change is stable (upward *or* downward change). Experiments 3 and 4 also tested our third hypothesis, that information about disease prevalence is likely to exert greater influence on people's risk judgments and disease-prevention efforts when new infections demonstrate a stable upward (vs. downward) change. Participants in these two experiments received five pieces of information that depicted either an upward or downward change of new cases with variations in only the level of prevalence (lowest to highest). As in Experiments 1 and 2, they reported risk judgments and willingness to engage in disease-prevention behaviors given the situation depicted in each graph they saw.

All experiments were approved by the Institutional Review Board of the University of Illinois at Urbana-Champaign (Protocol Number: 20372) and the Institutional Review Board of the University of Pennsylvania (Protocol Number: 849294). All participants of this research provided informed consent to use their data for scientific purposes without their identity being disclosed. All experiments were considered to pose a negligible risk, and therefore were approved as exempt research.

Experiment 1

Method

Participants

We recruited 322 participants in April 2021 through the survey company Qualtrics Panels to complete the study, which was preregistered through aspredicted.org (https://aspredicted.org/blind.php?x=wt7zs9) an online platform for researchers to pre-document their plans to conduct an experiment, including the experiment design, sample size, proposed analyses, and predicted outcomes. The sample size for Experiments 1 and 2 was determined based on an a priori power analysis that estimated 296 minimum participants required to achieve 90% power to detect a small effect (Cohen's $d = 0.20$). In both experiments, we oversampled to ensure adequate power. Eight participants (3%) did not complete all measures and therefore were excluded, resulting in the final sample of 314 participants (female = 165, $M_{age} = 49.20$, $SD_{age} = 19.54$). We note that the results reported in this article do not change as a function of this exclusion. The participant-recruitment frame comprised a national sample of American adults representative of the general population in terms of sex, race/ethnicity, and education level. The detailed demographic composition of Experiment 1 as well as the U.S. Census estimates of demographic composition of the general population are presented in eTable 1 in the online supplemental materials. As indicated in eTable 1 in the online supplemental materials, the sample was comparable to the U.S. Census data except for a slightly higher level of education in our sample. All participants were provided with monetary compensation upon completion, following the payment standards set by Qualtrics Panels.

Procedures

Upon entering the study, participants were informed that they would be presented with information about infectious diseases across several, unnamed regions worldwide. The study employed a 2 (changes in new infections: upward or downward change) × 2 (prevalence: lower or higher) within-subjects design. Participants were presented with visual depictions of four unique combinations of change and prevalence, which are presented in eFigure 1 in the online supplemental materials. Each depiction contained brief information about the disease (the name of the disease was unspecified, and all diseases were described as a respiratory illness that is contagious with slight wording differences) along with a graph showing either an upward or downward change (i.e., changes in new infections) and the total number of cases indicated in the center of the graph (i.e., prevalence). The order in which the depictions were presented to participants was randomized for each participant. We chose to frame the information as pertaining to unnamed regions worldwide rather than regions in the United States, to ensure that we test the effects of our experimental manipulation while avoiding calling attention to infectious diseases situation in participants' residence. However, to also ensure that our manipulations would reflect actual methods of information communication, in all of our experiments, we modeled our visual depictions of changes in infections after the graphs of changes in cases during the last 14-days presented in *The New York Times*' Coronavirus in the US: Latest Map and Case Count (Covid in the U.S.: Latest Map and Case Count, n.d.) as well as case trends presented in *CDC*'s COVID Data Tracker (CDC COVID Data Tracker, n.d.). In addition, as Experiment 1 dealt with respiratory infectious diseases, the levels of prevalence were set by considering the average prevalence of respiratory infectious diseases (e.g., Influenza, Pneumonia) in the United States at the time the experiment was conducted. Specifically, the lower level of prevalence was set below this average and the higher level of prevalence was set above this average. We also pilot tested our

Table 1

Effects of Changes in Infections and Prevalence Information on Risk Judgments, Intentions to Engage in Preventive Behaviors, and Intentions to Vaccinate: Experiment 1

Variables	Changes in infections *M* (*SE*)		
	Upward	Downward	Overall
Risk judgments			
Prevalence *M* (*SE*)			
Higher	3.32 (0.07)	2.96 (0.06)	3.14 (0.05)
Lower	3.14 (0.07)	2.75 (0.07)	2.95 (0.05)
Overall	3.23 (0.05)	2.86 (0.05)	
Main effect of changes in infections	$F(1, 313) = 45.11$, $p < .0001$, $\eta_p^2 = 0.13$		
Main effect of prevalence	$F(1, 313) = 19.57$, $p < .0001$, $\eta_p^2 = 0.06$		
Interaction	$F(1, 313) = 0.14$, $p = .71$, $\eta_p^2 = 0.000$		
Comparison of main effects	$t(313) = 2.68$, $p = .003$, $d = 0.15$		
Changes in infections	$M_{DIFF} = 0.38$, $SE_{DIFF} = 0.06$		
Prevalence	$M_{DIFF} = 0.20$, $SE_{DIFF} = 0.04$		
Intentions to engage in prevention behaviors			
Prevalence *M* (*SE*)			
Higher	3.99 (0.07)	3.79 (0.07)	3.89 (0.05)
Lower	3.90 (0.07)	3.65 (0.07)	3.77 (0.05)
Overall	3.94 (0.05)	3.72 (0.05)	
Main effect of changes in infections	$F(1, 313) = 28.7$, $p < .0001$, $\eta_p^2 = 0.08$		
Main effect of prevalence	$F(1, 313) = 10.79$, $p = .001$, $\eta_p^2 = 0.03$		
Interaction	$F(1, 313) = 0.53$, $p = .47$, $\eta_p^2 = 0.002$		
Comparison of main effects	$t(313) = 2.11$, $p = .02$, $d = 0.12$		
Changes in infections	$M_{DIFF} = 0.22$, $SE_{DIFF} = 0.04$		
Prevalence	$M_{DIFF} = 0.12$, $SE_{DIFF} = 0.04$		
Intentions to vaccinate			
Prevalence *M* (*SE*)			
Higher	3.75 (0.08)	3.48 (0.08)	3.61 (0.06)
Lower	3.56 (0.08)	3.41 (0.08)	3.49 (0.06)
Overall	3.66 (0.05)	3.44 (0.06)	
Main effect of changes in infections	$F(1, 313) = 21.33$, $p < .0001$, $\eta_p^2 = 0.06$		
Main effect of prevalence	$F(1, 313) = 11.63$, $p = .001$, $\eta_p^2 = 0.04$		
Interaction	$F(1, 313) = 2.78$, $p = .10$, $\eta_p^2 = 0.01$		
Comparison of main effects	$t(313) = 1.66$, $p = .05$, $d = 0.09$		
Changes in infections	$M_{DIFF} = 0.21$, $SE_{DIFF} = 0.05$		
Prevalence	$M_{DIFF} = 0.13$, $SE_{DIFF} = 0.04$		

Note. All ratings ranged from 1 (*not at all*) to 5 (*a great deal*). Participants were presented with different directions of change and varying levels of prevalence. As shown in the comparison of main effects, the mean difference across the directions of change is significantly greater than the mean difference across the levels of prevalence for all dependent measures. η_p^2 indicates partial eta-squared and *d* indicates Cohen's *d*.

experimental materials on a separate sample of participants recruited from Mechanical Turk ($n = 108$) to assess whether the materials made them think of a specific region (i.e., when you were evaluating the information about infectious diseases, to what extent did the information make you think of a specific region?), whether they believed that information was up to date (i.e., to what extent did you think that the information was up to date?), and whether they believed the information was real (i.e., to what extent did you think that the information was real?). Most participants from this sample reported that the information did not make them think of a specific region (62.1% vs. 37.9%; $\chi^2 = 2.26$, $p = .02$), believed that the information was up to date (67.4% vs. 32.6%; $\chi^2 = 3.28$, $p = .001$), and believed that the information was real (69.5% vs. 30.5%; $\chi^2 = 3.69$, $p < .0001$).

For each visual depiction, participants rated the perceived risk for infection (i.e., "If you lived in this region, how likely is it that you will get infected with the disease?" 1 = *not at all*, 5 = *a great deal*). Participants also rated their willingness to engage in disease-prevention behaviors, including their willingness to wear a mask (i.e., "If you lived in this region, how willing would you be to wear face masks in public?" 1 = *not at all*, 5 = *a great deal*) and willingness to engage in physical distancing (i.e., "If you lived in this region, how willing would you be to maintain physical distance from other people?" 1 = *not at all*, 5 = *a great deal*). There was a high internal consistency between the two items overall ($\alpha = 0.94$) and within each condition, so we created a single index of disease prevention intention by averaging the items within each condition. The Supplemental materials provide full reports of Cronbach's α for each condition. Participants also rated their willingness to receive the vaccine (i.e., "If you lived in this region, how willing would you be to get the vaccine to prevent getting infected?"; 1 = *not at all*, 5 = *a great deal*). Our items were adapted from previous, validated measures of risk judgments and prevention behaviors for infectious diseases (Albarracin et al., 2021; Jung & Albarracín, 2021). We further note that there was a high internal consistency between the three items that measured disease-prevention behaviors and willingness to vaccinate overall ($\alpha = 0.95$) and within each condition as reported in the Supplemental materials, although we report the results on vaccination separately given the current public interest in COVID-19 vaccination.

Results and Discussion

We analyzed the impact of changes in new infections and prevalence on participants' risk judgments, willingness to engage in preventive behaviors, and willingness to vaccinate using within-subjects analyses of variance. We also examined whether the impact of change information is greater than the impact of prevalence information (*H1*). Specifically, we first obtained the mean difference between the two directions of change and between the two levels of prevalence by subtracting ratings for downward change from upward change and subtracting ratings for lower prevalence from higher prevalence and then statistically compared the mean difference of directions of change with the mean difference of levels of prevalence using pairwise *t*-test. Table 1 presents all descriptive statistics, *F*-ratios for main and interaction effects, and *t*-test for comparisons of main effects. As shown by the main effects in Table 1, both the upward (vs. downward) change and higher (vs. lower) prevalence yielded stronger risk judgments, intentions to carry out preventive behaviors, and intentions to vaccinate. Significant effects of changes in new infections and prevalence and no significant interactions also suggested that their contributions in this case were additive. Importantly, as predicted and shown by the main effect comparisons in Table 1, the impact of changes in new infections was stronger than the impact of prevalence.

We additionally examined whether information about changes in new infections and prevalence impacted intentions to engage in disease prevention measures and vaccinate through changes in risk judgments, as theorized. To conduct the mediation analysis, we used participants' ratings on two directions of change (upward and downward) and two levels of prevalence (higher and lower). The results from a bias-corrected mediation analysis with bootstrapping showed that an upward (vs. downward) change in new infections heightened risk judgments and then increased disease-prevention intentions (indirect effect: 0.11, 95% CI [0.07, 0.18]) and intentions to vaccinate (indirect effect: 0.08, [0.03, 0.14]). Higher (vs. lower) prevalence also heightened risk judgments and then increased participants' intentions to engage in disease prevention measures (indirect effect: 0.03, [0.006, 0.08]) and intentions to vaccinate (indirect effect: 0.04, [0.02, 0.09]). Also, as shown by the indirect effect sizes, the mediating impact of changes in new infections via risk judgments was stronger than the same effect for prevalence ($z = 2.38$, $p = .02$ for disease prevention intentions, and $z = 2.33$, $p = .02$ for vaccination intentions).

The following experiment aimed to replicate the effects of Experiment 1 while introducing a modification to address one limitation. Specifically, participants in Experiment 1 might have relied more on the information about changes in new infections simply because the prevalence information was presented as the absolute number of total cases in the regions. Without knowing the size of the population in the regions, the number of total cases may not be useful to diagnose how common the disease is in a region. Therefore, Experiment 2 presented prevalence as rates (e.g., number of cases per 1 million people in a region) rather than raw numbers of total cases.

Experiment 2

Method

Participants

We recruited 325 participants in April 2021 to complete the study, which was preregistered through aspredicted.org (https://aspredicted.org/blind.php?x=2s2qu3). Seven participants (2%) did not complete all measures and therefore were excluded, resulting in the final sample of 318 participants (162 females, $M_{age} = 50.18$, $SD_{age} = 20.11$). We note that the results reported in this article do not change as a function of this exclusion. We recruited a national sample of American adults representative in terms of sex, race/ethnicity, and education level provided by the survey company Qualtrics Panels. The detailed demographic composition of Experiment 2 and the U.S. Census estimates of demographic composition of the general population presented in eTable 1 in the online supplemental materials, suggest that the sample was again comparable to the U.S. Census data except for a slightly higher level of education in our sample. All participants were provided with monetary compensation upon completion, following the payment standards set by Qualtrics Panels.

Procedures

The Experiment 2 procedures were identical to Experiment 1 with one exception. Unlike Experiment 1, which presented higher and lower total numbers of cases to manipulate prevalence, Experiment 2 presented higher and lower rates of cases per one million people. The experiment employed a 2 (changes in new infections: upward or downward change) × 2 (prevalence: low or high) within-subjects design, and participants were presented with visual depictions of four unique combinations of change and prevalence. As in Experiment 1, the levels of prevalence were set by considering the average prevalence rates of respiratory infectious diseases (e.g., Influenza, Pneumonia) in the United States at the time the experiment was conducted. That is, the lower level of prevalence was set below this average and the higher level of prevalence was set above this average.

For each visual depiction, participants rated the perceived risk for infection and willingness to engage in preventive behaviors, including mask wearing and physical distancing, using the same items as in Experiment 1. As in Experiment 1, there was a high internal consistency between the two items measuring intentions to engage in prevention behaviors overall ($\alpha = 0.94$) and within each condition (see the online supplemental materials for full reports of Cronbach's α for each condition), so we created a single index of disease prevention intention by averaging these items in each case. Lastly, participants rated their willingness to vaccinate against the disease using the same item as in Experiment 1.

Results and Discussion

As done in Experiment 1, we used within-subjects analyses of variance to gauge the impact of changes in new infections and prevalence on participants' risk judgments, willingness to engage in preventive behaviors, and willingness to vaccinate. Again, we obtained the mean difference between the two directions of change and between the two levels of prevalence and statistically compared these two mean differences using pairwise *t*-test. Table 2 presents all descriptive statistics, *F*-ratios for main and interaction effects, and *t*-test for our comparisons of main effects. As shown by the main effects in Table 2, an upward (vs. downward) change in new infections consistently yielded higher risk judgments and stronger intentions to engage in preventive behaviors and vaccinate. This was not the case for higher (vs. lower) prevalence, however, which had no significant influence

Table 2
Effects of Changes in Infections and Prevalence Information on Risk Judgments, Intentions to Engage in Preventive Behaviors, and Intentions to Vaccinate: Experiment 2

Variables	Changes in infections *M* (*SE*)		
	Upward	Downward	Overall
Risk judgments			
Prevalence *M* (*SE*)			
Higher	3.30 (0.06)	2.87 (0.06)	3.08 (0.04)
Lower	3.28 (0.06)	2.76 (0.06)	3.02 (0.05)
Overall	3.29 (0.05)	2.81 (0.04)	
Main effect of changes in infections	$F(1, 317) = 87.49$, $p < .0001$, $\eta_p^2 = 0.22$		
Main effect of prevalence	$F(1, 317) = 2.54$, $p = .11$, $\eta_p^2 = 0.01$		
Interaction	$F(1, 317) = 1.29$, $p = .26$, $\eta_p^2 = 0.00$		
Comparison of main effects	$t(317) = 6.39$, $p < .0001$, $d = 0.36$		
Changes in infections	$M_{DIFF} = 0.47$, $SE_{DIFF} = 0.05$		
Prevalence	$M_{DIFF} = 0.07$, $SE_{DIFF} = 0.04$		
Intentions to engage in prevention behaviors			
Prevalence *M* (*SE*)			
Higher	4.00 (0.06)	3.72 (0.06)	3.86 (0.05)
Lower	3.95 (0.06)	3.65 (0.06)	3.80 (0.05)
Overall	3.98 (0.04)	3.68 (0.04)	
Main effect of changes in infections	$F(1, 317) = 70.63$, $p < .0001$, $\eta_p^2 = 0.18$		
Main effect of prevalence	$F(1, 317) = 3.86$, $p = .05$, $\eta_p^2 = 0.01$		
Interaction	$F(1, 317) = 0.08$, $p = .78$, $\eta_p^2 = 0.00$		
Comparison of main effects	$t(317) = 4.92$, $p < .0001$, $d = 0.28$		
Changes in infections	$M_{DIFF} = 0.30$, $SE_{DIFF} = 0.04$		
Prevalence	$M_{DIFF} = 0.06$, $SE_{DIFF} = 0.03$		
Intentions to vaccinate			
Prevalence *M* (*SE*)			
Higher	3.73 (0.08)	3.53 (0.08)	3.63 (0.05)
Lower	3.69 (0.08)	3.44 (0.08)	3.57 (0.05)
Overall	3.71 (0.05)	3.49 (0.05)	
Main effect of changes in infections	$F(1, 317) = 30.21$, $p < .0001$, $\eta_p^2 = 0.09$		
Main effect of prevalence	$F(1, 317) = 2.53$, $p = .11$, $\eta_p^2 = 0.01$		
Interaction	$F(1, 317) = 0.41$, $p = .52$, $\eta_p^2 = 0.00$		
Comparison of main effects	$t(317) = 2.80$, $p = .003$, $d = 0.16$		
Changes in infections	$M_{DIFF} = 0.22$, $SE_{DIFF} = 0.04$		
Prevalence	$M_{DIFF} = 0.06$, $SE_{DIFF} = 0.04$		

Note. All ratings ranged from 1 (*not at all*) to 5 (*a great deal*). Participants were presented with different directions of change and varying levels of prevalence. As shown in the comparison of main effects, the mean difference across the directions of change is significantly greater than the mean difference across the levels of prevalence for all dependent measures. η_p^2 indicates partial eta-squared and *d* indicates Cohen's *d*.

on participants' risk judgments nor intentions to vaccinate although it produced stronger intentions to engage in other preventive behaviors. Accordingly, as shown in Table 2, the impact of changes in new infections was stronger than the impact of prevalence.

We next examined whether information about changes in new infections and prevalence impacted intentions to engage in prevention measures and vaccinate through changes in risk judgments using the same methods as in Experiment 1. Results showed that an upward (vs. downward) change in new infections heightened risk judgments which then increased intentions to engage in prevention measures (indirect effect: 0.13, 95% CI [0.08, 0.21]) and vaccinate (indirect effect: 0.12, [0.06, 0.21]). However, this indirect effect was not observed for higher (vs. lower) prevalence (indirect effect for prevention measures: 0.01, [−0.001, 0.04]; indirect effect for vaccination: 0.02, [0.000, 0.04]). Evidently, as shown by the indirect effect sizes, the mediating impact of changes in new infections via risk judgments was stronger than the same effect for prevalence ($z = 4.42$, $p < .0001$ for disease prevention intentions, and $z = 4.33$, $p < .0001$ for vaccination intentions).

Experiments 1 and 2 evaluated people's use of information about changes in new infections and prevalence when judging the disease risk and responding accordingly. Across the two experiments, we demonstrated that people use information about changes in new infections more than prevalence even though prevalence information is key to determining the level of disease threat in a region and therefore making sound decisions about the chance of contracting an airborne infectious disease.

In Experiments 3 and 4, we examined its influence when the direction of change in new infections is held constant, a presentation that might increase the impact of prevalence for the benefit of public health (*H2*). Consequently, these experiments examined how people respond to the levels of prevalence when presented with either an upward or downward change in new cases. These experiments also examined whether people's reliance on prevalence information depends on the direction of change, such that the influence of prevalence information on people's risk judgments and disease-prevention efforts is greater when new infections stably increase (vs. decrease; *H3*). In Experiment 3, prevalence information was

presented as rates, in the same way as in Experiment 2. Experiment 4 was a preregistered replication of Experiment 3, except that the prevalence information was presented as raw numbers rather than rates. Lastly, in these experiments, we explored the influence of curve shape (i.e., monotonic or non-monotonic) in addition to the direction of change in new infections (i.e., upward or downward), a decision that was practically rather than theoretically guided to reflect change curves that exist in real risk communication that are often non-linear. Thus, we did not have a directional hypothesis regarding the influence of the curve shape.

Experiment 3

Method

Participants

We recruited 572 participants in May 2021 from Amazon's Mechanical Turk to complete the study (female = 321, M_{age} = 34.98, SD_{age} = 13.27). There were no exclusions as all participants completed all measures. The detailed demographic composition of Experiment 3 is presented in eTable 1 in the online supplemental materials. The sample size for Experiments 3 and 4 was determined based on an a priori power analysis that estimated 566 minimum participants required to achieve 90% power to detect a small effect (Cohen's $d = 0.20$).

Procedures

Experiment 3 employed a 2 (changes in new infections: upward or downward change) × 2 (curve shape: monotonic or non-monotonic) × 5 (prevalence: five incremental levels of prevalence from lowest to highest presented as number of cases per 1 million people) between-within subjects design. Changes in new infections and curve shape were manipulated as between-subjects factors, and prevalence was manipulated as a within-subject factor. Participants were randomly assigned to one of four experimental conditions (i.e., monotonic upward change, non-monotonic upward change, monotonic downward change, and non-monotonic downward change). Participants saw visual depictions of change and curve shape corresponding to their assigned experimental condition, and each participant saw five randomly presented visual depictions of the same change and curve shape with varying levels of prevalence. Unlike in the previous experiments, the visual depictions were described as pertaining to the coronavirus disease across different regions, and the levels of prevalence were set by first ordering the COVID-19 prevalence rates of all states in the United States from the lowest to highest at the time the experiment was conducted, dividing the states into five separate categories that vary in levels of prevalence, and then randomly selecting one prevalence rate from each category. This process led us to represent five incremental levels of COVID-19 prevalence rates as our experimental stimuli. eFigure 2 in the online supplemental materials presents examples of depictions presented to participants.

For each visual depiction, participants rated the perceived risk for infection as in Experiments 1 and 2. Participants also rated their willingness to engage in preventive behaviors, including their willingness to wear a mask and engage in physical distancing as in the previous experiments. We also measured participants' willingness to avoid large social gatherings (i.e., "If you lived in this region, how willing would you be to avoid large social gatherings?" 1 = *not at all*, 5 = *a great deal*). Because there was a high internal consistency between the three items overall ($\alpha = 0.97$) and for each condition (see the Supplemental materials for full reports of Cronbach's α for each condition), we created a summary index of disease-prevention intentions by averaging the three items for each condition.

Results and Discussion

We used between-within analyses of variance to assess the impact of changes in new infections, curve shape, and prevalence on participants' risk judgments and willingness to engage in disease-prevention behaviors. We also obtained the mean difference between the directions of trend and levels of prevalence. To accomplish this, we first obtained the difference of the mean of the downward change from the upward one. We also obtained a comparable difference for the prevalence levels, although because there were five such levels, we subtracted the lowest level from the highest level of prevalence. We then statistically compared the mean difference for directions of change with the mean difference for levels of prevalence using Welch's *t*-test. This analysis allowed us to examine whether prevalence had as much or more influence than changes in new infections when participants only see one direction of change. We note that an alternative way to compare the mean difference for directions of change with those of prevalence is to obtain an average mean difference across all levels of prevalence (instead of obtaining only the mean difference between the lowest and highest levels of prevalence). Results from this alternative analysis are reported in the Supplemental materials.

Table 3 presents all descriptive statistics, *F*-ratios for main and interaction effects, and *t*-test for our main effect comparisons. We found that being presented with the upward (vs. downward) change and higher (vs. lower) levels of prevalence led to stronger risk judgments and disease prevention intentions. In contrast to the previous experiments, however, the impact of prevalence was stronger than the impact of changes in new infections (see *t*-test in Table 3), and these factors interacted significantly with each other. The decomposition of the interaction for risk judgments showed that prevalence affected participants' risk judgments more when there was an upward change in new cases, $F(4, 1168) = 72.19$, $p < .0001$, $\eta_p^2 = 0.20$, than when there was a downward change in new cases, $F(4, 1112) = 38.58$, $p < .0001$, $\eta_p^2 = 0.12$. The same decomposition for intentions also indicated that prevalence had a stronger impact when there was an upward change in new cases, $F(4, 1168) = 62.33$, $p < .0001$, $\eta_p^2 = 0.18$, than when there was a downward change in new cases, $F(4, 1112) = 29.49$, $p < .0001$, $\eta_p^2 = 0.10$. A graphic depiction of these patterns appears in Figure 2. Descriptive statistics for these interactions are reported in the online supplemental materials.

We further explored whether information about changes in new infections and prevalence impacted disease prevention intentions through changes in risk judgments using the same method as in the previous experiments. Results showed that an upward (vs. downward) change in new infections heightened risk judgments and in turn increased intentions (indirect effect: 0.05, 95% CI [0.01, 0.10]). Likewise, higher (vs. lower) prevalence heightened risk judgments and then increased intentions (indirect effect: 0.11, [0.06, 0.16]). In addition, the mediating role of risk judgments on the effect of prevalence information on prevention intentions was larger when there was an upward change in new cases (indirect effect: 0.46,

Table 3

Effects of Changes in Infections and Prevalence Information on Risk Judgments and Intentions to Engage in Preventive Behaviors: Experiment 3

Variables	Changes in infections *M* (*SE*)				
	Upward		Downward		
	Curve shape		Curve shape		Overall: prevalence
	Monotonic	Non-monotonic	Monotonic	Non-monotonic	
Risk judgments					
Prevalence *M* (*SE*)					
5 (Highest)	3.39 (0.08)	3.32 (0.08)	3.16 (0.09)	3.09 (0.09)	3.24 (0.04)
4	3.21 (0.09)	3.06 (0.08)	2.84 (0.08)	2.76 (0.08)	2.98 (0.04)
3	2.93 (0.08)	2.91 (0.07)	2.83 (0.08)	2.72 (0.08)	2.85 (0.04)
2	2.70 (0.08)	2.76 (0.07)	2.72 (0.09)	2.68 (0.09)	2.72 (0.04)
1 (lowest)	2.53 (0.08)	2.64 (0.08)	2.57 (0.09)	2.46 (0.08)	2.55 (0.04)
Overall: Curve shape	2.95 (0.04)	2.94 (0.04)	2.82 (0.04)	2.74 (0.04)	
Overall: Changes in infections	2.95 (0.03)		2.78 (0.03)		
Main effect of changes in infections	$F(1, 568) = 5.75$, $p = .02$, $\eta_p^2 = 0.01$				
Main effect of curve shape	$F(1, 568) = 0.45$, $p = .50$, $\eta_p^2 = 0.00$				
Main effect of prevalence	$F(4, 2272) = 106.53$, $p < .0001$, $\eta_p^2 = 0.16$				
Changes in infections × Curve shape interaction	$F(1, 568) = 0.26$, $p = .61$, $\eta_p^2 = 0.00$				
Curve shape × Prevalence interaction	$F(4, 2272) = 1.09$, $p = .36$, $\eta_p^2 = 0.00$				
Changes in infections × Prevalence interaction	$F(4, 2272) = 6.01$, $p < .0001$, $\eta_p^2 = 0.01$				
3-way interaction	$F(4, 2272) = 1.26$, $p = .29$, $\eta_p^2 = 0.00$				
Comparison of main effects of changes in infections and prevalence	$t(907.97) = 6.69$, $p < .0001$, $d = 0.40$				
Changes in infections	$M_{DIFF} = 0.16$, $SE_{DIFF} = 0.07$				
Prevalence	$M_{DIFF} = 0.69$, $SE_{DIFF} = 0.04$				
Intentions to engage in prevention behaviors					
Prevalence *M* (*SE*)					
5 (Highest)	4.37 (0.07)	4.41 (0.07)	4.17 (0.07)	4.04 (0.09)	4.25 (0.04)
4	4.23 (0.08)	4.29 (0.07)	4.00 (0.07)	3.94 (0.09)	4.12 (0.04)
3	4.17 (0.08)	4.12 (0.07)	4.01 (0.07)	3.89 (0.09)	4.05 (0.04)
2	3.98 (0.08)	4.12 (0.08)	3.86 (0.08)	3.87 (0.09)	3.96 (0.04)
1 (Lowest)	3.88 (0.09)	3.97 (0.08)	3.74 (0.08)	3.79 (0.09)	3.85 (0.04)
Overall: Curve shape	4.13 (0.04)	4.18 (0.03)	3.96 (0.03)	3.91 (0.04)	
Overall: Changes in infections	4.15 (0.02)		3.93 (0.03)		
Main effect of changes in infections	$F(1, 568) = 9.00$, $p = .003$, $\eta_p^2 = 0.02$				
Main effect of curve shape	$F(1, 568) = 0.003$, $p = .96$, $\eta_p^2 = 0.00$				
Main effect of prevalence	$F(4, 2272) = 88.64$, $p < .0001$, $\eta_p^2 = 0.13$				
Changes in infections × Curve shape interaction	$F(1, 568) = 0.52$, $p = .47$, $\eta_p^2 = 0.00$				
Curve shape × Prevalence interaction	$F(4, 2272) = 4.40$, $p = .002$, $\eta_p^2 = 0.01$				
Changes in infections × Prevalence interaction	$F(4, 2272) = 3.17$, $p = .01$, $\eta_p^2 = 0.01$				
3-Way interaction	$F(4, 2272) = 0.75$, $p = .56$, $\eta_p^2 = 0.00$				
Comparison of main effects of changes in infections and prevalence	$t(773.91) = 2.49$, $p = .01$, $d = 0.15$				
Changes in infections	$M_{DIFF} = 0.22$, $SE_{DIFF} = 0.07$				
Prevalence	$M_{DIFF} = 0.41$, $SE_{DIFF} = 0.03$				

Note. All ratings ranged from 1 (*not at all*) to 5 (*a great deal*). As shown in the comparison of main effects of changes in infections and prevalence, the mean difference across the directions of change is significantly smaller than the mean difference across the comparable levels of prevalence for all dependent measures. η_p^2 indicates partial eta-squaredand *d* indicates Cohen's *d*. Comparison of main effects used Welch's *t*-test which assumes unequal variances between groups of comparison.

[0.39, 0.54]) than when there was a downward change in new cases (indirect effect: 0.35, [0.27, 0.42]).

Finally, we found an unanticipated interaction between curve shape and prevalence. This interaction was due to prevalence affecting participants' preventive intentions more when the curve shape was monotonic, $F(4, 1168) = 62.31$, $p < .0001$, $\eta_p^2 = 0.18$, than when it was non-monotonic, $F(4, 1112) = 31.25$, $p < .0001$, $\eta_p^2 = 0.10$. We did not conduct a mediational analysis for this effect because we found no significant interaction between curve shape and prevalence on participant's risk judgments. Descriptive statistics for this interaction are reported in the online supplemental materials. No other significant main or interaction effects were observed (see Table 3).

Experiment 4

Experiment 4 was a preregistered replication of Experiment 3 with prevalence information presented as raw number of total cases rather than rates.

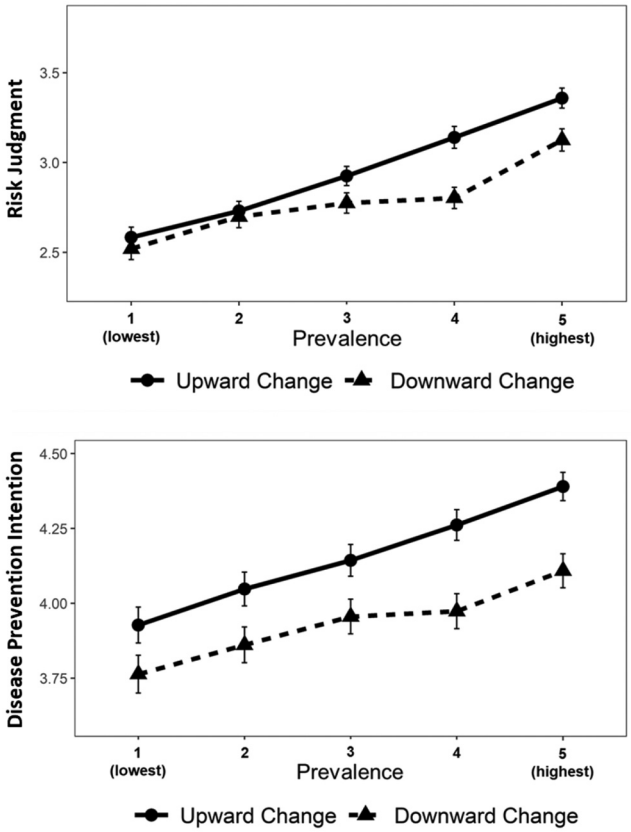
Method

Participants

We recruited 824 participants in August 2020 to complete the study, which was preregistered through aspredicted.org (https://aspredicted.org/blind.php?x=rn8a4u). The sample consisted of

Figure 2

Risk Judgments and Willingness to Engage in Preventive Behaviors



Note. The figure depicts the effects of information about changes in infections and prevalence on risk judgments (top panel) and willingness to engage in preventive behaviors (bottom panel) in Experiment 3. Participants were presented with only one direction of change with varying levels of prevalence information and all ratings ranged from 1 (*not at all*) to 5 (*a great deal*). The above pattern replicated in Experiment 4 (N= 736).

American adults representative of general population in terms of gender and race/ethnicity. The sample was provided by Dynata, which oversampled participants to meet their internal standards for data quality. Given that Dynata's internal standards were not part of our preregistered inclusion criteria, we used the full sample that met our inclusion criteria. Eighty-eight participants (11%) did not complete all measures and therefore were excluded, resulting in the final sample of 736 participants (female = 375, $M_{age} = 48.42$ $SD_{age} = 16.50$). We note that the results reported in this article do not change as a function of this exclusion. The detailed demographic composition of Experiment 4 is presented in eTable 1 in the online supplemental materials, which suggests that the sample was comparable to the U.S. Census data.

Procedures

The Experiment 4 procedures were identical to those of Experiment 3 except that prevalence information was presented as incremental levels of total cases rather than rates. The levels of prevalence were determined by using the same method as in Experiment 3. The internal consistency between the items that measured participants' willingness to engage in preventive behaviors (mask wearing, social distancing, avoiding large social gatherings) was satisfactory overall ($\alpha = 0.97$) as well as within each condition, as reported in the online supplemental materials.

Results and Discussion

We used between-within analyses of variance to assess the impact of changes in new infections, curve shape, and prevalence on participants' risk judgments and willingness to engage in disease prevention behaviors. We also obtained the mean difference between the directions of change and comparable difference between the levels of prevalence using the same method as in Experiment 3 and statistically compared these two average mean differences using Welch's *t*-test (see the Supplemental materials for an alternative way to compare the mean difference between the directions of change and the levels of prevalence). As in Experiment 3, this analysis allowed us to examine whether prevalence had as much or more influence than changes in new infections when participants only see one direction of change.

Table 4 presents all descriptive statistics, *F*-ratios for main and interaction effects, and *t*-test for our main effect comparisons. As in Experiment 3, participants perceived greater risk and had stronger prevention intentions for the upward (vs. downward) change and for higher (vs. lower) levels of prevalence. The impact of prevalence was similar to the impact of changes in new infections, and these two factors interacted significantly with each other. The decomposition of the interaction for risk judgments showed that prevalence affected participants' risk judgments more when there was an upward change in new infections, $F(4, 1500) = 26.00$, $p < .0001$, $\eta_p^2 = 0.06$, than when there was a downward change, $F(4, 1436) = 6.39$, $p < .0001$, $\eta_p^2 = 0.02$. The same decomposition for prevention intentions also indicated that prevalence had a stronger impact when there was an upward change in new infections, $F(4, 1500) = 19.00$, $p < .0001$, $\eta_p^2 = 0.05$, than when there was a downward change, $F(4, 1436) = 6.03$, $p < .0001$, $\eta_p^2 = 0.02$. Descriptive statistics for these interactions are reported in the online supplemental materials and no other significant or interaction effects were observed (see Table 4).

We next explored whether information about changes in new infections and prevalence influenced disease prevention intentions through changes in risk judgments using the same method as in the previous experiments. Results showed that an upward (vs. downward) change in new infections heightened risk judgments and then increased participants' intentions to engage in prevention measures (indirect effect: 0.13, 95% CI [0.06, 0.21]). Likewise, higher (vs. lower) prevalence heightened risk judgments and then increased disease prevention intentions (indirect effect: 0.08, [0.05, 0.12]). In addition, the mediating role of risk judgments on the effect of prevalence information on prevention intentions was larger when there was an upward change in new cases (indirect effect: 0.26, [0.19, 0.33]) than when there was a downward change in new cases (indirect effect: 0.16, [0.09, 0.23]).

General Discussions

How people make judgments about the risk of infectious diseases and other threats has been of great interest to academics, public

Table 4
Effects of Changes in Infections and Prevalence Information on Risk Judgments and Intentions to Engage in Preventive Behaviors: Experiment 4

Variables	Changes in infections *M* (*SE*)				
	Upward		Downward		
	Curve shape		Curve shape		Overall: prevalence
	Monotonic	Non-monotonic	Monotonic	Non-monotonic	
Risk judgments					
Prevalence *M* (*SE*)					
5 (Highest)	3.51 (0.08)	3.44 (0.09)	3.24 (0.08)	3.05 (0.08)	3.32 (0.04)
4	3.46 (0.09)	3.32 (0.09)	3.06 (0.08)	2.94 (0.08)	3.20 (0.04)
3	3.31 (0.09)	3.18 (0.09)	3.03 (0.08)	2.97 (0.08)	3.13 (0.04)
2	3.29 (0.09)	3.15 (0.09)	3.00 (0.08)	2.88 (0.08)	3.08 (0.04)
1 (Lowest)	3.13 (0.09)	2.88 (0.09)	2.97 (0.09)	2.84 (0.08)	2.96 (0.04)
Overall: Curve shape	3.34 (0.04)	3.19 (0.04)	3.06 (0.04)	2.93 (0.04)	
Overall: Changes in infections	3.27 (0.03)		3.00 (0.03)		
Main effect of changes in infections	$F(1, 732) = 14.42$, $p = .0002$, $\eta_p^2 = 0.02$				
Main effect of curve shape	$F(1, 732) = 3.69$, $p = .06$, $\eta_p^2 = 0.01$				
Main effect of prevalence	$F(4, 2928) = 27.44$, $p < .0001$, $\eta_p^2 = 0.04$				
Changes in infections × Curve shape interaction	$F(1, 732) = 0.03$, $p = .87$, $\eta_p^2 = 0.00$				
Curve shape × Prevalence interaction	$F(4, 2928) = 0.44$, $p = .78$, $\eta_p^2 = 0.00$				
Changes in infections × Prevalence interaction	$F(4, 2928) = 4.52$, $p = .001$, $\eta_p^2 = 0.01$				
3-Way interaction	$F(4, 2928) = 0.81$, $p = .52$, $\eta_p^2 = 0.00$				
Comparison of main effects of changes in infections and prevalence	$t(1095.81) = 1.12$, $p = .26$, $d = 0.06$				
Trend	$M_{DIFF} = 0.27$, $SE_{DIFF} = 0.07$				
Prevalence	$M_{DIFF} = 0.36$, $SE_{DIFF} = 0.04$				
Intentions to engage in prevention behaviors					
Prevalence *M* (*SE*)					
5 (Highest)	4.22 (0.08)	4.18 (0.08)	3.97 (0.08)	3.89 (0.08)	4.07 (0.04)
4	4.16 (0.08)	4.10 (0.08)	3.87 (0.08)	3.82 (0.08)	3.99 (0.04)
3	4.19 (0.08)	4.04 (0.08)	3.86 (0.08)	3.80 (0.08)	3.99 (0.04)
2	4.08 (0.08)	3.97 (0.08)	3.86 (0.08)	3.79 (0.08)	3.93 (0.04)
1 (lowest)	3.98 (0.08)	3.90 (0.09)	3.78 (0.08)	3.76 (0.08)	3.86 (0.04)
Overall: Curve shape	4.12 (0.04)	4.04 (0.04)	3.87 (0.04)	3.81 (0.04)	
Overall: Changes in infections	4.08 (0.03)		3.84 (0.03)		
Main effect of changes in infections	$F(1, 732) = 10.58$, $p = .001$, $\eta_p^2 = 0.01$				
Main effect of curve shape	$F(1, 732) = 0.89$, $p = .35$, $\eta_p^2 = 0.00$				
Main effect of prevalence	$F(4, 2928) = 22.36$, $p < .0001$, $\eta_p^2 = 0.03$				
Changes in infections × Curve shape interaction	$F(1, 732) = 0.04$, $p = .84$, $\eta_p^2 = 0.00$				
Curve shape × Prevalence interaction	$F(4, 2928) = 0.62$, $p = .65$, $\eta_p^2 = 0.00$				
Changes in infections × Prevalence Interaction	$F(4, 2928) = 2.57$, $p = .036$, $\eta_p^2 = 0.00$				
3-Way interaction	$F(4, 2928) = 0.69$, $p = .60$, $\eta_p^2 = 0.00$				
Comparison of main effects of changes in infections and prevalence	$t(912.98) = 0.38$, $p = .70$, $d = 0.02$				
Changes in infections	$M_{DIFF} = 0.24$, $SE_{DIFF} = 0.07$				
Prevalence	$M_{DIFF} = 0.21$, $SE_{DIFF} = 0.03$				

Note. All ratings ranged from 1 (*not at all*) to 5 (*a great deal*). As shown in the comparison of main effects of changes in infections and prevalence, the mean difference across the directions of change is equivalent to the mean difference across the comparable levels of prevalence for all dependent measures. η_p^2 indicates partial eta-squared and *d* indicates Cohen's *d*. Comparison of main effects used Welch's *t*-test which assumes unequal variances between groups of comparison.

health experts, and policy makers over the course of the COVID-19 pandemic. In this article, we examined a critical question not addressed in prior works: How people make use of and respond to dynamic and static information about epidemiological risk. Specifically, we explored the influence of two key epidemiological metrics commonly used in public health communications (CDC COVID Data Tracker, n.d.), which are the changes in new infections and disease prevalence. We examined their impacts on people's risk judgments and willingness to engage in prevention behaviors including wearing a mask, practicing social distancing, avoiding large social gatherings, and vaccinating against a pathogen. Based on prior findings on people's overreliance on comparative information as a basis for risk judgments and subsequent behavioral decisions (W. M. Klein, 1997; W. M. P. Klein, 2010), we predicted that information about changes in infections, which allows people to infer comparative risk between now and before, would be more impactful than information about disease prevalence. We also predicted that the way in which the changed information is presented may increase the impact of prevalence, which is critical for individual health decisions.

In the first two experiments, information about changes in new infections had a greater influence on people's risk judgments and willingness to engage in preventive behaviors than did information about prevalence. Specifically, participants estimated a

greater risk for infection and therefore were more willing to engage in disease prevention behaviors when presented with an upward change in infections than when presented with a downward change. The greater impact of information about changes in infections was such that even though the effect of prevalence was significant in Experiment 1, it was not always significant in Experiment 2.

Experiments 3 and 4 explored people's use of prevalence information when the direction of change in new infections is constant, such that they are presented with only an upward change or only a downward change. Specifically, if information about changes in infections has the critical advantage of allowing people to better discern whether their current risk has increased or decreased relative to the past, presenting only an upward change or only a downward change prevents such a determination. Therefore, a constant upward change or constant downward change in infections may heighten people's use of other relevant risk information, such as the disease prevalence. As predicted, when people were presented with only one direction of change, higher (vs. lower) levels of prevalence increased risk judgments and prevention behavior more than, or as much as, upward (vs. downward) change in new infections (Experiments 3 and 4) regardless of whether prevalence was presented as rates (Experiment 3) or raw numbers (Experiment 4). Experiments 3 and 4 also found that once people were presented with only one direction of change, they used prevalence information more when they witnessed an upward change in new infections than when they witnessed a downward change. This finding is consistent with prior evidence of people using information more carefully in negative (vs. positive) emotional states, which in our case, could have been induced upon seeing a constant upward (vs. downward) change in new infections.

Taken together, our findings demonstrate that information about changes in infections consistently influences people's risk judgments which then affects disease prevention efforts, such that an upward change in infections yielded higher risk judgments and therefore higher prevention intentions than a downward change. This pattern was consistent across all experiments, regardless of whether people saw both directions (upward and downward) of change or one direction (upward or downward) of change. On the other hand, the influence of information about disease prevalence was less consistent and varied more across contexts, such that higher (vs. lower) levels of prevalence reliably yielded higher risk judgments and therefore higher prevention intentions only when accompanied by a constant direction of change in new infections and particularly when there was a constant upward (vs. downward) change in infections.

Theoretical and Practical Implications

This research extends our current knowledge of epidemiological risk judgments in several ways. First, prior work has shown that people have a poor understanding of graphs depicting cumulative case counts. For example, they expect cumulative curves to decline when new cases decrease and to remain the same when new infections are stable (Lalwani et al., 2020). Our findings suggest that one potential cause for this misunderstanding is a lack of impact of cumulative case counts compared with other metrics of disease risk such as the changes in new cases. Therefore, if interventions are to increase the public's understanding of cumulative curves, they may first need to heighten people's use of prevalence information.

Prior work has stressed the importance of providing accurate health information to the public. Specifically, because communicating prevalence as total case counts is often misleading without knowing the size of the relevant population, reporting rates have been proposed as a more accurate form of conveying prevalence information (Pearce et al., 2020). Despite their accuracy, however, communicating prevalence information as rates was not sufficient for prevalence information to have an impact on our experiments. This finding thus demonstrates that increasing the accuracy of health statistics does not always increase good use of this information as a basis for decisions among the public. Therefore, how people differentially use raw numbers opposed to rates, as well as the correspondence between information accuracy and people's reliance on such information deserves more attention in future work. Importantly, there are downsides to relying solely on information about changes in infections. The concept of herd immunity, for example, involves the concept of prevalence of immunity, information that our research shows to have limited impact. Furthermore, if public interest in receiving the vaccine fluctuates according to changes in infections, reaching herd immunity may be even more difficult.

The above discussions all point to the need for public health interventions to increase the impact of prevalence information among citizens. One potential remedy may be to simply inform the public of the tendency toward and consequences of neglecting prevalence information. In a prior experiment (Small et al., 2007), for example, participants were informed that people typically donate more to a specific victim in need (e.g., a 7-year-old African girl named Rokia) than to groups of victims (e.g., millions of starving children in African countries). Fortunately, being provided with this information effectively de-biases decision makers and reduces their tendency to help specific victims more than the general cause.

Another possibility may be providing different metrics of epidemiological information separately rather than jointly. People frequently experience difficulties in weighing multiple pieces of information simultaneously (e.g., Reichle et al., 2009), which leads them to selectively use certain information that is deemed more diagnostic (in our case, information about changes in infections) over others. For example, daily updates on the COVID-19 pandemic may separate different types of information to ensure that both changes in infections and prevalence have an impact on the decisions of the population. Indeed, our experiments (Experiments 3 and 4) demonstrated that people are influenced by prevalence when information about the change is held constant within participants. Although such an intervention may not be feasible in all public health communications, people's use of prevalence information may increase when this information is accompanied by a standard that helps people gauge the severity of prevalence compared with a standard, such as a threshold that tells people when the level of community transmission is "severe," "moderate," or "low".

Limitations and Future Directions

This research is not without limitations, including those that pertain to our experimental design. Specifically, we examined the influence of risk information that more closely resembled those that are portrayed in popular media and public health communications

than those portrayed in prior relevant work (Berry et al., 2006; W. M. Klein, 2003; P. R. Harris & Smith, 2005). Also, we researched their influence during several years of the COVID-19 pandemic, which provided potentially important data for the future. Nonetheless, the experiments have inherent limitations such as relying on online volunteers, asking them to imagine situations in hypothetical regions, and measuring intentions rather than actual behaviors. Hence, further work is needed that can increase the generalizability of our results across samples with different health status, occupations, and ages. Thus, we remind the readers that our experiments and their outcomes relate primarily to population-level behaviors rather than considering the possibility of different subpopulations reacting differently to the information examined in this article. Future work should address different groups, such as vulnerable populations and samples from other countries.

Likewise, testing the impact of changes in new infections and prevalence information on actual disease prevention behaviors above and beyond intentions will also be important. A meta-analysis of meta-analyses on intention-behavior relations found a moderate-sized ($r = .53$) correlation between intention and behavior (Sheeran, 2011) suggesting that our findings on behavioral intentions have a good chance of getting translated into actual behaviors. Nonetheless, the ease with which a behavior can be performed affects the translation of intentions into actions (Ajzen & Schmidt, 2020; Sheeran et al., 2003), such that the fewer psychological, social, and structural barriers people experience to wear masks, practice social distancing, and vaccinate, the more their intentions will influence behavior. This point further stresses the importance of examining other contextual variables such as access to healthcare as a way of more fully understanding responses to epidemiological risk information.

One question that may arise is whether the difference in our results is a matter of calibration of the levels of prevalence and changes in new infections. Although this is a distinct possibility in the studies in which prevalence had less impact than changes in new infections (Experiments 1 and 2), Experiments 3 and 4 speak against this conjecture. In fact, once the changes in new infections demonstrated only an upward or downward change, the impact of prevalence increased even though the method we used to set the prevalence levels was identical to that of the previous experiments. Correspondingly, once the changes in new infections demonstrated only an upward or downward change, changes influenced judgments less even though these changes were of the same magnitude as in prior experiments. Therefore, our results cannot be explained by mere differences in calibration.

Also, our experiments relied on a single item measure of risk judgments rather than using multiple items to establish the reliability of the construct. However, this decision is unlikely to have a negative impact for several reasons. First, the perceived risk of contracting an infectious disease is a relatively simple construct that is easily understood, and similar decisions have been made in prior published works (Fagerlin et al., 2017; Figueiras et al., 2022; Jung & Albarracín, 2021; P. Harris et al., 2002). Second, a single-item measure of perceived risk seems not to have undermined our main results given consistent detection of effects across four experiments. Specifically, participants reported higher risk judgments when they saw an upward (vs. downward) change in new infections in each experiment. They also only reported higher risk judgments for higher (vs. lower) levels of prevalence when the prevalence information was accompanied by a constant upward or downward change. Had the measure been unreliable, changes have been either not detected or detected inconsistently.

The inconsistencies were rather observed in behavioral intentions and we used multiple items to establish the construct. Specifically, whereas we found a significant interaction between curve shape and disease prevalence on disease prevention intentions in Experiment 3, no such interaction emerged in Experiment 4. As we did not have a theoretically informed hypothesis about the role of curve shape, a separate investigation on the influence of curve shape in conjunction with other metrics of disease risk is needed.

Relatedly, in examining the influence of changes in new infections on people's risk judgments and disease-prevention efforts, we focused on the direction of change and did not consider other elements of change such as the slope in which new infections increase or decrease. Interestingly, however, past work has shown that people care more about the directionality of their risk compared with a reference point, such as whether their risk is higher or lower than average others, than their distance from this point (W. M. P. Klein, 2010). In this regard, people may attend more to whether new infections simply demonstrate an upward or downward trend than the amount of observed change. This possibility would be especially alarming since the lack of attention to the slope of change can substantially delay preventive measures when an infectious disease is spiraling out of control. Likewise, although we examined the influence of two commonly communicated metrics of infectious diseases, there is other information we did not test, including the number of hospitalizations, deaths, tests, and vaccinations, which could all impact people's risk-related judgments and decisions. Given our findings, we expect that the way in which these metrics are presented to play an important role, such that highlighting the change in the number of hospitalizations, deaths, test, and vaccinations from a previous timepoint may be more impactful than presenting the raw counts or rates of these metrics. This possibility can also be explored in future work.

In conceptualizing the distinct properties communicated through changes in new infections and disease prevalence, we relied on prior work on comparative and absolute risk to assume that people are more likely to use information about changes in new infections than disease prevalence as it facilitates easier evaluations of risk, which then leads to more corresponding behavioral responses. Accordingly, we consistently demonstrate, across all of our experiments, that when there are significant impacts of changes in new infections and disease prevalence on intentions to engage in prevention measures, these effects are always mediated by changes in risk judgments. Nonetheless, we cannot completely rule out the possibility that our effects could also reflect attentional processes, that people simply pay more attention to changes than to the total number of infections. In fact, the distinction between attentional versus judgmental processes involved in people's use of risk information has not been fully addressed nor systematically examined in prior work. Although this gap could be addressed in future work, the key message of our research is clear: that public health campaigns that heavily rely on the concept of prevalence, such as *flattening the curve* and *reaching herd immunity* may have underwhelming effects. Furthermore, if the goal is to communicate prevalence to drive risk judgments and corresponding actions, deemphasizing changes might be necessary, except during times of stable changes when prevalence would tend to carry the day.

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