Journal of Risk Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rjrr20

Americans' COVID-19 risk perceptions and risk perception predictors changed over time

Branden B. Johnson, Marcus Mayorga & Byungdoo Kim

To cite this article: Branden B. Johnson, Marcus Mayorga & Byungdoo Kim (2023): Americans' COVID-19 risk perceptions and risk perception predictors changed over time, Journal of Risk Research, DOI: 10.1080/13669877.2023.2208149

To link to this article: https://doi.org/10.1080/13669877.2023.2208149

Published online: 11 May 2023.

JOURNAL OF RISK RESEARCH
https://doi.org/10.1080/13669877.2023.2208149

Americans' COVID-19 risk perceptions and risk perception predictors changed over time

Branden B. Johnson[a], Marcus Mayorga[a] and Byungdoo Kim[b]

[a]Decision Research, Springfield, Oregon, USA; [b]Department of Psychology, Norwegian University of Science and Technology, Stavanger, Norway

ABSTRACT

Identifying and understanding risk perceptions—"how bad are the harms" to humans or to what they value that people see as potentially or actually arising from entities or events—has been critical for risk analysis, both for its own sake, and for expected associations between risk perceptions and subsequent outcomes, such as risky or protective behavior, or support for hazard management policies. Cross-sectional surveys have been the dominant method for identifying and understanding risk perceptions, yielding valuable data. However, cross-sectional surveys are unable to probe the dynamics of risk perceptions over time, which is critical to do while living in a dynamically hazardous world and to build causal understandings. Building upon earlier longitudinal panel studies of Americans' Ebola and Zika risk perceptions using multi-level modeling to assess temporal changes in these views and inter-individual factors affecting them, we examined patterns in Americans' COVID-19 risk perceptions in six waves across 14 months. The findings suggest that, in general, risk perceptions increased from February 2020 to April 2021, but with varying trends across different risk perception measures (personal, collective, affective, affect, severity, and duration). Factors in baseline risk perceptions (Wave 1) and inter-individual differences across waves differed even more: baseline ratings were associated with how immediate the threat is (temporal distance) and how likely the threat would affect people like oneself (social distance), and following the United States news about the pandemic. Inter-individual trend differences were shaped most by temporal distance, whether local coronavirus infections were accelerating their upward trend, and subjective knowledge about viral transmission. Associations of subjective knowledge and risk trend with risk perceptions could change signs (e.g. from positive to negative) over time. These findings hold theoretical implications for risk perception dynamics and taxonomies, and research design implications for studying risk perception dynamics and their comparison across hazards.

ARTICLE HISTORY
Received 7 January 2023
Accepted 1 April 2023

KEYWORDS
Risk perception dynamics; risk perception predictors; temporal change; COVID-19

1. Introduction

The study of risk perceptions is a central aspect of risk analysis. Sometimes we just want to know whether people see harm to humans or to what they value arising from a particular

CONTACT Branden B. Johnson branden@decisionresearch.org Decision Research, PO Box 72538, Springfield, OR 97475, USA

event, technology, activity, or organization, or whether these are associated with perceptions of benefits from those sources; sometimes we want to know why they believe this source is so (not) dangerous; sometimes we want to identify and understand risk perceptions so that we can predict or influence whether they are followed by risky or protective behaviour, policy support, or other outcomes relevant to hazard management. Whatever our specific goals, identification and understanding of risk perception is integral to hazard characterization, risk assessment, risk communication, and hazard management. However, most studies of risk perceptions are cross-sectional: that is, whether they use qualitative or quantitative methods of data collection, they tend to capture risk perceptions, and/or the antecedents and outcomes of risk perceptions, at one point in time. Although useful, this yields limited information. Whether and how risk perceptions change over time can affect personal protective behaviour, policy support, and preparedness for future hazards, while cross-sectional survey data constrain causal inferences (cross-sectional experimental data do better on assessing causality, but have their own limitations). Risk analysts acknowledge potential change, but we lack much empirical data. The novel coronavirus causing COVID-19 is only the latest, and not the last, threat for which we should expect changing risk perceptions. It allows us to build upon a small literature about disease risk perceptions over time *via* a longitudinal panel study of Americans' responses from February 2020 to April 2021.

2. Temporal dynamics of risk perceptions

Cross-sectional surveys dominate risk perception research due to cost and other logistical challenges of longitudinal quantitative research, but they cannot fully probe temporal dynamics of risk perceptions. This is despite that some conceptual frameworks, such as the social amplification of risk (Kasperson et al. 1988), deem understanding of those temporal dynamics critical for both risk management and risk communication. Concerns about the scarcity of longitudinal studies are long-standing (Loewenstein and Mather 1990) and persistent (Siegrist 2013), and questions addressed by these few are diverse. One is whether and how risk perceptions change given a single event, such as a disaster or policy change (e.g. Viscusi and O'Connor 1984; Smith and Michaels 1987), particularly for two-wave (in other words, before and after) studies (e.g. Flint 2007; Cutchin et al. 2008; Renner, Schüz, and Sniehotta 2008; Visschers and Siegrist 2013; Trumbo et al. 2014; Champ and Brenkert-Smith 2016; Raude et al. 2019). A second emphasis is the accuracy of risk perception changes: in other words, whether risk perceptions rise and fall with objective risks (e.g. Loewenstein and Mather 1990; Raude et al. 2019). The concept of 'elasticity-prevalence' of prevention decisions (e.g. Geoffard and Philipson 1996) emphasizes that the incidence, prevalence, and mortality of an infectious disease generally vary over time, versus health behaviour research's focus on more stable non-communicable diseases (Loewenstein and Mather 1990). Finally, for temporal relations of risk perceptions with risky or protective behaviour, Brewer et al. (2004) argued that testing behavioural motivation (high risk perceptions drive adoption of protective behaviour) and risk reappraisal (acting protectively reduces risk perceptions) requires a longitudinal panel or experimental studies.

Our focus here combines the accuracy emphasis with testing relationships between risk perceptions and associated factors. The COVID-19 pandemic is not one event, but even if it were conceptualized as such, it is not yet over, so we are assessing these perception-factor associations during its course, rather than in a before-after format. We probed the Brewer et al. (2004) hypotheses separately (Johnson and Kim 2023).

The COVID-19 pandemic in the United States offers several advantages for assessing risk perception trends. First, unlike Ebola (2014–2015) and Zika (2016–2017), which had small and declining caseloads in the mainland United States despite large caseloads in western Africa, and the Caribbean and Latin America, respectively, COVID-19 affected the United States more seriously than most nations (it has the second-highest mortality per 100,000 population in the world). This might shift significant predictors observed in previous longitudinal studies on those United States mainland outbreaks (Mayorga and Johnson 2019; Johnson and Mayorga 2021), or merely amplify prior signals. Second, the elasticity-prevalence model (e.g. Geoffard and Philipson 1996) predicts rising risk perceptions as cases and/or deaths increased in the United States, which had not been testable earlier. Unfortunately, the period of our surveys featured only rising trends, preventing testing this model while COVID-19 cases and deaths decline.

A third advantage is that a sufficiently extended longitudinal COVID-19 panel study can identify alternative patterns in risk perceptions' trends. Designs collecting data from the same subjects at three or more data collection points allow identification of varying *rates* of change in risk perception and in associated beliefs or characteristics across individuals (e.g. in Americans' reactions to the 2008 financial crisis across seven surveys; Burns, Peters, and Slovic 2012). Adaptation or habituation has been framed as hazard experience reducing risk perceptions given current and expected future trends (Loewenstein and Mather 1990), although this does not rule out panics, when risk perception drastically departs from objective risks or overall perception trends, particularly for unfamiliar hazards. Another stance is that increasing familiarity with the disease leads people to progressively underestimate or neglect its hazards (Raude et al. 2019, citing Thompson 2009, on repeated or prolonged exposure to a stimulus reducing cognitive, emotional or behavioural responses). Finally, Loewenstein and Mather (1990) found partial adjustment, defined as rising concern lagging behind rising objective risk. They thought this pattern might reflect delayed communication of objective risk data, expectation of regression to earlier levels, or expectation of measurement error, although they had limited direct public risk perception data. Of the two studies testing such hypotheses, Raude et al. (2019) surveyed French Guineans affected by a chikungunya epidemic in two within-person waves across 3 months. These respondents, before case numbers decreased, exhibited lower perceptions of personal infection risk, but not those who adopted a protective behaviour, consistent with risk habituation. In an eight-wave, 5-year longitudinal design before and after a waste incinerator began operation, Lima (2004) found habituation among closer neighbors, with decreasing risk perceptions over this lengthy and increasingly familiar experience. Longitudinal panel studies of Americans' risk perceptions of Ebola (five waves, five months; Mayorga and Johnson 2019) and Zika (four waves, 9 months; Johnson and Mayorga 2021) found significant mean declines in judgments of national risk, but decreases in personal risk perception only for Zika, with Ebola perceptions unchanging. Americans had similar factors affecting their baseline risk perceptions (e.g. dread, belief that the United States had just missed having a large outbreak and would likely suffer a large outbreak in the next five years, news following), but less convergence in factors associated with the relative speed of downward trends.

3. The present study

Our own longitudinal panel study of Americans' COVID-19 views allowed us to focus on trends in different risk perceptions, factors in baseline risk perceptions, *and* dynamic inter-individual differences in responses over time to this pandemic. First, among perception measures we employed several general risk ratings (Wilson, Zwickle, and Walpole 2019) also present in prior studies: personal (two ratings of risk to self and family tested risk perception-behaviour theses of Brewer et al. 2004, reported in Johnson and Kim 2023), and the United States and global measures labeled 'collective' risk perception in our summary measure here. We included as affective risk perceptions concern about the disease appearing locally (similar to the 'concern' measure recommended by Walpole and Wilson (2021) in their 'affective' risk perception category, which also measured worry and fear), dread (see below), and affect about the coronavirus (good-bad feelings). We also asked about COVID-19's collective severity—perceptions of how long the U.S. pandemic will last, and how many infections and deaths would result—to tap a different geographic scope than the severity category (e.g. how severe would personal impacts be if you suffered them?) in the proposed personal risk perception taxonomy focused 'in the community' (Walpole and Wilson 2021). Excluding severity measures (absent from Wave 1), all risk perception measures were asked in each wave. Given the number and type of our risk perception measures, the number of non-perception questions, and post-launch publication of the final taxonomy (Walpole and Wilson 2021), our results cannot test that taxonomy, which besides affective and severity categories also included exposure (e.g. how likely is the hazard to occur, or how often, in your community?) and susceptibility (e.g. how likely would you suffer consequences if the hazard occurred in your community?). Yet our results offer some considerations for further taxonomizing.

Finally, we focus here on predictor measures asked in every wave to maximize analytic granularity versus earlier longitudinal studies, where most predictors were asked in one wave. In this paper we exclude factors we asked about in just one or a few waves (e.g. culture and political ideology).

We believe our six-wave longitudinal study of U.S. dynamics of COVID-19 risk perceptions provides insights beyond those offered by the dominant cross-sectional COVID-19 social science literature on risk perceptions, but building upon the latter. For example, news following was an important factor in prior Ebola and Zika findings (Mayorga and Johnson 2019; Johnson and Mayorga 2021), and there is a larger literature also pointing to the impact of news media exposure (e.g. Wirz, Mayorga, and Johnson 2021). An enormous literature has concluded that trust in various organizations affects risk perceptions (e.g. see summary in Slovic 1993): in general, if you trust public health and government entities, you will agree with their assessment of 'how bad' a potential hazard is, while if you trust in citizen activist groups, you will agree with *their* (often opposite) assessment. Public health officials and academics expect that people who are well-informed will agree with them on the seriousness of the COVID-19 pandemic (McCormack et al. 2021). Thus, we posit that:

H1. *News following, trust in public health and government entities, and objective knowledge will increase Americans' COVID-19 risk perceptions.*

We also wanted to include factors unused earlier. These included psychological distance (Liberman and Trope 2008) whose spatial, temporal and social (e.g. feeling distance between those affected and people like oneself), and uncertainty dimensions have been posited to reduce engagement, protective or mitigative behaviour, and policy support for such hazards as climate change (e.g. Shwom, Dan, and Dietz 2008; Pahl and Bauer 2013). They also included subjective knowledge, or what people *think* they know, given that studies have found differing associations with risk perception of subjective and objective knowledge (e.g. Zhang and Liu 2015; Shou and Olney 2021).

RQ1. *Are psychological distance and subjective knowledge significantly associated with Americans' COVID-19 risk perceptions?*

We are unaware of any theory that posits how associations between risk perceptions and their potential predictors might or ought to vary across time. Social scientists presume in general that true associations (e.g. that X has a positive effect on Y, but a negative effect on Z) will persist across studies, and that predictors with a small versus medium effect in one study will also tend to have a small versus medium effect in another study. Such persistent effects across studies would presumably also endure across time, as in a longitudinal panel study.

H2. *The positive or negative sign, and size, of associations between risk perceptions and their potential predictors will not change across the six waves of this longitudinal study.*

Unfortunately, the population of longitudinal risk perception studies noted above is too small, and the consistency of predictors tested across studies too low, to support meta-analysis more rigorously testing temporal associations between variables and their magnitude. In other words, the presumptions underlying H2 lack an evidentiary basis. If we were to consider a counter-factual to H2 on changes across time, we would posit these as changes in the slope of the relationship between predictor and risk perception outcome, on two dimensions. We propose here a multi-label classification (Kosemen and Birant 2020). The Association dimension concerns whether the relationship between the two variables *generally* over time—the risk perception measure and the predictor measure—is Positive (higher risk perception with higher predictor levels), Negative (lower risk perception with higher predictor levels), or Shift (changing over time). The Slope dimension concerns changes in slope over survey waves: stable (in other words, similar slope), Up (slope increasing over time: differences in risk perceptions between low and high predictor levels become larger), or Down (slope decreasing over time). For example, coronavirus news following might yield quite different personal risk perceptions at one point in the pandemic, but quite similar personal risk perceptions at another point. So we proposed to probe the stability or liability of these two dimensions across our six waves:

RQ2. *Do predictor-risk perception associations differ in association and slope across risk perception measures and time?*

The lack of theoretical and empirical background on predictor-risk perception associations across time justifies this as a research question, but we can engage in further speculation about which predictors and/or risk perceptions, if any, might exhibit temporally dynamic associations. First, if adaptation (Loewenstein and Mather 1990) or increasing familiarity (Raude et al. 2019) are dominant processes over time, then convergence (lower variance) in risk perceptions over time should be observable. Second, severity risk perceptions may be constrained by feedback from official sources about the incidence of infections and deaths in the country, leading to less change in associations over time than for generic or affective risk perceptions.

H3a. *Temporal shifts in predictor-risk perception, if any, will be due to lessening variance in risk perceptions over time.*

H3b. *Temporal shifts in predictor-risk perception, if any, will be more frequent in generic or affective risk perceptions than in severity risk perceptions.*

4. Methods

4.1. Sampling

A six-wave longitudinal panel study over almost 14 months—February 28–29, 2020 (Wave 1, $n = 2{,}004$), April 27–May 6, 2020 (Wave 2, $n = 1{,}613$), August 5–13, 2020 (Wave 3, $n = 1{,}184$), October 12–22, 2020 (Wave 4, $n = 1{,}026$), January 22–February 11, 2021 (Wave 5, $n = 866$), and March 25–April 13, 2021 (Wave 6, $n = 1{,}019$)—recruited from the Prolific online panel of American adults. All answering a given wave were invited to the next, excluding Wave 6 where everyone answering Wave 1 was invited, allowing us to assess whether respondents staying for five or six waves, our focus here, differed from dropouts. This study was reviewed by the Decision Research Institutional Review Board (IRB); the Human Protections Officer deemed the study exempt, posing minimal risk to participants. Participant consent was obtained through the Decision Research web panel privacy and participation agreement.

Because much happened over this extended period, Table 1 summarizes the overall U.S. context (as an events timeline) for our six survey waves. Below we label waves by number (e.g. W1, W2, etc.).

Table 1. Timeline.

Month	Selected COVID-19 events	Study
Dec 2019	Dec 12: Wuhan cluster; Dec 31: WHO notified of cases of pneumonia of unknown etiology	
Jan 2020	Jan 5: China shares viral genetic sequence; Jan 20: first U.S. lab-confirmed case; Jan 22: WHO confirms human-to-human spread; Jan 31: WHO declares Public Health Emergency of International Concern	
Feb 2020	Feb 11: WHO announces COVID-19 name; Feb 26: CDC announces eventual community spread, warns 'disruption to everyday life may be severe'	W1 Feb 28–29
Mar 2020	Mar 2: 43 cases, 2 deaths; Mar 11: WHO declares COVID-19 pandemic; Mar 13: President Trump declares national emergency; Mar 17: first U.S. human trial of vaccine	
Apr 2020	Apr 3: CDC advises all wear mask outside home; Apr 13: most states report many cases; Apr 27: 981K cases, 55K deaths	W2 Apr 27–May 6
May 2020	May 9: U.S. unemployment 14.7%, worst since Depression	
June 2020		
July 2020		
Aug 2020	Aug 5: 4.7 M, 156 K	W3 Aug 5–13
Sept 2020		
Oct 2020	Oct 2: President Trump tests positive; Oct 12: 7.6 M, 212 K	W4 Oct 12–22
Nov 2020	Nov 3: national election after contentious campaign including COVID-19 pandemic response, with disputed result	
Dec 2020	Dec 11: 1st vaccine U.S.-approved; Dec 14: first vaccination; Dec 18: 2d vaccine approved; Dec 24: 1 + M estimated vaccinated	
Jan 2021	Jan 22: 24.5 M, 409 K	W5 Jan 22–Feb 11
Feb 2021	Feb 27: third (one-shot) vaccine approved	
Mar 2021	Mar 13: U.S. exceeds 100 M vaccinations; Mar 24: 29.8 M, 541K	W6 Mar 25–Apr 13
April 2021	Apr 2: CDC says fully vaccinated can travel in U.S. without COVID-19 test; Apr 21: U.S. exceeds 200 M vaccinations	

Note: U.S. case/death figures are from U.S. Centers for Disease Control and Prevention (CDC) figures posted on its website and recorded by the first author each Monday, Wednesday and Friday (initial frequency; CDC later reported figures every weekday). K = 1000s of cases/deaths; M = millions of cases/deaths/vaccinations. Timeline items otherwise are from CDC (2021). WHO = World Health Organization.

4.2. Measures

Risk perception and predictor items covered in the main text appear in Table 2, collected in all six waves excluding severity measures (W2–6). To simplify reporting of results, two other risk perception measures—affect and duration—are covered in Supporting Information I, although we retain them when visually reporting trends. Age, gender (male as reference category) and education (treated as an ordinal variable) came from all panelists in W1. Time was coded in weeks from the first survey (0, 9, 23, 33, 47 and 56), as averaged from intervals between each respondent's response to each wave; this allowed us an objective measure to control for potential changes in responses due to simply the passage of time, as opposed to actual changes in sentiment or to measurement error. This variable was independent from our risk trend measure (next paragraph), as the intervals would remain the same regardless of which risk trend measure we chose to use.

The predictor 'Risk trend (week)' summarized whether COVID-19 cases in the respondent's county had accelerated (risen faster) or decelerated (risen slower) their increase over the week before the respondent answered that wave, based on Johns Hopkins University case data from GitHub. We favored case over hospitalization or mortality data because the cases better represented both temporal and population impacts (e.g. there were zero U.S. COVID-19 deaths in the week preceding our first wave, with the first official death on the last day of that wave, when we received only one added response). Cases also occurred in people who were highly unlikely to suffer hospitalizations or deaths, because they were younger and/or lacked preexisting health conditions that might exacerbate COVID-19 impacts. These three impact measures were highly correlated as well. People in the same wave in the same county *might* experience a different weekly trend in the later, longer-duration survey waves, although most county trends

Table 2. Measures.

Measure	Scale
Risk perception	
Personal risk (action): 'How much risk does the coronavirus pose to you or your family, if you or your family do anything new to protect yourself against the coronavirus?'	1 *no risk*, 6 *very high risk*
Personal risk (no action): 'How much risk does the coronavirus pose to you or your family, if you or your family don't do anything new to protect yourself against the coronavirus?'	Same
U.S. risk: 'How much risk does the coronavirus pose to the U.S.?'	Same
Global risk: 'How much risk does the coronavirus pose to the world?'	Same
Concern: 'How concerned are you that the coronavirus will spread to where you live?'	1 *not at all concerned*, 6 *extremely concerned*
Dread: 'Where "dread" means to be in terror of, or fear intensely, how much do you dread the coronavirus?'	1 *no dread*, 6 *very high dread*
Infection: 'About how many people in the U.S. do you think will become infected in this outbreak?'	1 *less than 10,000*, 8 *100 million or more*
Death: 'About how many people in the U.S. do you think will die from the coronavirus in this outbreak?'	1 *less than 100*, 7 *10 million or more*
Predictors	
U.S. news following: 'How closely are you following news about the coronavirus infections in the United States [in China/the 50 states plus Washington, D.C.]?'	1 *not at all*, 4 *very closely*
Global news following: 'How closely are you following news about the coronavirus infections in China [Wave 1]/China and other foreign countries?'	Same
Trust in CDC: 'Please rate how much you trust the [U.S. Centers for Disease Control and Prevention] to help protect Americans from the coronavirus'	1 *no trust at all*, 6 *extreme trust*
Trust in WHO: 'Please rate how much you trust the World Health Organization (WHO) to help protect Americans from the coronavirus.'	Same
Trust in President: 'Please rate how much you trust the Office of the President (including staff people) to help protect Americans from the coronavirus.'	Same
Subjective knowledge: 'How much do you know about the coronavirus?'	1 *never heard of it*, 6 *I am an expert on the coronavirus*
Objective knowledge (2 items on viral transmission): 'The coronavirus can be transmitted to other people even when the infected person does not show any symptoms'; 'The coronavirus can be transmitted if an infected person coughs, sneezes, or talks virus-containing droplets directly onto another person'	1 *true*, 5 *false*
Temporal distance (reversed): 'The coronavirus is harming people right now'; 'The coronavirus is an immediate threat'	1 *strongly disagree*, 5 *strongly agree*
Social distance: 'The coronavirus is unlikely to affect my family and friends very much'; 'The coronavirus is unlikely to have a big impact on the average American'	Same

were the same for residents of a given county. Trend slopes were very small numbers, which yielded re-scaling warnings unless standardized and centered.

As for the four facets of psychological distance, we stress temporal and social distance here (one item each removed to improve reliability from $\omega = 0.21–0.42$ across six waves to $\omega = 0.54–0.79$ for temporal, and $\omega = 0.57–0.72$ to $\omega = 0.59–0.71$ for social distance). Spatial distance seemed irrelevant after W1 given rapid coronavirus spread in the United States, and uncertainty was unreliable regardless of item removal ($\omega \leq .49$, except for W4, $\omega = 0.52–0.68$). We use McDonald's omega versus Cronbach's alpha to measure reliability because the latter is sensitive to scale length, over-estimating reliability, and makes often-untrue assumptions about factor structure that obscure multidimensionality, leading statisticians to prefer the former (e.g. Trizano-Hermosilla and Alvarado 2016).

For the Severity factor, given a six-point scale for infection estimates and a seven-point scale for death estimates, we converted the latter to a six-point scale before combining the two scales into an index. This ordinal measure was treated as a continuous variable. Objective knowledge items on viral transmission were recoded to score as 4 if answered true, down to 0 if answered false, to reflect closeness to expert responses (Bostrom et al. 1994).

Table 3. Descriptive Statistics (mean and standard deviation; weighted data).

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Measure	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Risk perceptions						
Personal risk perception (1–6)	2.57 (0.97)	3.26 (1.13)	3.47 (1.20)	3.39 (1.21)	3.61 (1.21)	3.27 (1.21)
Action (1–6)	2.38 (0.98)	2.85 (1.10)	3.05 (1.19)	3.01 (1.20)	3.17 (1.21)	2.84 (1.20)
NO action (1–6)	2.77 (1.08)	3.68 (1.36)	3.89 (1.44)	3.78 (1.45)	4.04 (1.41)	3.69 (1.44)
Affective risk perception (1–6)	2.77 (1.08)	3.51 (1.37)	3.56 (1.44)	3.51 (1.45)	3.65 (1.46)	3.38 (1.47)
Concern (1–6)	2.89 (1.38)	3.86 (1.57)	3.87 (1.64)	3.84 (1.62)	4.05 (1.58)	3.67 (1.63)
Dread (1–6)	2.64 (1.34)	3.16 (1.46)	3.25 (1.55)	3.17 (1.55)	3.25 (1.61)	3.09 (1.61)
Collective risk perception (1–6)	4.01 (1.07)	4.86 (1.10)	4.88 (1.13)	4.76 (1.20)	4.90 (1.21)	4.73 (1.24)
US (1–6)	3.71 (1.15)	4.82 (1.14)	4.92 (1.16)	4.80 (1.23)	4.89 (1.25)	4.68 (1.26)
Global (1–6)	4.30 (1.11)	4.91 (1.12)	4.84 (1.16)	4.73 (1.22)	4.90 (1.20)	4.78 (1.27)
Severity (1–6)		3.89 (0.77)	4.23 (0.82)	4.37 (0.81)	4.41 (0.84)	4.28 (1.01)
Infection (1–6)		3.89 (0.98)	4.26 (1.04)	4.39 (1.02)	4.05 (1.00)	4.35 (1.24)
Death (1–7)		4.46 (0.86)	4.85 (0.89)	5.02 (0.88)	4.98 (1.01)	4.86 (1.13)
Predictors						
US news following (1–4)	2.97 (0.83)	3.38 (0.67)	3.25 (0.77)	3.16 (0.75)	3.24 (0.74)	2.51 (0.82)
Global news following (1–4)	2.78 (0.79)	2.86 (0.77)	2.66 (0.80)	2.58 (0.80)	2.58 (0.79)	2.51 (0.82)
Trust in CDC (1–6)	4.09 (1.24)	3.96 (1.30)	3.74 (1.39)	3.47 (1.38)	3.85 (1.36)	3.87 (1.41)
Trust in WHO (1–6)	3.90 (1.34)	3.51 (1.53)	3.45 (1.54)	3.38 (1.51)	3.48 (1.51)	3.42 (1.54)
Trust in President (1–6)	2.26 (1.49)	2.31 (1.58)	1.99 (1.46)	1.93 (1.60)	3.64 (1.55)	3.47 (1.63)
Subjective knowledge (1–6)	4.01 (0.63)	4.57 (0.55)	4.56 (0.56)	4.55 (0.56)	4.60 (0.58)	4.61 (0.58)
Objective knowledge (0–4)	3.63 (0.58)	3.89 (0.39)	3.90 (0.36)	3.90 (0.32)	3.87 (0.40)	3.88 (0.39)
Temporal distance (1–5)	1.75 (0.71)	1.38 (0.69)	1.37 (0.71)	1.40 (0.75)	1.39 (0.76)	1.43 (0.78)
Social distance (1–5)	3.02 (0.96)	2.19 (1.01)	2.14 (0.99)	2.22 (1.05)	2.09 (0.98)	2.16 (0.99)
Risk trend (week)	2.43E-10 (1.18E-09)	4.63E-06 (1.03E-05)	8.60E-06 (1.81E-05)	5.43E-06 (9.36E-06)	2.95E-05 (6.85E-05)	7.36E-06 (1.06E-05)

4.3. Analysis

For this online convenience sample, post-stratification weights were calculated to represent demographics of the United States adults (based on U.S. Census 2020 Current Population Survey estimates, as final 2020 U.S. Census results were not available during analysis). Raking ratio weights were calculated with 21 iterations based on gender (male, female), age (18–44, 45–64 and 65+), education (≤ high school, some college and ≥ bachelor's degree), and ethnicity (non-Hispanic white, others). Weights ranged from 20.01 (elderly white male and female with high school education) to 0.2 (young white male and female with bachelor's degree). We report only weighted descriptive statistics in Table 3, as these were used in later modeling results, but show raw data in Supporting Information I.

Baseline risk and individual trends in risk judgments were modeled using a multi-level approach for longitudinal data (Goldstein 2011; Siller and Sigman 2008). Data consisted of up to six time points (level-1) nested within people (level-2). Several multi-level models for longitudinal data were built, using R 4.1.1 software and the *lme4* package using maximum-likelihood estimation. Multi-level modeling (MLM) provides several benefits for longitudinal data versus general linear models (e.g. regression or repeated-measures ANOVA). MLM allows between-person linear slopes to vary randomly (to assess whether inter-individual differences affect trend rates) while also testing group trends (did people, on average, increase or decrease judged risk over time?). All predictors except gender were mean-centered and standardized. Two unconditional models were first run to test variability in dependent variables for initial ratings in February 2020 (intercepts) and growth trajectories (slopes) between subjects. As noted earlier, linear time was coded in weeks from the first survey. Then nine level-1 predictors (Table 2) were added to test their associations with baseline judged risk. Next interactions of predictors with time were added (in other words, between individual difference variables and between-person temporal trends). Level 1 variance components denote residual variance of the dependent variable in the main-effects-only model. Level 2 variance denotes variance in second-model intercepts, including interaction terms with time plus variance in second-model time. We also calculated, using the variance-covariance matrix, covariance between the intercept and slope. To account for multiple comparisons in our models, we used the false discovery rate (FDR) procedure to adjust p values of associations (Benjamini and Hochberg 1995), with FDR = 0.05 (Glickman, Rao, and Schultz 2014).

5. Results

5.1. Sample

W1 responses, compared to preliminary 2020 U.S. Census estimates for U.S. adults 18+, came from fewer females (49.6%, $n = 1977$, vs. 51.6% among U.S. adults), more non-Hispanic whites (72.1%, $n = 2001$ versus 62.8%), and people who were substantially younger (3.7% 65+, $n = 1999$, versus 21.7%), and far better educated (54.7% bachelor's degree or better, $n = 2001$, vs. 34.8%). Household income was under $100,000 for 81.6% of the sample, and under $15,000 for 10.8%, compared to 66.5% and 9.4% for the U.S. overall, so the sample was slightly lower-income. Half (49.6%) reported being Democrats, 15.4% Republican, and 34.9% independent or undeclared political partisanship; 61.4% reported slightly to extremely liberal political ideology, 19.6% reported conservative ideology.

We compared risk perception results and demographics of those ever dropping out ($n = 1241$, including 271 returning in W6) to those finishing all surveys ($n = 764$; 38.1%) to assess attrition effects. Most W1 and W6 risk perceptions did not differ significantly between dropouts and the never-left. W6 severity responses (questions unasked in W1) were significantly higher among the never-left than for W6 respondents dropping out after W2 (p = .048); see Supporting Information I on affect. On demographics, gender and political party exhibited no difference in attrition; the college-educated (χ^2 (10, $n = 2001$) = 28.93, $p < .01$) and non-Hispanic whites (χ^2 (5, $n = 2001$) =23.62, $p < .001$) were more likely to answer all surveys; younger people dropped out more often (χ^2 (10, $n = 1999$) = 113.58, $p < .001$). As we value demographic variables here only for their effect on risk perceptions, and the latter exhibited no substantive differences, we conclude there is no substantive attrition effect.

5.2. Item responses

Weighted descriptive statistics across waves appear in Table 3; later modeling used averages for weighted-data summary scales (see raw data, and results for individual affect and duration items, in Supporting Information I). Table 3 values are specific to each wave, whereas modeling includes only those responding to all six waves (or five for severity and duration), so trends may not be identical in descriptive and modeled statistics.

Descriptive statistics show (also see Figure 1) large rises in risk perceptions from W1 (February 2020) to W2 (late April–early May 2020) for the risk perceptions measured over all six waves, a period encompassing official pandemic/emergency declarations, among other events. Collective risk perceptions were substantially higher on the 1–6 scale than personal and affective risk perceptions, which closely tracked each other and remained at the scale midpoint for most of the period. All measures declined slightly in W6 (up to 4 months after vaccination began). We note that standard deviations for all risk perception types did not decline over time, contrary to H3a that temporally dynamic predictor-risk associations, if any, would be due to less variance in risk perceptions over time.

As for predictor trends, U.S. news following remained high until W6's moderate rating; global news following was always lower than U.S. news following until the last wave, peaking in W2. Trust measures exhibited wide disagreement (see high standard deviations); trust in CDC, although above the middle value, fell steadily until the Biden administration began, and trust in the Office of the President was below the middle value until the Trump administration left office; trust in WHO was moderately high and flat over this period. Belief that one is knowledgeable about the coronavirus (subjective knowledge) began above the middle value and jumped to a high plateau since. Objective knowledge about transmission routes began high and its subsequent higher plateau was essentially a knowledge ceiling effect. Temporal and (more sharply) social distance dropped W1-2, then remained flat despite the later geographic spread of COVID-19. Average trends in new cases in a respondent's county the week before that person's response were positive for each wave, but this average could conceal different trends for each respondent.

5.3. Modeling

Modeling results (Tables 4 and 5) in each table's top section ('Initial Rating') are modeling coefficients of predictors in baseline (W1) risk judgments. The middle sections ('Interaction with Time') show whether each variable interacts with time to predict the *slope* in individual-level risk perception ratings. The bottom sections include variable components for each model. Level 1 variance components denote residual variance of the dependent variable in the model;

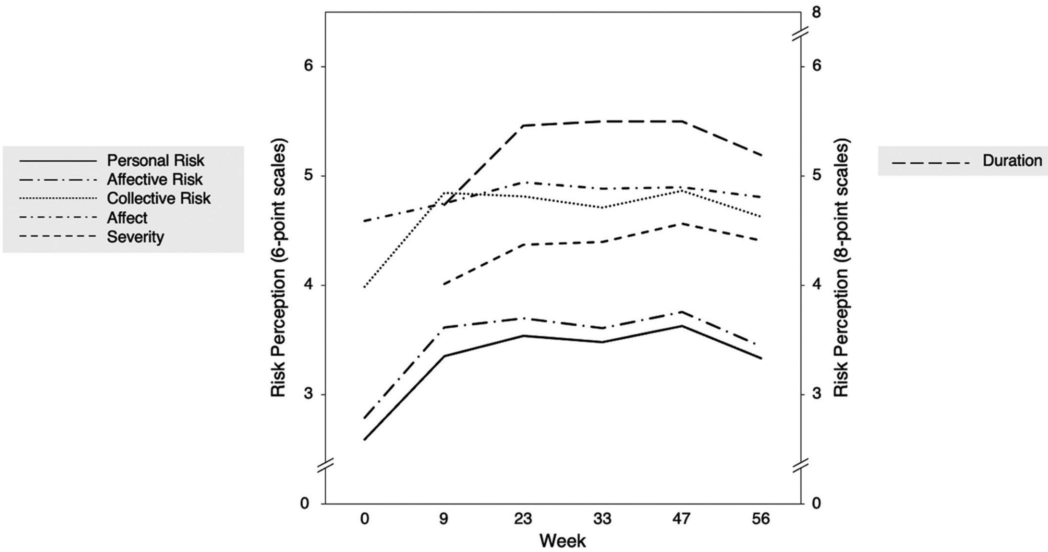

Figure 1. Risk perception patterns over 2020–2021.

Table 4. Risk perception baseline and trend data: three types over six waves.

Variable	Personal risk (Action + No Action)	Affective risk (Concern + Dread)	Collective risk (US + Global)
Initial rating			
(Intercept)	−0.0579 (0.0323)	−0.1136*** (0.0296)	−0.0307 (0.0266)
Time	0.0046*** (0.0007)	0.0020*** (0.0005)	0.0010 (0.0006)
US news following	0.1217*** (0.0147)	0.1376*** (0.0111)	0.1393*** (0.0116)
Global news following	0.0553*** (0.0136)	0.0512*** (0.0102)	0.0103 (0.0107)
Trust in CDC	−0.0577*** (0.0156)	0.0118 (0.0118)	0.0204 (0.0123)
Trust in WHO	0.1121*** (0.0165)	0.0941*** (0.013)	0.1243*** (0.0131)
Trust in President	−0.0274* (0.0109)	−0.0295*** (0.0082)	−0.0438*** (0.0086)
Subjective knowledge	0.0529*** (0.0132)	0.0304** (0.01)	0.0317** (0.0104)
Objective knowledge	−0.015 (0.0138)	0.0152 (0.0105)	0.0466*** (0.0109)
Temporal distance	−0.1328*** (0.0136)	−0.1056*** (0.0103)	−0.2052*** (0.0107)
Social distance	−0.1438*** (0.013)	−0.1194*** (0.0098)	−0.1283*** (0.0102)
Risk trend (week)	0.0113 (0.01)	0.046*** (0.0072)	0.0295*** (0.0077)
Age	0.0033 (0.0159)	0.0042 (0.0167)	0.0153 (0.0137)
Gender (female)	0.0527 (0.038)	0.2732*** (0.0375)	0.1839*** (0.0319)
Education	−0.006 (0.0181)	−0.026 (0.0184)	−0.033* (0.0154)
Interaction with time			
US news following	0.0005 (0.0008)	0.0004 (0.0006)	−0.0003 (0.0006)
Global news following	0.001 (0.0007)	0.0006 (0.0005)	−0.0009 (0.0006)
Trust in CDC	0.0008 (0.0008)	−0.0001 (0.0006)	0.0004 (0.0006)
Trust in WHO	0.0022** (0.0008)	0.0021*** (0.0006)	0.0018** (0.0006)
Trust in President	−0.0003 (0.0006)	0.0004 (0.0005)	0.002*** (0.0005)
Subjective knowledge	−0.0029*** (0.0007)	−0.0017*** (0.0005)	−0.0008 (0.0005)
Objective knowledge	−0.0012 (0.0007)	−0.0008 (0.0005)	−0.001 (0.0005)
Temporal distance	−0.0027*** (0.0007)	−0.0014** (0.0005)	−0.0027*** (0.0006)
Social distance	0.0016* (0.0007)	0.0016** (0.0005)	0.0033*** (0.0005)
Risk trend (week)	−0.0035*** (0.001)	−0.0028*** (0.0007)	−0.0042*** (0.0008)
Variance components: Level 1			
Within-person	0.3264	0.1624	0.1926
Variance components: Level 2			
Initial risk	0.4314	0.4758	0.3205
Rate of change	0.0001	0.0001	0.0001

* $p < .05$;
** $p < .01$;
*** $p < .001$.

level 2 variance denotes variance in intercepts and slopes, respectively; covariance between the intercept and slope was so low ($\leq 2.4 \times 10^{-5}$) as to be effectively zero across dependent variables.

Table 4 shows results across all six survey waves (February 2020–April 2021) for personal, affective, and collective risk perception measures (see Supporting Information I on affect). Some 30 of 42 (71%) baseline associations were significant, with no drop with adjustment for multiple comparisons. The top (Time) shows that all risk perceptions but the collective increased. Baseline (W1) risk perceptions of all types increased with U.S. news following, and decreased with trust in the Office of the (U.S.) President (occupied by President Trump for all but the last two waves), and temporal and social distance from the pandemic. Risk perceptions also increased with trust in WHO and subjective knowledge, global (non-U.S.) news following (except for collective risk), objective knowledge of transmission routes (only for collective risk), an accelerating rise in county-of-residence cases (only for affective and collective risk), and female gender (excluding personal risk perceptions), and decreased with education (only for collective risk). Trust in CDC reduced personal risk perception, but had no influence on baseline affective risk or collective risk, and age had no effect on risk perceptions.

As for factors in trends over time, 15 of 30 (50%) interactions were initially statistically significant, including when adjusted for multiple comparisons. The lone constant across these risk perception measures for six waves was that people feeling temporally distant from the pandemic accelerated the decrease in risk perceptions over time. People with an accelerating COVID-case

Table 5. Risk Perception Baseline and Trend Data: Four Types Over Five Waves.

Variable	Personal risk (Action + No Action)	Affective risk (Concern + Dread)	Collective risk (US + Global)	Severity (infection + deaths)
Initial rating				
(Intercept)	−0.1516*** (0.0351)	−0.1975*** (0.0315)	−0.0812** (0.029)	−0.4151*** (0.0374)
Time (Waves 2 – 6)	0.0036*** (0.0007)	0.0013* (0.0006)	−0.0006 (0.0006)	0.0144*** (0.0009)
US news following	0.1072*** (0.0149)	0.1158*** (0.0109)	0.1167*** (0.0116)	0.0406* (0.0169)
Global news following	0.0593*** (0.0141)	0.0535*** (0.0103)	0.0084 (0.0109)	−0.004 (0.0161)
Trust in CDC	−0.0554*** (0.0165)	0.0175 (0.0123)	0.0317* (0.0129)	−0.1175*** (0.0186)
Trust in WHO	0.1301*** (0.0177)	0.0986*** (0.0137)	0.1325*** (0.014)	0.1415*** (0.0195)
Trust in President	−0.0235* (0.0115)	−0.0272** (0.0084)	−0.0332*** (0.0089)	−0.0622*** (0.0133)
Subjective knowledge	0.0255* (0.0121)	0.0108 (0.0089)	0.0067 (0.0094)	0.0257 (0.0137)
Objective knowledge	−0.0269* (0.0136)	−0.0067 (0.0102)	0.0338** (0.0106)	0.073*** (0.0153)
Temporal distance	−0.1364*** (0.0139)	−0.1015*** (0.0103)	−0.1922*** (0.0108)	−0.1263*** (0.0159)
Social distance	−0.1165*** (0.0126)	−0.093*** (0.0092)	−0.0926*** (0.0098)	−0.1013*** (0.0144)
Risk trend (week)	0.0037 (0.0102)	0.044*** (0.0073)	0.0198* (0.0079)	0.0216 (0.0119)
Age	0.0048 (0.0168)	0.0059 (0.0175)	0.0124 (0.0149)	−0.0147 (0.0157)
Gender	0.0668 (0.0399)	0.292*** (0.0392)	0.1987*** (0.0345)	−0.0735 (0.0394)
Education	−0.0052 (0.0191)	−0.0209 (0.0193)	−0.0288 (0.0167)	0.0389* (0.0185)
Interaction with time				
US news following	0.0009 (0.0008)	0.0013* (0.0006)	0 (0.0006)	0.0021* (0.001)
Global news following	0.0008 (0.0008)	0.0003 (0.0006)	−0.0011 (0.0006)	0.0011 (0.0009)
Trust in CDC	0.0003 (0.0009)	−0.0009 (0.0007)	−0.0006 (0.0007)	0.0007 (0.0011)
Trust in WHO	0.0017 (0.0009)	0.0025*** (0.0007)	0.0019** (0.0007)	0.0006 (0.0011)
Trust in President	0.0005 (0.0007)	0.0008 (0.0005)	0.0025*** (0.0005)	0.0026** (0.0008)
Subjective knowledge	−0.0017** (0.0006)	−0.0011* (0.0005)	0.0005 (0.0005)	−0.0019* (0.0008)
Objective knowledge	−0.0007 (0.0007)	0.0003 (0.0005)	−0.0009 (0.0006)	−0.0013 (0.0008)
Temporal distance	−0.0028*** (0.0008)	−0.0014* (0.0006)	−0.0035*** (0.0006)	−0.0049*** (0.0009)
Social distance	0.0007 (0.0007)	0.0009 (0.0005)	0.0021*** (0.0005)	0.0007 (0.0008)
Risk trend (week)	−0.0016 (0.0012)	−0.003*** (0.0009)	−0.0011 (0.0009)	−0.0007 (0.0013)
Variance components: Level 1				
Within-person	0.3236	0.1533	0.1854	0.4432
Variance components: Level 2				
In initial risk	0.5141	0.5453	0.3789	0.5112
In rate of change	0.0002	0.0001	0.0001	0.0003

Note: Shading indicates association non-significant at $p < .05$ when adjusting for multiple comparisons.
* $p < .05$;
** $p < .01$;
*** $p < .001$

trend in their county, so that their area was experiencing an increasingly upward trend in cases, had smaller increases in all risk perceptions over time than others. However, counties for only four people—W2 (2), W5-6 (one each)—exhibited smaller upward case trends for the preceding week. Trust in WHO amplified all upward trends, trust in the President amplified only collective risk perceptions, and subjective knowledge slowed upward trends in personal and affective risk judgments (in other words, those who thought they knew a lot about COVID-19 had slower increases in these risk perceptions over time). Social distance amplified upward trends for all risk perceptions (in other words, those high in social distance had risk perceptions increasing faster than did those low in social distance, so that the slope flattened over time). This is the reverse of what we expected: people who believe those affected differ from themselves should have risk perceptions that rise at a lower rate, if they rise at all. Neither the two news following measures, trust in CDC, nor objective knowledge influenced trends.

Turning to Table 5 on risk perception measures across W2–6, which allowed us to add severity risk perceptions, 40 of 56 (71%) baseline associations were initially significant, although four were non-significant at $p < .05$ when adjusted for multiple comparisons. Perceived risk increased over time for all measures except collective risk (no significant effect). U.S. news following was associated with increased risk perception at baseline for all measures; global news following increased risk perceptions for personal and affective risk perception. Trust in CDC reduced personal risk and severity perceptions, increased collective risk perceptions at baseline, and had no significant effect on affective risk. Trust in WHO increased risk perceptions for all measures. Trust in the President decreased all but personal baseline risk perceptions (after multiple-comparison adjustment). Subjective knowledge was not associated with higher personal risk perception after adjustment, while objective knowledge of transmission routes was linked to higher collective risk and severity perceptions, and lower affective risk perceptions after adjustment. Temporal and social distance were associated with lower risk perception for all measures at baseline. If recent local infections accelerated, this was associated with higher affective and collective risk responses. Female gender was associated at baseline with significantly higher risk perceptions except for personal risk and severity (no gender difference). Age had no significant effects, while education was linked with expectations of greater severity only before adjustment for multiple comparisons.

Interactions of predictors with time over five waves varied widely; 15 of 40 (37.5%) interactions were statistically significant, although the two for U.S. news following became non-significant at $p < .05$ after adjustment for multiple comparisons. In the following descriptions, we discuss the effect of specific variables on the steepness of trends over time. If the overall trend is upward, but a high level of the variable makes the trend go up faster (a steeper slope) then we say the variable 'increased' or 'amplified' trends; if instead a high level of the variable makes the trend go up slower (a shallower slope) than a low level of the variable, then we say the variable 'flattened' or 'decreased' or 'dampened' trends. We use the same language for downward trends, but with inverted meaning: for example 'flattened' means that high variable levels reduce the slope of the downward trend relative to low variable levels. Trust in CDC had no significant effect on trends, but trust in WHO increased upward trends in affective and collective risk perceptions, and trust in the President flattened downward trends in collective risk and severity estimates. Greater subjective knowledge decreased upward trends in personal, affective, and severity risk perceptions, while objective knowledge had no significant effects on trends (likely due to its high and unchanging trend). Temporal distance dampened trends for all, while social distance amplified upward trends in collective risk perception (again, a finding the reverse of expectations). An accelerating upward trend in local coronavirus infections dampened rises in affective risk, also unexpected.

Jointly, these findings only partly support H1: news following (particularly of news about U.S. conditions) did increase baseline risk perceptions, but largely lacked temporal effects; trust yielded mixed results (e.g. largely positive effects from trust in WHO; mostly negative effects from trust in the Office of the President), and objective knowledge of viral transmission routes had varyingly signed (if significant) effects. RQ1 also yielded mixed results: subjective knowledge had only occasional association with risk perceptions, but psychological distance—particularly temporal, but also social, distance—reduced baseline risk perceptions, while temporal distance reduced and social distance increased cross-temporal effects.

5.4. Temporal changes in predictor-risk perception relationships

To further clarify these interaction effects, we graphed associations of each predictive factor with each risk perception measure at each wave when those predictors exhibited a statistically significant interaction with time in Tables 4 and 5, to focus on the Association and Slope dimensions (referred to in Section 3) of the line chart images (ordinarily time would be on the *X*-axis, but we believe these figures are more informative here). These two dimensions jointly form nine possibilities, but as we note below not all appear here. The classifications are admittedly not perfect: for example, in the Shift case the Up or Down change might only occur for most waves; some relationships are very nearly stable. These classifications are also not comprehensive, as (for example) they omit situations in which people high or low on a predictor persist in those ratings over time. But the typology allows us to summarize general patterns in response, rather than drown readers in detail, to address RQ2 on variation in predictor-risk perception associations across time and risk perception measures. All figures for statistically significant interactions with time (Tables 4–5) appear in Supporting Information II and III, including those non-significant after adjustment for multiple comparisons; an illustrative few are featured here.

The stable slope condition is technically absent (although a few patterns come close), meaning that H2 on the invariance of predictor-risk perception associations' magnitude can be rejected. Of the six of nine potential combinations that do occur, the dominant associative pattern is negative (17), so that people high in a predictive factor are relatively low on the risk perception; these responses occur twice as often for Up (12) than Down (5) slopes. In both 5-wave and 6-wave analyses temporal distance exhibits the Negative/Up pattern (Figure 2a) for personal, affective, and collective risk perceptions (plus severity in the 5-wave); over time differences in risk perceptions widened between those who felt the pandemic had already occurred and those who felt it had not yet occurred. In the 6-wave analysis social distance also exhibited this pattern for personal and affective risk perception. In both 5-wave and 6-wave analyses social distance exhibited the Negative/Down pattern (Figure 2b) for collective risk perceptions—over time differences in perceived risk to the U.S. and to the earth as a whole narrowed between those who felt the pandemic was or was not affecting people similar to themselves—as did differences for severity between those with high and low trust in the Office of the President in the 5-wave analysis. Given the transition to a President of another political party between W4-5, prompting a sharp rise in Democrats' and independents' trust and a modest drop in Republicans' trust in our data, this apparent convergence on risk perceptions among people with varying trust in the President probably reflects offsetting trends for Republicans and Democrats.

The next most common Association pattern (9, excluding two non-significant with adjustment) concerns the Shift pattern, in which one association dominates for most survey waves, but the slope changes sign in one or two waves. This indicates that H2 on the invariant sign of predictor-risk perception associations is mostly supported. Persistently significant results all exhibit the Down slope pattern (Figure 2c), for subjective knowledge in both 5- and 6-wave personal and affective risk perceptions: over early waves a positive but diminishing association of risk perception with subjective knowledge, reversed to a negative association in late waves (the same pattern occurred for severity in the 5-wave analysis). Similar patterns occurred for risk trend on personal and collective risk perceptions (6-wave). Collective risk perception exhibited for trust in the President a Shift-Down pattern in the 5-wave analysis, versus its Negative/Down pattern in 6-wave analysis. The lone Shift/Up example concerns a non-significant post-adjustment association: those high in following U.S. pandemic news at W2 in the 5-wave analysis saw its severity as slightly less, but with news following raising this perceived severity with time (Figure 2d).

Finally, seven cases (excluding one non-significant after adjustment) exhibited a positive association between risk perceptions and predictors, with mostly steepening slopes (Figure 2e). The Positive/Up pattern featured effects of trust in WHO on affective and collective risk perceptions in both 5- and 6-wave analyses (plus personal risk, 6-wave): the gap in risk perceptions between those with high versus low WHO trust widened. The widening gap in affective responses between those high versus low in following U.S. news was non-significant after adjustment. The Down pattern appeared in both sets of analyses for risk trend's association with affective risk perceptions, with the trend having a diminishing effect over time (Figure 2f).

Overall, temporal shifts were consistent with H3b: they occurred less often for severity (perceived infections or deaths) than for other risk perception types.

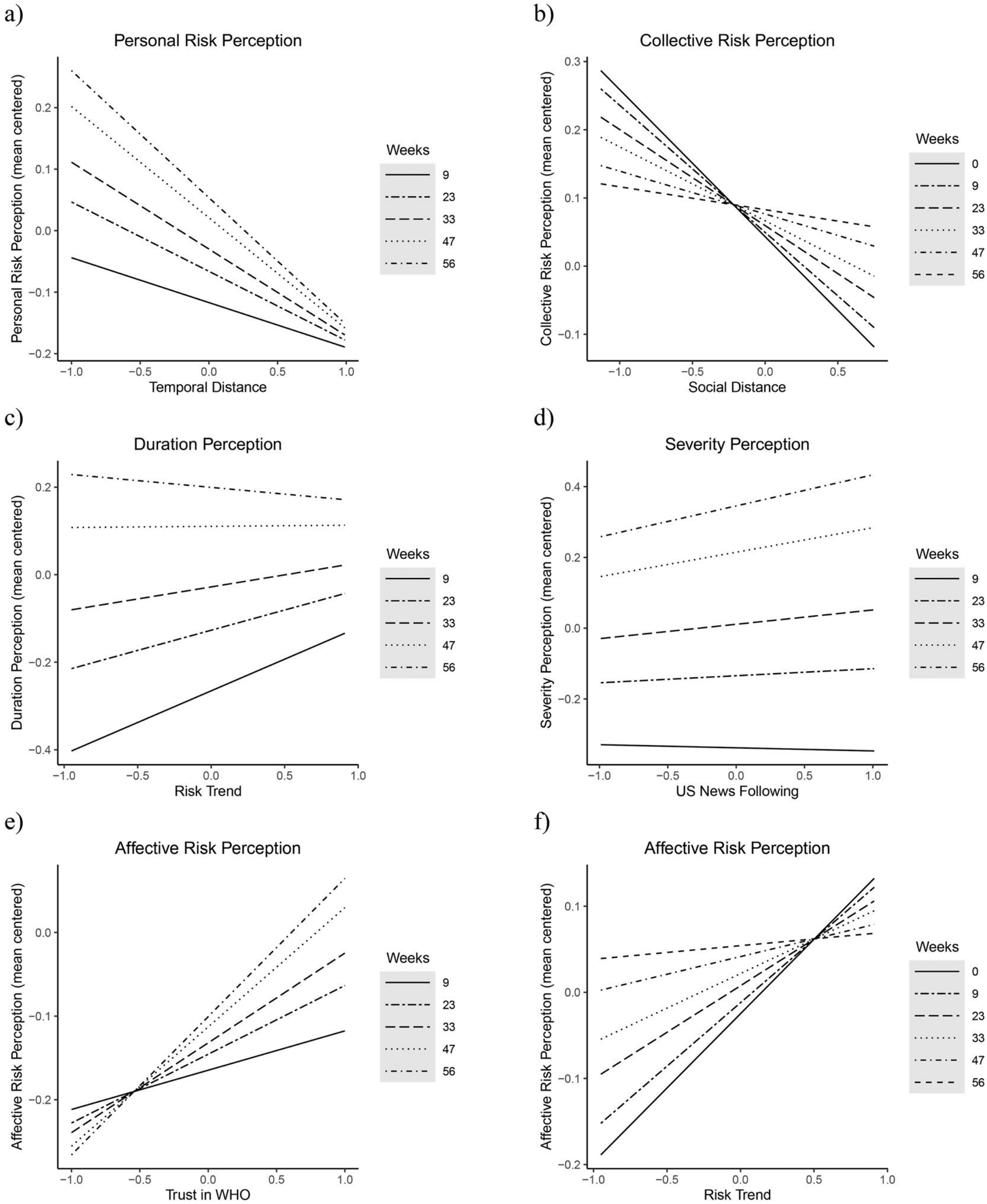

Figure 2. Examples of predictor-time interactions in affecting risk perceptions, defined by the proposed multi-label classification of figures based on association (positive; negative; shift) X slope (up; down; no strict examples of the stable exemplar occurred here). (a) Negative/Up; (b) negative/down; (c) shift/down; (d) shift/up; (e) positive/up; (f) positive/down.

6. Discussion

6.1. Major findings

Different risk perception measures regarding the COVID-19 pandemic, and their associations with predictors (refuting H2 on invariance of such associations), exhibited different temporal trends over 14 months, and factors in both baseline ratings of perceived risk and in the slopes of these trends differed even more across perception types (addressing RQ2). However, on average trends were upwards, consistent with the elasticity-prevalence model (e.g. Geoffard and Philipson 1996) that perceptions rise with disease incidence. It is unclear whether apparent slight drops in some risk perceptions in W6 reflected habituation to a persistent pandemic (i.e. risk perceptions drop as people become accustomed to their experience of it; Loewenstein and Mather 1990; also see Raude et al. 2019), the prospect at the time that vaccination would 'save' us, statistical noise, or insufficient data (e.g. if 14 months of data collection were too few to capture such patterns for this pandemic). However, the lack of lessening variance in risk perceptions over time, contradicting H3a, seems to be evidence against the habituation effect over this period; in other words, if increasing familiarity with COVID-19 was lessening perceived risk, we should have seen increasing agreement on how bad this pandemic was among our sample, which we did not.

Regarding H1 and RQ1, the most consistently influential factors on baseline and trends in risk perceptions were news following and psychological distance, followed by trust, while objective and subjective knowledge had few significant effects. The statistical significance and sign of associations for baseline factors shifted little between the 6-wave (Table 4) and 5-wave (Table 5) analyses for risk perception types these sets of analyses had in common. Among the few exceptions were 5-wave analyses where objective knowledge had a negative association for personal risk, subjective knowledge no significant effect for affective risk or collective risk, and trust in CDC a positive association with collective risk, differing from associations for 6-wave analyses. Overall, to answer RQ1, baseline risk perception ratings after adjustment for multiple comparisons were associated with temporal and social distance, U.S. news following, time, global news following, subjective knowledge, and trust in WHO in that order of frequency of association.

As for factors associated with the slope of trends, observed trends were unaffected by such factors as trust in CDC, U.S. and global news following, and objective knowledge, and other factors were often inconsistently influential across risk perception types. Only temporal distance consistently distinguished among respondents. Other risk-perception trend influencers included risk trend, subjective knowledge, trust in WHO, trust in the President, and social distance. Our graphical analyses of associations between risk perceptions and predictors over time (Figure 2 and Supporting Information II and III) revealed further subtleties, including that particularly for subjective knowledge and risk trend signs of associations could flip. The severity risk perceptions exhibited fewer shifts than the other risk perception measures, consistent with H3b.

6.2. Theoretical implications

These findings hold several implications for risk perception theory and future research. First, although our results hold no direct implications for proposed risk perception taxonomies—in other words, they cannot test whether such classifications as those of Walpole and Wilson (2021) are correct (but see comment below)—they underline that risk perception types should not be treated as interchangeable. Whether researchers *ought* to include distinctive risk perception measures depends upon their study goals, of course, but the value of multiple measures increases as such goals include advancing risk perception theory, including perception-behaviour relationships.

A second implication is to take variation in risk perceptions across time seriously. Hypothetically we already do: scholars acknowledge temporal variation when they discuss limitations of their cross-sectional studies, note the 'life cycle of an issue' (e.g. Downs 1972), or propose generic conceptual models of the social amplification or attenuation of 'risk' over time (e.g. Kasperson et al. 1988). Yet in practice, most risk perception studies are cross-sectional, with much rarer 'longitudinal' analyses comparing different samples of the public at different times as if equivalent; rare longitudinal panel studies are dominated by two-wave designs, which can assess before-after effects (e.g. relative to an event expected to change objective and/or subjective risks) but are one wave short of being able to assess predictors of trends at the individual level as we did here. We do not ignore barriers to longitudinal panel studies with three or more waves: for example, costs and potentially non-random retention, although here any resulting biases did not affect risk perceptions. Yet we argue that both researchers and funding agencies should be more open to such studies if we are to advance knowledge beyond existing models of temporal variation.

A third implication concerns the nature and source of potential factors in baseline and slope estimates of risk perceptions. Following news, particularly domestic, about the outbreak was a common factor in baseline risk perceptions for Ebola and Zika as well as for COVID-19, with no significant effect on inter-individual trend differences after adjustment. We also added other factors not applied in earlier studies, such as psychological distance which was influential here (particularly its temporal dimension) for both baseline and slope differences. This idiosyncratic approach, even if shaped by reasonable decisions about differences across hazards and testing new factors, is valuable primarily to inspire more systematic longitudinal risk perception research. Building such knowledge requires a standard core of risk perception and predictor measures across varied hazards, at minimum; it is unclear whether we need standardization of numbers of or intervals between waves. Defining that core will be challenging, although we suggest that the Social Amplification of Risk Framework (Kasperson et al. 1988) could be one source; despite its weaknesses, it is one of few conceptual frameworks that take temporal dynamics of risk perceptions seriously. Our tentative hypotheses (H3a-b) about factors behind shifting predictor-risk perception associations may contribute to this discussion despite their limitations. For example, the failure to 'explain' these shifts because variance in risk perceptions did *not* lessen over time might simply be a feature of this specific data set; the hypothesis that severity (perceived infections/deaths) might exhibit less temporal shifting in associations with predictors than other risk perception measures was consistent with the data, but we did not measure the supposed mediator (in other words, feedback from knowledge of official statistics to perceptions).

A fourth implication concerns risk perception's relationship with other important elements of risk science. If risk perceptions vary over time, in different patterns for different measures of risk perception, what does this entail for their relations with behavioural intentions, for example? The Protective Action Decision Model of Lindell and Perry (2012) posits 'threat perceptions' as just one factor in behavioural intentions; we also would need to probe for temporal mutability in stakeholder perceptions (e.g. trust), and in protective action perceptions (e.g. judged efficacy of the action at reducing risk). But we must at least consider the possibility that risk perception-intention and risk perception-behaviour associations will be highly susceptible to the temporal and measurement variability of risk perception measures reported here.

A fifth implication concerns the interaction effects of predictors and time on risk perceptions. Our draft multi-label classification of Association X Slope should be debated and improved. Some Association findings are expected (e.g. temporal or social distance reduces risk perceptions; trust in WHO yields higher risk perceptions). The shifting association of risk perceptions with U.S. news following is plausible, yet requires exploring its link to legacy and social media content (which we are pursuing separately). We lack any theory about the relationship of risk perceptions with subjective knowledge—what people think they know, versus what they do know—so this pattern is difficult to judge, but given shifting signs of the associations over time, this predictor may be unhelpful. The absence of statistically significant interactions for news following, trust in CDC, and objective knowledge of viral transmission warrant further attention. The Shift situations, in which most slopes per wave are positive or negative, but late waves (and in one case, the first wave) exhibit opposite signs—for example, for subjective knowledge and risk trends, and less often for trust in the President and news following—may be statistical anomalies, and mostly small. But if replicable, the possibility of risk perception-predictor associations changing in sign over time, not just in magnitude, deserves more empirical study.

Slope results are potentially more troubling for understanding the temporal dynamics of risk perceptions. If all predictors yielded declining gaps in risk perception over time, we might simply assign the cause to regression to the mean as the most parsimonious explanation, but our results are more complex. For example, why should different measures of psychological distance, which supposedly move in parallel (Liberman and Trope 2008), both widen (temporal) and narrow (social) differences over time between those who rate distance high versus low? For other factors, the puzzle is smaller, as the same pattern occurs across analyses but with often widely varying slope magnitudes. We offer no explanations here, but hope to inspire further research on this issue.

Despite commenting above that our findings do not directly test risk perception taxonomies, a sixth and final implication of these findings concerns how we define and apply such taxonomies. First, specific measures of risk perception may differ in important ways even if factor analyses in a companion paper suggest that they share patterns with other measures. For example, descriptive statistics here (Table 3) show that personal risk perception measures conditioned on one having acted protectively (action) were consistently lower than those conditioned on not so acting (no action); concern was consistently higher than dread; and U.S. risk was generally, but not always, deemed lower than that for the world. So even if certain risk perception measures cluster together, treating them as simple substitutes is imprudent; choice of one over another may greatly affect one's results. Second, the personal-risk, community-focused taxonomy of risk perception advocated by Walpole and Wilson (2021) appears cogent and worth testing and applying in future research focused on personal risk perceptions. That need not make it sufficiently comprehensive, however, as these authors acknowledged. For example, in contrast to the presumed association between personal risk perceptions and personal protective action, policy support might be more associated with collective risk perceptions (such as the U.S., global, severity and/or duration measures used here) than personal risk perceptions (affective, severity, exposure and susceptibility) in the Walpole–Wilson taxonomy. Pending empirical probing of these associations, it might be prudent to at least consider collective measures of affect, severity, exposure and susceptibility to parallel their personal risk perception taxonomy.

6.3. Limitations

Our findings about several factors in judged risk over time are limited by dependence on self-report and non-experimental design, although this is also true of nearly all risk perception studies. Concurrent use of psychophysical (e.g. to measure concern), observational, or other independent measures of changes in self-reported reactions could address the first issue in future longitudinal research. Field experiments—including natural experiments—could be exploited to extend this research, if joined with a longitudinal panel sampling design. Some potential factors in temporal dynamics were omitted, such as cultural biases or political ideology, to focus on factors measured in (because likely to differ across) each wave, but these other effects will be assessed elsewhere. Because the literature on risk-perception dynamics over time using at least three waves of data collection is tiny and dominated by disease—Ebola and Zika in the United States during 2014–2017 (Mayorga and Johnson 2019; Johnson and Mayorga 2021), and this report, versus Lima (2004) on waste incineration—generalization of these findings across hazards is limited. Our sample prevents generalization to non-United States populations.

7. Conclusion

Data on static (cross-sectional) risk perceptions have been used creatively over 40 years to greatly increase scientific understanding of human response to hazards. The recent initiative to systematize personal risk perception measures through a taxonomy (Wilson, Zwickle, and Walpole 2019; Walpole and Wilson 2021) is an important step forward, which we support but also suggest may need expansion at least to collective measures, and perhaps to conditional measures as well (Brewer et al. 2004). But we argue that at least as important a step forward is for funders and researchers to amplify attention to (necessarily longitudinal) studies that allow us to understand the temporal dynamics of risk perception, and thus bring to fruition a long-standing aspiration in the field (Kasperson et al. 1988; Siegrist 2013).

Our findings demonstrated that Americans' risk perceptions of the coronavirus/COVID-19 from February 2020 to April 2021 vary across time, risk perception measures, and explanatory factors in a complex manner. Given the limited literature, it is too early to say whether this is typical of such temporal dynamics, or simply an idiosyncrasy of time, place, and/or research design. Yet we hope that this ambiguity heightens the motivation of our colleagues to advance research on this vital topic.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The work contributing to this article was funded by the United States National Science Foundation under Grant No. 2022216.

ORCID

Branden B. Johnson http://orcid.org/0000-0003-2264-5419
Marcus Mayorga http://orcid.org/0000-0001-5471-0655
Byungdoo Kim http://orcid.org/0000-0002-0943-9461

References

Benjamini, Y., and Y. Hochberg. 1995. "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing." *Journal of the Royal Statistical Society: Series B (Methodological)* 57 (1): 289–300. doi:10.1111/j.2517-6161.1995.tb02031.x.

Bostrom, A., C. J. Atman, B. Fischhoff, and M. G. Morgan. 1994. "Evaluating Risk Communications: Completing and Correcting Mental Models of Hazardous Processes, Part II." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 14 (5): 789–798. doi:10.1111/j.1539-6924.1994.tb00290.x.

Brewer, N. T., N. D. Weinstein, C. L. Cuite, and J. Herrington. 2004. "Risk Perceptions and Their Relation to Risk Behavior." *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine* 27 (2): 125–130. doi:10.1207/s15324796abm2702_7.

Burns, W. J., E. Peters, and P. Slovic. 2012. "Risk Perception and the Economic Crisis: A Longitudinal Study of the Trajectory of Perceived Risk." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 32 (4): 659–677. doi:10.1111/j.1539-6924.2011.01733.x.

Champ, P. A., and H. Brenkert-Smith. 2016. "Is Seeing Believing? Perceptions of Wildfire Risk over Time." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 36 (4): 816–830. doi:10.1111/risa.12465.

Cutchin, M. P., K. R. Martin, S. V. Owen, and J. S. Goodwin. 2008. "Concern about Petrochemical Health Risk before and after a Refinery Explosion." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 28 (3): 589–601. doi:10.1111/j.1539-6924.2008.01050.x.

Dillon, R. L., C. H. Tinsley, and W. J. Burns. 2014. "Evolving Risk Perceptions about near-Miss Terrorist Events." *Decision Analysis* 11 (1): 27–42. doi:10.1287/deca.2013.0286.

Downs, A. 1972. "Up and down with Ecology: The 'Issue-Attention Cycle." *The Public Interest* 28: 38–50.

Flint, C. G. 2007. "Changing Forest Disturbance Regimes and Risk Perceptions in Homer, Alaska." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 27 (6): 1597–1608. doi:10.1111/j.1539-6924.2007.00991.x.

Geoffard, P.-Y, and T. Philipson. 1996. "Rational Epidemics and Their Public Control." *International Economic Review* 37 (3): 603–624. doi:10.2307/2527443.

Glickman, M. E., S. R. Rao, and M. R. Schultz. 2014. "False Discovery Rate Control is a Recommended Alternative to Bonferroni-Type Adjustments in Health Studies." *Journal of Clinical Epidemiology* 67 (8): 850–857. doi:10.1016/j.jclinepi.2014.03.012.

Goldstein, H. 2011. *Multi-Level Statistical Models*. John Wiley & Sons.

Ibuka, Y., G. B. Chapman, L. A. Meyers, M. Li, and A. P. Galvani. 2010. "The Dynamics of Risk Perceptions and Precautionary Behavior in Response to 2009 (H1N1) Pandemic Influenza." *BMC Infectious Diseases* 10 (1). doi:10.1186/1471-2334-10-296.

Johnson, B. B., and M. Mayorga. 2021. "Temporal Shifts in Americans' Risk Perceptions of the Zika Outbreak." *Human and Ecological Risk Assessment: An International Journal* 27 (5): 1242–1257. doi:10.1080/10807039.2020.1820852.

Kasperson, R. E., O. Renn, P. Slovic, H. S. Brown, J. Emel, R. Goble, J. X. Kasperson, and S. Ratick. 1988. "The Social Amplification of Risk: A Conceptual Framework." *Risk Analysis* 8 (2): 177–187. doi:10.1111/j.1539-6924.1988.tb01168.x.

Kosemen, C., and D. Birant. 2020. "Multi-Label Classification of Line Chart Images Using Convolutional Neural Networks." *SN Applied Sciences* 2 (7):1250. doi:10.1007/s42452-020-3055-y.

Liberman, N., and Y. Trope. 2008. "The Psychology of Transcending the Here and Now." *Science (New York, N.Y.)* 322 (5905): 1201–1205. doi:10.1126/science.1161958.

Lima, M. L. 2004. "On the Influence of Risk Perception on Mental Health: Living near an Incinerator." *Journal of Environmental Psychology* 24 (1): 71–84. doi:10.1016/S0272-4944(03)00026-4.

Lindell, M. K., and R. W. Perry. 2012. "The Protective Action Decision Model: Theoretical Modifications and Additional Evidence." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 32 (4): 616–632. doi:10.1111/j.1539-6924.2011.01647.x.

Loewenstein, G., and J. Mather. 1990. "Dynamic Processes in Risk Perception." *Journal of Risk and Uncertainty* 3 (2): 155–175. doi:10.1007/BF00056370.

Mayorga, M., and B. B. Johnson. 2019. "A Longitudinal Study of Concern and Judged Risk: The Case of Ebola in the United States, 2014–2015." *Journal of Risk Research* 22 (10): 1280–1293. doi:10.1080/13669877.2018.1466827.

McCormack, L. A., L. Squiers, A. M. Frasier, M. Lynch, C. M. Bann, and P. D. M. MacDonald. 2021. "Gaps in Knowledge about COVID-19 among US Residents Early in the Outbreak." *Public Health Reports (Washington, D.C.: 1974)* 136 (1): 107–116. doi:10.1177/0033354920970182.

Pahl, S., and J. Bauer. 2013. "Overcoming the Distance: Perspective Taking with Future Humans Improves Environmental Engagement." *Environment and Behavior* 45 (2): 155–169. doi:10.1177/0013916511417618.

Raude, J., K. McColl, C. Flamand, and T. Apostolidis. 2019. "Understanding Health Behaviour Changes in Response to Outbreaks: Findings from a Longitudinal Study of a Large Epidemic of Mosquito-Borne Disease." *Social Science & Medicine (1982)* 230: 184–193. doi:10.1016/j.socscimed.2019.04.009.

Renner, B., B. Schüz, and F. F. Sniehotta. 2008. "Preventive Health Behavior and Adaptive Accuracy of Risk Perceptions." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 28 (3): 741–748. doi:10.1111/j.1539-6924.2008.01047.x.

Shou, Y., and J. Olney. 2021. "Attitudes toward Risk and Uncertainty: The Role of Subjective Knowledge and Affect." *Journal of Behavioral Decision Making* 34 (3): 393–404. doi:10.1002/bdm.2217.

Shwom, R., A. Dan, and T. Dietz. 2008. "The Effects of Information and State of Residence on Climate Change Policy Preferences." *Climatic Change* 90 (4): 343–358. doi:10.1007/s10584-008-9428-7.

Siegrist, M. 2013. "The Necessity for Longitudinal Studies in Risk Perception Research." *Risk Analysis : An Official Publication of the Society for Risk Analysis* 33 (1): 50–51. doi:10.1111/j.1539-6924.2012.01941.x.

Siller, M., and M. Sigman. 2008. "Modeling Longitudinal Change in the Language Abilities of Children with Autism: Parent Behaviors and Child Characteristics as Predictors of Change." *Developmental Psychology* 44 (6): 1691–1704. doi:10.1037/a0013771.

Slovic, P. 1993. "Perceived Risk, Trust, and Democracy." *Risk Analysis* 13 (6): 675–682. doi:10.1126/science.3563507.

Smith, V. K., and R. G. Michaels. 1987. "How Did Households Interpret Chernobyl? A Bayesian Analysis of Risk Perceptions." *Economics Letters* 23 (4): 359–364. doi:10.1016/0165-1765(87)90145-5.

Thompson, R. F. 2009. "Habituation: A History." *Neurobiology of Learning and Memory* 92 (2): 127–134. doi:10.1016/j.nlm.2008.07.011.

Trizano-Hermosilla, I., and J. M. Alvarado. 2016. "Best Alternatives to Cronbach's Alpha Reliability in Realistic Conditions: Congeneric and Asymmetrical Measurements." *Frontiers in Psychology* 7: 769. doi:10.3389/fpsyg.2016.00769.

Trumbo, C., M. A. Meyer, H. Marlatt, L. Peek, and B. Morrissey. 2014. "An Assessment of Change in Risk Perception and Optimistic Bias for Hurricanes among Gulf Coast Residents." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 34 (6): 1013–1024. doi:10.1111/risa.12149.

U.S. Centers for Disease Control and Prevention (CDC). 2020. Statistics & maps, 2015–2017 case counts. Retrieved August 27, 2020, from https://www.cdc.gov/zika/reporting/index.html.

U.S. Centers for Disease Control and Prevention (CDC). 2021. CDC Museum COVID-19 Timeline. Retrieved February 17, 2022, from https://www.cdc.gov/museum/timeline/covid19.html.

Viscusi, W. K., and C. J. O'Connor. 1984. "Adaptive Responses to Chemical Labeling: Are Workers Bayesian Decision Makers?" *American Economic Review* 74 (5): 942–956.

Visschers, V. H. M., and M. Siegrist. 2013. "How a Nuclear Power Plant Accident Influences Acceptance of Nuclear Power: Results of a Longitudinal Study before and after the Fukushima Disaster." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 33 (2): 333–347. doi:10.1111/j.1539-6924.2012.01861.x.

Walpole, H. D., and R. S. Wilson. 2021. "Extending a Broadly Applicable Measure of Risk Perception: The Case for Susceptibility." *Journal of Risk Research* 24 (2): 135–147. doi:10.1080/13669877.2020.1749874.

Walpole, H. D., and R. S. Wilson. 2021. "A Yardstick for Danger: Developing a Flexible and Sensitive Measure of Risk Perception." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 41 (11): 2031–2045. doi:10.1111/risa.13704.

Wilson, R. S., A. Zwickle, and H. D. Walpole. 2019. "Developing a Broadly Applicable Measure of Risk Perception." *Risk Analysis: An Official Publication of the Society for Risk Analysis* 39 (4): 777–791. doi:10.1111/risa.13207.

Wirz, C. D., M. Mayorga, and B. B. Johnson. 2021. "A Longitudinal Analysis of Americans' Media Sources, Risk Perceptions, and Judged Need for Action during the Zika Outbreak." *Health Communication* 36 (12): 1571–1580. doi:10.1080/10410236.2020.1773707.

Zhang, M., and G.-L. Liu. 2015. "The Effects of Consumer's Subjective and Objective Knowledge on Perceptions and Attitude towards Genetically Modified Foods: Objective Knowledge as a Determinant." *International Journal of Food Science & Technology* 50 (5): 1198–1205. doi:10.1111/ijfs.12753.