



This postprint was originally published as:

Li, Y., Luan, S., Li, Y., & Hertwig, R. (2021). Changing emotions in the COVID-19 pandemic: A four-wave longitudinal study in the United States and China. *Social Science & Medicine*, 285, Article 114222.  
<https://doi.org/10.1016/j.socscimed.2021.114222>

Supplementary material to this article is available via [MPG.PuRe](#).

#### Nutzungsbedingungen:

Dieser Text wird unter einer Deposit-Lizenz (Keine Weiterverbreitung - keine Bearbeitung) zur Verfügung gestellt. Gewährt wird ein nicht exklusives, nicht übertragbares, persönliches und beschränktes Recht auf Nutzung dieses Dokuments. Dieses Dokument ist ausschließlich für den persönlichen, nicht-kommerziellen Gebrauch bestimmt. Auf sämtlichen Kopien dieses Dokuments müssen alle Urheberrechtshinweise und sonstigen Hinweise auf gesetzlichen Schutz beibehalten werden. Sie dürfen dieses Dokument nicht in irgendeiner Weise abändern, noch dürfen Sie dieses Dokument für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, aufführen, vertreiben oder anderweitig nutzen. Mit der Verwendung dieses Dokuments erkennen Sie die Nutzungsbedingungen an.

#### Terms of use:

This document is made available under Deposit Licence (No Redistribution - no modifications). We grant a non-exclusive, nontransferable, individual and limited right to using this document. This document is solely intended for your personal, non-commercial use. All of the copies of this documents must retain all copyright information and other information regarding legal protection. You are not allowed to alter this document in any way, to copy it for public or commercial purposes, to exhibit the document in public, to perform, distribute or otherwise use the document in public. By using this particular document, you accept the above-stated conditions of use.

#### Provided by:

Max Planck Institute for Human Development - Library and Research Information  
[library@mpib-berlin.mpg.de](mailto:library@mpib-berlin.mpg.de)

This paper was published by Elsevier as:

Li, Y., Luan, S., Li, Y., & Hertwig, R. (2021). Changing emotions in the COVID-19 pandemic: A four-wave longitudinal study in the United States and China. *Social Science & Medicine*, 285, Article 114222. <https://doi.org/10.1016/j.socscimed.2021.114222>

# Changing emotions in the COVID-19 pandemic: A four-wave longitudinal study in the United States and China<sup>1</sup>

Ying Li <sup>c</sup>, Shenghua Luan <sup>a,b,\*</sup>, Yugang Li <sup>a</sup>, Ralph Hertwig <sup>c</sup>

<sup>a</sup> CAS Key Laboratory for Behavioral Science, Chinese Academy of Sciences, China

<sup>b</sup> Department of Psychology, University of the Chinese Academy of Sciences, China

<sup>c</sup> Centre for Adaptive Rationality, Max Planck Institute for Human Development, Germany

---

## Abstract

**Rationale:** Tracking the trajectory of people's emotional and behavioral reactions to the COVID-19 pandemic sheds light on how people cope with the emerging crisis, evaluates the impact of emotional reactions on preventive behaviors, and provides insights into how preventive behaviors can be encouraged and maintained in the long term.

**Objective:** We addressed two related questions: How did emotions change across various stages of the COVID-19 pandemic, and to what extent were preventive behaviors predicted by emotional reactions and information acquisition?

**Methods:** We conducted a four-wave longitudinal study in the United States and China across four stages of the pandemic: prepandemic, onset of viral outbreak, ongoing risk, and contained risk. We measured emotions, life satisfaction, preventive behaviors, acquisition of COVID-19 related information, and risk perceptions. We used the Emotional Recall Task (ERT) to investigate people's emotions. By allowing people to describe their emotional experience in their own words, the ERT evaluates each individual based on emotions relevant to their personal experience, making it more suitable for a wider range of contexts and social groups.

**Results:** Boredom, anxiety, fear, and worry were common emotional reactions to the pandemic as it emerged. Surprisingly, participants' emotional experience did not mirror infection and death rates: Instead of negative emotions growing as the virus spread, emotions soon reverted back to normality. This pattern held regardless of whether the viral spread was contained. Consequently, people's preventive behaviors were predicted by fear, anxiety, and worry only at the onset of the viral outbreak. In contrast, actively acquiring information and knowledge about COVID-19 had a more enduring effect on the engagement of preventive behaviors in both countries.

**Conclusion:** Our research suggests a possible life cycle of emotional reactions towards a pandemic and highlights the importance of people acquiring information and knowledge about the threat in containing its spread.

---

**Keywords:** Pandemic, Emotion, Preventive behavior, Emotion recall task, Boredom

---

## 1. Introduction

The COVID-19 pandemic has turned people's lives upside down worldwide. Having declared the new coronavirus a public health emergency of international concern on January 30, 2020, the World Health Organization officially declared COVID-19 a pandemic on March 11, 2020 (World Health Organization, 2020a, World Health Organization, 2020b). More than a year later, the virus continued to pose a huge global risk to public health and to disrupt lives on an unprecedented scale. The impacts of the pandemic can be mitigated not only by government policies and regulations, but also by individual emotional and behavioral responses (e.g., actively avoiding social contact out of fear). By examining how people's emotional experience changed over the first year of the pandemic, our study aims to track how the general public reacted to the emerging crisis, to evaluate the consequences of widespread negative emotions on preventive behaviors, and to provide insights into how preventive behaviors can be encouraged and maintained in the long term.

---

<sup>1</sup> This study was approved by both ethical committees at Max Planck Institute for Human Development and at Chinese Academy of Science.

\* Corresponding author. Institute of Psychology, Chinese Academy of Sciences, Lincui Road 16, Beijing, 100101, China.  
E-mail address: [luansh@psych.ac.cn](mailto:luansh@psych.ac.cn) (S. Luan).

### 1.1. Emotions during a pandemic

Studies investigating emotional reactions during the COVID-19 pandemic have revealed complex emotional profiles. Unsurprisingly, most studies have found evidence of widespread fear, anxiety, and worry (e.g., Barari et al., 2020; Kleinberg et al., 2020; S. Li et al., 2020). Ahorsu et al. (2020) developed the Fear of COVID-19 Scale to capture fear specific to the context of the pandemic and to identify potential points of intervention for education and prevention programs. Other negative emotions identified as common during the pandemic include stress (Barari et al., 2020; S. Li et al., 2020; Emery et al., 2021), depression (S. Li et al., 2020), anger (Lwin et al., 2020; Stella et al., 2020), and boredom (Barari et al., 2020). Positive emotions such as trust and hope have also been observed (Stella et al., 2020).

Most empirical studies on emotional reactions to the pandemic are cross-sectional in design; longitudinal studies that track the dynamics of emotional responses across different stages of the pandemic are scarce. Yet the public's emotional experience can be expected to reflect changing conditions as the pandemic unfolds, mirroring external factors such as infection rates and government policies. Discrepancies between studies conducted at different stages of the pandemic may simply reflect how emotional reactions changed as the pandemic evolved. This may be why some studies have reported a substantially increased risk to public mental health during the pandemic (Goodwin et al., 2021; Pierce et al., 2020), while others have found little decrease in reported emotions and life satisfaction (Zacher and Rudolph, 2021).

Furthermore, the emotions researchers identify as prevailing often depend on the affective scale they select for their study. Almost all self-report affect scales take a checklist approach: Respondents are provided with a predetermined checklist of emotion words and are required to evaluate their emotional experience using the items provided. This approach makes two assumptions: (1) the checklist covers the full range of emotions for people of all social and cultural groups, and (2) participants are able to describe their emotional experience using the words provided.

However, as Y. Li et al. (2020) pointed out, these assumptions often do not hold. For example, the Positive Affect and Negative Affect Schedule (PANAS; Watson et al., 1988), arguably the most frequently used emotion scale, does not include any low-arousal words (such as *bored*, *tired* and *calm*), even though arousal is one of the two primary dimensions of emotion ((Russell, 1980)). Accordingly, the PANAS will not pick up low-arousal emotions that may characterize daily life in a pandemic. Indeed, with the exception of a few studies that either intentionally examined boredom (e.g., Barari et al., 2020; DiGiovanni et al., 2004) or employed an open-ended approach (e.g., Stella et al., 2020), most emotion research conducted during pandemics has failed to identify boredom as a prevailing emotion.

### 1.2. Subjective well-being during a pandemic

Judging one's subjective well-being involves retrospectively evaluating one's life. People often use pleasantness of emotional experience to inform their judgments of well-being (Larsen, 1989), leading to observed correlations between well-being and emotion experience (Y. Li et al., 2020). For example, Y. Li et al. (2020) measured emotion and subjective well-being in an American sample using a variety of popular scales and found that the correlations (Pearson's *r*) between an emotion scale and a well-being scale range between 0.60 and 0.70. However, emotion is not the only source of information people use to evaluate their life. Kahneman and Riis (2005) proposed that the belief that ongoing negative emotions are temporary and will be compensated in the future alleviates the impact of negative emotions on subjective well-being. Suh et al. (1998), meanwhile, found that social approval is important to how people in collectivistic cultures evaluate their own well-being.

Very few studies have tracked subjective well-being across various stages of the COVID-19 pandemic. Most longitudinal studies surveying well-being compared well-being in the early pandemic stage with prepandemic well-being, and the findings are mixed. For example, Kivi et al. (2020) found that despite an increased experience of pandemic-related negative emotions, older Swedish adults reported stable life satisfaction; Recchi et al. (2020) found improved well-being amongst the vast majority of French people who had not been infected by the virus; and Zacher and Rudolph (2021) reported that the well-being of German participants remained stable between December 2019 and March 2020, but decreased slightly from March to May 2020.

With a year-long four-wave longitudinal design, our study is well-positioned to provide a more complete picture of the impact of the pandemic on subjective well-being. We expect that people's evaluations of their well-being should be relatively stable and resilient to the emerging crisis, and therefore that the pandemic should have a weaker impact on subjective well-being than on emotional experience.

### 1.3. Negative emotions and preventive behaviors

Dread of infection tends to trigger negative emotional responses. Such responses can be adaptive because they often motivate people to adopt preventive behaviors in order to alleviate the negative emotions. Previous research on health behavior has shown that feeling fear or anxiety can either reduce engagement in risky behaviors, such as alcohol consumption (Kaplow et al., 2001) and aggression (Patrick et al., 2009), or promote preventive behaviors, such as cancer screening (Decruyenaere et al., 2000) and H1N1 vaccination (M. Li et al., 2012; van der Weerd et al., 2011). Most studies that investigated whether emotional reactions to the COVID-19 pandemic motivate preventive behaviors focused on fear alone or with its co-occurring emotions (e.g., anxiety and worry). They found that fear accounts for individual differences in preventive behaviors to varying extents (e.g., Harper et al., 2020; Pakpour and Griffiths, 2020).

That said, negative emotions do not always prompt preventive behaviors. For example, DiGiovanni et al. (2004) found that boredom was the main reason for breaking quarantine rules during the 2003 SARS outbreak in Toronto, Canada. Concerns that boredom could be the culprit behind violations of preventive behavioral code have also been raised by academics and policy makers during the COVID-19 pandemic (e.g., Harvey, 2020; Martarelli and Wolff, 2020).

When examining the role of negative emotions in preventive behaviors, it is therefore important to analyze discrete negative emotions separately rather than grouping them together under a general term such as emotional distress. This is because emotions, even experienced with similar valences, can differ from each other in terms of cause and function, and consequently may motivate distinct or opposing behaviors. For example, fear and anxiety are likely to result from perceived risk of infection and may motivate preventive behaviors to reduce the risk, while boredom is more likely caused by prolonged social isolation and may reduce motivation to engage in preventive behaviors.

### 1.4. Information acquisition and preventive behaviors

Living in prolonged fear and anxiety is costly to well-being. As the pandemic continues, negative emotions may fade away, along with the preventive behaviors they motivate. However, preventive behaviors can also be prompted through information acquisition. Instead of instinctively avoiding danger out of fear, people may engage in preventive behavior as a result of being well-informed of the situation and being able to identify why these behaviors are necessary. Indeed, while a variety of factors have been identified to explain individual differences in health behavior, including demographics, personality, social influence, emotion, and cognitive factors (Adler and Matthews, 1994), it is cognitive factors—for instance, beliefs and attitudes—that appear to mediate other factors' impacts on health behavior (Conner and Norman, 1998). Research on the COVID-19 pandemic also suggests the importance of cognitive factors: Preventive behavior has been found to be

associated with perceived risk (e.g., Y. Li et al., 2021; Jose et al., 2021; Yıldırım et al., 2021), conspiracy beliefs (Romer and Jamieson, 2020), deliberate moral reasoning (Oosterhoff and Palmer, 2020; Pfattheicher et al., 2020), exposure to misinformation (Lee et al., 2020), and belief in the effectiveness of preventive behaviors (Clark et al., 2020).

A key element underlying all these cognitive factors is information acquisition, which empowers people to exercise their own agency and make informed decisions. Interventions that enlist human cognition (“boosting”; Hertwig and Grüne-Yanoff, 2017) may have a stronger and more enduring influence on behavior compared to interventions that modify aspects of the choice architecture to subtly direct people’s intuitive responses (“nudging”; Thaler and Sunstein, 2009). Graphic warning labels on cigarettes, for instance, are meant to nudge people into quitting smoking or never taking it up in the first place, by invoking strong negative emotions toward smoking. One question, however, is whether preventive behavior is more persistent and causes less reactance when motivated by information acquisition than by temporarily strong but transient emotions. Due to a lack of longitudinal studies, the extent to which informed cognition and emotional reactions predict preventive behaviors during a pandemic remains unclear.

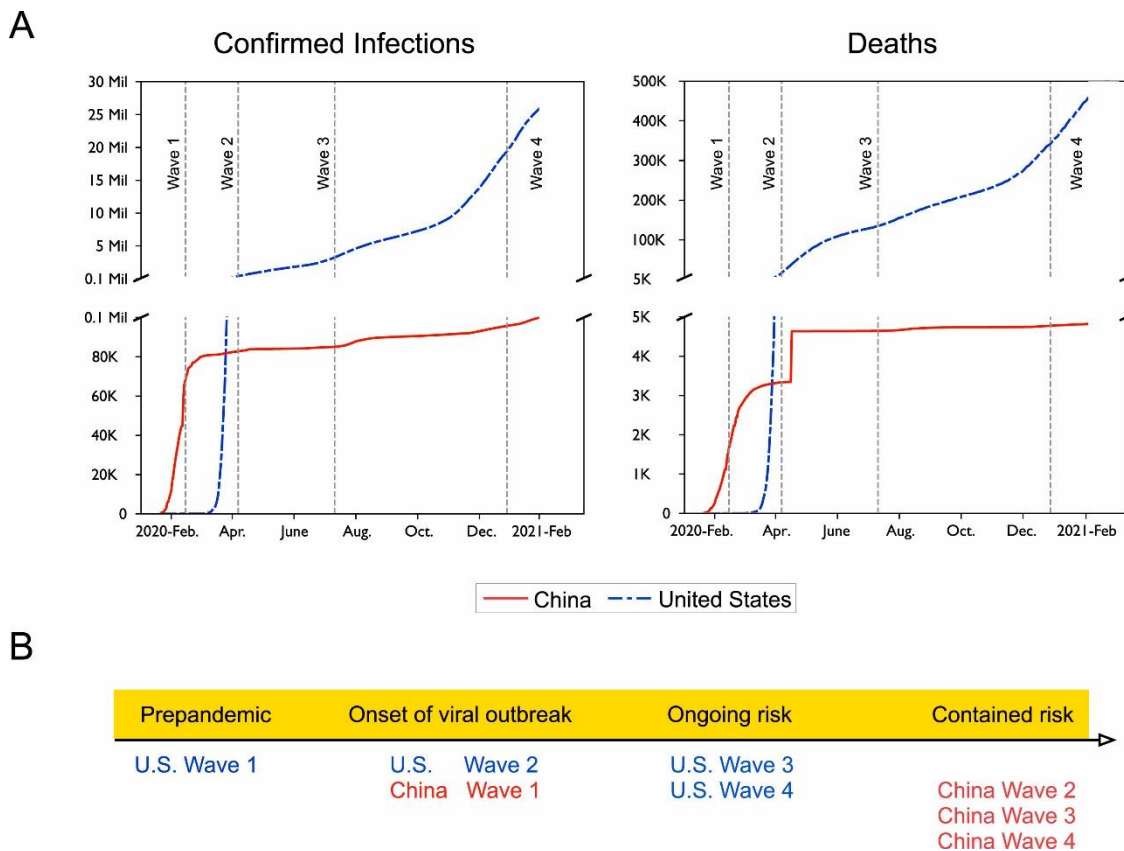
In the present study, we investigate two questions: How did emotions change across various stages of the COVID-19 pandemic, and to what extent were preventive behaviors predicted by emotional reactions and information acquisition? We took an exploratory approach to the first question without a priori expectation. Based on prior research on behavioral intervention and health behavior, we expected that compared to emotional experience, intake of information related to COVID-19 may have a larger and more enduring effect on preventive behavior. Due to their cross-sectional design and reliance on emotion checklists that may not be suitable for the context of a pandemic, previous studies are limited in their ability to examine the full range of emotions and their behavioral impact throughout a pandemic. To address these limitations, we used the Emotional Recall Task (ERT; Y. Li et al., 2020), an open-ended affect scale that allows people to use their own words to describe their emotional experience, and conducted a four-wave longitudinal study that spanned the first year of the COVID-19 pandemic (February 2020 to January 2021). Because the ERT evaluates each individual based on emotions relevant to their idiosyncratic experience, it is more suitable for a wider range of contexts and social groups.

## 2. Methods

### 2.1. Study design

We used a four-wave survey design to track people’s emotions as the COVID-19 pandemic unfolded, and to examine the extent to which preventive behaviors were predicted by emotional reactions and information acquisition. We administered the survey simultaneously to participants living in the United States and China (Fig. 1A). The first wave of data collection took place February 13–17, 2020, when China was experiencing the full force of the pandemic but only 15 cases of infection had been reported in the United States. The spread of the virus was subsequently largely contained in China, but took off exponentially in the United States. We collected the second wave of data on April 5–9, 2020, the third on July 9–13, 2020, and the fourth on December 22, 2020–January 8, 2021, when vaccinations for the coronavirus were starting to become available to the public in both countries.

In China, there was little increase in the numbers of infection cases and deaths between Wave 1 and Wave 4, with the exception of a one-off revision of the numbers of deaths in early April. In the United States, the number of infections increased dramatically, from around 300,000 in



**Fig. 1.** (A) Accumulated confirmed COVID-19 infections and deaths caused by COVID-19 in the United States and China from January 22, 2020 to February 1, 2021. (B) Mapping between the four waves of data collection and the four stages of the pandemic. Data retrieved from <https://data-humdata.org/dataset/novel-coronavirus-2019-ncov-cases>

Wave 2 to around 19 million in Wave 4. Our four waves thus cover four stages of the pandemic (Fig. 1B): pre-pandemic (United States: Wave 1), onset of viral outbreak (United States: Wave 2, China: Wave 1), ongoing risk (United States: Waves 3 and 4), and contained risk (China: Waves 2, 3, and 4).

## 2.2. Participants

The U.S. sample was recruited through Amazon Mechanical Turk. The Chinese sample was recruited through advertisements on WeChat (a social media platform) and by a professional survey company (LangHe Tech). For Waves 1–3, we aimed to have 1000 participants from the United States and 2000 from China in each wave. Anticipating that a proportion of respondents would fail our quality checks (see Appendix Section 1), we intentionally oversampled. For Wave 4, we only targeted participants who had completed Waves 1–3; thus, those who completed Wave 4 completed all four waves of our survey. Table 1 shows the numbers of participants who responded in each wave (total sample size) and who provided qualified responses (valid sample), as well as the gender and age distributions in each valid sample. Because all questions in our survey were forced-response questions, there were no missing data in our datasets, with one exception: In Wave 1, a few questions were mistakenly not set to forced-response, leading to missing values for seven participants. We excluded these participants from subsequent analyses.

## 2.3. Measures

Participants were asked to report their feelings, thoughts, perceptions, and behaviors in the week before the survey. The key variables of relevance to the present study are introduced below. A full list of survey questions can be found at: <https://osf.io/834qs/>.

### 2.3.1. Emotional experience

The ERT (Y. Li et al., 2020) used in our study asked participants to freely choose any five words to describe their emotional experience over the past week. We limited the number of words to five because Y. Li et al. (2020) showed that increasing the reported number of emotions beyond five provided little improvement in predicting related constructs such as depression, anxiety, and measures of well-being. We elicited emotions in general rather than emotions specifically related to COVID-19 in order to avoid evoking responses based on participants' knowledge of the disease (e.g., "COVID-19 is killing people, so I should report 'scared' even though I felt perfectly safe").

After describing their emotional experience during the past week, participants rated how frequently they had experienced each emotion and how pleasant it had been (valence). We computed the general affective state as the average valence score of the five emotion words, weighted by experienced frequency. This score compressed respondents' complex emotional experience onto a single dimension of valence

(unpleasant–pleasant), thus permitting comparison across individuals. In addition, we asked participants to rate the extent to which each reported emotion was related to COVID-19.

We used the ERT to measure emotion instead of affect scales with a checklist approach for the following reasons. First, the ERT has been shown to have good convergent validity and test-retest reliability (Y. Li et al., 2020). Second, it does not rely on the problematic assumption that a list of emotions developed on American populations is suitable for capturing the emotions of people with vastly different cultural backgrounds (see Jackson et al., 2019 for cultural variations in emotion semantics). Third, by letting participants evaluate the pleasantness of the emotions they list, the ERT makes it possible for the same words to take on different meanings for different individuals (e.g., thrill could feel more positive to younger adults than to older adults). Lastly, the ERT does not directly compare emotions across individuals due to the

**Table 1**  
Survey sampling information.

Country	Wave	Total sample	Valid sample		
			Sample size	Female %	Mean age in years ( <i>SD</i> )
United States	1	1168	797	41.8	39.6 (11.2)
	2	1180	926	43.3	39.5 (11.4)
	3	1104	879	43.1	39.1 (11.4)
	4 (overlap)	247	236	48.3	43.3 (10.7)
China	1	2343	1864	40.8	34.8 (12.2)
	2	2433	2032	39.6	38.9 (13.0)
	3	2443	2238	40.5	39.2 (14.1)
	4 (overlap)	715	665	47.4	32.6 (12.0)

complexity and high-dimensional nature of emotions (Tugade et al., 2004); instead, the ERT compares people on valence, the primary and universal dimension of emotion (Russell, 1980). As a personalized affect scale with an emotion word list that varies according to each individual's idiosyncratic experience, the ERT is able to get the valence score from a more relevant sample of emotions than other popular emotion scales with a predetermined emotion checklist (e.g., the PANAS).

### 2.3.2. Life satisfaction

We measured subjective well-being by one question that asked participants to report how satisfied they were with their life in general on a 7-point response scale. Cheung and Lucas (2014) show that such single-item measures of life satisfaction are highly correlated with longer life-satisfaction scales (Diener et al., 1985).

### 2.3.3. Preventive behaviors

Participants were asked how frequently they had engaged in each of four preventive behaviors in the week before the survey: social distancing, avoiding meeting people, handwashing, and wearing a mask. We did not administer the behavioral questions in Wave 1; instead, in Wave 2 we asked participants to recall their behaviors in mid-February 2020 (time of Wave 1).

### 2.3.4. Information acquisition

We examined how people accessed information about COVID-19. Specifically, we asked participants to report the amount of time they spent on acquiring COVID-19-related news per day (information-acquisition behavior), to indicate the valence of the COVID-19-related information to which they were exposed (emotional valence of acquired information), and to self-report their knowledge about COVID-19 (outcome of processed information).

### 2.3.5. Risk perception

We asked participants to assess the probability that they would contract COVID-19 in a multiple-choice question that included the following options: below 1%, 1–5%, 5–10%, 10–20%, 20–50%, 50–70%, 70–90%, and above 90%.

### 2.3.6. Demographic and personal data

Last, we collected demographic information, including age, gender, education, political affiliation (U.S. samples only), and whether participants personally knew anyone infected by COVID-19. We did not ask for political affiliation in the Chinese samples because the country has been governed by the same party since 1949.

## 2.4. Overview of analysis

We first explored how emotions and well-being changed across the COVID-19 pandemic using three analyses: We summarized emotion words people produced in the ERT with a network analysis in each wave,

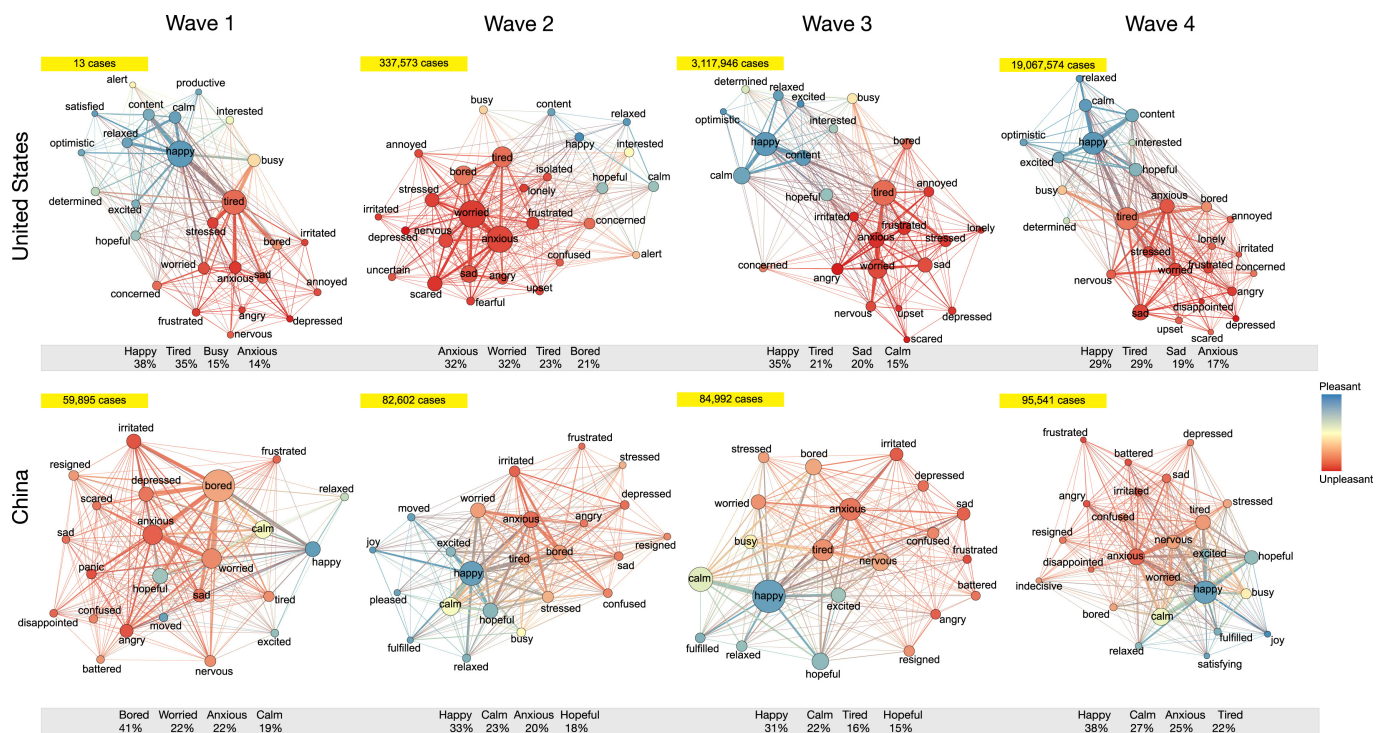


examined the trends of emotion valence, life satisfaction, and perceived risk as the pandemic evolved, and identified discrete emotions specific to life during the pandemic. We then examined whether acquisition of pandemic-related information had a greater and more enduring effect on preventive behavior than did emotions. Furthermore, leveraging the within-individual longitudinal design, we tested possible causal relationships among emotion, information acquisition, and preventive behavior with cross-lagged panel models. All results presented below are based on the overlap samples (i.e., participants taking part and providing qualified responses in all four waves). The within-individual analysis provides greater statistical power and removes concerns that observed changes may arise from changes in the demographics across different waves. In addition, we have also conducted analysis on the whole sample where within-person repeated measure is not required; the results are highly consistent with those based on the overlap samples (see details in Appendix Section 3). Study data, analysis code, and supplementary materials can be found at <https://osf.io/6x2bv/>.

### 3. Results

#### 3.1. Emotional profiles

Across the four waves, the 236 American participants produced 646 unique emotion words in the ERT, and the 665 Chinese participants produced 1948 unique emotion words (see Appendix Table S1 for a frequency table of recalled emotion words). Most words are not present in traditional emotion scales. For example, the 20 emotions on the PANAS scale (Watson et al., 1988) represent only 10.5% of all words produced by our American participants and 7.1% of all words produced by our Chinese participants (computed by taking the sum of number of times PANAS words were mentioned in the ERT divided by number of all emotion words produced in the ERT). Western or individualistic cultures value and experience high-arousal emotions (e.g., excited and enthusiastic) more than low-arousal emotions (e.g., calm and relaxed), whereas the opposite holds for Eastern or collectivistic cultures (see Lim, 2016 for a review). The smaller coverage of PANAS emotion words in the Chinese sample may reflect the fact that the PANAS was initially developed on American samples and does not include any low-arousal emotions. We used the ERT data to map out the emotional profiles of the Chinese and the American participants across the four waves (Fig. 2). The ERT data are represented in an experiential co-occurrence network, where nodes represent emotions reported in the ERT and the edges connecting nodes are weighted by the number of participants who reported experiencing both emotions. The network exhibits a clear structure, with emotions more likely to be experienced together clustered in the same neighborhood. The U.S. Wave 1 network shows the public's emotional profile in the pre-pandemic stage. It comprises two balanced clusters of emotions: positive emotions centered around *happy* and negative emotions centered around *tired*. At the onset of the viral outbreak (Wave 2 in the United States, Wave 1 in China), the patterns of emotion in both countries were similar—both were dominated by negative emotions such as *bored*, *anxious*, and *worried*. Feelings of boredom were more common in the Chinese sample (reported by 41% of participants) than in the U.S. sample (21%), likely reflecting the psychological impact of the strict quarantine and lockdown policies in China. In addition, whereas there was a clear divide between positive and negative emotions in the U.S. sample, in the Chinese sample two positive emotions appeared around the negative emotion cluster: *hopeful* and *moved*. The relevance ratings of these two emotions (i.e., the extent to which each emotion was caused by the pandemic) showed that they were closely associated with the pandemic (*hopeful*: 5.9 out of 7; *moved*: 6.5 out of 7). In the Chinese sample, the emotional profiles in Waves 2–4 were



**Fig. 2.** Responses in the ERT (Emotional Recall Task) visualized as experiential co-occurrence networks. Each node represents an emotion word reported in the ERT. Node size is proportional to number of people reporting the given emotion. Color denotes the valence of emotion on a continuous scale from negative (red) to positive (blue). The edges connecting two nodes are weighted by the proportion of participants who reported both emotions. To ensure readability, we present only those emotions reported by at least 4% of a sample in each wave. The four most frequently reported emotions are shown below each network, along with the proportions of participants reporting them. Cumulative numbers of infections on the first date of data collection in each wave are shown in the yellow boxes. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

both similar to each other and markedly different from that in Wave 1. A cluster of positive emotions began to emerge in Wave 2, when the risk of infection was well contained in China, and the two most frequently reported emotions changed from *bored* and *worried* to *happy* and *calm*. With relatively few newly diagnosed cases and domestic travel restrictions being lifted in most places, the circumstances in China had improved markedly from April 2020, accompanied by a brightening of public emotions.

In contrast, the United States experienced an exponential increase in infections that put citizens at even greater risk in Waves 3 and 4. One might therefore expect the emotional states of U.S. participants to continue to be dominated by negative emotions such as worry, anxiety, or anger—possibly to an even greater extent than in Wave 2. However, we found that in Waves 3 and 4, the U.S. sample's emotional profiles had largely reverted back to what we had observed in Wave 1: a large cluster of positive emotions.

### 3.2. Changes in emotional valence, life satisfaction, and perceived personal risk

We integrated participants' emotional experience into a single affective valence score by calculating the mean valence of reported emotions, weighted by experienced frequency, and examined how this score changed over the waves (Fig. 3A). This procedure allowed us to project participants' complex and high-dimensional emotional experience (as visualized in Fig. 1) onto a single dimension of valence ranging from *very unpleasant* to *very pleasant*. Although this measure discards much of the detailed information assessed by the ERT, it facilitates interindividual and intergroup comparisons along a primary and universal dimension of emotion (Barrett, 2006).

In each country, a repeated-measures ANOVA showed that time (wave) had a small but significant effect on emotional valence:  $F(3, 1964) = 28.5, p < 0.001, \eta^2 = 0.02$  for China; and  $F(3, 669) = 40.0, p < 0.001, \eta^2 = 0.06$  for the United States. Note that  $\eta^2$  is a measure of effect size, and Cohen (1988) suggested that  $\eta^2$  between 0.02 and 0.13 represents a small effect, between 0.13 and 0.26 a median effect, and larger than 0.26 a large effect. We also conducted six pairwise  $t$ -tests to make post-hoc comparisons between ERT scores in any two waves. We found that in the Chinese sample, affective states improved between Waves 1 and 2 ( $t[664] = 8.89$ , Bonferroni-adjusted  $p < 0.001$ ), and remained stable from Wave 2 to Wave 4 ( $t[664] = -2.04$ , Bonferroni-adjusted  $p = 0.25$ ). In the U.S. sample, in contrast, affective states became much more negative at the outbreak of the pandemic from Wave 1 to Wave 2 ( $t[233] = -9.60$ , Bonferroni-adjusted  $p < 0.001$ ), but recovered substantially from Wave 2 to Wave 4 ( $t[233] = 7.94$ , Bonferroni-adjusted  $p < 0.001$ ) despite the soaring infection numbers.

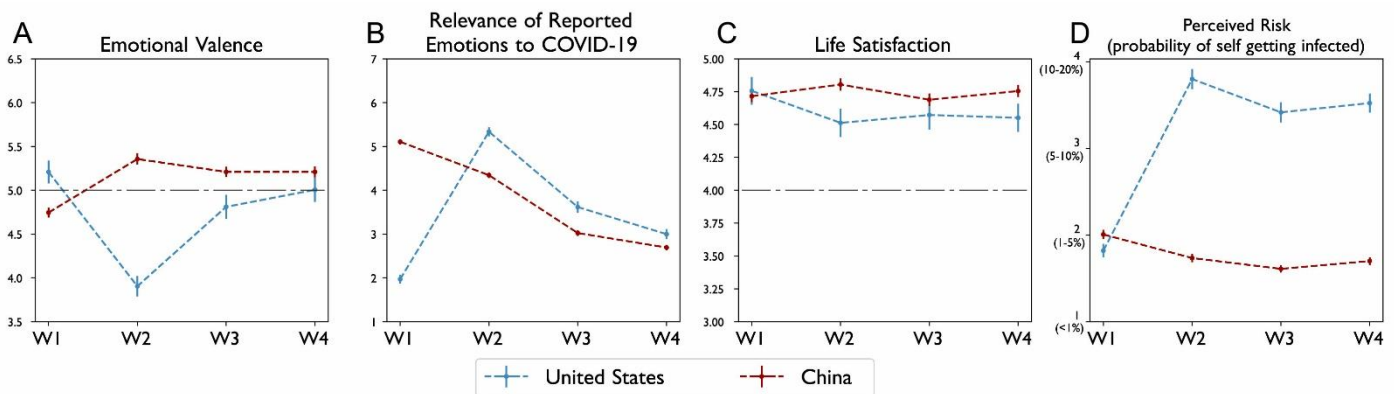
The improved emotional experience after the outbreak of the pandemic may be explained by the decreasing influence of the pandemic on participants' emotions as it persisted. Fig. 3B shows how the self-reported relevance of participants' emotions to the COVID-19 pandemic (i.e., the extent to which the emotions were caused by the pandemic) changed across the four waves. In both countries, participants' emotions were affected greatly by the pandemic at the onset of the viral outbreak (Wave 1 in China, Wave 2 in the United States). After that, however, the pandemic's influence declined steadily, regardless of whether the viral spread was contained (China) or accelerating (United States).

Recall that emotional experience is closely related to, yet distinct from, subjective well-being (life satisfaction). Whereas emotional experience reflects people's mental states in a specific time and context (here, during the pandemic), life satisfaction represents how people think about their lives in general (Kahneman and Riis, 2005). Changes in life satisfaction can therefore differ from changes in the daily emotions that people experience over time. We found that compared to emotional valence, life satisfaction fluctuated with a much smaller magnitude across the four waves (Fig. 3C): Repeated-measures ANOVA tests showed that although time also had a statistically significant effect on life satisfaction in both countries, the effect size ( $\eta^2$ ) is far below 0.02, Cohen's recommended threshold for small effects (1988):  $F[3, 1932] = 3.4, p = 0.02, \eta^2 = 0.001$  for China; and  $F[3, 669] = 6.5, p < 0.001, \eta^2 = 0.003$  for the United States. This suggests that life satisfaction is much more resilient than emotion to the impact of the pandemic.

Lastly, given that laypeople's risk perceptions are better predicted by their emotional reactions to a risk situation than by mortality statistics (Slovic, 1987), it is unsurprising that changes in personal risk perception (i.e., estimated probability of getting infected oneself) do not mirror changes in infection or mortality rates (Fig. 3D). Repeated-measures ANOVA tests showed a significant difference in perceived risks across the four waves:  $F[3, 1865] = 27.0, p < 0.001, \eta^2 = 0.015$  for the Chinese sample, and  $F[3, 624] = 137.7, p < 0.001, \eta^2 = 0.186$  for the American sample. Post-hoc comparisons showed that the difference is explained mostly by changes from Wave 1 to Wave 2: Chinese participants' risk perception decreased significantly from Wave 1 to Wave 2, then remained stable, while American participants' risk perception increased dramatically from Wave 1 to Wave 2, then remained stable (see Appendix Section 4 for detailed results of the statistical tests).

### 3.3. Prototypical emotions in the pandemic

We next identified the emotions most specific to COVID-19—in other words, emotions reported more frequently when the pandemic had the largest impact on emotional experience and less frequently in other times. COVID-19-specific emotions can be identified by looking for emotions whose frequencies changed the most between the onset of viral



**Fig. 3.** Changes in emotional valence, relevance of reported emotions to the COVID-19 pandemic, life satisfaction, and perceived risk across the four waves of data collection. Values shown in the figure are sample means, and error bars represent standard errors of the means. Displayed ranges for emotional valence and life satisfaction were chosen so that the center, indicated by a gray horizontal line, reflects the middle point of the respective scale (emotional valence: 1–9; life satisfaction: 1–7). W: Wave.

outbreak and the time when the pandemic has the least emotional impact (United States: Wave 1, China: Wave 4; Fig. 3B). Fig. 4 shows the 10 emotions most specific to COVID-19 and how their frequencies changed from Wave 1 to Wave 4. The frequencies were adjusted to Wave 1, so the figure shows Chinese participants' emotions gradually recovering from the onset of viral outbreak (Wave 1) and American participants' emotions being hit by the viral outbreak (Wave 2) then recovering.

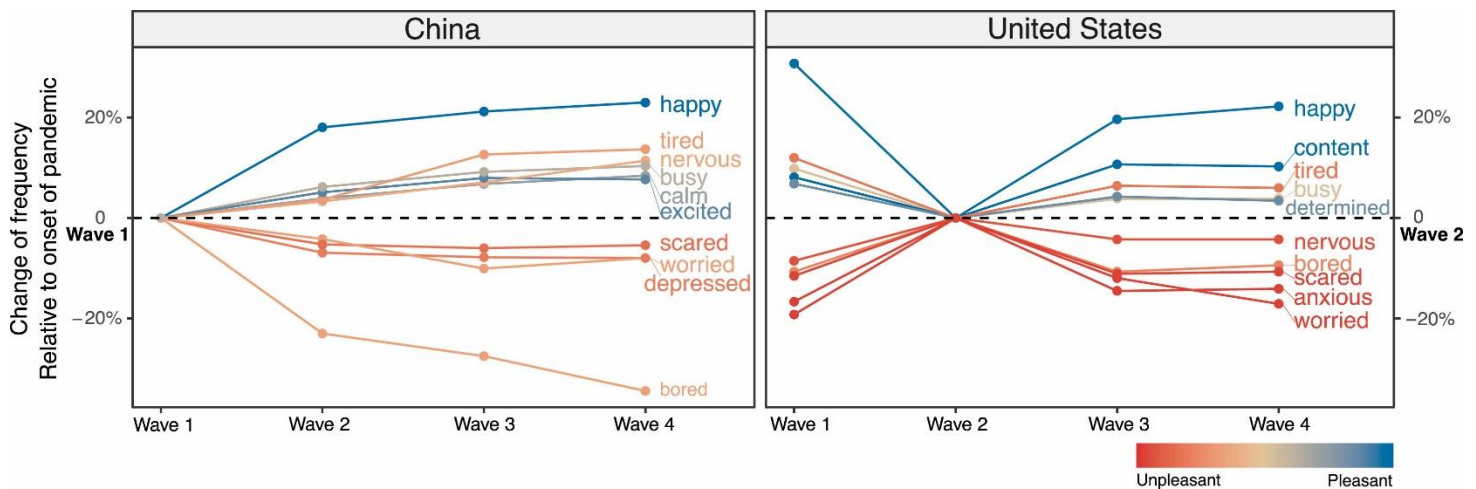
The profiles of pandemic-specific emotions at the time of national viral outbreak are highly similar in the two countries: We found increased frequencies of negative emotions such as *scared*, *worried*, and *anxious*, accompanied by decreased frequencies in positive emotions such as *happy* and *excited*. The pandemic also made participants in both countries less *busy* and *tired*, but more *bored*. After the initial outbreak, the emotions of American participants in Waves 3 and 4 had almost, though not completely, returned to their prepandemic state (Wave 1). In China, participants' emotional profile was largely stable from Wave 2 onward, with the exceptions of the continuously decreasing feeling of *bored* and the rising feelings of *tired* and *busy*. Furthermore, from Wave 2 on, there was barely any change in the proportion of Chinese participants who reported feeling of *scared*, arguably the most typical response to a pandemic, implying that fear levels had returned to normality in China. Similarly, in Waves 3 and 4, the proportions of U.S. participants reporting feeling of *scared* also reverted to the level observed in Wave 1, before the hit of the pandemic.

### 3.4. What predicts preventive behavior: emotion or information acquisition?

Fear and worry have been shown to motivate preventive behaviors during pandemics (Harper et al., 2020; M. Li et al., 2012; van der Weerd et al., 2011). But what happens when these emotions fade away? Fig. 5 shows that—similar to the changes in emotions observed over the course of the pandemic—changes in preventive behaviors did not fully mirror the severity of the pandemic, particularly in the United States. Chinese participants' engagement in preventive behaviors generally decreased across the four waves. This makes sense, given that relatively few new cases had been reported in China since Wave 1. American participants, on the other hand, increased their engagement in preventive behaviors from Wave 1 to Wave 2, but then reduced them from Wave 2 to Wave 4 despite the rising risk of infection. The one exception is wearing a mask, which continued to increase over time, likely because a gradually larger number of U.S. states, counties, and cities had mandated mask-wearing in public.

However, preventive behaviors may be motivated by factors other than public policy. One such factor is people's cognitive understanding of potential risks. Equipping decision makers with knowledge about potential risks has been found to improve their choices in areas such as financial planning, food choices, and medical decisions (Hertwig and Grüne-Yanoff, 2017). In a series of regression models (Table 2), we tested how a collection of variables, including acquisition of COVID-19-related information, affected engagement in preventive behaviors. In each wave, we regressed the averaged response of the four preventive behaviors onto three emotions: fear/anxiety, worry, and boredom (the valence of ERT was not included, because it was highly correlated with fear/anxiety and worry), and three aspects of pandemic-related knowledge and information: information acquisition (time spent on COVID-10-related news per day), emotional valence of acquired information (self-rated valence of the information acquired), and two possible outcomes of processed information (self-rated knowledge about COVID-19 and perceived personal risk). We selected fear/anxiety, worry, and boredom based on our analysis of emotional reactions most specific to the pandemic (Fig. 4). Fear and anxiety were grouped together because they are highly related: "Anxiety can be defined as unresolved fear" when avoiding danger is not possible (Epstein, 1972, p. 311). We also controlled for demographic factors, including age, gender, education, whether anyone in the participant's social network had been infected, and political affiliation (United States only).

In contrast, time spent on acquiring pandemic-related information predicted more engagement in preventive behaviors from Wave 2 to Wave 4 in both countries. In terms of the two measures on the outcomes



**Fig. 4.** Changes in reported frequencies of COVID-19-specific emotions from Wave 1 to Wave 4. The frequency of each emotion word is shown relative to its reported frequency at Wave 1; thus, a value of 10% indicates that compared to Wave 1, the word was reported by an additional 10% of participants. Color denotes the mean valence of an emotion as rated by participants. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



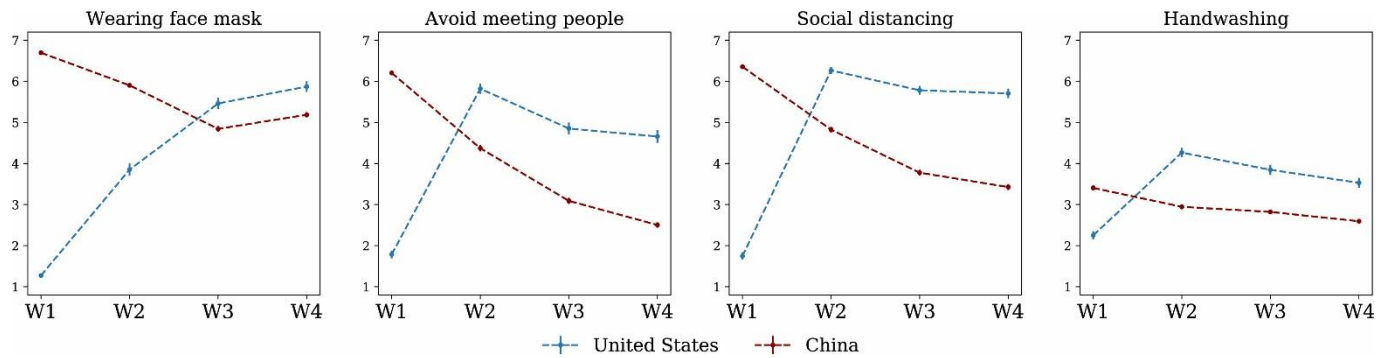


Fig. 5. Mean reported engagement in four preventive behaviors. Error bars represent standard errors of the means. W: Wave.

of information acquisition, self-rated knowledge level about COVID-19 predicted increased preventive behaviors in the Chinese sample across all waves, but not in the U.S. sample, whereas higher perceived personal risk predicted more engagement in preventive behaviors in the U.S. sample, but had no effect in the Chinese sample. The perceived valence of pandemic-related information, meanwhile, had little or no effect on preventive behaviors, suggesting that there is no need to actively evoke negative emotions when informing the public. Lastly, Bruine de Bruin et al.'s finding (2020) that Democrats were more engaged in preventive behaviors than Republicans was replicated. Note that the regression coefficients of political affiliation are fairly large, suggesting that recommendations about health behavior during the COVID-19 pandemic must consider this political reality.

Lastly, we explored the possible causal relationships between emotion and preventive behavior, as well as those between information acquisition and preventive behavior. To this end, we conducted a series of cross-lagged panel model (CLPM) analyses. CLPM is often deemed as the best method to infer causal precedence of one variable over another when experiment manipulation is not possible (Newsom, 2015). It is worth noting that CLPM only informs Granger-causality — that is, past values of  $X_1$  should contain information that helps predict  $X_2$  above and beyond the information contained in past values of  $X_2$  alone — but is not sufficient to prove true causality because it cannot rule out a third factor that accounts for the relationship between  $X_1$  and  $X_2$ . The CLPM results shown in Fig. 6 include all statistically significant within- and cross-wave relationships between two variables, controlled for age, gender, and education level. We also performed CLPM analyses including all three variables. The main results are consistent with those from the two-variable models.

The CLPM analyses show that there were no stable causal relationships between emotional valence and preventive behavior in each country, but there was a fairly consistent one between information acquisition and preventive behavior in both countries: Acquiring more information predicted more engagement in preventive behavior from Wave 1 to Wave 2, but the direction of influence was reversed in the next waves—that is, engaging in preventive behavior predicted more information acquisition in Waves 3 and 4. This complex relationship shows that information acquisition and preventive behavior could reinforce each other, sustaining the positive relationship between the two as the pandemic progresses. In sum, despite some cross-cultural differences, a convergent pattern emerged: Acquiring and processing COVID-19 relevant information had a more enduring effect on engagement in preventive behaviors than did the experience of negative emotions.

#### 4. Discussion

In a four-wave longitudinal study conducted in China and the United States, we tracked changes in people's emotional profiles over the first year of the COVID-19 pandemic and explored how emotion, information acquisition, and other factors predicted preventive behaviors. We found that emotional reactions and preventive behaviors did not always mirror infection and death rates. At the time of initial domestic outbreak of the pandemic, both Chinese and U.S. participants experienced strong negative emotions and actively engaged in preventive behaviors.

Subsequently, however, people from both countries started to revert back to prepandemic states, reporting fewer negative emotions and preventive behaviors (except for mask wearing for U.S. participants, see Figs. 3 and 5). Regression and CLPM analyses suggest that emotion played only a weak and inconsistent role in predicting preventive behaviors, whereas actively acquiring information about COVID-19 had a much more enduring effect (see Table 2 and Fig. 6).

Our results highlight the importance of knowledge and information in containing the spread of the virus: Its effect is more sustainable, and it does not necessarily lead to psychological distress. Reducing the impact of false information is therefore crucial, especially considering that increasing numbers of people now get their news from social media (Newman et al., 2020), where false information spreads faster than truth (Vosoughi et al., 2018). Keeping the public informed is especially important after the initial shock of the outbreak, as negative emotions and their impact on preventive behavior begin to subside.

The dissociation between emotions, preventive behaviors, and infection rates observed in the United States, where the pandemic showed no sign of abating by the end of 2020, could be caused by what Slovic (2007) called "psychic numbing"—a widely observed phenomenon that affective responses to tragedies do not increase proportionally to human mortality. The discrepancy between the urge to protect individual lives and emotional indifference to mass suffering has become embedded in the information landscape that shapes people's understanding of the world: An analysis of around 100,000 news articles and social media posts that mentioned death found that events involving larger numbers of deaths often received less attention and were discussed in less negative and less emotional language (Bhatia et al., 2021). It is possible that, over time, people who learn about the pandemic from news reports become less sensitive to the soaring numbers of COVID-19 deaths and infections and consequently less likely to take actions to protect themselves and others.

Another reason for the dissociation could be that maintaining strong negative emotions over an extended period is simply too costly to well-being. Unpleasant feelings generally motivate actions or thoughts anticipated to avoid those feelings (Epstein, 1994). While the decrease in negative emotions observed in China could be explained by the concurrent decrease in the risk of contracting the virus, the decrease in negative emotions in the United States, where a high level of risk persisted, suggests the importance of individuals' coping strategies. For instance, avoiding fear and anxiety may be achieved by a shift in cognition (e.g., re-evaluating the risk of infection as less dreadful than originally thought) or by engaging in preventive behaviors to increase a sense of self-efficacy and reduce personal risk. These could be the drivers behind the reduction in perceived personal risk in the U.S. sample from

**Table 2**  
Summary of regression models predicting preventive behaviors.

Predictors	United States								China							
	Wave 1		Wave 2		Wave 3		Wave 4		Wave 1		Wave 2		Wave 3		Wave 4	
	Estimates	p	Estimates	p	Estimates	p	Estimates	p	Estimates	p	Estimates	p	Estimates	p	Estimates	p
(Intercept)	0.43	0.06	-0.14	0.53	0.18	0.41	0.31	0.18	-0.26	0.12	-0.22	0.17	-0.34	0.03	0.01	0.94
Fear & anxiety	-0.06	0.37	0.13	0.04	0.01	0.85	0.00	0.96	0.08	0.05	0.00	0.94	-0.01	0.85	-0.05	0.19
Worry	0.02	0.73	0.24	<0.001	0.14	0.03	0.09	0.11	0.07	0.06	0.00	0.99	0.04	0.23	0.02	0.67
Boredom	0.08	0.18	0.04	0.52	0.07	0.27	0.02	0.70	0.07	0.08	-0.01	0.72	-0.03	0.46	-0.08	0.03
Information acquisition	0.13	0.06	0.14	0.02	0.17	<0.01	0.19	<0.01	0.07	0.10	0.18	<0.001	0.22	<0.001	0.22	<0.001
Knowledge about COVID-19	0.11	0.10	0.09	0.15	0.10	0.09	0.08	0.15	0.09	0.02	0.20	<0.001	0.09	0.02	0.13	<0.01
Emotional valence of information	0.04	0.54	-0.06	0.32	-0.09	0.15	-0.02	0.78	0.05	0.26	0.01	0.71	0.12	<0.01	0.04	0.30
Perceived personal risk	0.19	<0.01	0.11	0.07	0.21	<0.01	0.32	<0.001	-0.01	0.71	0.02	0.58	0.01	0.81	0.07	0.06
Age	-0.29	<0.001	-0.03	0.65	-0.02	0.70	0.03	0.62	0.17	<0.01	0.12	<0.01	0.15	<0.01	0.07	0.11
Gender (female)	-0.28	0.03	0.16	0.17	0.06	0.65	0.06	0.63	0.29	<0.01	0.24	<0.01	0.12	0.19	0.23	<0.01
Education	-0.12	0.10	0.06	0.37	-0.01	0.89	-0.04	0.58	0.04	0.44	0.03	0.51	0.09	0.08	-0.03	0.50
Infections in one's social circle (TRUE)	-0.05	0.96	0.34	0.02	0.22	0.08	0.06	0.64	-0.01	0.95	0.12	0.41	0.22	0.13	-0.18	0.17
Political affiliation (Republican)	0.04	0.77	-0.33	0.02	-0.52	<0.001	-0.53	<0.001								
Political affiliation (Independent)	0.03	0.85	-0.32	0.04	-0.42	<0.01	-0.42	<0.01								
Observations	236		236		236		236		665		665		665		665	
Adjusted R-squared	0.17		0.24		0.24		0.27		0.04		0.09		0.10		0.08	

Note: All non-categorical variables are standardized so that their means equal to 0 and standard deviations equal to 1. Categorical variables (i.e., gender, education, infections in one's social circle, and political affiliation) are not standardized.

Wave 2 to Wave 4. Although U.S. participants were more likely to wear masks from Wave 2 on, their compliance with social distancing and avoiding meeting other people declined. This may be attributed to the unusually intense feeling of boredom during the lockdown, which motivated behaviors inconsistent with isolation.

The decline in preventive measures other than wearing a mask may also be the result of risk compensation (e.g., Hedlund, 2000; Peltzman, 1975; Wilde, 1982), a phenomenon in which people respond to a perceived risk reduction brought about by a safety intervention (e.g., wearing a safety belt) by increasing related risk behaviors (e.g., driving faster). Wilde (1982) provided a psychological explanation that he termed "risk homeostasis": People can tolerate a certain amount of risk; thus, if an intervention (e.g., mask wearing) reduces overall perceived risk, they would feel more comfortable taking other risks (e.g., meeting with friends) that would return them to their tolerated risk level. Viewing our results from the perspectives of risk homeostasis and risk compensation, the stable risk perception in the U.S. sample in Waves 3 and 4 (Fig. 3D) may represent a tolerable level of risk within which individuals vary their practice of preventive behaviors. Mask wearing may be seen as a license to exercise less discipline in other behaviors, such as social distancing and meeting in groups.

In addition to the empirical findings, our study also demonstrated the advantages of the ERT in capturing a wide range of emotional experiences in the context of a pandemic. In contrast to affect scales, which depend on a predetermined checklist of emotions, the ERT allows participants to describe their experience in their own words and evaluate their affective states on a personalized basis. This makes it possible for the ERT to identify emotions that may not be experienced as frequently in nonpandemic settings (e.g., boredom and hopefulness) and therefore tend to be neglected by affect scales designed for nonspecific situations (see Figs. 2 and 4).

#### 4.1. Limitations

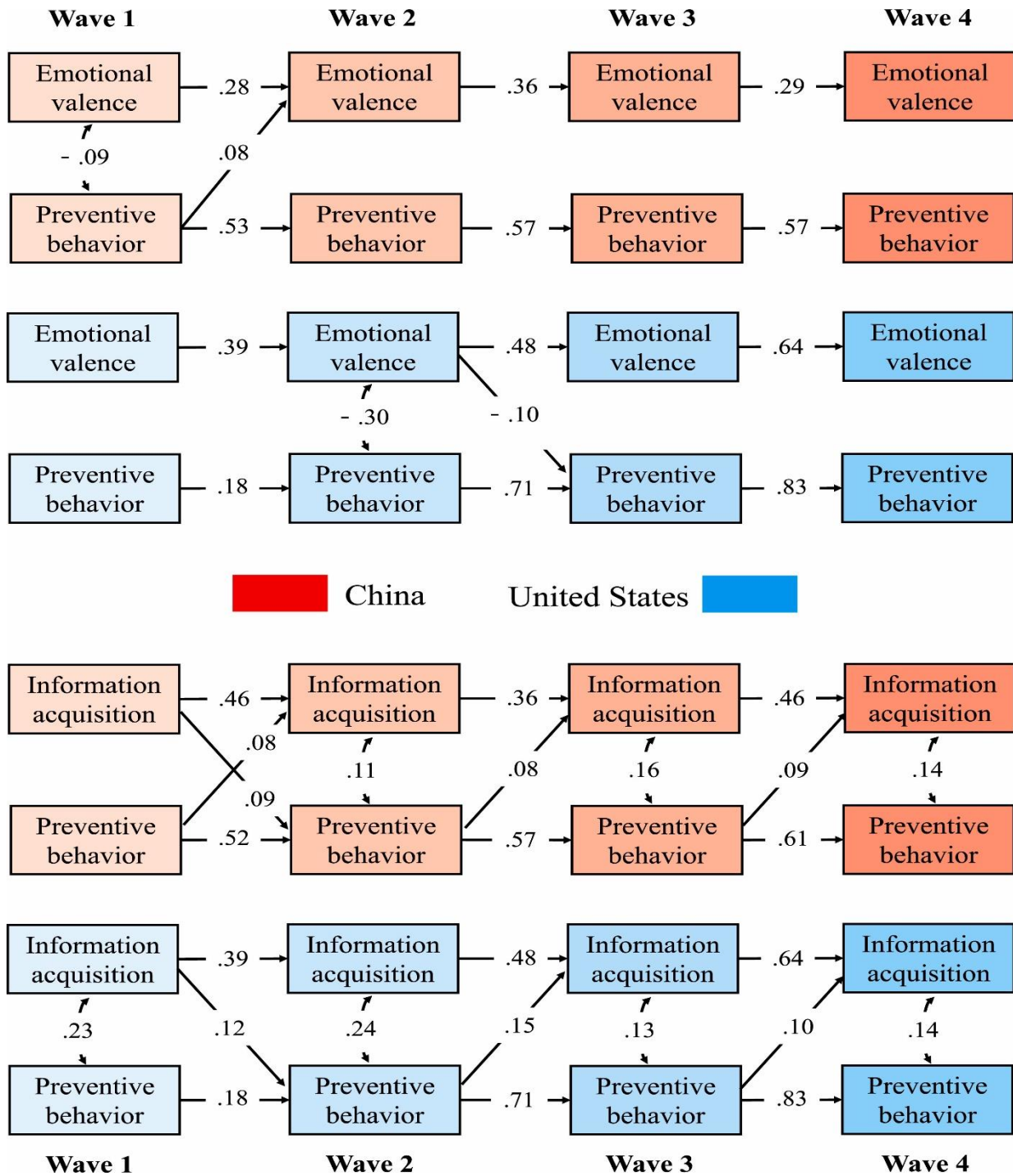
Our goal in this study was to identify a general pattern of changes in emotional and behavioral responses as a pandemic unfolds. However, caution must be taken in generalizing our findings to other social groups. Because our research was conducted online with nonrepresentative samples, we may have systematically excluded groups who had neither the time nor the resources to complete an online survey—for instance, medical practitioners, families of infected patients, people with no Internet access, or undocumented immigrants. These groups may be more susceptible to posttraumatic stress symptoms (e.g. Wu et al., 2009) and would likely experience a different range of emotions and exhibit different behaviors during a pandemic.

#### 5. Conclusion

During the COVID-19 pandemic, people's emotions are not simply mirroring the spread of the virus. Emotional and behavioral responses observed at one point in the pandemic should not be assumed to be generalizable to another. Through four waves of data collection in two countries that cover four stages of the pandemic (prepandemic, onset of viral outbreak, ongoing risk, and contained risk), we tracked the trajectory of people's psychological and behavioral reactions to the pandemic and highlighted the importance of acquiring information and knowledge about the virus in containing its spread. A pandemic of the scale of COVID-19 is rare, yet it is inevitable that further pandemics will follow. Understanding how humans react to the current crisis is an essential step in preparing for the next.

#### Credit author statement

Ying Li, Shenghua Luan: Conceptualization, data collection, analysis, draft preparation, revision. Yugang Li: data collection, analysis. Ralph Hertwig: Conceptualization, draft preparation, revision.



**Fig. 6.** Results of four cross-lagged panel models, all controlled for age, gender, and education level. Single-headed arrows indicate either autoregressive effects for the same variable between two waves or cross-lagged effects for one variable predicting another between adjacent waves, and double-headed arrows indicate correlations between two variables within the same wave. Only statistically significant relationships ( $p < 0.05$ ) are shown in the figure. Model fits from top to bottom:  $\chi^2(12) = 54.86, p < 0.001, CFI = 0.97, RMSEA = 0.07,$  and  $SRMR = 0.04$ ;  $\chi^2(12) = 105.36, p < 0.001, CFI = 0.89, RMSEA = 0.18,$  and  $SRMR = 0.07$ ;  $\chi^2(12) = 75.16, p < 0.001, CFI = 0.96, RMSEA = 0.09,$  and  $SRMR = 0.04$ ; and  $\chi^2(12) = 32.83, p < 0.001, CFI = 0.98, RMSEA = 0.09,$  and  $SRMR = 0.03$ .

#### Declaration of competing interest

There is no competing interest in this study.

#### Acknowledgments

We thank Susannah Goss, Deborah Ain, and Ziyong Lin for their wonderful editing and constructive feedbacks, and Baizhou Wu for his assistance in data collection and participant management.

This research was jointly supported by two research grants from the Chinese Academy of Sciences (Y8CX153 and E1CX0230) and by Max Planck Institute for Human Development.

#### Appendix A. Supplementary data

Supplementary data to this article can be found via [MPG.PuRe](https://www.mpg.de/PuRe).

## References

- Adler, N., Matthews, K., 1994. Health psychology: why do some people get sick and some stay well? *Annu. Rev. Psychol.* 45 (1), 229–259.
- Ahorsu, D.K., Lin, C.-Y., Imani, V., Saffari, M., Griffiths, M.D., Pakpour, A.H., 2020. The Fear of COVID-19 scale: Development and initial validation. *Int. J. Ment. Health Addict.*
- Barari, S., Caria, S., Davola, A., Falco, P., Fetzer, T., Fiorin, S., Hensel, L., Ivchenko, A., Jachimowicz, J., King, G., Kraft-Todd, G., Ledda, A., MacLennan, M., Mutoi, L., Pagani, C., Reutskaja, E., Roth, C., Slepici, F.R., 2020. Evaluating COVID-19 public health messaging in Italy: self-reported compliance and growing mental health concerns. *MedRxiv*.
- Barrett, L.F., 2006. Are emotions natural kinds? *Perspect. Psychol. Sci.* 1 (1), 28–58.
- Bhatia, S., Walasek, L., Slovic, P., Kunreuther, H., 2021. The more who die, the less we care: evidence from natural language analysis of online news articles and social media posts. *Risk Anal.* 41 (1), 179–203.
- Bruine de Bruin, W., Saw, H.-W., Goldman, D.P., 2020. Political polarization in US residents' COVID-19 risk perceptions, policy preferences, and protective behaviors. *J. Risk Uncertain.* 61, 177–194.
- Cheung, F., Lucas, R.E., 2014. Assessing the validity of single-item life satisfaction measures: results from three large samples. *Qual. Life Res.* 23 (10), 2809–2818.
- Clark, C., Davila, A., Regis, M., Kraus, S., 2020. Predictors of COVID-19 voluntary compliance behaviors: an international investigation. *Global Transit.* 2, 76–82.
- Cohen, J., 1988. *Statistical Power Analysis for the Behavioral Sciences*, second ed. Erlbaum.
- Conner, M., Norman, P., 1998. Editorial: social cognition models in health psychology. *Psychol. Health* 13 (2), 179–185.
- Decruyenaere, M., Evers-Kiebooms, G., Welkenhuysen, M., Denayer, L., Claes, E., 2000. Cognitive representations of breast cancer, emotional distress and preventive health behaviour: a theoretical perspective. *Psycho Oncol.* 9 (6), 528–536.
- Diener, E., Emmons, R.A., Larsen, R.J., Griffin, S., 1985. The satisfaction with life scale. *J. Pers. Assess.* 49 (1), 71–75.
- DiGiovanni, C., Conley, J., Chiu, D., Zaborski, J., 2004. Factors influencing compliance with quarantine in Toronto during the 2003 SARS outbreak. *Bio Secur. Bioterrorism Biodefense Strategy, Pract. Sci.* 2 (4), 265–272.
- Emery, R.L., Johnson, S.T., Simone, M., Loth, K.A., Berge, J.M., Neumark-Sztainer, D., 2021. Understanding the impact of the COVID-19 pandemic on stress, mood, and substance use among young adults in the greater Minneapolis-St. Paul area: findings from project EAT. *Soc. Sci. Med.* 276, 113826.
- Epstein, S., 1972. The nature of anxiety with emphasis upon its relationship to expectancy. In: Spielberger, C.D. (Ed.), *Anxiety: Current Trends in Theory and Research*, vol. 2. Academic Press, pp. 291–337.
- Epstein, S., 1994. Integration of the cognitive and the psychodynamic unconscious. *Am. Psychol.* 49 (8), 709–724.
- Goodwin, R., Hou, W.K., Sun, S., Ben-Ezra, M., 2021. Psychological and behavioural responses to covid-19: a China–Britain comparison. *J. Epidemiol. Community Health* 75 (2), 189–192.
- Harper, C.A., Satchell, L.P., Fido, D., Latzman, R.D., 2020. Functional fear predicts public health compliance in the COVID-19 pandemic. *Int. J. Ment. Health Addict.* Advance online publication.
- Harvey, N., 2020. Behavioral fatigue: real phenomenon, naïve construct, or policy contrivance? *Frontiers in Psychology*, 11, Article 589892.
- Hedlund, J., 2000. Risky business: safety regulations, risk compensation, and individual behavior. *Inj. Prev.* 6 (2), 82–89.
- Hertwig, R., Grüne-Yanoff, T., 2017. Nudging and boosting: steering or empowering good decisions. *Perspect. Psychol. Sci.* 12 (6), 973–986.
- Jackson, J.C., Watts, J., Henry, T.R., List, J.-M., Forkel, R., Mucha, P.J., Greenhill, S.J., Gray, R.D., Lindquist, K.A., 2019. Emotion semantics show both cultural variation and universal structure. *Science* 366 (6472), 1517–1522.
- Jose, R., Narendran, M., Bindu, A., Beevi, N., Manju, L., Benny, P.V., 2021. Public perception and preparedness for the pandemic COVID 19: a Health Belief Model approach. *Clin. Epidemiol. Global Health* 9, 41–46.
- Kahneman, D., Riis, J., 2005. Living and thinking about it: two perspectives on life. In: Huppert, F.A., Baylis, N., Keverne, B. (Eds.), *The Science of Well-Being*. Oxford University Press, pp. 285–304.
- Kaplow, J.B., Curran, P.J., Angold, A., Costello, E.J., 2001. The prospective relation between dimensions of anxiety and the initiation of adolescent alcohol use. *J. Clin. Child Psychol.* 30 (3), 316–326.
- Kivi, M., Hansson, I., Bjälkebring, P., 2020. Up and about: older adults' well-being during the COVID-19 pandemic in a Swedish longitudinal study. *J. Gerontol.: Ser. B* 76 (2), e4–e9.
- Kleinberg, B., van der Vegt, I., Mozes, M., 2020. Measuring emotions in the COVID-19 real world worry dataset. *arXiv*.
- Larsen, R.J., 1989. Personality as an affect dispositional system. August. In: Clark, L.A., Watson (Chairs), D. (Eds.), *Emotional Bases of Personality*. Symposium Conducted at the Meeting of the American Psychological Association (New Orleans).
- Lee, J.J., Kang, K.-A., Wang, M.P., Zhao, S.Z., Wong, J.Y.H., O'Connor, S., Yang, S.C., Shin, S., 2020. Associations between COVID-19 misinformation exposure and belief with COVID-19 knowledge and preventive behaviors: cross-sectional online study. *J. Med. Internet Res.* 22 (11), e22205.
- Li, M., Chapman, G.B., Ibusa, Y., Meyers, L.A., Galvani, A., 2012. Who got vaccinated against H1N1 pandemic influenza? a longitudinal study in four US cities. *Psychol. Health* 27 (1), 101–115.
- Li, S., Wang, Y., Xue, J., Zhao, N., Zhu, T., 2020. The impact of COVID-19 epidemic declaration on psychological consequences: a study on active Weibo users. *Int. J. Environ. Res. Publ. Health* 17 (6), 2032.
- Li, Y., Masitah, A., Hills, T.T., 2020. The Emotional Recall Task: juxtaposing recall and recognition-based affect scales. *J. Exp. Psychol. Learn. Mem. Cognit.* 46 (9), 1782–1794.
- Li, Y., Luan, S., Li, Y., Wu, J., Li, W., Hertwig, R., 2021. Does risk perception motivate preventive behavior during a pandemic? A longitudinal study in the United States and China. *Am. Psychol.*
- Lim, N., 2016. Cultural differences in emotion: differences in emotional arousal level between the East and the West. *Integr. Med. Res.* 5 (2), 105–109.
- Lwin, M.O., Lu, J., Sheldenkar, A., Schulz, P.J., Shin, W., Gupta, R., Yang, Y., 2020. Global sentiments surrounding the COVID-19 pandemic on Twitter: analysis of Twitter trends. *JMIR Publ. Health Surveill.* 6 (2), e19447.
- Martarelli, C.S., Wolff, W., 2020. Too bored to bother? Boredom as a potential threat to the efficacy of pandemic containment measures. *Humanit. Soc. Sci. Commun.* 7, 28.
- Newman, N., Fletcher, R., Schulz, A., Andi, S., Nielsen, R.K., 2020. Reuters Institute digital news report 2020. Reuters Institute for the study of journalism.
- Newsom, J.T., 2015. Cross-lagged panel analysis. In: Whitbourne, S.K. (Ed.), *The Encyclopedia of Adulthood and Aging*. Wiley Blackwell.
- Oosterhoff, B., Palmer, C., 2020. Psychological correlates of news monitoring, social distancing, disinfecting, and hoarding behaviors among US adolescents during the COVID-19 pandemic. *PsyArXiv Preprints*.
- Patrick, C.J., Fowles, D.C., Krueger, R.F., 2009. Triarchic conceptualization of psychopathy: developmental origins of disinhibition, boldness, and meanness. *Dev. Psychopathol.* 21 (3), 913–938.
- Peltzman, S., 1975. The effects of automobile safety regulation. *J. Polit. Econ.* 83 (4), 677–725.
- Pfafftheicher, S., Nockur, L., Böhm, R., Sassenrath, C., Petersen, M.B., 2020. The emotional path to action: empathy promotes physical distancing and wearing of face masks during the COVID-19 pandemic. *Psychol. Sci.* 31 (11), 1363–1373.
- Pierce, M., Hope, H., Ford, T., Hatch, S., Hotopf, M., John, A., Kontopantelis, E., Webb, R., Wessely, S., McManus, S., Abel, K.M., 2020. Mental health before and during the COVID-19 pandemic: a longitudinal probability sample survey of the UK population. *Lancet Psychiatr.* 7 (10), 883–892.
- Recchi, E., Ferragina, E., Helmeid, E., Pauly, S., Safi, M., Sauger, N., Schradie, J., 2020. The “eye of the hurricane” paradox: an unexpected and unequal rise of well-being during the Covid-19 lockdown in France. *Res. Soc. Stratif. Mobil.* 68, 100508.
- Romer, D., Jamieson, K.H., 2020. Conspiracy theories as barriers to controlling the spread of COVID-19 in the U.S. *Soc. Sci. Med.* 263, 113356.
- Russell, J.A., 1980. A circumplex model of affect. *J. Pers. Soc. Psychol.* 39 (6), 1161–1178.
- Slovic, P., 1987. Perception of risk. *Science* 236 (4799), 280–285.
- Slovic, P., 2007. “If I look at the mass I will never act”: psychic numbing and genocide. *Judgment Decision Making* 2 (2), 79–95.
- Stella, M., Restocchi, V., De Deyne, S., 2020. #lockdown: network-enhanced emotional profiling at the times of COVID-19. *Big Data Cognit. Comput.* 4 (2), 14.
- Suh, E.M., Diener, E., Oishi, S., Triandis, H., 1998. The shifting basis of life satisfaction judgments across cultures: emotions versus norms. *J. Pers. Soc. Psychol.* 74 (2), 482–493.
- Tugade, M.M., Fredrickson, B.L., Barrett, L.F., 2004. Psychological resilience and positive emotional granularity: examining the benefits of positive emotions on coping and health. *J. Pers.* 72 (6), 1161–1190.
- Thaler, R.H., Sunstein, C.R., 2009. *Nudge: Improving Decisions about Health, Wealth, and Happiness*. Penguin.
- van der Weerd, W., Timmermans, D.R.M., Beaujean, D.J.M.A., Oudhoff, J., van Steenberghe, J.E., 2011. Monitoring the level of government trust, risk perception and intention of the general public to adopt protective measures during the influenza A (H1N1) pandemic in The Netherlands. *BMC Publ. Health* 11 (1), 575.
- Vosoughi, S., Roy, D., Aral, S., 2018. The spread of true and false news online. *Science* 359 (6380), 1146–1151.



- Watson, D., Clark, L.A., Tellegen, A., 1988. Development and validation of brief measures of positive and negative affect: the PANAS scales. *J. Pers. Soc. Psychol.* 54 (6), 1063–1070.
- Wilde, G.J., 1982. The theory of risk homeostasis: implications for safety and health. *Risk Anal.* 2 (4), 209–225.
- World Health Organization, 2020a. Statement on the second meeting of the International Health Regulations (2005) Emergency Committee regarding the outbreak of novel coronavirus (2019-nCoV). January 30.
- World Health Organization, 2020b. WHO Director-General's opening remarks at the media briefing on COVID-19 — 11 March 2020. March 11.
- Wu, P., Fang, Y., Guan, Z., Fan, B., Kong, J., Yao, Z., Liu, X., Fuller, C.J., Susser, E., Lu, J., Hoven, C.W., 2009. The psychological impact of the SARS epidemic on hospital employees in China: exposure, risk perception, and altruistic acceptance of risk. *Can. J. Psychiatr.* 54 (5), 302–311.
- Yıldırım, M., Geçer, E., Akgül, Ö., 2021. The impacts of vulnerability, perceived risk, and fear on preventive behaviours against COVID-19. *Psychol. Health Med.* 26 (1), 35–43.
- Zacher, H., Rudolph, C.W., 2021. Individual differences and changes in subjective wellbeing during the early stages of the COVID-19 pandemic. *Am. Psychol.* 76 (1), 50–62.