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Does Risk Perception Motivate Preventive Behavior During a Pandemic? A Longitudinal Study in the United States and China

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Controlling the spread of an infectious disease depends critically on the general public's adoption of preventive measures. Theories of health behavior suggest that risk perceptions motivate preventive behavior. The supporting evidence for this causal link is, however, of questionable validity. The COVID-19 pandemic provides a rare opportunity to examine how risk perceptions, preventive behavior, and the link between them develop in a fast-changing risky environment. In a 4-wave longitudinal study conducted in the United States and China, we found that for Chinese participants, there was little relationship between risk perceptions and preventive behavior. This may be a result of the Chinese government's strict control and containment policies and a collectivistic culture that encourages conforming to norms—both of which limit individuals' nonconformist behavior. For U.S. participants, risk perceptions did motivate preventive behavior in the early stage of the pandemic; however, as time went by and the risk of COVID-19 persisted, preventive behavior also led to perception of higher infection risk, which in turn further motivated preventive behavior. Thus, instead of the presumed unidirectional influence from perception to behavior, our results indicate that the two could mutually reinforce each other. Overall, our findings suggest that risk perceptions—at least in the context of a dynamic health hazard—may only motivate preventive behavior at specific stages and under specific conditions. They also highlight the importance of early interventions in promoting preventive behavior.

Public Significance Statement

In a 4-wave longitudinal study conducted in the United States and China, we examined the link between risk perception and preventive behavior in the context of the COVID-19 pandemic. We found that although individuals' risk perception had little effect on engagement in preventive behavior in China, it did motivate preventive behavior in the United States, particularly at the early pandemic stage. These findings suggest that the perception–behavior link can be influenced by culture, policy, and stage of a dynamic health hazard, and that campaigns promoting preventive behavior by increasing risk perception are more likely to succeed if implemented early, when risk perception is still in its formative stage.

Keywords: COVID-19, perceived susceptibility, dread risk, unknown risk, health behavior

Supplemental materials: https://doi.org/10.1037/amp0000885.supp

Preventive measures are critical for controlling the spread of an infectious disease. During the COVID-19 pandemic, measures such as reduced social and physical contacts, handwashing, and wearing masks have been recommended (e.g., Centers for Disease Control & Prevention, 2020) and often actively enforced (e.g., Hessler, 2020) by governments around the

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world. Whether individuals comply with such recommendations and regulations, however, often remains a personal choice. According to theories of health behavior such as the health belief model (Rosenstock et al., 1988) and protection motivation theory (Rogers, 1985), risk perception is a crucial factor in motivating individual preventive behavior. From this perspective, one way to boost preventive behavior is to highlight the potential health risks posed by COVID-19, thus amplifying risk perception and, consequently, promoting preventive behavior.

The evidence for the causal link between risk perception and preventive behavior is, however, far from conclusive. Most studies examining the relationship—whether for pandemics or other health issues—are cross-sectional and regard a positive correlation between the two as supporting evidence (e.g., Brewer et al., 2007; Leppin & Aro, 2009). But correlation is not causation. The positive correlation may occur because of a third factor, such as physical health: People with poor health may both perceive greater risk and engage in more preventive behavior. The observed correlation may thus simply reflect an accurate mapping between perception and behavior (i.e., the "accuracy" hypothesis; Brewer et al., 2004).

Given that an experiment is not possible, a longitudinal design is the best option for drawing causal inferences about the perception–behavior relationship (e.g., Brewer et al., 2004; Newsom, 2015; Weinstein, 2007). With measurements of perception and behavior taken at different times (see Figure 1), a perception-to-behavior causal link can be inferred if higher risk perception at Time 1 leads to more preventive behavior at Time 2 (i.e., the "perception-motivates-behavior" hypothesis; Brewer et al., 2004). This is the link endorsed by most theories of health behavior (Gerrard et al., 1996). Two other intertemporal links are also possible: First, people may observe their behavior and use it as a cue to construct perceptions (Bem, 1972). In the context of preventive behavior and risk perception, engagement in preventive behavior may be interpreted as a signal of greater risk in the environment, thus leading to increased risk perception (i.e., the "behavior-amplifies-perception" hypothesis). Alternatively, taking more preventive measures may endow people with a stronger sense of safety and consequently lower their risk perception (i.e., the "behavior-attenuates-perception" hypothesis).

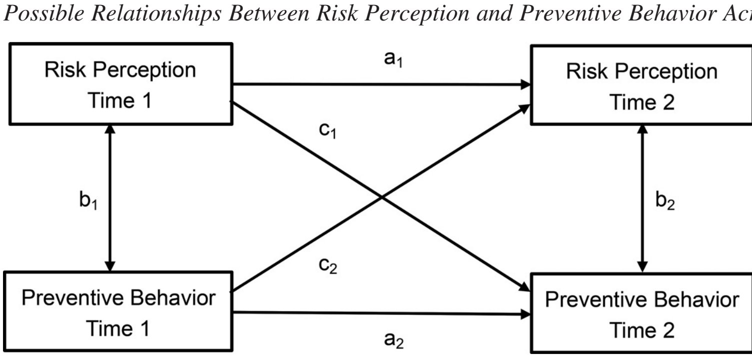
Figure 1 depicts these four hypotheses; a hypothesis is supported if evidence is found for the corresponding relationship(s). Using a four-wave longitudinal design that measured participants' risk perception and preventive behavior during the COVID-19 pandemic, our goal was to track the dynamics of risk perception and preventive behavior and to analyze their relationship over different stages of the pandemic.

Risk perception may motivate preventive behavior cognitively (e.g., "I wear a mask because people like me are more likely to get infected") and/or emotionally (e.g., "I wear a mask because I dread contracting COVID-19"). We therefore used two measures that tap into people's cognitive evaluation of and affective response to the risk of COVID-19, examining how each relates to preventive behavior. The first is *perceived susceptibility*—people's estimated likelihood of contracting the virus—which has been assessed widely in studies of pandemics (e.g., Bish & Michie, 2010; Leppin & Aro, 2009). This measure is in line with the actuarial evaluation of a risk, as it represents the probability component of the standard technical definition of risk.

The second measure is the "psychometric" measure of risk perception. Many past studies have shown that laypeople's risk feelings often diverge from actuarial quantities and are shaped by two major risk factors: *unknown* and *dread* (e.g., Fischhoff et al., 1978; Slovic, 1987). Unknown risks are novel risks that are not fully known to those exposed or to science and whose effects are delayed. Dread risks are fatal

Figure 1

Possible Relationships Between Risk Perception and Preventive Behavior Across Two Time Points

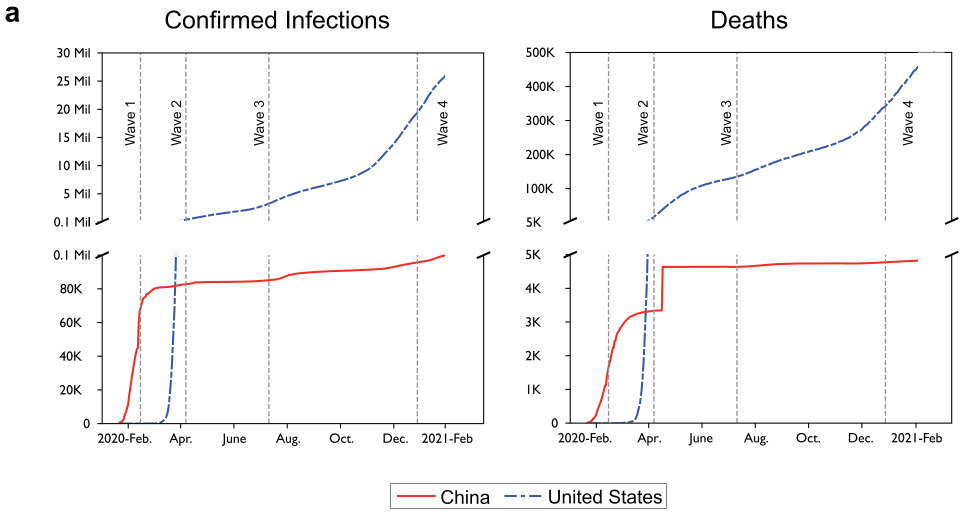


Hypothesis	Supporting evidence
Accuracy	Positive b_1 and b_2
Perception-motivates-behavior	Positive c_1
Behavior-amplifies-perception	Positive c_2
Behavior-attenuates-perception	Negative c_2

Note. Values of a_1 and a_2 indicate stabilities of the measures across time; positive values of b_1 and b_2 would support the accuracy hypothesis (i.e., perception and behavior are accurately matched at the time of measurement); a positive value of c_1 would support the perception-motivates-behavior hypothesis (i.e., higher risk perception leads to more preventive behavior); a positive value of c_2 would support the behavior-amplifies-perception hypothesis (i.e., more preventive behavior leads to higher risk perception); and a negative value of c_2 would support the behavior-attenuates-perception hypothesis (i.e., more preventive behavior leads to lower risk perception).

Figure 2

Pandemic Statistics and Stages Over the Period of Data Collection



b

Stage	Prepandemic	Onset of viral outbreak	Ongoing risk	Contained risk
Data	Wave 1 U.S.	Wave 2 U.S. Wave 1 China	Waves 3 & 4 U.S.	Waves 2, 3, & 4 China

Note. (a) Accumulated confirmed infections and deaths from COVID-19 in the United States (U.S.) and China from January 22, 2020 to February 1, 2021. The approximate dates of the four waves of data collection in this study are marked by dashed lines. Data are from Humanitarian Data Exchange (2020). (b) Mappings between four pandemic stages and the four waves of data collection. See the online article for the color version of this figure.

risks that people take involuntarily, whose consequences can be catastrophic and uncontrollable, and that people dread on a gut level. The dread risk factor captures people's negative affective responses more than the unknown risk factor and is associated with the demand for stricter policy regulation (e.g., Loewenstein et al., 2001; Slovic, 1987; Slovic et al., 2004). Following the method used in this research paradigm (Fischhoff et al., 1978), we asked participants to evaluate the risk of COVID-19 on nine basic characteristics and extracted the unknown and dread risk factors from their ratings.

A person's decision to engage in preventive behavior can be influenced not only by their own perception but also by public recommendations, regulations, and the behavior of others. Theories such as the theory of reasoned action and the theory of planned behavior (e.g., Ajzen, 1991; Ajzen & Fishbein, 1980) emphasize the important role that social norms can play in shaping individuals' behavioral intentions. During a pandemic, wearing masks may become a strong social norm (even a social contract; see Betsch et al., 2020); people may therefore do so irrespective of how they perceive the risk.[1] Likewise, strict government policies that enforce preventive measures and penalize noncompliance may suppress the effect of individuals' risk perception, attenuating the link between perception and preventive behavior.

Previous studies examining the perception–behavior link in the context of pandemics have yielded mixed results, showing mostly positive correlations but occasionally no correlations (e.g., Bish & Michie, 2010; Sadique et al., 2007). Such inconsistencies may be attributable to factors such as culture and governmental policies. We collected data in two countries, the United States and China, whose governments have implemented starkly different policies to contain viral spread (e.g., He et al., 2020) and whose cultures differ markedly in terms of people's willingness to conform to social norms (e.g., Markus & Kitayama, 1991; Shi & Wang, 2011). By comparing results between these two countries, we can explore how the perception–behavior link may be impacted by political and cultural factors.

Pandemics advance in stages, and people are expected to adjust their risk perception and preventive behavior accordingly. Our study covers four stages of the COVID-19 pandemic in terms of infection and death statistics (see Figure 2). The results will shed light on how participants' risk perception and preventive behavior developed over these stages and how the two were coupled or decoupled over time.

[1] Depending on the political and cultural context, the refusal to wear masks can also become a strong social norm, as witnessed throughout the COVID-19 pandemic.

Table 1
Survey Sampling Information

Country	Wave	No. of respondents	Valid sample: Sample size	Female %	*M* age (*SD*)	Below bachelor degree %
United States	1	1,168	797	41.8	39.6 (11.2)	36.6
	2	589	504	45.0	41.6 (11.2)	39.3
	3	356	332	44.6	42.3 (11.0)	40.4
	4	247	236	48.7	43.0 (10.7)	39.4
China	1	2,343	1,864	41.0	34.8 (12.2)	34.2
	2	1,216	1,063	45.4	33.2 (12.0)	33.5
	3	868	797	47.6	32.6 (12.1)	30.7
	4	715	665	47.2	32.3 (12.0)	29.9

Method

We conducted a four-wave survey study in the United States and China. The first wave took place February 13–17, 2020, 3 to 4 weeks after the Wuhan lockdown in China; the second took place April 5–9, 2020, 3 to 4 weeks after a national emergency was declared in the United States; the third took place July 9–13, 2020, when the pandemic was progressing rapidly in the United States but was largely contained in China; and the fourth took place between December 22, 2020 and January 8, 2021,[2] when vaccinations against COVID-19 were soon to become available in both countries. Figure 2 shows the accumulated infections and deaths from COVID-19 from January 22, 2020 to February 1, 2021 in each country. The study was approved by the Ethics Committee at the Max Planck Institute for Human Development.

Participants

Participants in the United States were recruited through Amazon Mechanical Turk, and only U.S. residents were admitted to the study. Chinese participants were recruited through advertisements on the WeChat app and by a professional survey company (LangHe Tech). We aimed to have 1,000 U.S. participants and 2,000 Chinese participants in the first wave. Anticipating that a proportion of participants would not pass data quality checks, we intentionally oversampled (see Table 1). The survey took about 10 minutes to complete, and participants were paid $1 (United States) or 10RMB (China) for completing the survey in the first wave. All participants who left contact information and whose responses passed quality checks in the first wave were invited to the second wave and informed that their payment would be doubled ($2/20RMB) if they completed the second survey. This recruitment process was repeated in the third and fourth waves; to encourage continued participation, participants in each of these two waves were paid $3 or 30RMB for completing the survey.[3]

Multiple checks for response quality were applied. Participants' data were excluded if they gave wrong answers to attention-check questions, if one system-generated identification code appeared multiple times, if they gave illogical responses, or if they did not follow instructions when answering questions. For participants who took part in multiple waves, a participant's data were excluded if their reported ages across the waves differed by more than 2 years, if their reported education levels differed by more than one category, or if their reported gender changed.

Table 1 shows the numbers of participants who responded to our invitation and finished the survey (number of respondents) and who provided qualified responses (valid sample), as well as statistics on gender, age, and education in each valid sample. Not surprisingly, the sample size became progressively smaller in each wave. A total of 236 U.S. participants and 665 Chinese participants provided qualified responses in all four waves, amounting to 29.6% and 35.7%, respectively, of those who did so in the first wave. Figures S1 and S2 in the online supplemental materials show the distributions of these participants' residency in each country in each wave. Note that our samples in each country were convenience samples; caution must therefore be taken in generalizing the descriptive results of our study to the national populations.

Key Study Variables

The survey asked participants to report their feelings, thoughts, perceptions, and behaviors around the time of the survey. Key variables pertaining to the research questions and analyses of the present study are listed in Table 2; all measured variables are shown in Table S3 in the online supplemental materials, and the full list of survey questions can

[2] All data in China and most data in the United States were collected between December 22 and 27, 2020. In order to increase the U.S. sample size, we resumed data collection in the United States for 1 week after the New Year holiday.

[3] In the second and third waves, we also recruited some new participants. The sampling statistics for the entire samples in these two waves can be found in Table S1 in the online supplemental materials.

Table 2
Key Study Variables

Category	Name	Measurement
Personal	Gender	Female = 1; Male = 2
	Education	High school or below = 1; College or associate degree = 2; Bachelor degree = 3; Graduate degree = 4
	Age	Years
Risk perception	Unknown risk	Average of four of nine dimensions (1–7 scale)
	Dread risk	Average of five of nine dimensions (1–7 scale)
	Perceived susceptibility	Nine probabilistic categories
Preventive behavior	Practicing social/physical distancing	1–7 scale
	Avoiding meeting people	1–7 scale
	Willingness to wear mask	1–7 scale
	Handwashing times per day	Integer (the maximum reported value is 7)

be found at https://osf.io/g68nx. Participants were asked to estimate the likelihood that they would get infected (perceived susceptibility) in a multiple-choice question whose options ranged from 0% to >90%. They were also asked to rate their engagement in four preventive behaviors—handwashing to prevent coronavirus infection, practicing social/physical distancing, avoiding meeting people, and willingness to wear a mask in public space—in the week prior to taking the survey. The behavioral questions were not administered in the first wave due to a design oversight. Rather, participants in the second wave were additionally asked to recall those behaviors for mid-February (time of the first wave), thereby answering the questions retrospectively.

To assess participants' unknown and dread risk perceptions of COVID-19, we administered the nine questions used in the psychometric paradigm (Fischhoff et al., 1978). These questions tap nine dimensions: newness, immediacy, known to exposed, known to science, voluntariness, controllability, chronic–catastrophic, common–dreadful, and severity of consequences. A recent study on risk perceptions relating to 30 technologies and activities (Fox-Glassman & Weber, 2016) found that while there were no change in the dimensions associated with unknown or dread risk factors since the original study by Fischhoff and colleagues (1978), there were changes in factor loadings. Therefore, instead of using a set of unstable loadings, we calculated each factor's score by taking the simple average of the dimensions that were deemed relevant to each factor in a review study by Slovic (1987). This simple equal-weighting rule has been shown to be as predictive and diagnostic as (and sometimes more so than) complex differential-weighting methods in studies of other psychological constructs (e.g., Dawes & Corrigan, 1974; Piacentini et al., 1992; Weathers et al., 1999). The dimensions relevant to the unknown risk factor are newness, immediacy, known to exposed, and known to science; those relevant to the dread risk factor are voluntariness, controllability, chronic–catastrophic, common–dreadful, and severity of consequences.

Results

All results reported and discussed below are based on analyses of the valid overlap sample (i.e., participants who provided qualified responses in all four waves) in each country. The data can be accessed at https://osf.io/2phyv.

Preventive Behaviors

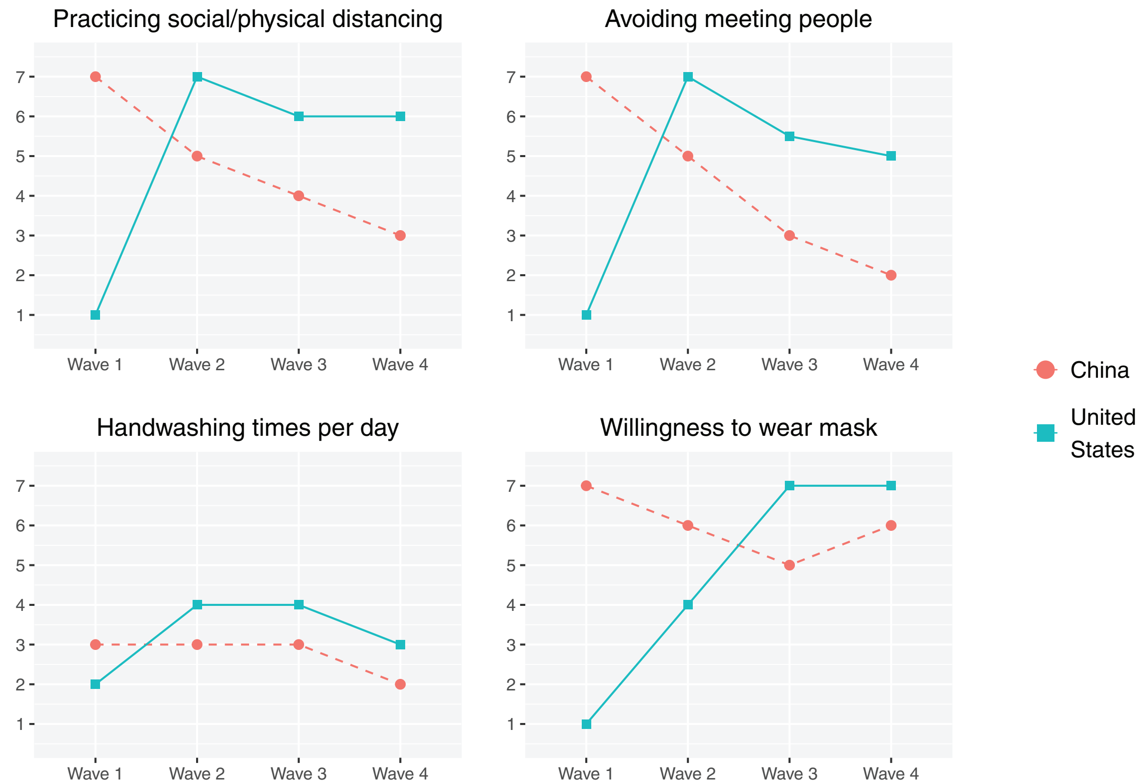
Chinese and U.S. participants demonstrated very different patterns in their reported engagement in the four preventive behaviors (see Figure 3). From Wave 1 to Wave 4 (onset to contained risk), Chinese participants' engagement in each behavior generally decreased, with the exception of a small increase in willingness to wear masks from Wave 3 to Wave 4. This pattern corresponds with the gradual reduction in infection rates in China during that period. U.S. participants' engagement in all four behaviors increased from Wave 1 to Wave 2 (prepandemic to onset), when COVID-19 began spreading widely in the United States; however, except for the willingness to wear masks, engagement in preventive behaviors declined from Wave 2 to Wave 4 (onset to ongoing risk), when infections were increasing drastically in the United States.

A study by Wei and colleagues (2020) has shown that prior to the COVID-19 pandemic, Americans had very low expectations that wearing masks would protect against seasonal influenza. This low perceived efficacy may be one key reason for the slow adoption of mask wearing by our U.S. participants early in the pandemic. However, as scientific evidence accumulated and authorities began to clearly endorse mask wearing (e.g., Centers for Disease Control & Prevention, 2020), most U.S. participants became more willing to wear masks in public space.

We took a participant's mean response across the four behavioral items as an overall index of their engagement in preventive behavior. For each country and in each wave, the responses were moderately correlated, with

Figure 3

Median Reported Engagement in the Four Preventive Behaviors in Each Wave



Note. See the online article for the color version of this figure.

average pairwise correlations around .35. Moreover, when we treated each response as an item in a "preventive behavior scale," the Cronbach αs of the scale were around .70, indicating good levels of internal consistency. The mean preventive behavior scores are plotted in Figure 4. We conducted a repeated-measures ANOVA to examine whether the cross-wave changes in each country were statistically significant (the detailed test statistics on this and other repeated-measures ANOVAs can be found in the online supplemental materials). For Chinese participants, the decreasing trend was statistically significant; for U.S. participants, there was an increase from Wave 1 to Wave 2 but no change from Wave 2 to Wave 4, probably because the relatively large increase in willingness to wear masks counterbalanced the declines in the other three behaviors.[4]

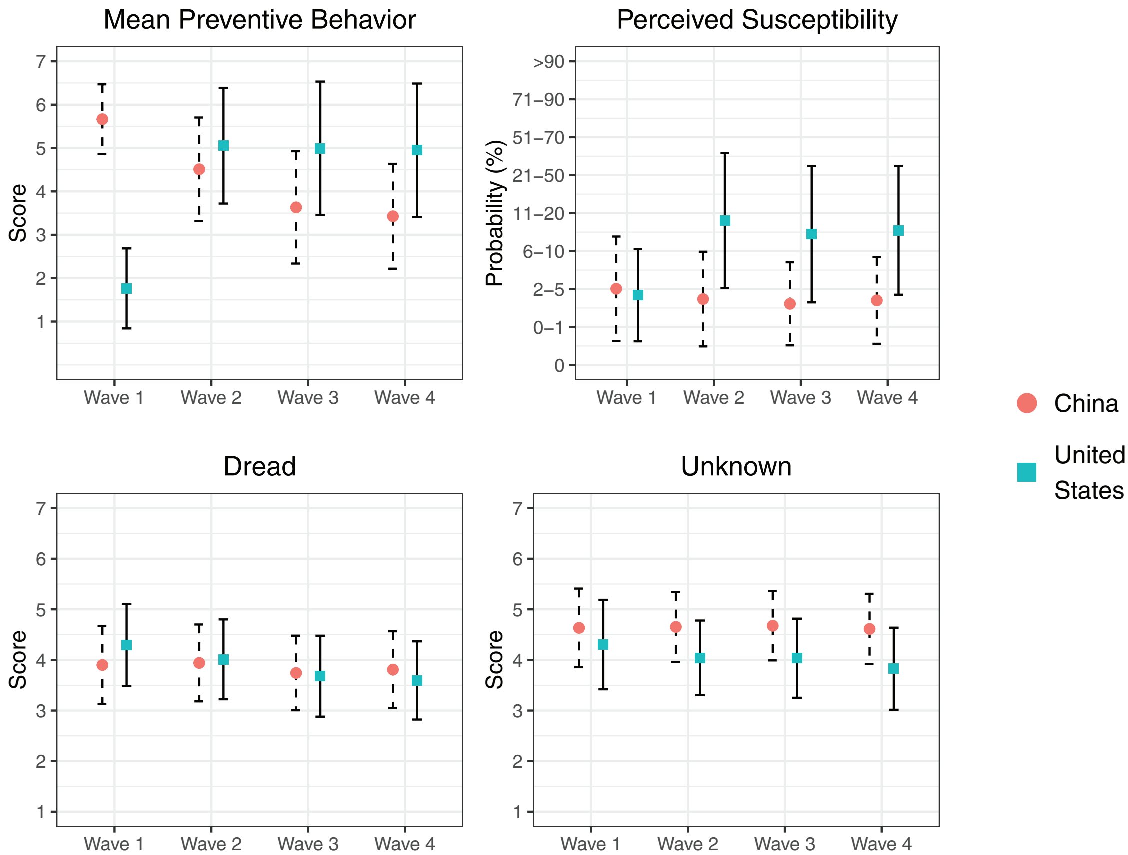
Perceived Susceptibility

There were also distinct patterns in perceived susceptibility in the two countries (see Figure 4). For Chinese participants, perceived susceptibility decreased after Wave 1 and remained low in Waves 2, 3, and 4, which corresponds with the much decreased infection rates in China during that period. For U.S. participants, perceived susceptibility increased substantially from Wave 1 to Wave 2, when infections were also rising quickly in the United States, and then stayed at roughly the same level in the latter two waves, despite the soaring infection numbers during that period (see Figure 2).

When interpreting the perceived susceptibility responses in Figure 4, one should keep in mind that the scale is nonlinear. For example, the mean perceived susceptibility of Chinese participants in Wave 1 (onset) was around 3, which corresponds to a 2–5% estimated probability of getting infected, and the value for U.S. participants in Wave 2 (also onset) was slightly below 5, which corresponds to a 10–20% estimated probability of infection. Thus, the actual difference in perceived susceptibility between the two samples at the onset of the pandemic was larger than it appears to be on this measurement scale.

[4] For U.S. participants, we also analyzed changes in preventive behavior by political affiliation. The results show that there was no difference among Democrats, Republicans, and Independents in Wave 1, but that Democrats engaged in significantly more preventive behavior than the other two groups in Waves 2, 3, and 4. The latter two groups did not differ in these waves either. The detailed results are shown in Figure S3 in the online supplemental materials.

Figure 4
Mean Scores of the Four Key Variables Investigated



Note. Mean preventive behavior is the averaged response across the four preventive behaviors: practicing social/physical distancing, avoiding meeting people, handwashing times per day, and willingness to wear a mask. Dread and Unknown stand for perceptions of dread risk and unknown risk, respectively. Error bars indicate standard deviations. See the online article for the color version of this figure.

Perceptions of Unknown Risk and Dread Risk

Unlike preventive behavior and perceived susceptibility, the perceptions of unknown risk and dread risk changed little in absolute terms across the four waves in either country (see Figure 4). For Chinese participants, repeated-measures ANOVAs showed a statistically significant but small drop in perceived dread risk from Wave 2 to Wave 3, but no difference between Waves 1 and 2 or Waves 3 and 4, and no change in perceived unknown risk over the four waves. The remarkable stability of these two measures of risk perception departs from the much reduced infection rates from Wave 1 to Wave 4 in China. For U.S. participants, perceptions of both dread risk and unknown risk decreased gradually from Wave 1 to Wave 4, running contrary to the increasing infection rates in the United States over that period. For participants in both countries, perceptions of the dread and unknown risks of COVID-19 were thus evidently divorced from the infection statistics.

To provide points of reference for the reported risk perceptions, Figure 5 shows participants' risk perceptions of COVID-19 in the unknown–dread space together with 73 previously studied risks, including 30 technologies and activities (Fox-Glassman & Weber, 2016); 22 natural disasters (Fox-Glassman, 2015); and 21 diseases (Brun, 1992). The mean rating of each risk dimension and the specific unknown risk and dread risk scores for all risks can be found in the online supplemental materials. Although the studies were conducted at different times and with different participants, some broad conclusions can nevertheless be drawn, including the general characteristics of each risk category: Many diseases are perceived to be high in both the unknown and dread risk dimensions; natural disasters tend to score high in dread but relatively low in unknown; and technologies/activities cover a wide range in unknown but tend to score low in dread. COVID-19 could conceivably be perceived as either a natural disaster or a disease. The comparative results in Figure 5 show that it was consistently perceived

Figure 5
Risk Perceptions of COVID-19 in the Unknown–Dread Space, Along With Risk Perceptions for 73 Previously Studied Risks

Note. To enhance display, the *x*-axis ranges from 1.5 to 6.0, while the *y*-axis ranges from 1.5 to 5.0. The axes cross at the medians of the unknown (2.90) and dread (3.64) risk scores of the previously studied risks. CHN = China; US = United States. See the online article for the color version of this figure.

as relatively high in both unknown risk and dread risk, linking it more closely to diseases than to other risk categories.

Summary of Descriptive Results

The results presented in Figures 3, 4, and 5 show the dynamics of participants' risk perceptions and preventive behaviors over the first year of the COVID-19 pandemic. In both countries, participants' perceptions of the unknown and dread risks of COVID-19 did not change much across the four waves, despite the drastic local and global developments of the pandemic. Perceived susceptibility changed somewhat more from wave to wave. However, U.S. participants' perceived susceptibility barely changed after Wave 2 (onset), despite soaring rates of infection and death in the United States. Their mean preventive behaviors also followed the same pattern (i.e., increasing in Wave 2 and remaining at the same level afterward).

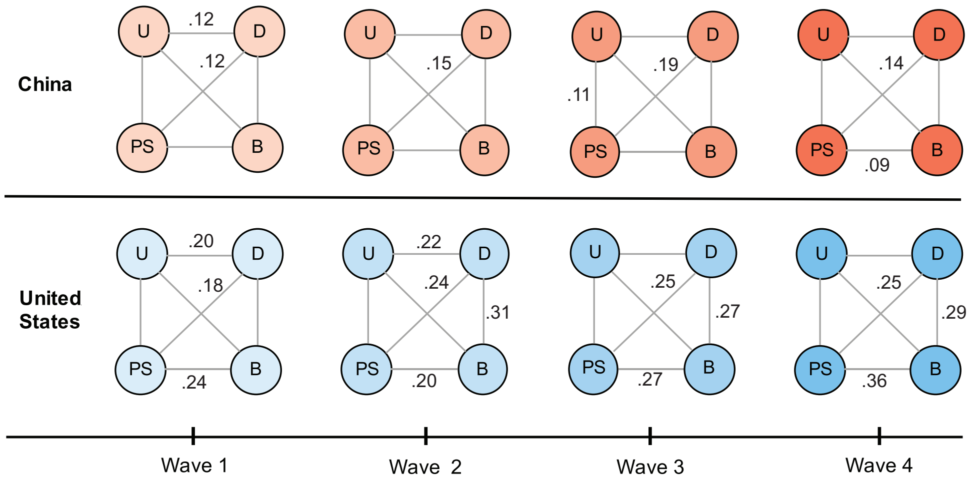
Relationships Between Risk Perception and Preventive Behavior

We examined the relationships between risk perception and preventive behavior with this central question in mind: Did higher (lower) risk perception lead to more (less) engagement in preventive behavior? Preventive behavior was represented as the averaged response across the four preventive behaviors, and risk perception was measured in terms of both perceived susceptibility and the perceived unknown risk and dread risk of COVID-19.

We first examined the pairwise correlations among these four variables. Figure 6 shows all within-wave correlations that were statistically significant; the full correlation matrices including the cross-wave correlations can be found in Table S6 in the online supplemental materials. There are three general patterns: First, perception of unknown risk was not correlated with preventive behavior in any wave or country; second, perception of dread risk and perceived susceptibility were correlated in all waves and in both

Figure 6

Within-Wave Pairwise Correlations Among the Four Key Variables Investigated



Note. Age, gender, and education level were controlled for in samples of both countries, and political affiliation was controlled for additionally in the U.S. sample. Only correlations with $p < .01$ are shown. U = perception of unknown risk; D = perception of dread risk; PS = perceived susceptibility; B = mean preventive behavior. See the online article for the color version of this figure.

countries, suggesting a robust link between the affective response to and the cognitive evaluation of the risk posed by COVID-19; third, while both perceived susceptibility and perception of dread risk were consistently correlated with preventive behavior in the United States, almost all correlations between measures of risk perception and preventive behavior in China were nonsignificant. Therefore, the accuracy hypothesis (see Figure 1) was generally supported in the United States, but not in China.

The accuracy hypothesis, however, cannot cast light on the possible causal link between risk perception and preventive behavior. To this end, we performed a series of cross-lagged panel model (CLPM) analyses. CLPM is a statistical tool for investigating relationships between two or more variables in a longitudinal study. It is generally considered the best method for establishing the causal precedence of one variable over another in studies with nonexperimental designs (Newsom, 2015). In CLPM, statistically significant coefficients of the cross-wave paths from one variable to another are treated as evidence in support of directions of influence between the variables.

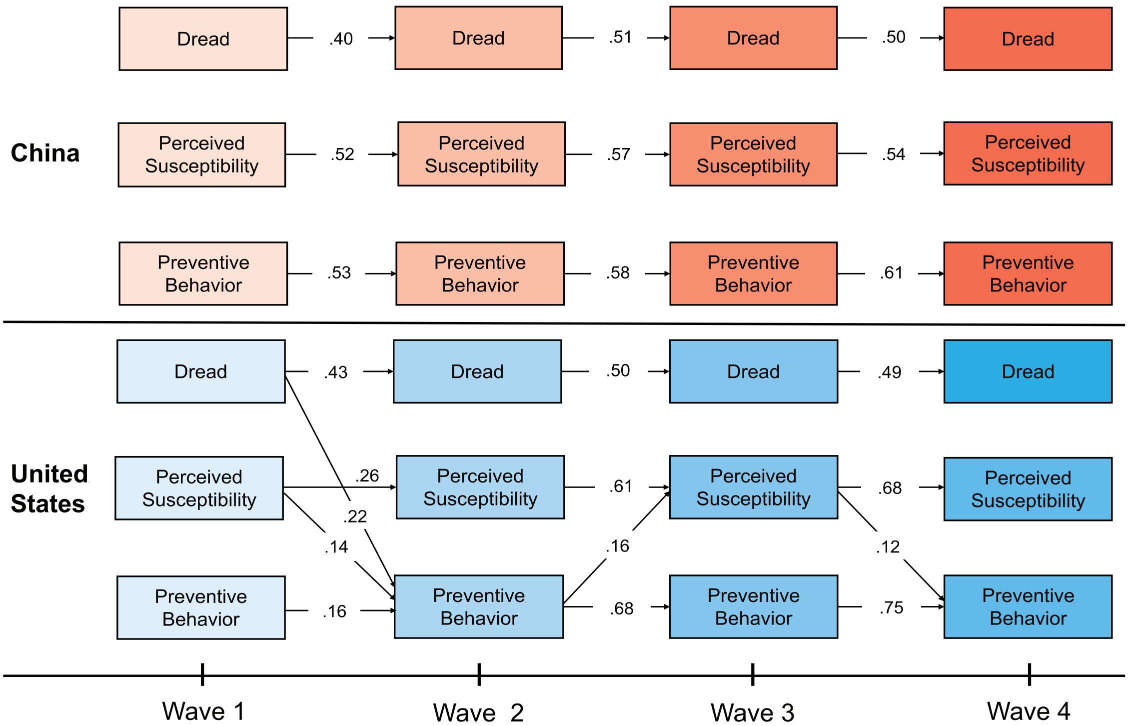
We started by examining the relationship between each risk perception measure and preventive behavior separately in a series of two-variable CLPM models. In both countries, there were barely any statistically significant within- or cross-wave relationships between perception of unknown risk and preventive behavior, consistent with results of the correlation analyses. In light of these results, we tested a three-variable CLPM model that included two risk perception measures (perceived susceptibility and perception of dread risk) and preventive behavior, and considered all possible within-wave and cross-wave relationships between each perception measure and preventive behavior (see Figure 7).[5]

For Chinese participants, none of the cross-wave paths were statistically significant; thus, the perception-motivates-behavior, behavior-amplifies-perception, and behavior-attenuates-perception hypotheses (see Figure 1) were all rejected. The results for U.S. participants, however, are more complex. First, none of the coefficients of the behavior-to-perception paths was negatively valued; thus, the behavior-attenuates-perception hypothesis was rejected. Second, there was an intricate, *zig-zag-zig* relationship between perceived susceptibility and preventive behavior: The cross-wave path from Wave 1 to Wave 2 supported the perception-motivates-behavior hypothesis; the path from Wave 2 to Wave 3 supported the behavior-amplifies-perception hypothesis; and the path from Wave 3 to Wave 4 again supported the perception-motivates-behavior hypothesis. These results indicate that risk perception could indeed motivate preventive behavior among U.S. participants; however, as the pandemic persisted, the ratcheting up of one's own and others' preventive behaviors (e.g., more mask wearing) might have also been interpreted as a signal of an unsafe environment, which in turn amplified individuals' risk perception.

[5] We also tested a four-variable model that included perception of unknown risk in each country. The results confirmed that perception of unknown risk was barely associated with preventive behavior in either China or the United States. Results of the four-variable models and all the two-variable models can be found in the online supplemental materials.

Figure 7

Results of a Three-Variable Cross-Lagged Panel Model (CLPM) in Each Country



Note. Age, gender, and education level were controlled for in samples of both countries, and political affiliation was controlled for additionally in the U.S. sample. Arrows indicate either autoregressive effects (for the same variable between two waves) or cross-lagged effects (for one variable predicting another one over time). Values in the arrows are standardized coefficients; only effects with $p < .01$ are shown. Model fits are: χ^2 (33) = 277.23, $p < .001$; CFI = .90; RMSEA = .11; SRMR = .06 for the Chinese sample, and χ^2 (33) = 105.30, $p < .001$; CFI = .95; RMSEA = .10; SRMR = .05 for the U.S. sample. See the online article for the color version of this figure.

Finally, the cross-wave path from perception of dread risk to preventive behavior between Wave 1 and Wave 2 was significant. Therefore, the motivating effect of risk perception, including both perception of dread risk and perceived susceptibility, on preventive behavior appears to be most pronounced at the early pandemic stage.

Discussion

Many health campaigns are designed to amplify people's perceptions of risks such as AIDS (Agha, 2003); smoking (Romer & Jamieson, 2001); and stroke (Marx et al., 2009). The common rationale is that this amplification will boost people's willingness to adopt preventive behaviors, thus diminishing the risks. However, the success of this pathway to encourage preventive behavior depends on the validity of the perception-motivates-behavior hypothesis—that is, the proposition that higher risk perception will lead to more preventive behavior. Because most studies that have examined the perception–behavior link were cross-sectional and did not consider the potential influence of factors such as culture and regulatory framework, the evidence for this hypothesis and its generalizability is severely limited.

Our longitudinal study spans the first year of the COVID-19 pandemic, during which people's risk perceptions and engagement in preventive behaviors changed, sometimes dramatically, as the pandemic evolved. This was a unique opportunity to examine thoroughly the presumed perception–behavior link. We found that whereas risk perception was barely related to preventive behavior in the Chinese sample, the two were intricately and not unidirectionally associated in the U.S. sample: Perception motivated preventive behavior in the early stage of the pandemic, followed by an amplifying effect of behavior on perception as the pandemic persisted, after which perception again motivated behavior as the situation worsened (see Figure 7).

The distinct patterns of results in China and the United States highlight the importance of cultural and social factors in understanding and promoting preventive behaviors to counteract health risks. The Chinese government adopted strict policies once COVID-19 broke out, locking down whole cities and closely monitoring individuals' preventive behaviors (He et al., 2020). This strict control likely led to the establishment of unambiguous norms. Coupled with a collectivistic culture that encourages conformity to social norms, there was little room for individual risk perceptions to influence preventive behaviors. In contrast, the much less forceful imposition of preventive behaviors in the United States, coupled with a highly individualistic culture, gave citizens more freedom to decide for themselves how to behave, leaving ample room for individuals' perceptions and feelings to influence their behaviors.

For the most part, theories of health behavior have been formulated and tested in Western cultures, where personal agency is deemed a critical factor in human–environment interactions and individuals are assumed to have significant behavioral autonomy. Yet this type of culture is far from universal (Markus & Kitayama, 1991). In Eastern and collectivistic cultures, such as China and Japan, personal agency is understood more in conjunction with the actions of others, and following rules and conforming to the majority can be perceived as acts enabling instead of debilitating agency (Markus et al., 2006). Therefore, a more general theory of health behavior should go beyond individual factors such as perceived susceptibility and emotions, offering an account of how social, regulatory, and cultural factors may also affect health behavior.

Our findings also suggest that in the absence of heavy-handed regulatory interventions (as in China), campaigns to encourage preventive behavior in the face of a highly dynamic risk should be implemented early, when people's risk perception is still in its formative stage. Results in the U.S. sample suggest that risk perception at the prepandemic stage—in terms of both perceived susceptibility and perception of dread risk—motivated preventive behavior when the pandemic broke out. However, this impact unraveled as the pandemic dragged on: Preventive behavior became less susceptible to influences other than previous behaviors, and in turn started to amplify risk perception (see Figure 7). This pattern may emerge in other health issues as well. For instance, young people with a higher risk perception of smoking were found to be less likely to take up smoking as they got older, and their risk perception remained high over time; in contrast, those who started with a lower risk perception were more likely to smoke, and their risk perception remained low (Romer & Jamieson, 2001). Therefore, early interventions can both help promote preventive behaviors and reinforce risk perceptions, potentially making preventive behaviors more sustainable.

A significant contribution of our study is that it describes how risk perception and preventive behavior have evolved throughout an ongoing pandemic. For participants in both countries, the levels of perceived unknown risk and dread risk—the two higher order characteristics of risk perception identified in psychometric analyses of risks (e.g., Slovic, 1987)—remained fairly stable over the period of our study, despite the sometimes drastic changes in infection statistics. News about the availability of effective vaccinations against COVID-19 was widely reported prior to our last wave of data collection. Even this medical breakthrough did not reduce the perceived dread risk and unknown risk in Chinese participants or the perceived dread risk in U.S. participants, and only slightly reduced the perceived unknown risk in U.S. participants (Figures 4 and 5). These results are consistent with past findings that perceptions of unknown risk and dread risk can depart substantially from objective measures of risk, such as incidence and death rates (e.g., Slovic, 1987). The unique contribution of our study is that it tracked both perceptions dynamically, recording how they resonated with or deviated from the dynamic changes in the risk itself.

Participants' perceived susceptibility to COVID-19 changed more substantially over time and was to some extent synchronized with the pandemic's development in each country. That said, as the pandemic advanced aggressively in the United States from April through the end of 2020, U.S. participants' perceived susceptibility, as well as their overall engagement in preventive behaviors, remained largely unchanged (see Figure 4). Why? One possible explanation is habituation. People can become habituated to a stimulus after repeated exposure (Blumstein, 2016). Much as an animal trainer becomes less fearful of a lion after days of close contact, our U.S. participants may have grown accustomed to COVID-19, becoming insensitive to the soaring infection numbers. One condition for such habituation, however, is a lack of direct harmful experience. Previous research has shown that when learning by sampling from their own experiences, people tend to underestimate the probabilities of small-chance events because they rarely experience them (e.g., Hertwig & Wuff, 2021). Indeed, in light of the still-low infection rate in the United States in absolute terms, most of our participants were unlikely to have had the personal experience of being infected. Therefore, this condition for habituation is likely to have been met. In addition to habituation, factors such as risk framing (Borah, 2011), motivated reasoning (Kahan, 2013), and selective information exposure (Metzger et al., 2020) may also have contributed to the observed pattern of results in the U.S. participants.

In conclusion, we conducted a four-wave longitudinal study to examine the relationship between risk perception and preventive behavior during the COVID-19 pandemic. We found that the link between perception and behavior is complex, and that it is subject to the influence of various factors, including culture, policy, and stage of the pandemic. Interventions designed to increase engagement in preventive behaviors by amplifying risk perceptions can still work, but our results suggest that they need to be administered during the early stage of a dynamic health hazard, when risk perception is still in its formative stage. In order to predict the effectiveness of such interventions, it is also indispensable to consider them in conjunction with government regulations as well as the cultural and social norms of the targeted population.

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