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COVID-19 risk perception measures: factoring and prediction of behavioral intentions and policy support

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ABSTRACT

Although early concepts of risk perception measures distinguished cognitive from affective items, until recently multi-dimensional taxonomies were absent from risk perception studies, and even more from tests of their association with behavior or policy support. Six longitudinal panel surveys on U.S. COVID-19 views (n=2004 February 2020, ending April 2021) allowed testing of these relationships among ≤ 10 risk perception items measured in each wave. Confirmatory factor analyses revealed consistent distinctions between personal (conditioning perceived risk on taking further or no further protective action), collective (U.S., global), affective (concern, dread), and severity (estimates of eventual total U.S. infections and deaths) measures, while affect (good-bad feelings) and duration (how long people expect the outbreak to last) did not fit with their assumed affective and severity (respectively) parallels. Collective and affective/affect risk perceptions most strongly predicted both behavioral intentions and policy support for mask wearing, avoidance of large public gatherings, and vaccination, controlling for personal risk perception (which might be partly reflected in the affective/affect effects) and other measures. These findings underline the importance of multi-dimensionality (e.g. not just asking about personal risk perceptions) in designing risk perception research, even when trying to explain personal protective actions.

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behavioral intentions; COVID-19; policy support; Risk perception; taxonomy

Introduction

Risk perception has been central to risk analysis since its onset as a formal field (e.g. Cole & Withey 1981; Lindell & Perry 2012; Siegrist 1999), but how we define and measure "risk perception" can greatly affect cumulative understanding of its antecedents or consequences. Unfortunately, use of one or more types of risk perception measures has been unsystematic, at most researchers agreeing to distinguish cognitive and affective measures. Examining COVID-19 risk perception measures' differentiation and variation in explaining U.S. protective behavioral intentions and policy support can advance our understanding of such choices.

Risk perception literature

Early on risk analysis and associated fields attended little to the possibility of different "risk perceptions," despite recognition that cognitive (e.g. perceived probabilities) and affective (e.g.

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emotions like fear or anger) risk perceptions could diverge in patterns or effects (e.g. Slovic 1987; Slovic et al. 2004; Sjöberg 1998 on worry's weak association with judgments of personal risk, family risk, or general risk [i.e. unspecified hazard target], and concern as quite different from worry). Yet no systematic attempt emerged from these suggestions to empirically clarify these variations, much less generate systematic classifications of risk perception measures.

Uncertainty about perceived threat-protective behavior relationships can be due to use of both correlational research designs unable to resolve causality, and different threat measures across studies Sheeran et al. (2014). Sheeran et al. (2014) distinguished (as "distinct but related constructs"; p. 512) "risk perception" (cognitive evaluations of one's vulnerability: e.g. likelihood of experiencing negative outcomes); "anticipatory emotions" (immediate feelings about possible harm: e.g. fear, worry); "anticipated emotions" (expected to be experienced with negative outcomes; e.g. regret, guilt, shame); and "perceived severity" (expected severity of the threat once occurring). Although correlational analyses suggested anticipated emotions had the strongest effects on intentions and behavior, meta-analysis of experimental data suggested that heightening perceived severity had the strongest effects alone, although overall effects were strongest with risk perception and anticipatory emotion both heightened, particularly for behavioral intentions (Sheeran et al. 2014).

A health behavior study examined for cancer, heart disease and diabetes a model complementing cognitive (e.g. likelihood, probability, possibility, odds, and chance of getting the disease) and affective (worry, fear, nervousness, anxiety about the disease or of developing it themselves) measures with experiential risk perceptions, deemed gut-level reactions that were not "fully fledged affective responses" but rather founded on slowly changing learned associations bound up in "concrete images, metaphors, and narratives" (e.g. "that could be me someday"; "have fun when you can"; Ferrer et al. 2016). Experiential measures included concern, ease of imagining, felt vulnerability to, and identification with someone else getting the disease. Although the tripartite model fit better (with "borderline" fit indices) than single- or dual-factor models, their data produced unexpectedly stronger deliberative-experiential associations than affective-experiential associations, with each type of measure yielding unique variance in protective-behavior intentions (Ferrer et al. 2016).

Another initiative suggested distinguishing likelihood from severity of consequences, and both from affective responses (Wilson et al. 2019), then proposed splitting likelihood into hazard exposure and susceptibility (suffering consequences if exposed) categories (Walpole & Wilson 2021b). The Wilson et al. (2019) literature review identified "general" items (e.g. "How risky is X?") as the most common, used by 40% of reviewed studies, concluding that these items were too broad and not "measuring risk perception in the most complete and theoretically accurate manner" (p. 781). Their empirical work suggested such general measures were best predicted by affect and consequence across four hazards, with probability statistically significant for only two hazards. Adding affect, consequences, and probability measures in turn substantially increased explained variance in self-protective behavioral intentions over general risk perception alone. Wilson et al. (2019) acknowledged that collectively their risk perception measures did not fully explain behavioral intentions, and general risk perception items might capture otherwise untapped dimensions in such predictions.

Walpole and Wilson (2021b) then developed 3-4 item subscales to measure each exposure, susceptibility, severity, and affective factor as personal risk perceptions about the local community. This focus provides useful specificity (e.g. Ajzen & Fishbein 1980), on grounds that "personal and localized risks are more critical to understanding risk perception" (Wilson et al. 2019). The affect subscale comprised concern "about X", "to what extent do you feel worried" about X, and "How afraid are you … of X?"). The severity subscale comprised "How severe would you expect the consequences of X to be?," its impacts' severity "to you… if you were to suffer them," and "how severe would" consequences of X "likely to be" if you suffered them. Susceptibility (e.g. "If X were to occur in your community, how vulnerable would you be to the impacts?") and exposure (e.g. "To what extend do you feel you might experience X in your community?") filled out the proposed taxonomy.

These varied distinctions are informative, but contradictory across if not within each taxonomy: e.g. Sjöberg's (1998) "risk perception" measures (versus "worry") seem examples of "general" measures as cited by Wilson et al. (2019), indicating these two studies were making different comparisons, and Ferrer et al. (2016) novel set of experiential measures included "concern" categorized as affective by Walpole and Wilson (2021b). General risk perception measures are very common, might tap otherwise uncovered aspects of protective action intentions, or could be appropriate if sufficient for research goals or used only as a control variable rather than for prediction, but are omitted from the most recent taxonomizing (Walpole & Wilson, 2021a, 2021b; Wilson et al. 2019). That classification also omits risk perceptions at non-community levels (e.g. national), although these authors acknowledged that including risk perceptions regarding harms to others, particularly for hazards posing little threat to oneself, could improve measurement (Wilson et al. 2019), and might be more important than personal risk perceptions for some outcomes (e.g. predicting policy support, or contributing to collective protection, as in mitigating climate change).

This study

This study had three objectives, using COVID-19 longitudinal panel data in the U.S.: 1) understand how different risk perception measures relate to each other simultaneously and over time; 2) explore relations of different risk perceptions to behavioral intentions and actions; and 3) similarly explore their relations to policy support.

Current results came from an instrument not originally intended to test alternative taxonomic classifications, but rather to inform understanding of variations in threat perceptions, behavioral intentions, and other responses related to the COVID-19 pandemic among Americans over an extended period (14 months of 2020-2021). As a result, no claims regarding the relative validity of any taxonomies discussed earlier can be based on these results. Instead, our taxonomic aim was to explore, and perhaps clarify, associations between diverse risk perception measures, some of which were included, or are variants of those included, in prior taxonomies. Thus below we put our measures in the context of the risk perception taxonomic literature.

First, as Wilson et al. (2019; Walpole & Wilson, 2021b) reported, general risk perception questions have dominated risk analysis literature. They concluded that these offer no insight into specific dimensions (e.g. severity) driving risk perceptions. However, some earlier classifying studies, and prior longitudinal panel studies on Americans' responses to much less prominent infectious episodes in the U.S. (Johnson & Mayorga, 2021; Mayorga & Johnson, 2019), had used such general risk perception measures. This study therefore included three types of general risk perception measures. These included perceptions of personal risk (combining self and family, versus Sjöberg's 1998 distinction between those estimates in his first study), U.S. risk, and global risk. Their inclusion allowed for probing whether general risk perception measures differ collectively from non-general measures, or diverge due to their vast difference in geographic scope. We included two separate measures of personal risk perception, to test whether a measure conditional or not on whether new protective behaviors might be expected makes a difference in longitudinal perception-behavior associations (Brewer et al. 2004). That analysis, reported elsewhere (Johnson & Kim, 2023), found higher risk perception and stronger associations with behavior for the no-action contingent measure, but in the context of other risk perception measures they might group together.

Second, COVID-19 affective risk perception measures included a measure tapping concern about the novel (SARS-CoV-2) coronavirus arriving in one's community, the same phrasing as in one of Walpole and Wilson's (2021b) affective measures. Another measure entailed dread of the coronavirus, as a heightened fear about the hazard, a critical element in psychometric research on public hazard characterizations (e.g. Slovic, 1987), and a prime factor in general baseline risk perceptions for Ebola or Zika (Johnson & Mayorga, 2021; Mayorga & Johnson, 2019). The last measure was of affect, good or bad feelings about the virus without referencing discrete emotions. Due to earlier heterogeneity of affective measures (e.g. concern, worry, fear; Walpole & Wilson, 2021b; concern defined as experiential by Ferrer et al. 2016, with worry and fear—among others—treated as affective measures; Sjöberg's, 1998, focus on worry), it was unclear whether the current three measures would reflect a singular underlying affective response.

Third, we aimed to track perceived magnitude of the COVID-19 pandemic among Americans over time. Our first data collection occurred in late February 2020, when official coronavirus-infected cases in the entire country were in the low double digits, versus the millions to come. Thus we assessed perceived likelihood of a large outbreak of infections in the next five years, paralleling Ebola and Zika questions (Johnson & Mayorga, 2021; Mayorga & Johnson, 2019). In those earlier infectious-disease outbreaks, cases on the mainland U.S. were never many, and declined over the many-months' period of these longitudinal panel surveys, so asking this question seemed appropriate there, and in the first COVID-19 panel wave when the U.S. had < 50 cases.

However, cases quickly accelerated, so by our second wave two months later, we omitted this likelihood question as now irrelevant. Instead, we probed another cognitive form of risk perception, related to Walpole and Wilson's (2021b) severity category. The second (April 2020) and subsequent waves asked how long people thought the epidemic would last (duration), how many Americans they thought would ultimately be infected, and how many they thought would die. These severity measures characterize the expected state of the nation, versus perceived severity of the disease (e.g. asymptomatic versus mild versus hospitalization) if the respondent becomes infected (Walpole & Wilson, 2021b). We could explore whether (e.g.) the general U.S. risk perception measure might cluster with U.S.-focused severity measures.

Given these ruminations and the literature review, several potential classifications might arise empirically from these ten COVID-19 risk perception items. Examples include 1) a one-factor model finding no distinction among risk perception measures, despite their seeming heterogeneity and the literature's emphasis on multi-dimensional categorizations; 2) personal, US, and global risk perceptions cluster, as they are all general risk perception measures as conceived by Wilson et al. (2019); 3) personal and affective (concern, dread, affect) risk perceptions cluster, as all personally relevant and reflecting Wilson et al. (2019) on affect as the most prominent factor in cross-sectional explanation of general risk perceptions, including personal risk items; 4) the U.S. risk perception measure and national severity measures cluster together, as all address the same American geography; and 5) personal, collective (general risk perceptions for the U.S. and globe, as how people conceive of threats to collective entities of which they are members may differ from how they conceive of threat to themselves [Wilson et al. 2019]), affective, and likelihood or severity[1] risk perceptions will cluster separately. Given these multiple possibilities, we treat this as a research question.

RQ1. How do COVID-19 risk perception measures cluster?

Do diverse risk perception measures have different associations with COVID-19 behavioral intentions and actions? The perception-behavior relationship has long interested risk analysts, but researchers have not always been clear about hypotheses they could versus would test. Brewer et al. (2004) helped clarify these distinctions by distinguishing hypotheses about behavioral motivation (risk perceptions at time T yield more protective behavior at $T+1$), risk reappraisal (protective behavior at T yields lower risk perceptions at $T+1$), and accuracy (at any one time people with higher risk perception also exhibit lower behavioral intentions than other people, although positive or null associations also might occur, e.g. because people are skeptical that behaviors are indeed protective). Only the accuracy hypothesis can be tested in the cross-sectional survey design dominating risk perception-behavior studies, so most alleged tests of behavioral motivation (the most commonly discussed perception-behavior relationship) may be misleading. As noted earlier, we have separately tested these three hypotheses with COVID-19 data, finding the behavioral motivation hypothesis was strongly supported; the risk reappraisal hypothesis was strongly refuted (protective behavior increased versus decreased future risk perceptions); and the accuracy hypothesis' negative-association form was mostly supported (Johnson & Kim, 2023). Here we keep the analytic difficulties and reader burden relatively low by conducting only wave-specific analyses, equivalent to doing six cross-sectional analyses, to examine relative effects of different risk perception measures on behavioral intentions/actions.

The logical and empirical assumption has been that behavioral intentions should be shaped by personal (i.e. self, or self-plus-family) risk perceptions, as these intentions concern personal or household behaviors. Scovell et al. (2022) noted that expectancy value theories presume a positive relation, but the empirical literature yields mixed results (on the latter point, also see Asgarizadeh Lamjiry & Gifford, 2022): studies from health and natural hazards research had variously found equal effects of both risk perception and protective action perceptions (e.g. the action's efficacy at reducing risk), stronger effects of protective action perceptions, or risk perception as a non-significant or negative predictor of behavior. Similarly, perceived personal risk did not affect U.S. COVID-19 protective behavior in April and October 2020 (Fullerton et al. 2022), but other studies found positive associations (e.g. Dryhurst et al. 2020; Frounfelker et al. 2021). Here we presume from both theory and our earlier behavioral motivation analyses that

H1. Behavioral intentions are positively associated with personal risk perception.

Perceived personal risk is our baseline measure for risk perceptions' associations with behavioral intentions and actions, but no published analysis seems to address differences among risk perception measures, with most items used being cognitively-oriented personal risk perceptions. Often they are general: e.g. they do not break down cognitive measures into those that assess perceived likelihood versus perceived severity if the hazard is experienced (Walpole & Wilson, 2022). One observation—"There may be a distinction between how people conceptualize threats on a personal level versus a population level. It may be worthwhile for researchers to explore whether these more nuanced factor structures correspond to any important empirical distinction in risk perceptions or behavior" (LaCour et al. 2022, p. 518)—was prompted by observed mean differences between items specifying personal versus more general risk targets (e.g. "The coronavirus poses a serious risk"), but the authors used reliability statistics rather than factor analysis to directly assess their items' dimensionality (see Johnson & Swedlow, 2023 for a critique of using reliability, a measure of internal consistency, to determine dimensionality). We thus evaluated how much more—if any—variance in intentions and actions is explained by including other risk perception types, either for specific measures or jointly. For example, Wilson et al. (2019) finding that affective responses were most related to general risk perception items—e.g. the personal, U.S., and global risk perception items used here—suggested that behavioral intentions also might be influenced by affective measures, even controlling for logically prior effects of personal risk perception.

Infectious diseases mean that how one protects—or does not protect—oneself could affect the risk faced by others, whether occupants of one's household or strangers, and conversely, infectious risks faced by others, and their degree of protective action, might affect one's own risk. Other-directed risk perception measures—i.e. U.S. and global items, and expectations of total U.S. infections and deaths, and duration of the U.S. outbreak—also might contribute to behavioral intentions (e.g. see empathy for virus-vulnerable people as affecting social distancing compliance; Pfattheicher et al. 2020). The few empirical studies tend to conflict with this hypothesis, but do not explicitly use different risk perception measures. For example, Vignoles et al. (2021) found in a United Kingdom sample that family identification helped shape physical distancing, community identification increased helping of both near and distant strangers, national identification had no effect on personal behavior but increased proximal and decreased distal helping, and identification with humanity in this global pandemic only had psychological effects. In multi-national samples Bor et al. (2022) found moralizing of social distancing based primarily on self-interest, not altruistic motives. In a negative example, Bazzi et al. (2021) found "rugged individualism" behind collective inaction at the U.S. county level; each county's total frontier experience (decades it was within 100 km of the official U.S. frontier) was associated with lower voter turnout and opposition to government intervention, which they took to indicate low civic culture and low willingness to accept personal costs for the greater good.

H2. Behavioral intentions are positively associated with affective (concern, dread, affect) and other-directed (U.S., global, infection, mortality, duration) risk perceptions, controlling for personal risk perception.

RQ2. How large is the contribution of personal versus other risk perceptions to explanation of variance in behavioral intentions/actions?

An important caveat about predicting behavior is needed. Many if not most studies supplement risk perception with other factors, such as perceived attributes of the actions themselves (e.g. response efficacy; resources needed to enact it), perceptions of stakeholders in the issue area (e.g. trust in relevant business, government, and other actors), general attitudes towards a hazard or technology, and others (e.g. Lindell & Perry, 2012; Scovell et al. 2022; Siegrist & Árvai, 2020), to identify their relative contributions to behavioral intentions and actions. As our aim here is to explore relative contributions of different kinds of risk perceptions to intentions/actions, we exclude other potential factors for simplicity and brevity, as all else equal these other factors pose a constant effect. While risk perceptions on their own might explain low amounts of variance in behavioral intentions/actions, this is a minor problem as we are not claiming that risk perceptions are the only factors.

The scholarly literature has paid less attention to policy support's relationship to risk perceptions. Most such studies emphasize domain-specific policies, often finding positive associations. For example, risk perception was the strongest predictor of climate-change policy support (Zahran et al. 2006); hurricane-related coastal flood risk perceptions raised support for adaptation policies (Shao et al. 2017); both risk perceptions and trust influenced climate change policy support, but trust reduced risk-perception effects on policy support somewhat while not altering its behavioral effects (Smith & Mayer, 2018); and risk perception increased COVID-19 policy support in China (Ding et al. 2020). A few studies assessed general measures. For example, demand for risk reduction (comprising budget allocation, priority setting, and necessity; rank correlations > .90) exhibited lower association with risk perception across multiple hazards (e.g. rank correlation with priority rank = .62 and budget allocation = .49; Placer & Delquié, 1999). A recent theme has been potential for aversion to certain hazard solutions to reduce personal risk perceptions (e.g. Campbell & Kay, 2014; Johnson, 2022; Ponce de Leon, 2020), yielding mixed results: the first two papers generally find positive results, while the third paper found weak solution-aversion effects for both perceived personal and U.S. risk perceptions, but very strong negative effects on policy support. Based on this, we posit that

H3. Risk perceptions will exhibit positive associations with policy support.

Policy support studies also use quite heterogeneous risk perception measures, but generally seem to use general or cognitive (e.g. likelihood, severity if experienced) measures. An exception is Ding et al. (2020), who found that cognitive and affective risk perceptions exhibited about equal associations with COVID-19 policy support. However, as policies express at least implicit collective action in republican democracies—i.e. the people elect representatives who then develop and implement policies (directly, or *via* government agencies) on behalf of the population—we suggest that

> **H4**. Policy support will be more associated with collective and national severity risk perception measures, and less with personal and affective risk perceptions.

A further novelty of this study is our ability to assess these associations between different risk perception measures at six different times across 14 months of the pandemic, thus probing our findings' robustness more than is feasible in cross-sectional studies. The lone paper probing such temporal variation beyond two waves and with multiple general risk (personal, U.S.) perception measures, on Zika (Johnson & Mayorga, 2021), does not offer a foundation for clear hypotheses about temporal variation in risk perception measures' clustering or effects.

Our aim here, then, is to analyze relationships among up to ten risk perception measures at a time (when severity items were available; eight measures in Wave 1), and then explore how the identified classes of risk perception similarly or differentially explain behavioral and policy-support responses to COVID-19.

Methods

Data came from a six-wave longitudinal panel study over almost 14 months—February 28-29, 2020 (Wave 1, $n = 2{,}005$, April 27-May 6, 2020 (Wave 2, $n = 1{,}613$), August 5-13, 2020 (Wave 3, $n = 1{,}184$), October 12-21, 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 people answering a given wave were invited to the next one, except for Wave 6 where everyone answering Wave 1 was invited, testing whether respondents persisting for five or six waves—our focus—differed from dropouts. This study was reviewed by the Decision Research Institutional Review Board (IRB) for adherence to ethical research standards, and determined to be exempt by the Human Protections Officer, posing no more than minimal risk to participants (under federal regulation 45 CFR part 46). Participant consent was obtained by their choice to answer the survey after exposure to informed consent materials.

Risk perception measures (Table 1) were collected in Waves 1-6 except for severity measures (Waves 2-6), and the likelihood item (Wave 1), the latter omitted in later waves as irrelevant to what the World Health Organization had by then declared a global pandemic.

Behavioral intentions were measured by the ordinal-scale item "My household…" has never considered taking this action, is considering it, decided against taking this action, decided to take this action, has taken this action, or has taken this action and will continue to take this action as needed. Specifically, anyone who had decided to take the action, had taken the action, or had taken and will continue taking the action were coded as intending/acting for subsequent analyses. We asked about hand-washing, mask-wearing, avoiding travel to infected areas, avoiding large public gatherings, avoiding Asians, vaccination, and (Waves 2-6) self-isolation at home, but here just focus on mask-wearing, avoiding gatherings, and vaccination. Our criteria were to include actions for which we probed both intentions and support in all six waves, and which showed some temporal variation in intentions, while limiting reader burden.

Policy support was measured by an ordinal item (1 strongly oppose, 4 neither support nor oppose, 7 strongly support) "I would ___ the government adopting this option." Among the various policies in the survey we focus on three to parallel those for behavior: "require that people wear face masks when they are in public"; "ban large public gatherings (formal organized events or informal gatherings)"; and "mandate vaccination against the coronavirus when a

Table 1. Risk perception measures.

Measure	Scale	Source
General Risk Perception (Waves 1-6)		
Personal, no action: "How much risk does the coronavirus pose to you or your family, if you or your family doesn't do anything new to protect yourself against the coronavirus?"	1 *no risk*, 6 *very high risk*	Adapted from Mertz et al. 1998, Brewer et al. 2004
Personal, action: "Now, 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?"	Same	Adapted from Mertz et al. 1998, Brewer et al. 2004
U.S.: "How much risk does the coronavirus pose to the U.S.?"	Same	Mertz et al. 1998
Global: "How much risk does the coronavirus pose to the world?"	Same	Mertz et al. 1998
Affective Risk Perception (Waves 1-6)		
Concern: "How concerned are you that the coronavirus will spread to where you live?"	1 *not at all concerned*, 6 *extremely concerned*	Johnson & Mayorga, 2021
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*	Slovic, 1987; Fischoff et al. 1978
Affect: "How does considering the coronavirus make you feel, from very bad to very good?"	Slider, 0-100 (reversed, converted to 1-6 scale)	Johnson, 2022
Severity Risk Perception (Waves 2-6)		
Duration: "How long do you think this outbreak will last, to the best of your knowledge?"	1 *less than a month*, 8 *more than 24 months (2 years)*	
Infection: "About how many people in the U.S. do you think will become infected in this outbreak?"	1 *less than 10,000*, 6 *100 million or more*	
Deaths: "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*	
Likelihood Risk Perception (Wave 1)		
"How likely do you think it is that there will be a large outbreak of coronavirus infections in the U.S. in the next five years?"	Slider, 0%-100%	Johnson & Mayorga, 2021

vaccine becomes available." All three policies were mandates, versus seeking voluntary compliance, so may be more resisted than other policies.

People providing erroneous vaccination behavioral intentions (taken the action, continuing) in one or more of Waves 1-4, when COVID-19 vaccines were not available until December 2020, were removed from all analyses as inattentive. A check in Wave 4 confirmed that none of those remaining who gave these answers had been in clinical trials, the only valid explanation.

Correlational and regression analyses were conducted with SPSS 27, with exploratory factor analyses and confirmatory factor analyses (CFAs) conducted with the lavaan package in R software (Rosseel, 2012). Differences in chi-square across models were calculated with the lavTestLRT function in R. Descriptive results (sample demographics; reported behavior and policy support) analyses here are weighted, using the R anesrake package, to reflect U.S. Census 2020 Current Population Survey estimates for gender (male, female), age (18–44, 45–64, 65+), education (high school or less, some college, bachelor's degree or more), and ethnicity (non-Hispanic white, others). CFAs and multiple regression analyses are unweighted because weights apply only to the first wave, thus errors from weighting would accumulate over time.

Results

Respondents to Wave 1 (Table 2) were, versus 2020 U.S. Census estimates for U.S. adults 18+, slightly less female, perhaps older, more non-Hispanic White, far better educated, and somewhat lower in income. Half (49.6%) reported being Democrats, 15.4% Republican, and 34.9% independent or undeclared political partisanship; 61.4% reported being slightly to extremely liberal political ideology, 19.6% reported conservative ideology.

We compared risk perception results and demographics of dropouts ($n = 1241$, including 271 who returned in Wave 6) to those finishing all surveys ($n = 764$; 38.1%) to assess attrition effects. Most W1 and W6 risk perception results (personal, collective, affective, affect) did not differ significantly between dropouts and those who never left. However, W1 affect responses were significantly higher among the never-left group than for those dropping out after W2 (p = .003) according to pairwise comparisons (Tukey's HSD). W6 severity responses (questions not asked in W1) were also significantly higher among the never-left group than for W6 respondents dropping out after W2 (p = .048; Tukey's HSD). There was no statistically significant difference for W6 duration responses. On demographics, gender and political party exhibited no difference in attrition; those with college educations were less likely to drop out in W1-2 and more likely to answer all surveys (χ^2 (10, $n = 2001$) = 28.93, $p < .01$); non-Hispanic whites also were more likely to stay in (χ^2 (5, $n = 2001$) =23.62, $p < .001$); and younger people dropped out more than others (χ^2 (10, $n = 1999$) = 113.58, $p < .001$). As our interest in demographic variables is only in their effect on risk perceptions, and there were no substantive differences in risk perceptions, we conclude there is no substantive attrition effect.

Supporting Information features inter-item correlations (Table 1), and confirmatory factor analyses (CFA; Tables 2–5) presuming either a single factor, or three variant three-factor, models for risk perception models presented as models 1-4 preceding RQ1, omitting them from future discussion because their fit was so poor.

We then ran the fifth (4-factor) model separating out personal, collective, affective, and either likelihood (Wave 1) or severity (Waves 2-6) risk perception items (Supporting Information, Table 6). Model fit statistics were much improved, but chi-square/df ratios and RMSEA values were still unsatisfactory; Wave 1 results (i.e. with likelihood not severity as a separate category) had generally worse fit, which might be substantive (likelihood conceptually fits worse than severity) or methodological (e.g. poorer fit because likelihood has only a single indicator). Affect (.473-.593) and duration (.368-.554) had substantially lower regression weights than other items in their respective categories (.722-.901 affective, .708-.887 severity). Six-factor models, with affect separate from the affective category, and duration from the severity category, for Waves 2-6 (Supporting Information, Table 7), improved on all prior results, although again RMSEA and particularly chi-square/df ratios were unsatisfactory. Chi-square difference tests of the 4-factor and 6-factor models in Waves 2-6 found all differences significant at $p < .001$ (Supporting Information, Table 8). The Wave 1 model (substituting likelihood for the severity items) was still the worst-fitting of the six analyses.

However, with affect and duration omitted entirely (Table 3) from the four-factor model, model fit improved markedly over both the original four-factor model and the six-factor model (chi-square difference $p < .001$; Supporting Information, Table 8). Although with large sample sizes most chi-square values were still statistically significant, the Wave 5 model was not significant, indicating a very well-fitting model (that this wave's chi-square values were lower than for any other wave, yet each analysis had the same number of parameters, probably reflected

Table 2. Sample and U.S. demographics for adults.

Variable	Sample, Unweighted	Sample, Weighted	U.S.
Gender (female)	49.6%	52.9%	51.6%
Age (median)	32.0	47.0	37.5 (includes children)
Age (65+)	3.7%	20.6%	21.7%
Non-Hispanic White ethnicity	72.1%	64.3%	62.8%
Education (bachelor's degree +)	54.7%	35.4%	34.8% (25+ years old)
Household income (< \$100,000)	81.6%	87.7%	66.5%
Household income (< \$15,000)	10.8%	13.3%	9.4%

Table 3. Confirmatory factor analyses for 4-factor models: Personal, collective, affective, severity (with affect and duration omitted).

Waves	1	2	3	4	5	6
Model Fit						
Chi-square	55.330***	54.480***	69.943***	34.945**	14.931	30.440**
Degrees of freedom (df)	9	14	14	14	14	14
Chi-square/df	6.148	3.891	4.996	2.496	1.067	2.174
Root mean square of approximation [RMSEA] (90% confidence interval)	.051 (.038, .064)	.042 (.031, .055)	.058 (.045, .072)	.038 (.022, .054)	.009 (.000, .035)	.034 (.017, .050)
Comparative Fit Index [CFI]	.995	.994	.990	.996	1.000	.997
Correlation among factors (total)						
Personal-Collective	.661	.575	.696	.721	.700	.693
Personal-Affective	.838	.795	.876	.845	.865	.809
Personal-Likelihood	.514	NA	NA	NA	NA	NA
Personal-Severity	NA	.316	.423	.384	.383	.311
Collective-Affective	.801	.773	.794	.827	.826	.830
Collective-Likelihood	.641	NA	NA	NA	NA	NA
Collective-Severity	NA	.364	.433	.444	.394	.395
Affective-Likelihood	.631	NA	NA	NA	NA	NA
Affective-Severity	NA	.375	.418	.402	.442	.373
Standardized regression weights						
Factor 1: Personal						
No-Action	.932	.867	.858	.878	.914	.921
Action	.838	.781	.774	.742	.763	.738
Factor 2: Collective						
US	.972	.968	.974	.981	.975	.979
Global	.818	.918	.904	.930	.957	.944
Factor 3: Affective						
Concern	.905	.893	.910	.914	.913	.901
Dread	.717	.696	.717	.721	.720	.714
Factor 4: Severity						
Infection	NA	.664	.694	.701	.699	.748
Deaths	NA	.876	.844	.852	.838	.933
Factor 5: Likelihood	1.00	NA	NA	NA	NA	NA

NA: not applicable.
***$p < .001$.

Table 4. Proportion of protective behavior intentions/actions, and support for federal mandates, for selected behaviors.

Behavioral Intentions/ Reports	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6
Mask wearing	10.6%	86.0%	97.0%	96.0%	97.0%	96.6%
Avoiding large public gatherings	26.4%	94.3%	91.9%	88.9%	92.7%	88.5%
Getting vaccinated	20.4%	40.9%	42.5%	43.7%	64.1%	69.3%
Mandatory Federal Policies						
Mask wearing	34.7%	78.9%	84.5%	84.3%	81.5%	79.7%
Avoiding large public gatherings	33.1%	83.0%	80.1%	80.8%	80.9%	78.4%
Getting vaccinated	57.1%	62.0%	54.6%	47.3%	51.7%	50.0%

Weighted sample results. People with erroneous vaccination responses for Waves 1-4 were removed from all analyses (see Section 4.4). Intentions/actions represent all who said that they had decided to take the action, or who reported having taken it and/or continue to take it.

that the sample size was at its smallest in this wave). Chi-square/df ratios were < 5 for all but Wave 1, and < 2 for Wave 5; RMSEA was < .05 for four of six waves; CFI values were ≥ .99, indicating excellent fit. As for inter-factor correlations, the general personal-risk factor was most correlated with the affective factor (consistent with Wilson et al. 2019), less but still highly

Table 5. Relative associations of alternative risk perception measures with selected protective behavior intentions.

	Mask Wearing				Avoiding Public Gatherings				Getting Vaccine When Available			
Wave 1	I	II	III	IV	I	II	III	IV	I	II	III	IV
Personal	.279***	.147***	.151***	.141***	.261***	.117***	.106***	.109***	.212***	.117***	.107***	.091**
Affective		.208***	.219***	.192***		.203***	.173***	.182***		.150***	.123**	.083*
Affect		−0.044†	−0.042	−0.033		.003	−0.004	−0.007		−0.030	−0.037	−0.023
Collective			−0.021	−0.061†			.061†	.075*			.053	−0.008
Likelihood				.100***				−0.035				.155***
F(df)	143.75***	60.44***	45.42***	38.80***	124.33***	55.74***	42.74***	34.46***	80.49***	32.85***	25.28***	25.66***
	(1,1706)	(3,1704)	(4,1703)	(5,1702)	(1,1705)	(3,1703)	(4,1702)	(5,1701)	(1,1706)	(3,1704)	(4,1703)	(5,1702)
R^2	.078	.096	.096	.102	.068	.089	.091	.092	.045	.055	.056	.070
R^2_{adj}	.077	.095	.094	.100	.067	.088	.089	.089	.044	.053	.054	.067
ΔR^2	.078***	.018***	.000	.006***	.068***	.021***	.002†	.001	.045***	.010***	.001	.014***
Wave 2												
Personal	.213***	.053	.025	.005	.162***	.051	.014	.003	.203***	.108***	.097**	.077*
Affective		.165***	.023	.011		.085*	−0.063	−0.074†		.144***	.057	.047
Affect		.145***	.112***	.109***		.173***	.139***	.135***		.011	−0.009	−0.012
Collective			.269***	.233***			.286***	.260***			.166***	.143***
Severity				.078**				.071**				.086***
Duration				.092***				.056*				.032
F(df)	63.21***	47.78***	52.23***	39.96***	43.51***	38.96***	50.30***	36.78***	69.32***	31.12***	30.05***	22.82***
	(1,1335)	(3,1333)	(4,1332)	(6,1330)	(1,1607)	(3,1605)	(4,1604)	(6,1602)	(1,1606)	(3,1604)	(4,1603)	(6,1601)
R^2	.045	.097	.136	.153	.026	.068	.111	.121	.041	.055	.070	.079
R^2_{adj}	.044	.095	.133	.149	.026	.066	.109	.118	.041	.053	.067	.075
ΔR^2	.045***	.052***	.039***	.017***	.026***	.042***	.044***	.010***	.041***	.014***	.015***	.009***
Wave 3												
Personal	.276***	.093*	.015	−0.002	.294***	.096*	.022	.007	.214***	.067†	.042	.036
Affective		.113**	−0.050	−0.056		.163***	.008	.003		.183***	.132**	.131**
Affect		.241***	.185***	.186***		.194***	.141***	.142***		.042	.024	.027
Collective			.361***	.335***			.342***	.321***			.114**	.106**
Severity				.096***				.086**				.057†
Duration				.017				.009				−0.025
F(df)	98.49***	67.29***	77.59***	54.47***	113.04***	68.84***	76.10***	52.73***	57.31***	29.08***	23.93***	16.54***
	(1,1190)	(3,1188)	(4,1187)	(6,1185)	(1,1191)	(3,1189)	(4,1188)	(6,1186)	(1,1192)	(3,1190)	(4,1189)	(6,1187)
R^2	.076	.145	.207	.216	.087	.148	.204	.211	.046	.068	.075	.077
R^2_{adj}	.076	.143	.205	.212	.086	.146	.201	.207	.045	.066	.071	.072
ΔR^2	.076***	.069***	.062***	.009***	.087***	.061***	.056***	.007**	.046***	.022***	.0006**	.003
Wave 4												
Personal	.257***	.064	−0.021	−0.043	.308***	.073†	.008	−0.001	.198***	.122**	.084†	.089*
Affective		.182***	−0.005	−0.010		.261***	.119*	.117*		.104*	.020	.021
Affect		.155***	.106**	.099**		.129***	.091**	.088**		.009	−0.014	−0.012
Collective			.377***	.323***			.286***	.255***			.169***	.178***
Severity				.115***				.131***				.005

(*Continued*)

Table 5. Continued.

	Mask Wearing				Avoiding Public Gatherings				Getting Vaccine When Available			
Wave 1	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**
Duration				.075*				−0.019				−0.034
F(df)	72.14***	45.72***	56.00***	42.48***	107.40***	66.02***	62.92***	45.55***	41.75***	16.19***	15.63***	10.56***
	(1,1023)	(3,1021)	(4,1020)	(6,1018)	(1,1023)	(3,1021)	(4,1020)	(6,1018)	(1,1023)	(3,1021)	(4,1020)	(6,1018)
R^2	.066	.118	.180	.200	.095	.162	.198	.212	.039	.045	.058	.059
R^2_{adj}	.065	.116	.177	.196	.094	.160	.195	.207	.038	.043	.054	.053
ΔR^2	.066***	.053***	.062***	.020***	.095***	.067***	.035***	.014***	.039***	.006*	.012***	.001
Wave 5												
Personal	.311***	.048	−0.023	−0.041	.304***	.025	−0.031	−0.042	.229***	.055	.003	.012
Affective		.219***	.047	.027		.314***	.176***	.168**		.239***	.112*	.110†
Affect		.258***	.220***	.203***		.127***	.097**	.090*		.005	−0.024	−0.027
Collective			.337***	.307***			.271***	.253***			.249***	.261***
Severity				.158***				.050				.070*
Duration				.035				.055†				−0.119***
F(df)	92.52*** (1,864)	73.39***	73.35***	55.36***	88.06*** (1,864)	60.31***	55.90***	38.54***	48.03***	25.22***	26.14***	19.80***
		(3,862)	(4,861)	(6,859)		(3,862)	(4,861)	(6,859)	(1,864)	(3,862)	(4,861)	(6,859)
R^2	.097	.203	.254	.279	.092	.173	.206	.212	.053	.081	.108	.122
R^2_{adj}	.096	.201	.251	.274	.091	.171	.202	.207	.052	.077	.104	.115
ΔR^2	.097***	.107***	.051***	.025***	.092***	.081***	.033***	.006*	.053***	.028***	.028***	.013**
Wave 6												
Personal	.285***	.129***	.029	.027	.334***	.101**	.009	.015	.232***	.039	−0.024	−0.009
Affective		.137***	−0.095*	−0.097*		.306***	.092*	.092*		.225***	.080	.080†
Affect		.205***	.167***	.151***		.087**	.051	.047		.131***	.107**	.104**
Collective			.439***	.404***			.406***	.399***			.276***	.276***
Severity				.168***				.071*				.081*
Duration				−0.045				−0.059*				−0.117***
F(df)	89.96***	57.79***	76.17***	57.52***	127.68***	76.77***	88.01***	60.31***	57.81***	43.59***	43.93***	32.51***
	(1,1020)	(3,1018)	(4,1017)	(6,1015)	(1,1017)	(3,1015)	(4,1014)	(6,1012)	(1,1020)	(3,1018)	(4,1017)	(6,1015)
R^2	.081	.146	.231	.254	.112	.185	.258	.263	.054	.114	.147	.161
R^2_{adj}	.080	.143	.228	.249	.111	.183	.255	.259	.053	.111	.144	.156
ΔR^2	.081***	.064***	.085***	.023***	.112***	.073***	.073***	.006*	.054***	.060***	.033***	.014***

Standardized correlation coefficients.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Table 6. Relative associations of alternative risk perception measures with selected federal mandate policies.

	Mask-Wearing				Avoiding Public Gatherings				Getting Vaccine When Available			
Wave 1	I	II	III	IV	I	II	III	IV	I	II	III	IV
Personal	.288***	.126***	.110***	.114***	.344***	.182***	.161***	.162***	.079***	−0.027	−0.040	−0.045
Affective		.205***	.161***	.170***		.227***	.171***	.174***		.109**	.074†	.061
Affect		.056*	.046†	.043		.013	−0.001	−0.002		.094**	.085**	.089**
Collective			.087**	.100**			.112***	.116***			.070*	.050
Likelihood				−0.033				−0.011				.049
F(df)	154.10***	72.90***	56.68***	45.59***	229.57***	97.54***	76.73***	61.39***	10.62***	15.17***	12.45***	10.46***
	(1,1706)	(3,1704)	(4,1703)	(5,1702)	(1,1706)	(3,1704)	(4,1703)	(5,1702)	(1,1706)	(3,1704)	(4,1703)	(5,1702)
R^2	.083	.114	.117	.118	.119	.147	.153	.153	.006	.026	.028	.030
R^2_{adj}	.082	.112	.115	.116	.118	.145	.151	.150	.006	.024	.026	.027
ΔR^2	.083***	.031***	.004**	.001	.119***	.028***	.006***	.000	.006***	.020***	.002*	.001
Wave 2												
Personal	.349***	.088**	.040	.034	.292***	.068*	.014	.012	.263***	.094**	.054†	.051†
Affective		.366***	.172***	.167***		.276***	.053	.050		.244***	.080*	.077*
Affect		.088***	.042†	.040		.145***	.093***	.093***		.042	.004	.004
Collective			.373***	.360***			.429***	.425***			.316***	.310***
Severity				.025				.046†				.035
Duration				.039				−0.022				−0.001
F(df)	223.53***	161.22***	176.68***	118.97***	149.43***	115.55***	152.78***	102.60***	119.71***	68.75***	80.56***	54.05***
	(1,1608)	(3,1606)	(4,1605)	(6,1603)	(1,1608)	(3,1606)	(4,1605)	(6,1603)	(1,1608)	(3,1606)	(4,1605)	(6,1603)
R^2	.122	.231	.306	.308	.085	.178	.276	.277	.069	.114	.167	.168
R^2_{adj}	.122	.230	.304	.306	.084	.176	.274	.275	.069	.112	.165	.165
ΔR^2	.122***	.109***	.074***	.002†	.085***	.093***	.098***	.002	.069***	.045***	.053***	.001
Wave 3												
Personal	−0.165***	.003	.030	.025	.417***	.067†	−0.032	−0.044	.326***	.099*	.027	.029
Affective		−0.202***	−0.143**	−0.149**		.407***	.189***	.184***		.261***	.106*	.110*
Affect		−0.056	−0.035	−0.038		.143***	.070*	.070*		.098**	.046	.051
Collective			−0.129**	−0.141***			.469***	.451***			.337***	.344***
Severity				−0.010				.060*				.044
Duration				.059†				.019				−0.078*
F(df)	29.69***	20.78***	17.98***	12.50***	223.26***	153.99***	278.54***	122.31***	122.91***	66.52***	71.11***	48.76***
	(1,1062)	(3,1060)	(4,1059)	(6,1057)	(1,1062)	(3,1060)	(4,1059)	(6,1057)	(1,1036)	(3,1034)	(4,1033)	(6,1031)
R^2	.027	.056	.064	.066	.174	.304	.406	.410	.106	.162	.216	.221
R^2_{adj}	.026	.053	.060	.061	.173	.302	.404	.406	.105	.159	.213	.216
ΔR^2	.027***	.028***	.008**	.003	.174***	.130***	.102***	.004*	.106***	.056***	.054***	.005*
Wave 4												
Personal	.447***	.162***	.033	.019	.428***	.122***	−0.002	−0.014	.236***	.051	−0.018	−0.006
Affective		.351***	.067†	.064		.389***	.115**	.112**		.223***	.069	.071
Affect		.099**	.024	.019		.087**	.015	.011		.069†	.028	.032
Collective			.573***	.543***			.552***	.523***			.311***	.332***
Severity				.030				.057*				.033

(*Continued*)

Table 6. Continued.

	Mask-Wearing				Avoiding Public Gatherings				Getting Vaccine When Available			
Wave 1	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**
Duration				.075**				.044				−0.101**
F(df)	255.52***	139.87***	195.08***	133.21***	229.61***	136.96***	183.76***	125.09***	60.52***	35.39***	40.16***	28.39***
	(1,1023)	(3,1021)	(4,1020)	(6,1018)	(1,1023)	(3,1021)	(4,1020)	(6,1018)	(1,1023)	(3,1021)	(4,1020)	(6,1018)
R^2	.200	.291	.433	.440	.183	.287	.419	.424	.056	.094	.136	.143
R^2_{adj}	.199	.289	.431	.437	.183	.285	.417	.421	.055	.092	.133	.138
ΔR^2	.200***	.091***	.142***	.006**	.183***	.104***	.132***	.006**	.056***	.038***	.042***	.007*
Wave 5												
Personal	.459***	.100*	−0.015	−0.020	.469***	.114**	.003	−0.007	.310***	.024	−0.053	−0.041
Affective		.425***	.143***	.140***		.439***	.167***	.160***		.402***	.214***	.217***
Affect		.129***	.066*	.063*		.093**	.032	.027		−0.007	−0.049	−0.048
Collective			.553***	.545***			.533***	.518***			.369***	.387***
Severity				.019				.044				.020
Duration				.026				.045				−0.112***
F(df)	231.01***	147.39***	195.05***	130.32***	243.07***	147.96***	188.36***	127.44***	92.00***	59.85***	65.48***	46.16***
	(1,864)	(3,862)	(4,861)	(6,859)	(1,864)	(3,862)	(4,861)	(6,859)	(1,863)	(3,861)	(4,860)	(6,858)
R^2	.211	.339	.475	.477	.220	.340	.467	.471	.096	.173	.233	.244
R^2_{adj}	.210	.337	.473	.473	.219	.338	.464	.467	.095	.170	.230	.239
ΔR^2	.211***	.128***	.136***	.001	.220***	.120***	.127***	.004*	.096***	.076***	.061***	.011**
Wave 6												
Personal	.435***	.131***	.003	.003	.422***	.130***	.007	.004	.278***	.031	−0.057	−0.044
Affective		.412***	.114**	.114**		.392***	.105**	.104**		.333***	.127**	.127**
Affect		.089**	.038	.030		.094**	.045	.040		.078*	.044	.045
Collective			.564***	.547***			.544***	.533***			.390***	.400***
Severity				.091***				.038				.035
Duration				−0.034				.008				−0.098***
F(df)	237.09***	152.38***	208.44***	142.61***	220.29***	139.12***	185.24***	123.96***	85.02***	63.56***	73.86***	51.45***
	(1,1015)	(3,1013)	(4,1012)	(6,1010)	(1,1015)	(3,1013)	(4,1012)	(6,1010)	(1,1014)	(3,1012)	(4,1011)	(6,1009)
R^2	.189	.311	.452	.459	.178	.292	.423	.424	.077	.159	.226	.234
R^2_{adj}	.189	.309	.450	.455	.178	.290	.420	.421	.076	.156	.223	.230
ΔR^2	.189***	.122***	.141***	.007**	.178***	.113***	.131***	.001	.077***	.081***	.068***	.008**

Standardized correlation coefficients.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

correlated with the collective factor, moderately correlated with likelihood in Wave 1, and weakly correlated with severity in Waves 2-6. The general collective factor was most correlated with the affective factor (again consistent with Wilson et al. 2019), followed by the personal and likelihood factors, and again weakly correlated with severity. The affective factor was most associated with the personal factor, followed by the collective, likelihood, and severity factors, with the latter correlations again far weaker than the others.[2]

Although the best-fitting CFA model was the four-factor model excluding affect and duration entirely, to probe risk perception associations we used the six risk perception factors in Waves 2-6 to understand how affect and duration associations differ from those of the best-confirmed factors: personal, affective, collective, severity. We ignored Wave 1 due to its worse model fit.

Positive responses to all three behaviors (i.e. intentions and self-reported actions) and all three policies (i.e. any degree of support) for all survey waves appear in Table 4. Wave 1 was a clear outlier in low intentions/support for all three actions and two policies, although vaccination policy support was a majority view at this early stage; policy support for each action was greater in February 2020 than personal intentions to enact that behavior. By contrast, intentions for mask wearing and avoiding gatherings exceeded federal mandate support for those two actions for Waves 2-6, while intentions for vaccination during those waves were flat—and did not exceed support for a federal vaccination mandate—until Wave 5, when vaccines were publicly available. The trend for supporting mandatory vaccination might have been affected by increasing political polarization in the U.S. over vaccines during 2020: support peaked to almost two-thirds in late April during the first pandemic surge and lockdowns, bottomed out at less than half the sample just before the presidential election, and barely recovered when vaccines had become available. Although these later proportions seem quite high, particularly for mask wearing and avoiding large public gatherings, we must point out that they include intentions as well as actual actions (though at this point in the pandemic unimplemented intentions were rare for such behaviors as mask wearing), that whether they had become normative or not they were among the most accessible to implement, and our stimuli (e.g. "Wear a face mask when going out in public") might not have provided enough constraint on boundary conditions—e.g. indoors in close proximity to others; outdoors in close proximity to others; wearing it so that both nose and mouth were securely covered—to have limited reported compliance.

Hierarchical linear regression analyses for the three behavioral intentions (Table 5) presume personal risk perception as the baseline motivation, then add affective (including affect), collective, and finally likelihood (Wave 1) or severity (including duration; Waves 2-6) risk perception measures. Adjusted R^2 was lowest in Wave 1 (7% vaccination, to 10% masks), versus Wave 2 (8%-15%), Wave 3 (7%-21%), Wave 4 (5%-21% gatherings), Wave 5 (12%-27%), and Wave 6 (16%-26% gatherings). There was a temporal increase in how much risk perception measures collectively explained variance for all three behaviors, with vaccination always the least-explained behavior and mask-wearing (excluding Waves 4 and 6) the best-explained.

When we examine statistical significance of changes in adjusted R^2, in Wave 1 adding the collective risk perception index to the personal risk perception index was marginally significant or non-significant at $p < .10$ for all three behaviors; in Waves 3 and 4 adding severity measures for vaccination intentions was non-significant at $p < .10$; and the remaining additions (49 of 54, or 90.7%) were significant at $p < .05$ or better. Thus we answer RQ1 affirmatively: overall COVID-19 risk perception measures that omit explicit mention of personal risk, and often explicitly mention other risk targets (i.e. U.S. or global), add to explained variance in behavioral intentions/actions beyond what personal risk perceptions offer.

On the relative contribution of different risk perception measures, assessed through changes in adjusted R^2 when moving from personal risk perception only to all variables, the change is relatively small in Wave 1 (~ .023, or about a 30% increase), which might reflect the early stage of the pandemic in the U.S., the worse fit of the model when it includes likelihood, or both. Changes in R^2 are much larger in later waves for mask wearing (.131-.178) and avoiding gatherings (.092-.148), but of roughly similar magnitude for vaccination intentions (.015-.034), excluding the last two waves with actually-available vaccines (Wave 5: .063; Wave 6: .103). Jointly non-personal risk perceptions explained more variance in mask wearing and avoiding gathering intentions than did personal risk perceptions, excluding Wave 1.

Comparing contributions to behavioral intentions using model IV's standardized regression coefficients (Table 5) yields a much more complex pattern. For mask wearing and avoiding public gatherings, the most explanatory risk perception measures in each wave, controlling for all other measures' effects, are the affective index for Wave 1, but the collective index for subsequent waves. For vaccination, the most explanatory measures are likelihood in Wave 1, collective in Wave 2, affective in Wave 3, and collective in Waves 4-6. Overall, then, according to standardized regression coefficients collective (U.S., global) risk perception better explained behavioral intentions than did personal risk perceptions. As discussed in detail later, this should not be interpreted as meaning that personal risk perceptions have no role, but that their relatively minor role in model IV columns—except for having the second largest regression coefficient in the three Wave 1 models—indicates that other risk perception measures took up the slack. Focusing on Waves 2-6, with all their six risk perception measures shared, personal risk perception had the weakest or second-weakest regression coefficient for all but four of the 15 multiple regression analyses (two for which it was the third-weakest), with three of those concerning vaccination. By contrast, collective risk perceptions were the most influential for all intentions except for Wave 3 on vaccination; the second strongest coefficient was the affect item for five regression analyses, severity for four, affective and duration for two each, and personal and collective for one each.

Finally, if we examine standardized regression coefficients significant at $p < .05$, we find that these are positive, as hypothesized (H1-2). However, there were three exceptions: in Wave 5 high duration estimates were associated with lower vaccination intentions, and in Wave 6 high duration estimates were associated with lower gathering-avoidance and vaccination intentions, and affective risk perceptions were associated with lower mask wearing intentions.

Hierarchical linear regression analyses for the three hypothetical mandatory federal policies (Table 6) again—for consistency with behavioral analyses, plus the finding that moralizing about compliance with social distancing linked to self-interest, not altruism (Bor et al. 2022)—presumed that personal risk perception would provide the baseline motivation, and then added the same sequence of other risk perception measures. Adjusted R^2 was lowest in Wave 1 (3% vaccination, to 15% gatherings), compared to Wave 2 (17% vaccination-31% masks), Wave 3 (6% masks-41% gatherings), Wave 4 (13% vaccination-44% gatherings), Wave 5 (23% vaccination-47% masks/gatherings), and Wave 6 (22% vaccination-46% masks). Again there was a temporal increase in how much risk perception measures collectively explained variance, although less with policies than behaviors; more variability in policy support than behavioral comparisons, but vaccination support was usually (excluding Wave 3) the least-explained, with mask-wearing and avoiding gatherings splitting as the best-explained; and risk perceptions overall did better explaining variance in policy support than variance in behavioral intentions.

Examining statistical significance of changes in adjusted R^2, in Wave 1 adding likelihood was non-significant at $p < .05$ for all three policies, as adding severity and duration were in Wave 2; adding severity and duration was non-significant in Waves 3 and 5 for mask wearing, and in Wave 6 for avoiding gatherings. Remaining additions (45 of 54, or 83.3%) were significant at $p < .05$ or better. RQ1 is answered in the affirmative for policy support too, although with less conclusive evidence: overall COVID-19 risk perception measures that omit explicit mention of personal risk, and often explicitly mention other risk targets (i.e. U.S. or global), add to explained variance in policy support beyond what personal risk perceptions offer.

On the relative contribution of different risk perception measures through changes in adjusted R^2, the increase due to moving from personal risk perception only to all variables is again relatively small in Wave 1 (< .034). Changes in R^2 are much larger in later waves: mask wearing (.184-.266, excluding Wave 3 = .035), avoiding gatherings (.191-.248), and vaccination (.083-.154). Jointly other risk perceptions were adding substantially to explained variance in policy support beyond that from personal risk perceptions, excluding Wave 1, echoing earlier behavioral intention results.

Comparing contributions to policy support using model IV standardized regression coefficients (Table 6), Wave 1 was again an outlier, with affective, personal, and collective risk perceptions associated positively, in that order, with support for both mask wearing and gatherings policies, but only affect positively associated with vaccination policy support. For Waves 2-6, affective risk perceptions had the strongest association with policy support for 12 of 15 regression analyses, with the others associated most strongly with affect, collective, and duration perceptions. The second strongest associations were with collective risk perceptions for all but one regression analysis, that being with affective measures.

Discussion

Despite several alternative potential clusters, the answer to RQ1 is that diverse risk perception measures deployed here (up to 10 depending upon the wave) tend to factor into four distinct groups: personal, affective (i.e. dread and concern), collective (i.e. U.S. and global), and severity (i.e. expectations of U.S. total infections and deaths from the COVID-19 pandemic). Confirmatory factor analyses (CFA) showed that model fit became better when affect (good-bad feelings about the hazard) and duration (expectation of the pandemic's length) were excluded from the CFA (Table 3), but that treating these as separate items yielded better fit (Supporting Information, Table 7) than if affect and duration were included in their conceptually similar indices (affective and severity risk perceptions, respectively; Supporting Information, Table 6). Personal, collective, and affective categories were most closely associated, with the severity category a clear outlier. Model fit was worse early than later in the pandemic, and item loadings differed in their temporal variation, although changes within item were modest (≤.139).

Behavioral intentions (H1) and policy support (H3) were both positively associated with personal risk perception, but after adding other types of risk perception measures these positive associations generally disappeared. Behavioral intentions (H2) and policy support (H3) were partly supported by non-personal risk perceptions, particularly collective and affective measures (partly supporting H4). Overall, adding non-personal risk perceptions decreased effects of personal risk perceptions to general non-significance, and collective risk perception measures were the dominant explanatory variable tested here (RQ2).

Darwin is credited with distinguishing between splitters and lumpers regarding species taxonomies in an 1857 letter (Sober, 2015). Our data clearly favor splitters for risk perception items, which may be unsurprising given the heterogeneity of our measures, but we note the plausibility of alternative clusters (Background). We do not believe there are currently grounds for speculation on when (if ever) splitting becomes less common than lumping, or personal risk perceptions become more associated than collective risk perceptions with behavioral intentions or policy support. This underlines again the value of more systematic effort on classifying risk perceptions.

Despite differences in some concepts and/or items used, our results converge remarkably with those in previous studies that used other hazards: e.g. separating affective and severity perceptions (e.g. Walpole & Wilson, 2021b), cognitive, emotions, and severity perceptions (e.g.

Sheeran et al. 2014), and likelihood from other perceptions (e.g. Walpole & Wilson, 2021b). General risk perceptions do indeed factor separately from more specific measures, as Wilson et al. (2019) argued, although in further support of splitting we found personal items using general language clustered separately from collective (U.S. or global) items using general language, a distinction they could not test given their community-level focus.

Although the focus of the Walpole & Wilson (2021b) taxonomy on personal risk due to hazards in the locality ("community") is valuable and consistent with the behavior change and health risk foci of other taxonomizers (e.g. Ferrer et al. 2016; Sheeran et al. 2014), it should not exhaust our classification efforts. Given Wilson et al.'s (2019) suggestion that general risk perception items might be useful beyond what personal risk items offer (e.g. as proposed by Walpole & Wilson, 2021b), we find not only that general risk perceptions are not themselves a homogeneous category, but that they correlated little with perceptions of national-level pandemic severity (expected infections and deaths), despite conceptual similarity.

For unknown reasons affect differed from other seemingly affective indicators (concern and dread). We do not see this as due to the reversal and recoding of this measure's responses, because the slider was clearly labeled and mean responses across waves prior to reversing responses were 14-23, indicating that people were feeling quite bad on average about the emerging pandemic. As this distinction between affect and other affective items here seemed unrelated to others made by risk-perception taxonomy scholars: e.g. immediate versus anticipatory feelings (Sheeran et al. 2014), and experiential versus affective items (Ferrer et al. 2016), we offer further speculations here. For example, the affect question may have triggered a heuristic response (Visschers & Siegrist, 2008) that yielded intuitive good-bad responses, whereas other items might have evoked more processing to offer an answer (e.g. "Do I actually feel terror about this?" for dread, or "what is my specific concern about the virus becoming locally transmissible, as opposed to my concerns about other outcomes?"). As these hypothetical mental reasonings indicate, our affect measure may also differ in as-yet-unexplored ways from the other items, as might affective items unused here. "Dread" seems a much more intense feeling than affect, even though both are rather unfocused responses relative to (say) specific emotions, so both intensity and focus may be relevant dimensions for the structuring of an affective taxonomy. Concern about local occurrence of a hazard like the coronavirus is an explicitly recommended affective measure of risk perception in a recent prominent risk perception taxonomy (Walpole & Wilson, 2021b), but if people have other, or additional, elements of their mental model of how they might be exposed to or become vulnerable to a hazard, focusing exclusively on the spatial dimension of concern might be imprudent. We do not think that these speculations make it improper to refer to all of these responses as "affective" (even with our comment on concern, and the earlier one on degree of processing, raising the possibility of an overlap with cognitive measures). But that convenient grouping may not preclude exploration of its potential multi-dimensionality.

Duration was even more an outlier, including from other severity measures, which might reflect that it captures time, not impacts. Not that time is unrelated to impacts and their severity—consider the extended-duration heat domes that have recently been afflicting large swathes of the planet in summer 2023, or the damage caused by an earthquake that shakes for several minutes rather than the more usual seconds—but duration might bring in another factor that creates ambiguity about impacts. Alternatively, the severity items about mortality and morbidity might vary their effect on risk perceptions if we had added a time element to it: i.e. rather than leave the time unspecified ("in this outbreak"), we might have specified "in the next 12 months" or some other time period. Or we might have had duration load with the other severity items if we had built severity into the question: e.g. "How long do you think we will have at least 500 people dying each day in the U.S. from the coronavirus?" That this was a pandemic, whose end is inherently uncertain (as it is for drought, economic depression, toxic contamination of groundwater, and famine among other hazards), also might have made a difference in the factoring, compared to hazards with more defined durations (e.g. hurricane, earthquake, terrorist attack, acute release of toxins from an industrial plant). (We thank a reviewer for the combined severity-duration and the different-hazards suggestions.)

Further analysis of how and why such items diverge from other apparently similar affective and severity items is warranted. Systematic tests (e.g. duplicating the Walpole & Wilson, 2021b taxonomy at national or global scales as well as at the personal scale) could be cost-effective.

The final taxonomic issue is the absence of time in such proposals, even rarer than in risk perception research generally (e.g. Siegrist, 2013). In a companion paper (Johnson et al. 2023), these classes of risk perceptions varied over time as well in their associations with potential predictors (e.g. news following, trust, knowledge, psychological distance). Here we merely note that model fit varied between early- and middle-pandemic periods (our data collection ended in spring 2021).

Overall, when controlling for personal risk perceptions, adding other risk perception types (particularly collective, and less so affective, risk perceptions) increased explanatory power for behavioral intentions/actions and policy support regarding mask wearing, avoiding of large public gatherings, and vaccination. Given that in practice COVID-19 self-protective behaviors could affect others' risk, and vice versa, and the previous finding that self-interest better explained social distancing than did altruism (Bor et al. 2022), the finding here that collective risk perceptions dominated risk perceptions' joint effect on both intentions and policy support raises an important, and hitherto unexamined, perspective on both behavioral motivation (Brewer et al. 2004) and attitudes towards governance. Sociotropic motivations, a term used by political scientists to characterize voting intentions that focus on what seems good for the societal economy overall rather than on what is good for oneself (e.g. Kinder & Kiewiet, 1981), also apply to at least some hazards (e.g. pandemics and wildfire in wildland-urban interfaces; Brenkert-Smith et al. 2006). Examining when and why perceptions of risk faced by larger entities than oneself and one's household (which might or might not reflect beliefs about perceived interactions between one's own and others' risk) become important should be part of risk science research.

Our findings that non-personal risk perceptions add substantively to explaining behavior and policy support should not be taken to mean that personal risk perceptions are immaterial, even though our multiple regression analyses show no statistically significant effect of personal risk perception in most cases once these other risk perception types are accounted for. Because some variance is held in common across risk perception measures—particularly shared variance between personal and affective/affect measures; the latter were the second-most influential perceptions for policy and behavior, respectively—these affective measures may reflect personal risk perceptions. What has yet to be probed in risk perception research and theory is whether affective/emotion measures primarily reflect fear, bad feelings, etc. regarding one's own fate or that of one's own household or family, or might also reflect wider social groupings. The sketchy evidence seems to favor the former interpretation, but this presumption needs testing.

As for limitations, our opportunity sample of Americans from an online panel—despite demographic weighting (Methods)—might limit our generalization to the entire adult population of descriptive statistics (e.g. proportions of behavioral intentions and policy support) despite our weighting by Census data, but is less pertinent to modeled relationships. The same can be said for extrapolating our findings to under-represented groups, or to non-U.S. populations, as with most risk perception papers. Our idiosyncratic set of risk perception measures for a single hazard over a single (if much longer than usual, at 14 months) time period also may limit generalization (prior taxonomic studies included multiple hazards—e.g. Sheeran et al. 2014 meta-analysis of others' studies; three diseases by Ferrer et al. 2016; Wilson-Walpole studies with multiple disparate hazards—but this does not provide context for generalizing our behavioral and policy support findings).

Conclusions

Risk perception is such a vital if debated aspect of risk analysis that it is somewhat surprising that it has taken decades for the initial recognition (beyond the cognitive-affective distinction) that not all perception measures are alike to yield a more systematic approach, as in the Walpole-Wilson typology. Our results emphasize the value of building upon this initial foundation to generate an even broader system to both advance theory about perceived risk's antecedents and consequences, and to allow researchers to choose the best subset of risk perception measures for their particular empirical research goals. Further, until we can clarify for which outcomes, hazards, and other situations personal risk perceptions are indeed the superior predictor, our tendency to be parsimonious in the number of perception measures we use in our survey instruments should be weighed against the benefits of multi-factorial measurement of risk perceptions to uncover explanatory power that personal risk perception measures might miss. Outcomes of such systematization may include parallel advances in risk communication and behavior change campaigns. We invite our colleagues to join in this effort.

Notes

1. A corollary might be that the global risk perception measure also belongs in this cluster, particularly for duration, which does impose a geographical limit on the area where the pandemic "ends." A separate analysis (unreported here) showed results similar to those for this fifth model.
2. Backup exploratory factor analyses for Waves 2-6 identified six factors out of the 10 items: collective, severity (infection, deaths), personal, affect, duration, and dread. Concern loaded on both collective and personal factors ($\geq$ .49 and $\geq$ .41, respectively). The personal connection might be prompted by the measure's reference to "where you live"; its association with collective measures is unclear. Models clustering personal, collective, and concern measures, including affect and duration as single-item factors, had poor fit (e.g. Wave 2: chi-square/df = 26.849; RMSEA = .127 [.118, .135]; CFI = .928; AIC = 42,991.443).

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