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Exploring the dynamic relationships between risk perception and behavior in response to the Coronavirus Disease 2019 (COVID-19) outbreak

Hua Qin [a,*], Christine Sanders [a], Yanu Prasetyo [a], Muh. Syukron [a], Elizabeth Prentice [b]

[a] University of Missouri-Columbia, Division of Applied Social Sciences, Columbia, MO, USA
[b] Columbia/Boone County Department of Public Health and Human Services, Columbia, MO, USA

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ABSTRACT

The relationships between risk perception and related behavior form a fundamental theme in risk analysis. Despite increasing attentions on the temporal dimension of risk perception and behavior in recent literature, the dynamic relationships between these two constructs remain understudied. Infectious disease outbreaks, such as the Coronavirus Disease 2019 (COVID-19) pandemic, provide a key setting for analyzing evolving perceptions of and responses to natural or human-induced hazards. The main objectives of this research are: (1) to assess temporal changes in cognitive and affective dimensions of perceived COVID-19 risk as well as related protective behavior; and (2) to explore the dynamic relationships between COVID-19 risk perception and behavioral responses. Timely data on changing risk perception and behavior related to the COVID-19 outbreak were collected through two series of online surveys from four major cities (Seattle, Los Angeles, Chicago, and New York City; $N = 736$) and the central Midwest region of the United States ($N = 1240$) respectively during March–August 2020. The analysis revealed that: (1) the cognitive and affective dimensions of perceived COVID-19 risk and preventive behavior all changed over time; (2) there were both within- and across-time correlations between COVID-19 risk perception indicators and preventive actions; and (3) preventive actions showed varied feedback effects on individual aspects of perceived COVID-19 risk over time. Findings from this research support and expand major conceptual approaches to changing relationships between risk perception and behavior, particularly the risk reappraisal hypothesis. The study also has useful implications for health risk management and future research directions.

1. Introduction

The frequencies and magnitudes of hazards and associated risks in modern society can be exacerbated by the globalization process and environmental change across local, regional, and global scales. The relationships between risk perception and related behavior form a fundamental theme in risk analysis. Longitudinal research design is traditionally lacking in this field as previous studies mostly used cross-sectional data (Bubeck and Botzen, 2013; Loewenstein and Mather, 1990; Rogers, 1997; Siegrist, 2013). The interactions between risk perception and behavior are mutual, dynamic processes. To better understand the causal associations between these two constructs, it is important to track their temporal changes and examine their changing interrelationships both within and across time.

Despite increasing attentions on the temporal dimension of risk perception and behavior, their dynamic relationships remain understudied in the existing literature. Infectious disease outbreaks provide a key setting for analyzing evolving perceptions of and responses to natural or human-induced hazards. Since its emergence from Wuhan, China in late December 2019, Coronavirus Disease 2019 (COVID-19 or novel coronavirus) has spread to 237 countries or areas and infected nearly 180 million people worldwide (World Health Organization, 2021) including over 33 million confirmed cases within the United States (Centers for Disease Control and Prevention, 2021). There has been growing research on public perceptions and protective behavior related to the COVID-19 pandemic in various countries, largely conducted at a single point or stage in time (e.g., de Bruin et al., 2020; Faasse and Newby, 2020; Ning et al., 2020; Oyetunji et al., 2021). In this study, we examine changing risk perception and behavior in response to the COVID-19 outbreak using three-phase panel survey data collected respectively from four major cities (Seattle, Los Angeles, Chicago, and New York City) and the central Midwest region of the United States. The

* Corresponding author. 228 Gentry Hall, Columbia, MO, 65211, USA.
E-mail address: qinh@missouri.edu (H. Qin).

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main objectives of this research are: (1) to assess temporal changes in cognitive and affective dimensions of perceived COVID-19 risk as well as related protective behavior; and (2) to explore the dynamic relationships between COVID-19 risk perception and behavioral responses. Our conceptual lens and empirical findings can help to enhance understanding of the temporal interactions between risk perception and behavior, strengthen research infrastructure for longitudinal risk studies, and support the development of future pandemic management strategies.

2. Literature review

2.1. Conceptual approaches to the dynamic risk perception–behavior relationships

Risk perception is generally assumed to be a key determinant of risk-related behavior in disaster and risk studies (Bubeck et al., 2012; Flint and Luloff, 2005; Qin et al., 2015b). The construct of risk or threat appraisal is differentiated into a multifaceted process (perceived probability, perceived severity, and fear) in the protection motivation theory, which is widely applied in socio-psychological analysis of preventive and adaptive behavior in response to health and environmental hazards (Grothmann and Patt, 2005; Rogers, 1983; Rogers and Prentice-Dunn, 1997). Nevertheless, the empirical relationship between risk perception and behavioral responses is often found to be weak or even counterintuitive because of the dominant cross-sectional approach adopted in existing research (Bubeck et al., 2012; Bubeck and Botzen, 2013; Siegrist, 2013; Weinstein et al., 1998).

The mixed findings in the current literature largely reflect the dynamic, complex relationships between risk perception and risk-related behavior. Weinstein and colleagues posited three possible paths in the interrelationships between health risk perception (measured as perceived likelihood of infection) and preventive behavior: relative accuracy (risk perception accurately reflects the adoption or non-adoption of protective behavior), behavior motivation (risk perception causes the adoption of protective behavior), and risk reappraisal (protective behavior in turn lowers risk perception) (Weinstein et al., 1998; Weinstein and Nicolich, 1993). These hypotheses focus on perceived probabilities of risk events and precautionary actions (e.g., vaccination, engagement in low-risk sexual practices) that can effectively reduce related risk and risk perception. Although relative accuracy typically means a negative cross-sectional relationship between risk perception and behavior, the statistical correlation representing such accuracy can be negative, positive, or non-significant depending on people's actual pre- and post-action levels of risk perception (Brewer et al., 2004). Additionally, the evolvement of specific risk perception dimensions, risk behavior, and their interrelationships may exhibit varied patterns in broader risk contexts. The well-known social amplification of risk framework suggests that social experience of risk and behavioral responses can either heighten or attenuate risk perception (Kasperson et al., 1988). Related scholarship also identifies shared risks as nonlinear, dynamic processes in which modes of learning and collective action hold important roles (Comfort, 1999). Altogether, these different theoretical perspectives can provide a more holistic view on the dynamic relationships between risk perception and behavior.

2.2. Previous research on changing risk perception and behavior

Considering the potential feedback effects of prevention or mitigation measures on perceived risk, it can be problematic to use cross-sectional data to analyze the causal relations between risk perception and related behavior. Existing empirical risk studies have examined changing perceptions of a range of environmental and technological risks, such as wildfire hazard, forest insect disturbance, extreme rainfalls, global warming, and transport accidents (Champ and Brenkert-Smith, 2016; Milfont, 2012; Nordfjærn and Rundmo, 2010; Qin et al., 2015a, 2021; Su et al., 2015). However, previous research along this line rarely addressed temporal changes in both risk perception and behavior, let alone their dynamic relationships.

Whereas recent research on public perceptions and behavior in response to the COVID-19 risk has been mainly cross-sectional in design, a few studies employed a longitudinal approach or included a longitudinal component in data collection and analysis. Wise et al. (2020) conducted both repeated cross-sectional and panel surveys on psychological and behavioral responses during the first week of the COVID-19 outbreak in the United States (March 11–16, 2020). They found that both perceived probability of infection and engagement in protective behavior increased during the study period. Hand washing and social distancing were strongly affected by perceived probability of infection but not by perceived severity of illness. Using six repeated cross-sectional surveys in major Chinese cities during February 7 – April 23, 2020, Rui et al. (2021) showed that perceived likelihood and severity of a COVID-19 infection and adoption of preventive actions (except for decreasing level of staying at home) remained largely stable over time. Perceived likelihood of infection only had limited effects on preventive actions, suggesting that behavioral responses might depend more on other factors such as compliance with the Chinese government's executive orders.

A group of trend studies (also known as repeated cross-sectional studies) of temporal changes in public risk perception and protective behavior in response to the H1N1 influenza pandemic is particularly relevant to the present research. Researchers found that perceived risk of being infected with H1N1 largely followed an inverted U-shape curve whereas perceived severity of infection and behavioral responses or intentions decreased over time (Gidengil et al., 2012; Ibuka et al., 2010; Jones and Salathé, 2009; Sherlaw and Raude, 2013). In contrast, the level of anxiety or worry demonstrated varied patterns of change (i.e., steadily declined, remained relatively constant, or showed large fluctuations) depending on the study sites and periods (Jones and Salathé, 2009; Rubin et al., 2010; Sherlaw and Raude, 2013). The various dimensions of perceived H1N1 risk were all shown to be positively associated with protective actions or behavioral intentions across these studies.

Because of the limitations of research data and settings, these longitudinal COVID-19 and H1N1 studies did not examine how people's risk perception accurately reflected their risk-related behavior or how precautious behavior might influence risk perception in turn. Compared to trend studies, longitudinal research utilizing panel data can readily explore the complex interactions between risk perception and behavior. Using panel survey data on Lyme disease risk perception and vaccinations, Brewer et al. (2004) provided evidence supporting the behavior motivation, relative accuracy, and risk reappraisal hypotheses (Weinstein et al., 1998; Weinstein and Nicolich, 1993). Their results showed that: (1) respondents who got vaccinated had higher initial risk perception (measured as perceived likelihood of infection) than those who were not vaccinated; (2) respondents who were vaccinated had relatively lower risk perception than those not vaccinated in the follow-up survey; and (3) vaccinated respondents had a greater decline in risk perception than those not vaccinated over the study period (Brewer et al., 2004). Additionally, some studies produced empirical evidence for a risk reappraisal effect of other interventions such as alcohol use disorder treatment and colorectal cancer screening (e.g., Glenn et al., 2011; Klepper et al., 2017). However, Raude et al. (2019) contended that the risk reappraisal hypothesis was not applicable in a longitudinal study of a large epidemic of chikungunya (a mosquito-borne disease) in Guinea.

It is also important to note the relevance of two previous panel studies involving risk perception and related emotions or views, even though they were not specifically about the dynamic relationships between risk perception and behavior. Kobbeltved et al. (2005) tracked the relationships between perceived probability of being seriously injured, worry about general and domestic matters, and emotional distress using data collected from 156 navy sailors at three stages of a five-month international operation. Similarly, Trumbo et al. (2014) examined the changing perceived hurricane likelihood and optimism bias (perceived risk to self vs. to others) of Gulf Coast residents over a two-year study period following Hurricanes Katrina and Rita. Both studies estimated cross-lagged path models (or structural equation modeling) and identified a causal effect from risk perception to other factors such as worry and the optimistic bias.

2.3. Summary and hypotheses

Overall, there has been increasing research on temporal changes in risk perception and related behavior in recent literature. However, the dynamic relationships between risk perception and behavior, particularly the feedback effects of precautious actions on risk perception (the risk reappraisal process), are still an understudied area. Previous longitudinal studies have also mainly adopted the trend study design, and have not fully incorporated both cognitive and affective dimensions of risk perception into the analysis. The present study attempts to address these literature gaps by collecting and analyzing panel data on perceived risk and behavioral responses during the COVID-19 pandemic. Based on a synthesis of relevant theoretical perspectives and empirical research, we developed the following research hypotheses to guide our data analysis and interpretation of results:

(1) Perceived COVID-19 risk (including cognitive and affective factors) and preventive behavior can change over time.
(2) COVID-19 risk perception is significantly related with preventive behavior both within and across time (relative accuracy and behavior motivation hypotheses).
(3) Preventive behavior has strong effects on changes in individual dimensions of perceived COVID-19 risk (adapted risk reappraisal hypothesis).

3. Methods

The data collection and analysis for this research consisted of two separate case studies sharing similar research methods and instruments. This approach represented an effort toward a holistic methodological strategy in social-ecological research that involves the coordination of individual research projects and the replication of research designs across geographic regions (Luloff et al., 2007; Qin et al., 2015a). Evaluating our research hypotheses with empirical data collected from different spatial and temporal contexts can provide a more informative understanding of the complicated interactions between risk perception and behavior.

3.1. Sampling and participants

In early February 2020, Centers for Disease Control and Prevention (CDC) officials announced that a novel coronavirus outbreak in the United States would be inevitable. Four major metropolitan areas (Seattle, Los Angeles, Chicago, and New York City) were selected for Case Study 1 (CS1) as they are located in the states where evidence of community transmission of the COVID-19 disease first emerged. We conducted three sequential online surveys at major stages of the COVID-19 outbreak in the four study cities. Potential panel survey participants were recruited via email by the survey management company Qualtrics. This company has a large pool of individuals who have consented to receive invitations for online surveys. The initial sample for the first survey was generated based on the age, gender, and race/ethnicity distributions of the four study cities' adult populations. We collected 2000 responses (approximately 500 for each city) for this baseline survey during the initial weeks of the COVID-19 outbreak (March 6–16, 2020). Internet surveys were then replicated with these respondents at two subsequent key junctures of the pandemic. The timing of the second survey corresponded with a period of rapidly increasing confirmed cases and the emergence of a peaking trend (March 27 – April 14, 2020), while the third survey aligned with another surge of the COVID-19 outbreak in the study cities and across the whole country (July 9 – August 7, 2020). The response rates for original respondents in the two follow-up surveys were 59.9 % (1197 out of 2000) and 61.5 % (736 out of 1197), respectively. In the two re-surveys, non-responders were also replaced with new participants so that each survey had about 2000 respondents. There was no additional incentive for respondents other than typical rewards provided by the Qualtrics research services team. In total, 736 respondents participated in all three surveys and were included in a panel survey dataset for CS1.

To collect relevant data from wider geographic and temporal contexts, we started another online survey of people's perceptions and actions related to the COVID-19 outbreak in Missouri and adjacent states (Kansas, Iowa, Illinois, and Arkansas) on March 9, 2020 (Case Study 2; or CS2). This survey was also administered using the Qualtrics survey platform and mostly distributed through electronic listservs of the University of Missouri and social media (particularly Facebook page promotion). All adult residents 18 years of age or older were eligible to participate. The survey was ended on June 9, 2020 and in all 7392 surveys were completed. To assess how attitudes and behavior related to COVID-19 may change over time, two follow-up surveys were conducted with those respondents who indicated an interest in the re-surveys and provided an email address. Respondents who participated in all three surveys were also entered into a prize draw to win one of five $50 Walmart gift cards. The first re-survey was sent to 2858 participants who responded to the initial survey at the early stage of the study (March 9 – April 30, 2020; considered as Phase 1). It was open from May 19 to June 1 and received 1625 valid responses (a response rate of 56.8 %). During July 13–31, a second re-survey was emailed to 3792 respondents of the initial survey, including those 1625 participants who also completed the first follow-up survey. In total, 2066 valid responses were returned, yielding a response rate of 54.5 % (response rate for the 1625 Survey #2 respondents was 76.3 %). Data collected from the 1240 participants who completed all three surveys of CS2 were merged into another panel dataset (see Qin et al., 2020 for reports for the full initial survey and the three survey waves).

3.2. Measurement of variables

The two case studies used largely the same survey instruments, which were designed to get a timely assessment of respondents' perceived severity of the COVID-19 outbreak, knowledge of the novel coronavirus, satisfaction with relevant management entities, sources of information, risk perception, and preventive behavior. We built on relevant measures and scales in the existing disaster and risk literature to develop major survey questions. The instrument was pilot tested by colleagues with related specialties and further checked during the soft launch stage of the first CS1 survey.

Respondents were asked to describe the severity of the COVID-19 outbreak in their cities/towns and in the whole country using a scale ranging from 1 (not at all severe) to 5 (very severe). Knowledge of the novel coronavirus was evaluated with a series of five True/False questions based on COVID-19 materials from CDC, such as "The main symptoms of the novel coronavirus disease include fever, cough, and difficulty breathing." Responses were recoded ("0" incorrect and "1" correct) and summed to create an aggregate knowledge measure.

We asked participants to identify whether or not they relied on any of the thirteen COVID-19 information sources listed in the surveys, such as newspaper, radio, social media, healthcare providers, city government, and federal government. A variable representing the total number of information sources was created based on answers ("0" no and "1" yes) to these questions. Respondents also indicated their satisfaction or dissatisfaction with how the COVID-19 issue had been managed by a number of entities: school districts, employers, local healthcare providers, city government, county government, state government, and federal government. Response options ranged from 1 (very dissatisfied) to 5 (very satisfied).

Key dimensions of perceived COVID-19 risk were measured by asking respondents to describe their perceived likelihood of infection, perceived potential harmfulness if infected, and level of anxiety using a 5-point ordinal scale ranging from 1 (very unlikely, not at all harmful, or not at all anxious) to 5 (very likely, very harmful, or very anxious). They were also asked if they had taken any of a series of ten actions, such as washing hands frequently and avoiding public gatherings, in response to the novel coronavirus outbreak during the past month. A composite preventive activeness index was created by summing dichotomous answers ("0" no and "1" yes). The surveys then ended with a few questions on socio-demographic characteristics including age (years), gender ("0" male and "1" female), race/ethnicity (five primary categories), education (six levels ranging from "1" less than a high school degree to "6" advanced degree, i.e. Master's, JD, MD, PhD), political views (five categories ranging from "1" liberal to "5" conservative), and income (five groups ranging from "1" less than $35,000 to "5" more than $100,000).

3.3. Data analysis

This research focuses on analysis of the panel datasets from CS1 (four major metropolitan areas; $N = 736$) and CS2 (central Midwest region; $N = 1240$). Potential non-response bias in the re-surveys was evaluated by comparing panel respondents and non-respondents to follow-up surveys on socio-demographic characteristics and answers to major questions in the previous surveys. Data analysis procedures generally followed the primary research objectives and hypotheses discussed above. First, we examined descriptive statistics of the personal characteristic indicators for panel survey respondents, and then ran one-way repeated measures ANOVAs with post hoc tests to determine whether there were significant changes in risk perception, preventive actions, and other major variables across different study phases. Next, longitudinal cross-lagged path analysis was used to explore the dynamic relationships between individual risk perception dimensions (perceived likelihood of infection, perceived harmfulness if infected, and anxiety) and preventive behavior. This approach allows the simultaneous testing of a series of regression equations. The relative accuracy, behavior motivation, and risk reappraisal hypotheses were evaluated using the within-time relationships between risk perception indicators and preventive actions, the across-time correlations from risk perception measures to preventive actions, and the across-time feedback effects of preventive actions on risk perception indicators in the path models, respectively. Variables with highly skewed distributions were first transformed to reduce the degree of skewness. We generated final reduced models by removing non-significant parameters from initial saturated models. Model fitness was assessed using the chi-square test of absolute model fit (probability level), the Root Mean Square Error of Approximation (RMSEA), and the Comparative Fit Index (CFI), with respective thresholds set at > 0.05, < 0.05, and > 0.95. Good fit statistics indicate that a reduced model fits the data as well as a saturated model which contains as many parameter estimates as possible, or substantially better than an independence model which assumes there is no relationship between observed variables.

Finally, we built a series of repeated measures ANCOVA models of perceived likelihood of infection, perceived potential harmfulness, and the level of anxiety. The models included an interaction effect between study phase and the number of preventive actions at Phase 1 to assess the risk reappraisal process, while controlling for variations in major socio-demographic characteristics including age, gender, education, political views, and personal income. We used Phase 1 and Phase 3 as the reference group of study phase and the interaction effect term in turn so as to compare estimates across individual categories of these variables. Significant interaction variables would indicate strong effects of preventive activeness at Phase 1 on risk perception in subsequent stages. All the statistical analyses were conducted with SPSS and AMOS software (Version 26). There were a few marginally significant estimates in the whole data analysis. We chose to include them in the final results considering the exploratory nature of this research.

4. Results

The presentation of results is organized by main data analytical procedure and then by case study. Phases 1 and 2 of CS1 generally corresponded to Phase 1 of CS2, and Phases 3 of the two case studies largely overlapped with each other.

4.1. Characteristics of panel respondents

Table 1 summarizes the personal characteristics of panel survey respondents for both case studies.

4.1.1. Case study 1

Respondents from Los Angeles (27.3 %), New York City (26.6 %), and Chicago (25.3 %) accounted for a relatively larger proportion than those from Seattle (20.8 %) in the CS1 panel dataset. The average age of the 736 respondents was 55.2 years, with a majority of them (58.7 %) in the 35–64 age category. They reported living in their cities for an average of 36.7 years. Female and male respondents accounted for 44.7 % and 55.3 % of this sample, respectively. Slightly more than two thirds of the respondents (68.1 %) were white, 9.0 % African American, 14.7 % Asian, and 5.4 % Hispanic/Latino. More than 60.0 % of these respondents attained four-year college or higher degrees, while nearly 75.0 % of them earned $50,000 or more in 2019. The average education and income levels were between a two-year technical/associate degree and a four-year college degree, and between $50,000–74,999 and $75,000–99,999, respectively. The sample as a whole held largely balanced political views. 36.3 % of the respondents described their views as liberal or moderate liberal, 35.8 % as moderate, and 27.9 % as moderate conservative or conservative.

The age, gender, and racial/ethnic structures of the survey samples of CS1 were largely comparable to available census data for the four study cities. Compared to the three full survey samples, the CS1 panel sample had a higher mean age, relatively larger proportions of male and white participants, higher average levels of educational attainment and

Table 1
Personal characteristics of panel survey respondents.

Personal characteristics	Case Study 1 panel survey respondents (N = 736)	Case Study 2 panel survey respondents (N = 1240)
Age	12.4 % age 18–34, 58.7 % age 35–64, 28.9 % age 65 and over (mean = 55.2)	33.5 % age 18–34, 51.1 % age 35–64, 15.3 % age 65 and over (mean = 44.5)
Gender	44.7 % female	71.8 % female
Race/Ethnicity	68.1 % white, 9.0 % African American, 14.7 % Asian, 5.4 % Hispanic/Latino	96.8 % white, 1.5 % American Indian/Alaska Native, 0.4 % African American, 1.6 % Asian, 2.3 % Hispanic/Latino[a]
Education	62.2 % Bachelor's degree or higher	73.5 % Bachelor's degree or higher
Income	74.2 % $50,000–$74,999 or more	58.6 % $50,000–$74,999 or more
Political views	36.3 % liberal/moderate-liberal, 35.8 % moderate, 27.9 % conservative/moderate-conservative	59.6 % liberal/moderate-liberal, 16.0 % moderate, 24.4 % conservative/moderate-conservative

[a] The sum of race/ethnicity percentages for CS2 is greater than 100.0 % as respondents could choose multiple answers.

personal income, but similar political views. Further analysis showed that panel respondents were older and had higher levels of education and income than those respondents who did not participate in one or both of the two re-surveys. Panel respondents also reported relatively lower levels of perceived COVID-19 risk and preventive actions than non-panel participants in the first survey. No significant difference was found between the two subgroups regarding these major variables in Phase 2.

4.1.2. Case study 2

The 1240 panel respondents in CS2 were mostly from Missouri (50.9 %), followed by Illinois (18.7 %), Kansas (11.3 %), Iowa (10.2 %), and Arkansas (8.3 %). To obtain a bigger sample size for the panel data, we chose to include those respondents (0.6 %) from other states (e.g., Nebraska and Oklahoma) in the analysis. The average age of CS2 panel respondents was 44.5 years. They on average reported living in their communities for 17.5 years. Females and males accounted for 71.8 % and 26.3 % in this dataset, respectively. A large majority of these participants (96.8 %) were white. Nearly three quarters (73.5 %) of them attained four-year college or higher degrees. 41.4 % of the respondents earned less than $50,000, and 34.5 % earned $75,000 or more in 2019. The average education and income levels of this sample were close to a four-year college degree and $50,000–74,999, respectively. Nearly 60.0 % of these respondents described their views as liberal or moderate-liberal, 16.0 % as moderate, and 24.4 % as moderate-conservative or conservative.

Compared to the full initial survey sample ($N = 7392$) of CS2, this panel sample had a larger proportion of Missouri participants, a relatively lower mean age, higher educational attainment, more liberal political views, but similar gender and racial/ethnic compositions as well as personal income levels. The full samples for Phases 1–3 and the panel sample had largely similar socio-demographic characteristics. Further analysis showed that panel respondents had higher levels of education and income than those initial respondents who provided an email address but did not participate in the second and/or the third surveys. However, there was no significant difference between the two subgroups regarding other personal characteristic indicators or major variables in Phase 1 or 2.

4.2. Temporal changes in perceptions and actions

As shown in Table 2, there were significant changes across the three survey phases of both case studies regarding perceived severity of the COVID-19 outbreak, sources of information, satisfaction with management entities, perceptions of COVID-19 risk, and preventive actions.

4.2.1. Case study 1

In CS1, reported levels of COVID-19 severity in the study cities and in the whole country were moderate at first and increased substantially during the second phase. In Phase 3, perceived severity in the four cities decreased (but was still higher than the initial level), while perceived severity in the country remained largely the same. These panel respondents also generally showed good knowledge about COVID-19 and relied on multiple sources for relevant information. Whereas both the knowledge and the information source indicators increased from Phase 1 to Phase 2, only the latter exhibited a statistically significant change (a reduction) in Phase 3.

The CS1 respondents were largely satisfied with all management entities except for the federal government regarding how the COVID-19 outbreak was handled. Satisfaction with these entities was higher in Phase 2 than in the other two phases, and there was generally no significant difference in this aspect between Phases 1 and 3. Nevertheless, satisfaction with local health providers was relatively greater in Phase 3 than in Phase 1. Respondents indicated similar levels of dissatisfaction with the federal government in the first two phases, and became even less satisfied in Phase 3.

Overall, these respondents indicated moderate to high perceptions of COVID-19 risk. In each study phase, the reported level of perceived harmfulness if infected was relatively greater than the levels of perceived likelihood of infection and anxiety. These three dimensions of COVID-19 risk perception also showed different patterns of change over time. The values of both perceived likelihood of infection and perceived potential harmfulness became significantly higher in Phase 2 and stayed mostly unchanged afterward. The level of anxiety about COVID-19 also initially saw an increase, but dropped to some extent in Phase 3. Overall, this panel survey sample exhibited a high level of actions in response to the COVID-19 pandemic. The reported total number of preventive actions increased consistently across the three study phases, particularly the first two.

Table 2
Temporal change in perceptions and actions[a].

Variable	Case Study 1			Case Study 2		
	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3
Perceived COVID-19 severity in city[b]	$2.68^{P2,P3}$	$3.95^{P1,P3}$	$3.64^{P1,P2}$	2.20^{P3}	2.23^{P3}	$2.77^{P1,P2}$
Perceived COVID-19 severity in the whole country[b]	$3.01^{P2,P3}$	4.22^{P1}	4.30^{P1}	4.01^{P3}	3.99^{P3}	$4.36^{P1,P2}$
Knowledge about COVID-19[b]	$4.47^{P2,P3}$	4.59^{P1}	4.54^{P1}	4.88	4.89	4.87
Number of information sources[c]	$4.18^{P2,P3}$	$4.91^{P1,P3}$	$4.47^{P1,P2}$	$6.23^{P2,P3}$	$5.79^{P1,P3}$	$5.51^{P1,P2}$
Satisfaction with school districts[b]	3.33^{P2}	$3.91^{P1,P3}$	3.27^{P2}	3.82^{P3}	3.77^{P3}	$2.83^{P1,P2}$
Satisfaction with employers[b]	3.30^{P2}	$3.58^{P1,P3}$	3.38^{P2}	3.49^{P3}	3.53^{P3}	$3.03^{P1,P2}$
Satisfaction with local healthcare providers[b]	$3.51^{P2,P3}$	$3.98^{P1,P3}$	$3.82^{P1,P2}$	3.79^{P2}	$3.95^{P1,P3}$	3.76^{P2}
Satisfaction with city government[b]	3.31^{P2}	$3.76^{P1,P3}$	3.41^{P2}	3.41^{P3}	3.44^{P3}	$3.10^{P1,P2}$
Satisfaction with county government[b]	3.30^{P2}	$3.73^{P1,P3}$	3.33^{P2}	3.34^{P3}	3.37^{P3}	$3.00^{P1,P2}$
Satisfaction with state government[b]	3.32^{P2}	$3.88^{P1,P3}$	3.47^{P2}	$3.06^{P2,P3}$	$2.89^{P1,P3}$	$2.59^{P1,P2}$
Satisfaction with federal government[b]	2.69^{P3}	2.77^{P3}	$2.17^{P1,P2}$	$2.05^{P2,P3}$	$1.81^{P1,P3}$	$1.64^{P1,P2}$
Perceived likelihood of infection[b]	$2.41^{P2,P3}$	3.03^{P1}	3.02^{P1}	$2.81^{P2,P3}$	$2.65^{P1,P3}$	$2.95^{P1,P2}$
Perceived harmfulness if infected[b]	$3.47^{P2,P3}$	4.00^{P1}	3.95^{P1}	3.54^{P3}	3.56^{P3}	$3.70^{P1,P2}$
Level of anxiety[b]	$2.89^{P2,P3}$	$3.65^{P1,P3}$	$3.44^{P1,P2}$	3.49^{P2}	$3.17^{P1,P3}$	3.47^{P2}
Number of preventive actions[d]	$6.39^{P2,P3}$	$8.26^{P1,P3}$	$8.80^{P1,P2}$	$8.19^{P2,P3}$	$8.81^{P1,P3}$	$8.66^{P1,P2}$

[a] Given as variable means. Superscript codes indicate significant differences with other study phases (P1 = Phase 1; P2 = Phase 2; P3 = Phase 3) according to the results of post hoc tests.
[b] All of these variables were measured on a 5-point scale.
[c] The information source measure had a possible range of 0–13.
[d] The preventive activeness indicator had a possible range of 0–10. In both case studies, wearing a face mask in public places was the least implemented preventive action in Phase 1, but its adoption increased substantially during the following study phases.

4.2.2. *Case study 2*

The CS2 panel respondents generally indicated higher severity of the COVID-19 outbreak for the whole country than for their cities/towns. Perceived levels of severity were much higher in Phase 3 than in the first two study phases. While these respondents consistently showed very good knowledge about COVID-19, they reported decreased reliance on information sources over time. Like the respondents for CS1, the CS2 participants were less satisfied with the federal government than with other management entities regarding responses to the COVID-19 outbreak. Levels of satisfaction with school districts, employers (or schools for student participants), and city and county governments were relatively higher in Phases 1 and 2, compared to Phase 3. The CS2 respondents were also increasingly dissatisfied with state and federal governments in subsequent phases. In contrast, they were rather positive in their views of local healthcare providers throughout the entire study period (particularly Phase 2).

Trends of change again varied across different aspects of perceived COVID-19 risk. Both perceived likelihood of infection and the level of anxiety decreased significantly in Phase 2, but rose back to or above the initial levels in Phase 3. Perceived harmfulness of infection remained largely the same in the first two study phases and became even greater during the last stage. Moreover, reported levels of preventive actions were generally quite high despite some fluctuations over time.

4.3. *Cross-lagged path models*

We built three path models to evaluate the dynamic relationships between individual dimensions of COVID-19 risk perception and preventive behavior across different study phases of CS1 and CS2, respectively. The preventive activeness indicators for Phases 2 and 3 of CS1 and for Phases 1–3 of CS2 were transformed accordingly in the path analysis as they had negatively skewed distributions. All of these models had satisfactory fit statistics.

4.3.1. *Case study 1*

Fig. 1 presents the final reduced models of the reciprocal relations between risk perception indicators and preventive actions for CS1. Values associated with the paths in these models are equivalent to standardized regression coefficients representing the amount of change in outcome variables (in units of standard deviation) given a standard deviation unit change in predictors. For example, the level of perceived likelihood of infection at Phase 2 increases by 0.47 (coefficient 0.48 × standard deviation 0.97) for every standard deviation unit change (1.04) in the level of perceived likelihood at Phase 1. Because estimates related to the two transformed preventive activeness measures (Actions_P2 and Actions_P3) are not directly meaningful, we focus on the significance of variable relationships in the presentation of results from the path analysis (same for CS2).

All three models identified strong temporal autocorrelations and within-time positive correlations for included variables across the study phases. None of the cross-lagged links between perceived likelihood of infection and preventive actions showed a significant effect. The analysis revealed significant cross-lagged relationships between perceived harmfulness and preventive action. Respective regression paths from perceived harmfulness in Phases 1 and 2 to action in Phases 2 and 3, and from action in Phases 1 and 2 to perceived harmfulness in Phases 2 and 3 all demonstrated a positive effect. Two cross-lagged regression paths between the level of anxiety and preventive actions were also positive and significant: one from Phase 1 actions to Phase 2 anxiety, and the other from Phase 2 anxiety to Phase 3 actions.

4.3.2. *Case study 2*

The three final path models for CS2 also showed strong temporal autoregressive paths (from Phase 1 to Phases 2 and 3, and from Phase 2 to Phase 3) for all variables (Fig. 2). Except for the perceived likelihood of infection in Phase 2, all risk perceptions measures were positively correlated with preventive actions at each study stage. The analysis revealed significant cross-lagged relationships between perceived likelihood of infection and preventive actions. Respective regression paths from perceived likelihood in Phases 1 and 2 to actions in Phases 2 and 3, from actions in Phases 1 and 2 to perceived likelihood in Phases 2 and 3, and from actions in Phase 1 to perceived likelihood in Phase 3 were all

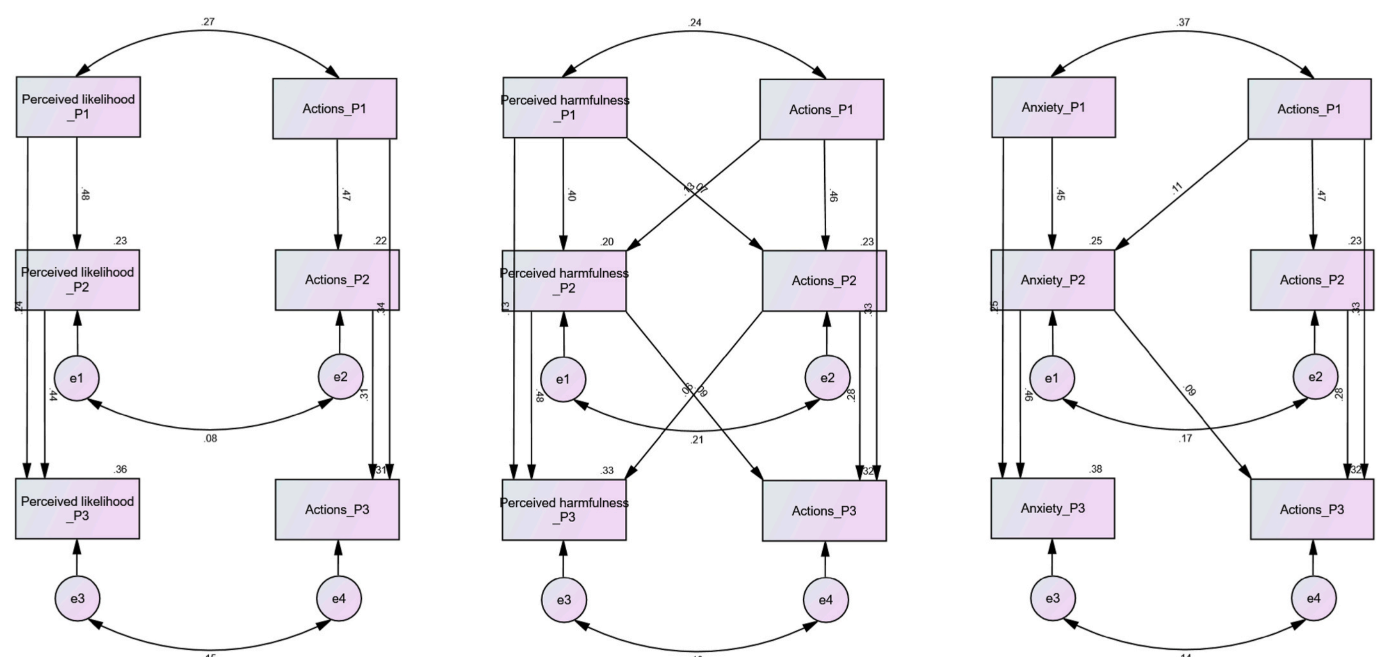

Fig. 1. Path models of cross-lagged relationships between risk perception indicators and preventive actions (Case Study 1). Variable correlations and causal relationships are represented by bi- and single-directional arrows, respectively. Values associated with paths are standardized estimates. All coefficients included in the models, except for the path from Actions_P2 to Perceived harmfulness_P3 ($p = 0.052$), were significant at the 0.05 or higher level. Model fit statistics: (1) perceived likelihood and actions ($\chi^2 = 12.036$, df = 6, $p = 0.061$; RMSEA = 0.037; CFI = 0.994); (2) perceived harmfulness and actions ($\chi^2 = 3.560$, df = 2, $p = 0.169$; RMSEA = 0.033; CFI = 0.998); and (3) anxiety and actions ($\chi^2 = 3.510$, df = 4, $p = 0.476$; RMSEA = 0.000; CFI = 1.000).

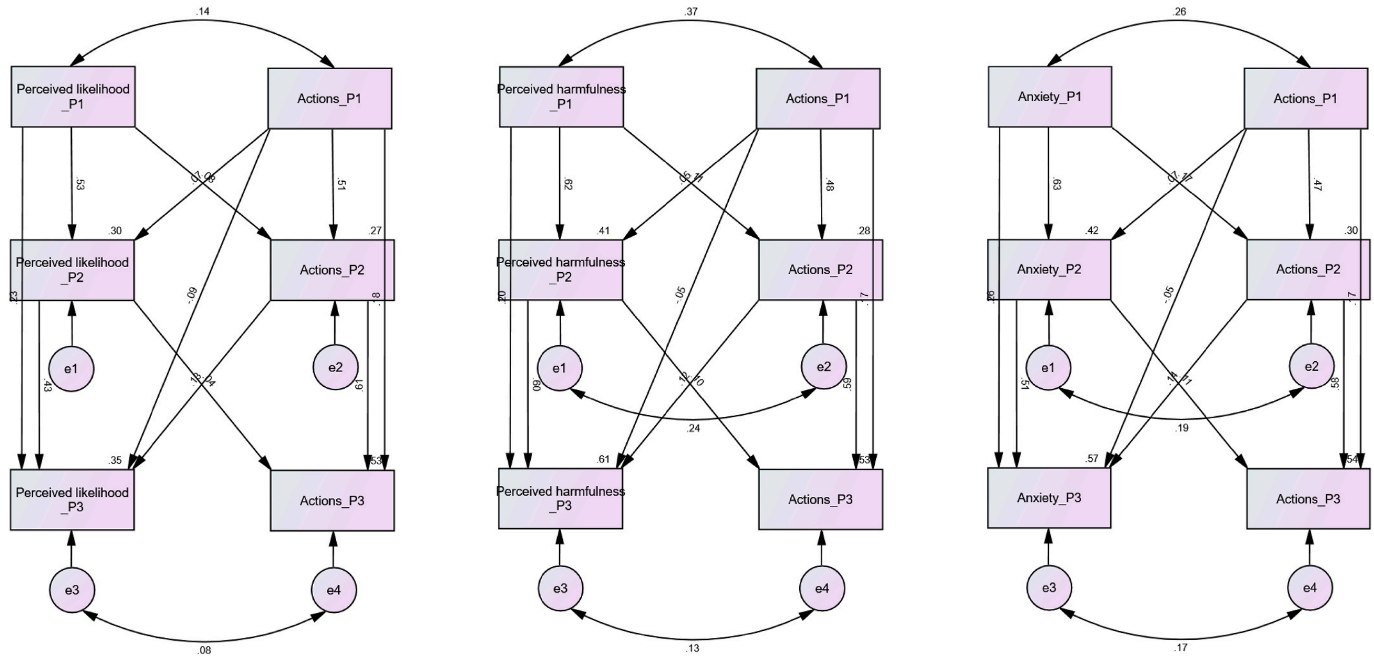

Fig. 2. Path models of cross-lagged relationships between risk perception indicators and preventive actions (Case Study 2). Variable correlations and causal relationships are represented by bi- and single-directional arrows, respectively. Values associated with paths are standardized estimates. All coefficients included in the models were significant at the 0.05 or higher level. Model fit statistics: (1) perceived likelihood and actions ($\chi2 = 3.967$, df = 2, $p = 0.138$; RMSEA = 0.028; CFI = 0.999); (2) perceived harmfulness and actions ($\chi2 = 0.297$, df = 1, $p = 0.586$; RMSEA = 0.000; CFI = 1.000); and (3) anxiety and actions ($\chi2 = 0.186$, df = 1, $p = 0.667$; RMSEA = 0.000; CFI = 1.000).

statistically significant. All regression estimates were positive except for the negative effect of Phase 1 actions on Phase 3 perceived likelihood. The models for the other two risk perception measures (perceived potential harmfulness and the level of anxiety) and preventive actions indicated identical patterns of cross-lagged effects.

Table 3
Repeated measures ANCOVA models of risk perception indicators (Case Study 1)[a].

Variable	Perceived likelihood of infection	Perceived potential harmfulness	Level of anxiety
Intercept	1.893***	2.708***	2.151***
Phase 2 (ref = Phase 1)[b]	0.965***	0.630***	1.185***
Phase 3 (ref = Phase 1)[b]	0.886***	0.604***	1.052***
Actions_P1	0.123***	0.103***	0.189***
Phase 2 * Actions_P1 (ref = Phase 1 * Actions_P1)[c]	−0.054***	−0.016	−0.066***
Phase 3 * Actions_P1 (ref = Phase 1 * Actions_P1)[c]	−0.044*	−0.021	−0.079***
Age	−0.003^(*)	0.011***	−0.001
Gender (ref = female)	−0.022	−0.136*	−0.131*
Education	0.017	−0.031	−0.007
Political views	−0.080***	−0.072***	−0.124***
Personal income	0.026	−0.030	0.013
N	720	720	720
−2 Restricted Log Likelihood	5643.222	5638.812	6077.846

^(*)$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

[a] Given as estimates of fixed effects. All three models had high goodness-of-fit statistics.

[b] The estimates for Phase 2 and Phase 3 were not significantly different in the three models. The aggregate fixed effect of the Phase variable was significant at the 0.001 level in all three models.

[c] The estimates for Phase 2 * Actions_P1 and Phase 3 * Actions_P1 were not significantly different in the three models. The aggregate fixed effect of the Phase * Actions_P1 interaction was significant at the 0.01 or higher level in the first and the third models.

4.4. Repeated measures ANCOVA models

4.4.1. Case study 1

Results of the repeated measures ANCOVA models of individual risk perception indicators for CS1 are summarized in Table 3. The main effect of the study phase factor largely confirmed trends identified in the one-way repeated measures ANOVA tests (see Section 4.2.1): perceived likelihood of infection, perceived potential harmfulness if infected, and the level of anxiety were consistently lower in Phase 1 than in the other two phases. In addition to the positive main effect of the number of preventive actions at Phase 1 in all three models, there was a significant interaction effect of study phase and Phase 1 preventive actions on perceived likelihood of infection and the anxiety level. As shown in Fig. 3, higher levels of preventive actions in Phase 1 led to lower increases in these two risk perception measures for Phases 1 vs. 2 and for Phases 1 vs. 3.

Among the personal characteristics of respondents, political views showed the strongest influence on the dependent variables. Those with more conservative views indicated lower levels of COVID-19 risk perception. Several socio-demographic factors were related with specific aspects of perceived COVID-19 risk. Age had a positive effect on perceived potential harmfulness if infected, and was also almost significant in its negative relationship with perceived likelihood of infection. Additionally, females tended to report lower perceived harmfulness of infection and anxiety level than males.

4.4.2. Case study 2

Compared to the statistical models for CS1, those for CS2 produced both similar and different results (see Table 4). The main effect of the study phase factor in the CS2 models was not quite meaningful because of the significant interaction items. The analysis detected a strong interaction effect of study phase and Phase 1 preventive actions on all three aspects of perceived COVID-19 risk (see Fig. 4). The higher the

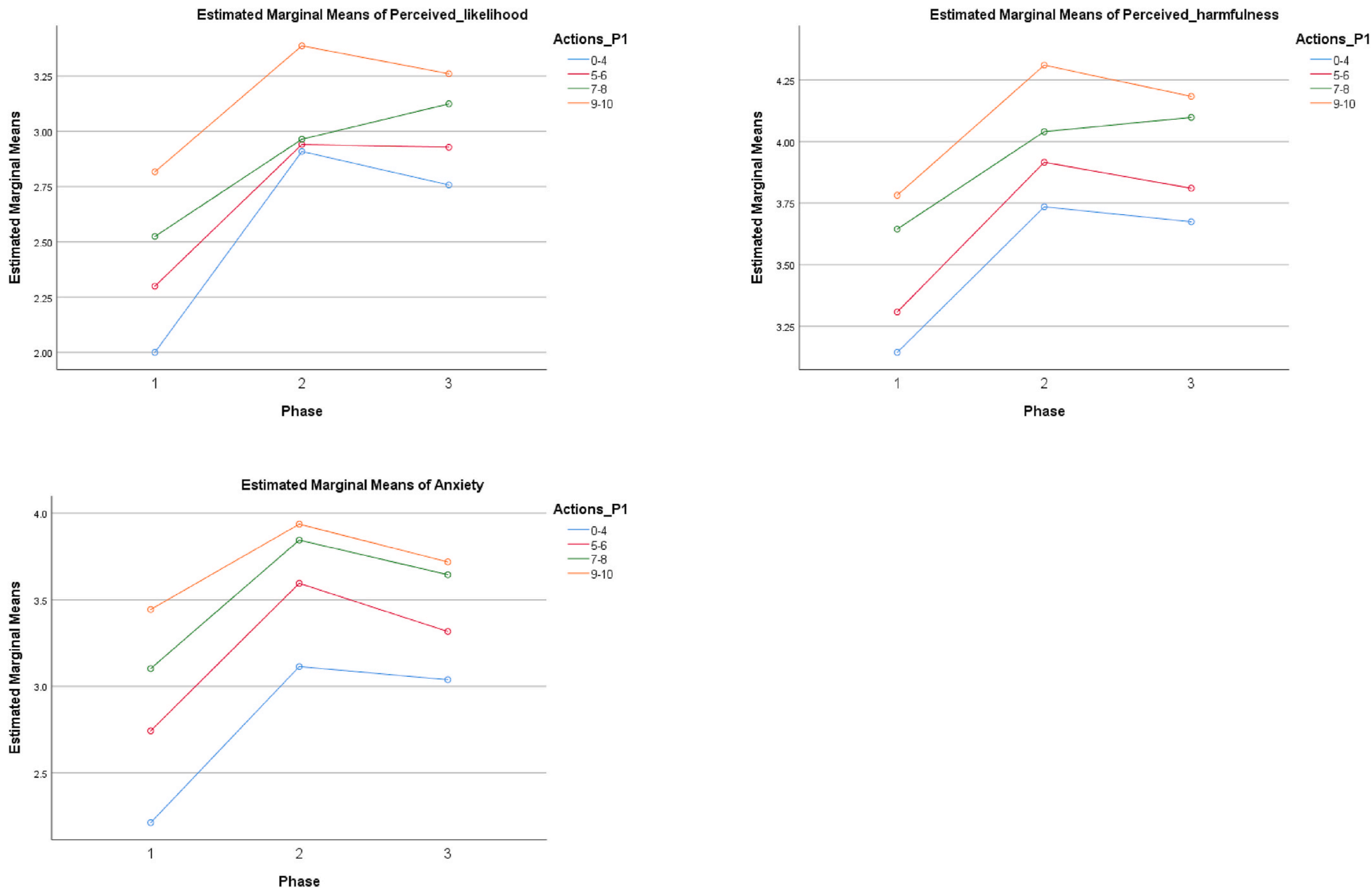

Fig. 3. Interaction effects of study phase and Phase I preventive actions on risk perception indicators (Case Study 1). To facilitate the visualization of interaction effects, the action indicator for Phase 1 was first converted to a 4-level categorical variable and then included with the study phase factor in the mixed ANOVA analysis. The interaction effects in the models of perceived likelihood and anxiety were statistically significant at the 0.01 or higher level.

level of preventive actions in Phase 1 was, the smaller an increase in perceived likelihood of infection would be for Phases 1 vs. 3 or Phases 2 vs. 3. Likewise, greater preventive activeness in Phase 1 corresponded to lower increases, relative stabilization, or even decreases in perceived harmfulness of infection and the level of anxiety for Phases 1 vs. 2 and for Phases 1 vs. 3.

Both gender and political views were consistently associated with all three COVID-19 risk perception indicators. Male respondents and those with more conservative political views exhibited lower levels of perceived risk than their counterparts. Age had a negative and positive effect on perceived likelihood of infection and perceived potential harmfulness if infected, respectively. Additionally, educational attainment and total personal income were negatively related with perceived harmfulness of infection.

Table 4
Repeated measures ANCOVA models of risk perception indicators (Case Study 2)[a].

Variable	Perceived likelihood of infection	Perceived potential harmfulness	Level of anxiety
Intercept	2.465***	1.815***	2.754***
Phase 2 (ref = Phase 1)[b]	−0.096	0.605***	0.137
Phase 3 (ref = Phase 1)[b]	0.608**	0.931***	0.498**
Actions_P1	0.093***	0.210***	0.206***
Phase 2 * Actions_P1 (ref = Phase 1 * Actions_P1)[c]	−0.007	−0.071***	−0.055**
Phase 3 * Actions_P1 (ref = Phase 1 * Actions_P1)[c]	−0.056*	−0.094***	−0.063**
Age	−0.003*	0.021***	−0.002
Gender (ref = female)	−0.112*	−0.130*	−0.180**
Education	0.022	−0.039(*)	0.002
Political views	−0.145***	−0.235***	−0.314***
Personal income	−0.004	−0.051**	−0.020
N	1131	1131	1131
−2 Restricted Log Likelihood	8741.775	8300.922	8963.042

(*)$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

[a] Given as estimates of fixed effects. All three models had high goodness-of-fit statistics.

[b] The estimates for Phase 2 and Phase 3 were significantly different at the 0.05 or higher level in all three models. The aggregate fixed effect of the Phase variable was also significant at the 0.05 or higher level in these models.

[c] The estimates for Phase 2 * Actions_P1 and Phase 3 * Actions_P1 were significantly different at the 0.01 level in the first model. The aggregate fixed effect of the Phase * Actions_P1 interaction was significant at the 0.05 or higher level in all three models.

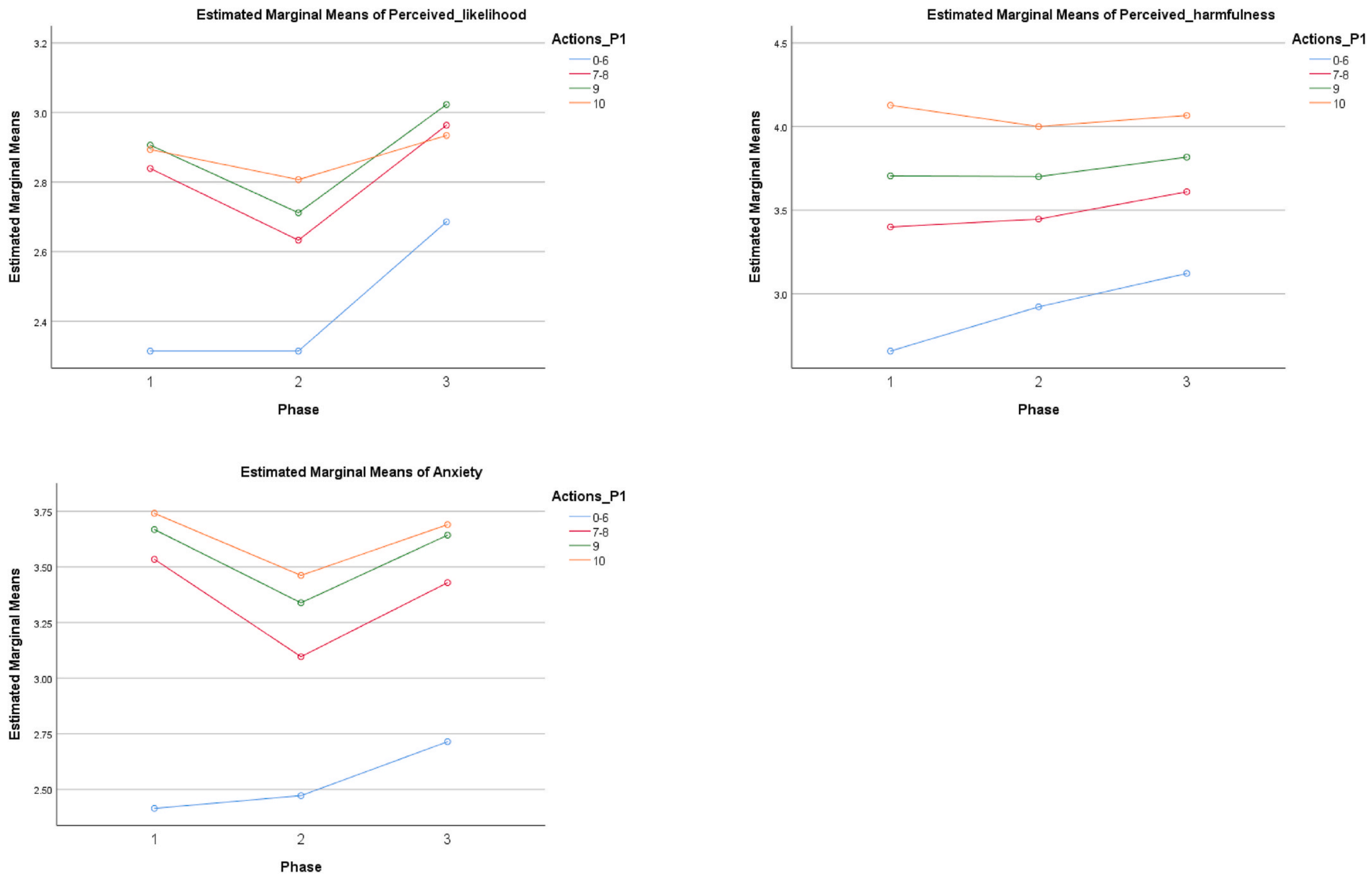

Fig. 4. Interaction effect of study phase and Phase I preventive actions on risk perception indicators (Case Study 2). To facilitate the visualization of interaction effects, the action indicator for Phase 1 was first converted to a 4-level categorical variable and then included with the study phase factor in the mixed ANOVA analysis. The interaction effects in all three models were statistically significant at the 0.05 or higher level.

5. Discussion

This research examines the dynamic relationships between risk perception and related behavior within the context of the COVID-19 pandemic. The two case studies largely produced consistent evidence regarding our research hypotheses, and many of the notable discrepancies in their results can be attributed to differences in study timelines (also varied intervals between study phases), COVID-19 severity levels, and possibly panel data sample sizes. The four cities selected for CS1 generally represented areas that were at the front line of COVID-19 exposure and impacts, whereas situations in the study region for CS2 depicted a more typical scenario that occurred across the whole country. The analysis of both panel datasets revealed significant temporal changes in different dimensions of COVID-19 risk perception and preventive actions, as well as in perceived severity of the COVID-19 outbreak, use of information sources, and satisfaction with management entities. Overall, these variations closely reflected the evolvement of the COVID-19 pandemic in the study sites of the two cases.

Cross-lagged path models exhibited significant temporal autocorrelations of risk perception and behavior indicators, positive within-time correlations between risk perception and preventive actions, and varied across-time relationships between individual dimensions of risk perception and preventive actions. In particular, there were strong and positive reciprocal relations between perceived harmfulness of infection and preventive actions across the three study phases of CS1. Such relationships existed between all aspects of risk perception and preventive behavior in CS2. The path models of CS2 also suggested a negative feedback effect of Phase 1 preventive actions on Phase 3 risk perception indicators. Additionally, the repeated measures ANCOVA analysis consistently indicated significant interaction effects of the study phase factor and initial preventive activeness (in Phase 1) on perceived COVID-19 risk. For both case studies, respondents' levels of Phase 1 preventive actions generally represented their activeness during the whole study period as the action indicators for individual study phases were highly correlated with each other. Several personal characteristics, particularly gender and political views, were also found to be important predicators of all or specific risk perception measures.

Overall, findings from this research provide empirical support for the relative accuracy, behavior motivation, and risk reappraisal hypotheses on evolving relationships between risk perception and behavior, albeit to different degrees. A negative cross-sectional relationship between risk perception and related behavior is often used to assess the accuracy of risk perception when actual risk cannot be readily measured (Weinstein et al., 1998). However, their empirical correlations are framed by various factors such as the types of risk, the specific aspects of risk perception, the effectiveness of preventive actions, and the timing of study. The relationships between individual risk perception dimensions and risk behavior tend to be more positive than negative if the risk of interest involves a high level of uncertainty, if actions cannot completely prevent risk events (and thus fail to substantially reduce risk perception), and/or if evaluations are conducted before the potential negative feedback of precautious behavior on risk perception takes effect. Therefore, the positive within-time correlations between COVID-19 risk perception indicators and preventive actions identified in our path analysis are largely in line with the results of previous cross-sectional and longitudinal studies of risk perception and behavior in various research settings (e.g., Dickinson et al., 2015; Ibuka et al., 2010; Qin et al., 2015b, 2021; Rubin et al., 2010). Such conjoint linkages between risk perception and behavior can support the relative accuracy hypothesis as well in broader risk contexts.

The present study also contributes to a better understanding of the causal effect of risk perception on risk-related behavior by including both cognitive and affective aspects of perceived risk in the longitudinal analysis. The relative roles of individual risk perception dimensions in behavioral motivation may vary depending on specific risk and vulnerability conditions. Across-time correlations in the path models suggested that all three risk perception indicators, particularly perceived potential harmfulness of infection (see Fig. 1 and Fig. 2), could motivate preventive actions in response to the COVID-19 pandemic. Moreover, the repeated measures ANCOVA analysis of CS1 suggested that preventive actions had relatively weaker feedback effects on perceived harmfulness of infection than on perceived probability of infection and the level of anxiety. These findings are not surprising as it is widely believed that older people and those with underlying health conditions (e.g., heart disease, diabetes) are at elevated risk of serious illness if infected with this disease.

Finally, findings from this research can expand the evidence base for the risk reappraisal hypothesis. The feedback of behavioral responses on risk perception is considered a prerequisite for identifying relative accuracy. Nevertheless, other than the counter-effects of highly effective protective behavior (e.g., vaccination, substance misuse treatment, health risk screening) on the perceived likelihood of some risk events (Brewer et al., 2004; Glenn et al., 2011; Klepper et al., 2017), empirical evaluations of the risk reappraisal mechanism are largely lacking. The applicability of this hypothesis in real-time epidemic or pandemic settings is still unclear (Raude et al., 2019). Our findings showcase several other possibilities for risk reappraisal in addition to the original risk reduction effect (Weinstein et al., 1998; Weinstein and Nicolich, 1993). The cross-lagged path models included both positive and negative across-time correlations from preventive actions to individual risk perception dimensions. The significant interaction effects of study phase and initial preventive actions on COVID-19 risk perception indicators also revealed that greater preventive activeness was related with slower increases, absolute decreases, or relative steadiness in perceived risk. Altogether, these results suggest that risk reappraisal is a rather complex process and does not merely involve reductions of risk perception.

6. Conclusions and implications

Thus far, there have been limited studies on the changing relationships between risk perception and behavior, which mainly focused on aggregate perceived risk or a specific risk perception dimension such as the perceived probability of a risk event (e.g., Brewer et al., 2004; Bubeck and Botzen, 2013; Qin et al., 2021; Raude et al., 2019; Weinstein et al., 1998). This research further advances conceptual approaches and empirical knowledge in this understudied area by examining the dynamic perceptions and actions in response to the COVID-19 outbreak. In summary, our data analysis and results support the three research hypotheses discussed earlier (Section 2.3): (1) the cognitive and affective dimensions of perceived COVID-19 risk and preventive behavior all changed over time; (2) there were both within- and across-time correlations between COVID-19 risk perception indicators and preventive actions; and (3) preventive actions showed varied effects on individual aspects of perceived COVID-19 risk over time. These observations can inform further development of the conceptual linkages between risk perception and behavioral responses. In particular, this study suggests that the risk reappraisal process is more complicated than conventionally conceived and can be modified to encompass multiple alternative scenarios for evolving risk perception, including substantive reduction, qualified amplification, relative stabilization, and potentially, further reinforcement.

Findings from this research can be used to support risk management and decision making in health and related sectors. First, the analysis showed that all COVID-19 risk perception indicators, particularly perceived harmfulness of infection, were important drivers of preventive actions. Therefore, measures to increase public awareness of specific aspects of health threats and impacts could be especially effective in promoting proactive behavioral responses. Second, health risk prevention and mitigation should adopt a dynamic perspective as both risk perception and related behavior do evolve over time. Community health management entities should track changing risk perception and responses, and accordingly adjust their risk communication and preparedness strategies. Furthermore, since preventive actions may have diverse feedback effects on risk perception, special attention is needed for strengthening cognitive and behavioral responses to health risks over an extended time span.

This research can also provide useful implications for future longitudinal risk studies. There was severe urgency regarding quick response research at the early stages of the COVID-19 pandemic. The panel survey data collected in this study were quite timely as the disease was spreading fast in the United States and many other countries. Although we tried to match the socio-demographic characteristics of our survey samples with those of the general populations in the study areas, the final panel samples were not completely representative of local populations because of the limitations in Qualtrics survey administration and the attrition of panel survey respondents across study phases. The levels of risk perception and preventive behavior could also be greater among study participants than for the general population. Nevertheless, the perishable nature of collected data and our emphasis on panel data analysis can lessen this concern to an extent. The potential generalizability of study findings is also enhanced by a research design involving two parallel case studies under different spatio-temporal contexts of the COVID-19 pandemic. Further research on the dynamic relationships between risk perception and behavior can benefit from a refined sampling process and improved representativeness of panel data. Additionally, the reciprocal relationships between risk perception and risk-related behavior are contingent on a range of factors such as specific categories of hazards and risks, dimensions of risk perception, characteristics of behavioral responses, and stages of evolving risk events. Thus, it is necessary to repeat and expand this longitudinal research design in the contexts of other health, socioeconomic, technological, and environmental risks. Convergent research approaches, such as comparative reviews and meta-analyses (Qin and Grigsby, 2016), can eventually help to identify common patterns across individual case studies when sufficient empirical evidence is accumulated in the risk analysis literature.

Author statement

Hua Qin: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Project administration. Christine Sanders: Methodology, Investigation, Visualization, Writing – review & editing. Yanu Prasetyo: Methodology, Investigation, Visualization, Writing – review & editing. Muh. Syukron: Methodology, Investigation, Writing – review & editing. Elizabeth Prentice: Investigation, Writing – review & editing.

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