Social Science & Medicine 301 (2022) 114949

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Risk perceptions and COVID-19 protective behaviors: A two-wave longitudinal study of epidemic and post-epidemic periods

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ARTICLE INFO

Keywords:
Longitudinal study
Affective risk perception
Cognitive risk perception
Affect heuristic
Cultural worldviews
Social norms
COVID-19
Protective behavior

ABSTRACT

We investigated how perceived risk and protective behaviors changed as the coronavirus epidemic progressed. A longitudinal sample of 538 people responded to a COVID-19 risk perception questionnaire during the outbreak and post-epidemic periods. Using Structural Equation Modeling (SEM), we examined the mean level change of selected constructs and differences in their relationships. We tested a risk perception pathway in which affective attitude, informed by experience, shaped risk perceptions and protective behaviors. The model also postulated a social pathway in which cultural worldviews, like individualism and hierarchy, predicted risk perceptions and protective behaviors through social norms. Latent mean difference analyses revealed a decrease in social distancing behaviors and an increase in hygiene-cleanliness, corresponding to a reduction in risk perceptions and social norms and a rise in direct and indirect experience, while affective attitude remained substantially stable. Cross-sectional and longitudinal path analyses showed that affective risk perception, primarily informed by affective attitude, and social norms promoted behavior consistency regardless of epidemic contingencies. Instead, analytic risk perceptions were linked to protective behaviors only during the outbreak. Although risk perceptions dropped over time, analytic risk perceptions dropped more steeply than affective risk perceptions. Our findings supported the distinction between affective and deliberative processes in risk perception, reinforcing the view that affective reactions are needed to deploy analytic processes. Our study also supports the claim that perceived social norms are essential to understanding cultural worldview-related protective behaviors variability.

1. Introduction

The COVID-19 pandemic offered an opportunity to investigate how risk perceptions evolve as risk contingencies change. Fig. 1 depicts the daily infected cases and deaths during the 2020 epidemic in Italy. The number of infected individuals and deaths increased and then decreased within a few months. In response to the outbreak, the Government issued a 57-day lockdown (i.e., March 9 – May 4, 2020). The curve stabilized at about 200 daily new cases by the end of May, and life returned almost to normalcy. In the post-epidemic period (i.e., June 1 – August 15, 2020), lockdown restrictions were eased. The most common protective actions were using facemasks, sanitizing hands, and keeping social distance in public places.

1.1. Risk perception and the affect heuristic

Risk perception theory defines two ways humans perceive and act on risk: “risk as feelings” and “risk as analysis” (Slovic et al., 2004). Risk as feelings is an instinctive, emotional, and immediate process that builds a risk judgment from the overall affective attitude (i.e., assessing how positive or negative something makes one feel), a process known as the “affect heuristic” (Finucane et al., 2000). This heuristic assumes that the affective attitude is the main direct predictor of risk perception’s “feelings” component and has primary behavioral importance compared to the cognitive attitude. Indeed, several studies have found that affective attitudes are central in predicting health behaviors (e.g., Conner et al., 2011, 2015; Lawton et al., 2009).

Risk as analysis, on the contrary, is a systematic, serial, slow, and conscious process (Slovic et al., 2004) that builds a risk judgment using logic and statistical reasoning. Risk as analysis is slower, effortful, and less efficient than risk as feelings to navigate a complex environment but can reach conclusions that intuitive, emotional reasoning cannot (Slovic et al., 2004). Analytical thinking controls and corrects affect-laden judgments provided the decision-maker has sufficient time,

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https://doi.org/10.1016/j.socscimed.2022.114949
Received 20 August 2021; Received in revised form 20 March 2022; Accepted 23 March 2022
Available online 26 March 2022
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information, and cognitive resources (Evans and Stanovich, 2013).

A tripartite account of risk perceptions has also been proposed, splitting "risk as feelings" into experiential (i.e., the "gut" feeling of being vulnerable) and affective (i.e., the overall positive and negative feelings) components (Ferrer et al., 2016). However, these components had often been combined because they were not empirically distinct (e.g., Ma and Ma, 2021; Riedinger et al., 2022; Savadori and Lauriola, 2021). This does not imply that the tripartite model is invalid but that there might be empirical reasons that lead to the use of a lower number of components in specific research contexts.

1.2. Experience shapes risk perceptions

Direct experience with a hazard informs the affective attitude, which shapes risk perceptions (Loewenstein et al., 2001; Russell, 2003; Slovic et al., 2004). For example, our proximity to people affected by airborne transmitted infections is positively related to our perceived risk (Tagini et al., 2021). Similarly, personally knowing coronavirus patients, living in a neighborhood where COVID-19 cases were reported, or testing positive increased anxiety and worry (Liu et al., 2020; Petrocchi et al., 2021). In general, people who had personal experience of coronavirus perceived higher risk than those with no direct experience (Dryhurst et al., 2020; Schneider et al., 2021). Direct experience can also influence the analytical component of risk perception. According to the availability heuristic, people who have personal experience with life-threatening diseases tend to overestimate their likelihood of getting sick (Peters et al., 2006). This also seems to apply to COVID-19 (e.g., Rosi et al., 2021). However, the reverse relationship was also found. People with relatives infected with coronavirus assessed a lower case fatality rate than people with no infected relatives (Attema et al., 2021).

Indirect experience shapes risk perceptions, as well. For instance, greater media exposure to disease-related information has been linked with higher perceived threat, severity, and susceptibility to infectious diseases (Tagini et al., 2021). Previous research (Zeballos Rivas et al., 2021) found a link between coronavirus anxiety, fear, and risk perception, in some cases regardless of infection incidence (Liu and Liu, 2020; Liu et al., 2020). Indirect experience of coronavirus was also associated with the perceived probability of being infected when the epidemic curve was flattening (Lin et al., 2020).

1.3. Risk perception and protective behaviors

The "feelings" component of risk perception is deemed more important than the "analysis" component in predicting protective behaviors (e.g., Ferrer et al., 2018). For instance, the perceived severity of COVID-19 and fears of contracting coronavirus predicted intention to engage in social distancing and sanitizing behaviors to a larger extent than the perceived probability of being infected (Magnan et al., 2021; Seale et al., 2020). However, a higher perceived likelihood increased handwashing and social distancing (Bruine de Bruin and Bennett, 2020; Wise et al., 2020). These cross-sectional studies leave open the question of how risk perceptions evolve according to epidemic contingencies and how this change influences protective behaviors.

Longitudinal studies showed that people's worry and anxiety decrease once the epidemic peak has passed (e.g., Wang et al., 2021). Two longitudinal studies reported an increase in protective behaviors as perceived COVID-19 risk increased (Rubaltelli et al., 2020; Schneider et al., 2021). Likewise, Siegrist and Bearth (2021) found a decrease in acceptance of epidemic containment measures as perceived risk decreased. Last, another study found that the engagement in protective behaviors increased according to a corresponding rise in the perceived likelihood of infection (Wise et al., 2020). Thus, risk perceptions and health protection behaviors appear to change jointly according to epidemic contingencies. Most studies either used total or affective risk perception scores (Rubaltelli et al., 2020; Schneider et al., 2021; Siegrist and Bearth, 2021); another study measured the perceived likelihood of infection only (Wise et al., 2020). Therefore, previous research has entangled the "feelings" and "analysis" components of risk perception or only analyzed one of the two.

Affect has a primary role in motivating behavior (Slovic et al., 2004). Moreover, the analytic process is less likely to activate without an affective foundation to mobilize and sustain cognitive resources to process statistical-epidemiological information and guide appropriate protective actions (Peters et al., 2009). According to the "affective signal" hypothesis, affective reactions are needed to deploy analytical processes to reduce bias (Lench and Bench, 2015). Thus, higher processing of probability information was found in medical risk communication when the outcome's severity increased (Pighin et al., 2011). Similarly, Janssen et al. (2014) demonstrated that affective risk perception overrides analytical risk perception in predicting health-protective behaviors using a longitudinal design. Accordingly, we expected risk as feelings and risk analysis to be activated during the epidemic surge, whereas the

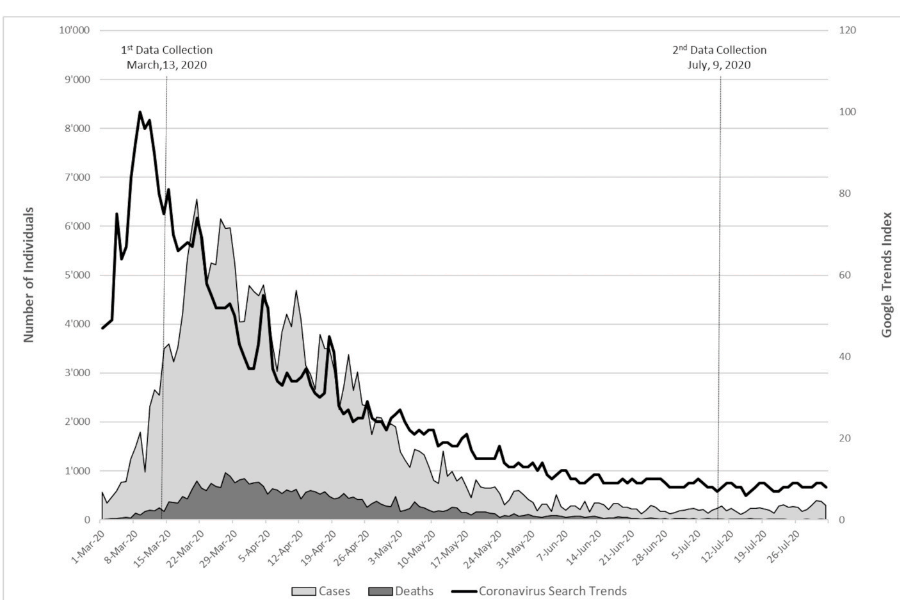

Fig. 1. Coronavirus search trend in Google, new daily positive coronavirus cases, and COVID-19 deaths in Italy between March and August 2020.
[1]The Google Trends Index provides a standardized measure of information search intensity by specific topic over a specific period in a specific geographical area. Internet searches for "coronavirus" in Italy reached 100% in the same week SW1 was conducted, compared to 9% in the week SW2 began. This pattern demonstrates the difference in attention paid to coronavirus-related issues between survey waves.

former to be triggered primarily in the post-epidemic period.

1.4. Worldviews, social norms, and protective behaviors

Cultural worldviews, such as *individualism* and *hierarchy*, can shape risk perceptions (e.g., Kahan, 2012; Shi et al., 2015). Individualism reflects the belief that individuals should make decisions themselves rather than delegating institutions. Individualism was associated with a lower perception of coronavirus risk and lower acceptance of public health measures (Dryhurst et al., 2020; Schneider et al., 2021; Siegrist and Bearth, 2021). Hierarchical worldviews include the belief that the stratification of wealth and power in society is natural and beneficial. Hierarchical individuals were more willing to accept nuclear power plants and rated climate-change risk lower than egalitarians (Kahan et al., 2012; Peters and Slovic, 1996). However, hierarchy was not associated with accepting epidemic containment measures (Siegrist and Bearth, 2021). Because cultural worldviews are stable attitudes, we expect they will not change between outbreak and post-epidemic periods, especially regarding their relationship with risk perception and behaviors.

Cultural worldviews also provide the basis for a "socially constructed" perception of risk (e.g., Joffe, 2003). Many psychological theories consider social norms as predictors of health-protective behaviors (Sheeran et al., 2016). Social norms are subjective perceptions of what significant others do and what one is expected to do (Cialdini et al., 1990). Social norms have been suggested to trigger protective actions during the COVID-19 pandemic (e.g., Andrews et al., 2020). Young and Goldstein (2021) proposed social norms interventions to prevent coronavirus spread. Thus, Martinez and colleagues (2021) showed that social norms were needed to increase social distancing. Therefore, we expected that cultural worldviews could influence health behaviors through social norms.

1.5. A working model of COVID-19 risk perception

Our previous study (Savadori and Lauriola, 2021) proposed a working model in which the affective attitude toward coronavirus, informed by experience, had a central role in shaping risk perceptions and protective behaviors. The model also postulated that cultural worldviews predicted affective attitude and risk perception. Lastly, the model assumed that cultural worldviews could influence protective behaviors through social norms (Fig. 2).

The same study used hygiene & cleaning and social distancing as endpoints of two pathways through which people have engaged in protective behaviors. A *risk perception pathway* led to increasing compliance with hygiene & cleaning and was triggered by the affective evaluation of coronavirus, mediated by the affective appraisal of risk. Risk analysis was also part of this pathway, but it predicted primarily social distancing. Last, a *social pathway* involving cultural worldviews and social norms led to social distancing, hygiene & cleaning.

The current study uses data from two waves to test the mean level change of selected constructs and differences in construct relationships

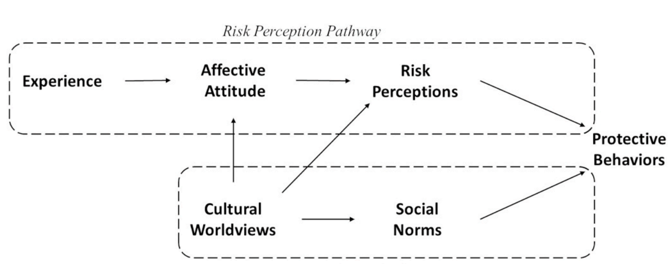

Fig. 2. Working model of COVID-19 Risk Perception (Adapted from Savadori and Lauriola, 2021).

between the outbreak and post-epidemic periods. The first Survey Wave 1 (SW1) took place on March 13, under the threat of the new yet unknown virus. The second Survey Wave 2 (SW2) started on July 9, during the post-epidemic period. The epidemic course (Fig. 1) created the conditions for a "natural" experiment in which data were collected during two distinct stages of the crisis management (the outbreak and the post-epidemic period).

2. Method

2.1. Participants

In SW1, 572 people were recruited through a crowdsourcing platform (https://prolific.co/). The same participants were invited to a follow-up four months later. In SW2, 94% of the original pool of participants agreed to participate, yielding a longitudinal sample of 538 cases (54% men; $M_{age} = 26$ years; $SD_{age} = 6.4$ years; Range 18–45 years). Most respondents (45%) lived in the country's north, 26% in the center, and 29% in the south or islands. Education was as follows: 4% middle school, 51% high school, 43% university, and 3% Ph.D. Most respondents (55%) self-categorized themselves as being in a medium socioeconomic status (4–6), 9% as low (1–3), and 36% as high (7–10). According to census data, the Italian population is older (Italian $M_{age} = 45.7$) and less educated (e.g., 34% and 11% of high school and university, respectively) than our sample. The gender composition and distribution of the Italian population across geographic areas were comparable to those found in our sample.

2.2. Materials and procedure

The survey was anonymous, and each participant received a payment of £ 2.82. In SW1, all participants completed the survey on the same day. SW2 was advertised on July 9, 2020, and 77% of the sample ($n = 415$) completed it within 20 days. The remaining participants ($n = 123$; 23%) completed the survey after a reminder by the end of August. Data from 8 participants (0.02%) were collected in early September after a second reminder. The risk perception, emotional attitude, and social norms sections were randomized. The parts assessing protective behaviors, direct and indirect experience, cultural worldviews, and sociodemographic data were presented in a fixed order at the end of the survey. The Ethics Committee of the University of Trento approved the study (Protocol n. 2020-020).

2.2.1. Measures

2.2.1.1. Experience. *Indirect experience* asked how often participants heard about coronavirus in the mass media either as a cause of death or as a cause of suffering (Supplementary Materials Table S1). *Direct experience* was measured by asking whether participants knew others that died or suffered from coronavirus (Supplementary Material Table S1). Two composite scores were obtained, ranging from 2 to 12 and 0 to 4 for Indirect and Direct Experience, respectively. Cronbach's alpha-s were insufficient and good for Indirect ($\alpha_{t1/t2} = 0.22/0.45$) and Direct Experience ($\alpha_{t1/t2} = 0.89/0.76$), respectively. Test-retest coefficients for Indirect and Direct Experience were $r_{tt} = 0.37$ and 0.54, respectively.

2.2.1.2. Affective attitude. Four bipolar scales adapted from previous research asked participants to disclose their feeling toward coronavirus (Supplementary Table S1). We obtained an *Affective Attitude* index, with higher scores reflecting a more positive attitude ($\alpha_{t1/t2} = 0.91/0.92$; $r_{tt} = 0.70$).

2.2.1.3. Risk perception. The affective component of risk perception, *Risk as Feelings*, was measured using seven items adapted from previous research (Supplementary Table S1). The analytical component, *Risk Analysis*, was measured using three items asking the perceived likelihood of becoming infected with coronavirus (Supplementary Table S1). Following Savadori and Lauriola (2021), two composite scores were calculated, with higher scores reflecting higher affective risk perception and perceived likelihood, respectively. Reliability coefficients were high for Risk as Feelings ($\alpha_{t1/t2} = 0.90/0.90$; $r_{tt} = 0.75$) and acceptable for Risk Analysis ($\alpha_{t1/t2} = 0.67/0.73$; $r_{tt} = 0.58$).

2.2.1.4. Protective behavior. Thirteen items were used to assess self-reported compliance with protective behaviors (Supplementary Table S1). A principal component analysis supported two factors reflecting *Hygiene & Cleaning* and *Social Distancing*, respectively (Savadori and Lauriola, 2021). Two composite scores were obtained, with higher scores reflecting greater compliance with protective behaviors. One item (PREVBEH5 in Supplementary Table S1) was omitted from the SW2 survey due to oversight. We used only the twelve items administered at both survey waves, seven for Hygiene & Cleaning and five for Social Distancing. The reliability coefficients were high ($\alpha_{t1/t2} = 0.84/0.82$; $r_{tt} = 0.69$ for Hygiene & Cleaning; $\alpha_{t1/t2} = 0.83/0.73$; $r_{tt} = 0.58$ for Social Distancing).

2.2.1.5. Cultural worldviews. Worldviews were measured using the Cultural Cognition Worldview Scale (CCWS) (Kahan et al., 2011). The scale consists of 12 statements with which people were asked to rate their agreement using a Likert scale (1 = completely agree; 7 = completely disagree). Two composite scores were obtained: *Hierarchy* ($\alpha_{t1/t2} = 0.86/0.88$) and *Individualism* ($\alpha_{t1/t2} = 0.74/0.77$). They both had a good test-retest reliability ($r_{tt} = 0.86$ and $r_{tt} = 0.71$).

2.2.1.6. Social norms. Three items for *Social Norms* tapped into descriptive norms; four intercepted prescriptive norms. We calculated a single composite score ($\alpha_{t1/t2} = 0.90/0.89$; $r_{tt} = 0.88$) based on evidence that descriptive and prescriptive items reworded in the context of COVID-19 protective behaviors were empirically indistinguishable (Savadori and Lauriola, 2021).

2.3. Statistical analyses

We used Structural Equation Modeling (SEM) with ten latent variables corresponding to the composite scores described in the previous section. Survey questions, coding, data, and R-scripts for reproducibility are publicly available at OSF (osf.io/pa573). We carried out a Longitudinal Mean and Covariance Structures analysis (LMCS) to investigate whether a shift in the latent variables means occurred over the study period. The latent variables were allowed to correlate between and within waves, and the same items' residual terms were free to covary between waves. No assumption was made regarding the latent variables' variances and covariances, while allowing residual terms to covary accounted for non-independence of observations in a repeated measurement design. Before testing the latent mean differences, we examined the model's measurement invariance, a prerequisite for unbiased comparisons (details below).

Next, we investigated the predictive relationships among variables within each wave. Hierarchy, Individualism, Direct and Indirect Experience of COVID-19 were set as exogenous variables; Social Norms, Affective Attitude, Risk as Feelings, Risk Analysis, Promoting Hygiene & Cleaning, and Social Distancing were the endogenous ones. The model hypothesized experience variables to influence affective attitudes and risk perceptions. Cultural orldviews were used to predict affective attitudes, risk perceptions, and social norms. Last, the model posited risk perceptions and social norms as the most proximal predictors of protective behaviors (Fig. 2).

Because the survey used ordered categorical items, scale internal consistency used ordinal Alpha (Zumbo et al., 2007). For the same reason, we analyzed the polychoric correlations using Diagonally Weighted Least Squares estimators (DWLS). This method is recommended for handling ordinal data and has no distributional assumptions (Rhemtulla et al., 2012). To ensure an adequate sample size for DWLS analyses, we decided "a priori" to collect data from at least 500 participants. A posteriori power analysis (Preacher and Coffman, 2006) using our current sample (N = 538), with an α level = 0.001, 1104 df, and a null RMSEA = 0.05, yielded nearly 100% power to detect a poor-fitting model. Model fit was assessed using the following fit indexes and the associated cut-offs: Comparative Fit Index (CFI >0.95), Tucker-Lewis Index (TLI >0.95), Root Mean Square Error of Approximation (RMSEA<0.06), and Standardized Root Mean Square Residual (SRMR <0.05).

Testing for measurement invariance evaluates the decay in model fit over a series of increasingly constrained models. Configural invariance tests whether the same items measure the same latent variables across waves. Metric Invariance adds factor loadings equality constraints across waves. For ordered categorical variables, item thresholds are estimated instead of item intercepts. Item thresholds are the cut-off points used to map the observed categories on the underlying latent variables continuum in polychoric correlations analysis. Accordingly, scalar invariance of ordered categorical variables assumes item thresholds equality. Whereas metric invariance ensures that a unit difference in the latent variables is comparable over time, scalar invariance warrants that the latent variable change is not confounded by construct-irrelevant item-level bias. The scaled chi-square difference test assesses whether a more parsimonious model fits the data equally well as a less parsimonious one, hence which level of invariance is supported. For large samples, a change in CFI ≤.010, paired with changes in RMSEA of −0.015 and SRMR of −0.030 (for metric invariance) or −0.015 (for scalar invariance), support the substantial equivalence of model fit even in the presence of a significant chi-square difference (Chen, 2007).

3. Results

We addressed the longitudinal measurement invariance of the latent variables before testing the latent mean differences (Table 1). The configural invariance model (M0) was an excellent fit, supporting the factor structure equivalence over time and establishing a baseline model for subsequent tests. The metric invariance model (M1) was also an excellent fit. Changes in CFI, RMSEA, and SRMR relative to the baseline model (M0) indicated that the models did not differ substantially. The scalar invariance model (M2) showed significant deterioration in the fit. Although the changes in RMSEA and SRMR (over M1) achieved the recommended standards, the CFI change was too large to support scalar invariance. Because the fit indexes for M2 were acceptable, we investigated whether partial scalar invariance could be supported. In doing so, we examined the model's modification indices in a series of sequential analyses (M2a-M2g) to see if releasing a small number of item thresholds would improve the model fit enough to make the CFI difference acceptable. This search led us to dismiss equality constraints for six items before achieving the partial scalar invariance (M2g in Table 1).

Under partial scalar invariance, one can still make valid comparisons if most indicators per latent variable are invariant (e.g., Byrne et al., 1989). This requirement was met for all latent variables. However, to see how model changes might impact the results, we compared the results obtained from M2 and M2g. The modified M2 model was a good fit to the data after freeing the latent means at SW2 ($\chi2 = 12093.72$; df = 4688; $p < 0.001$; CFI = 0.955; TLI = 0.954; RMSEA = 0.054; p-close = 0.000; SRMR = 0.066) and a significant improvement compared to M2 in which the latent means were equalized ($\Delta\chi2 = 1865.72$; df = 10; $p < 0.001$). Similarly, the modified M2g fitted the data very well ($\chi2 = 11121.62$; df = 4657; $p < 0.001$; CFI = 0.961; TLI = 0.960; RMSEA = 0.051; p-close = 0.091; SRMR = 0.066) and outperformed M2g ($\Delta\chi2 = 952.06$; df = 10; $p < 0.001$).

Table 2 reports the latent mean differences obtained from the full

Table 1
Fit statistics and tests of longitudinal measurement invariance (MI) across Outbreak (SW1) and post-epidemic (SW2).

Invariance	Configural	Metric	Scalar						
Models	M0	M1	M2	M2b	M2c	M2d	M2e	M2f	M2g
Fit statistics									
Chi^2	9815.83	10275.33	13958.70	13319.27	13112.79	12801.23	12617.41	12318.36	12073.68
Df	4416	4455	4698	4693	4688	4683	4677	4673	4667
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
CFI	.967	.965	.944	.948	.949	.951	.952	.954	.955
TLI	.965	.962	.943	.947	.948	.950	.951	.953	.954
RMSEA	.048	.049	.061	.059	.058	.057	.056	.055	.055
p-close fit	ns	ns	<.001	<.001	<.001	<.001	<.001	<.001	<.001
SRMR	.064	.066	.066	.066	.066	.066	.066	.066	.066
Relative fit									
ΔChi^2	–	459.5	3683.4	3043.9	2837.5	2525.9	2342.1	2043.0	1798.3
Δdf	–	39	243	238	233	228	222	218	212
Δp	–	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
ΔCFI	–	.003	.021	.017	.016	.014	.013	.011	.010
ΔRMSEA	–	-.002	-.011	-.009	-.009	-.008	-.007	-.006	-.005
ΔSRMR	–	.002	.000	.000	.000	.000	.000	.000	.000

Note. Chi^2 = chi-square; df = degrees of freedom; p-value = chi-square probability; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; p-close fit = RMSEA close-fit test probability, testing of the null hypothesis that the RMSEA equals .05, i.e. a close-fitting model; SRMR = Standardized Root Mean-square Residual; ΔChi^2 = chi-square difference; Δdf = degrees of freedom difference; Δp = probability value for the $\Delta\chi 2$ test; ΔCFI = change in CFI; ΔRMSEA = change in RMSEA; ΔSRMR = change in SRMR. The $\Delta\chi 2$ tests were conducted to compare more constrained models to less constrained models. The metric invariance model (M1) was compared with the configural invariance model (M0), all scalar invariance models (M2-M2g) were compared with the metric invariance model (M1).
M2b = Unconstrained thresholds for PREVBEH13; M2c = Unconstrained thresholds for PREVBEH13, PREVBEH6; M2d = Unconstrained thresholds for PREVBEH13, PREVBEH6, PREVBEH4; M2e = Unconstrained thresholds for PREVBEH13, PREVBEH6, PREVBEH4, NORMD2; M2f = Unconstrained thresholds for PREVBEH13, PREVBEH6, PREVBEH4, NORMD2, RISKCOND2; M2g = Unconstrained thresholds for PREVBEH13, PREVBEH6, PREVBEH4, NORMD2, RISKCOND2, NORMD3. N = 538.

Table 2
Latent mean differences under full and partial scalar invariance between outbreak (SW1) and post-epidemic (SW2).

	Full Scalar Invariance Model				Partial Scalar Invariance Model				Raw Scores	
Latent Variable	*LMD*	*z-score*	*p*	*d*	*LMD*	*z-score*	*p*	*d*	*CMD*	*d*
Indirect Experience	0.14	4.81	<.001	0.29	0.14	4.80	<.001	0.29	0.17	0.18
Direct Experience	0.96	12.45	<.001	1.20	0.96	12.44	<.001	1.20	0.36	0.70
Affective Attitude	−0.10	−3.65	<.001	−0.11	−0.10	−3.65	<.001	−0.11	−0.08	−0.11
Feelings of Risk	−0.17	−9.68	<.001	−0.23	−0.17	−9.68	<.001	−0.23	−0.17	−0.26
Risk Analysis	−0.33	−16.02	<.001	−0.70	−0.24	−11.69	<.001	−0.54	−0.54	−0.65
Social Norms	−0.41	−23.15	<.001	−0.53	−0.33	−16.03	<.001	−0.42	−0.46	−0.40
Hierarchy	−0.10	−5.66	<.001	−0.12	−0.10	−5.66	<.001	−0.12	−0.12	−0.16
Individualism	0.13	7.69	<.001	0.19	0.13	7.69	<.001	0.19	0.20	0.21
Hygiene and Cleaning	0.23	12.31	<.001	0.34	0.07	3.55	<.001	0.10	0.27	0.35
Social Distancing	−0.36	−17.32	<.001	−0.59	−0.11	−3.73	<.001	−0.17	−0.40	−0.45

Legend. LMD = Latent Mean Difference; z-score = parametric test of the Latent Mean Difference; p-value = z-score probability; d = Cohen's d effect size; CMD = Composite score Mean Difference, N = 538.
Note. A negative effect size (*d*) indicates a decrease in mean score between SW1 and SW2. Conversely, a positive effect size indicates an increase in score.

and partial scalar invariance models, with composite score differences for comparison. All differences were significant. Coronavirus experience had increased over time, especially the direct one (with a large effect size according to Cohen's *d* standards). Risk perceptions diminished. However, Risk Analysis decreased more than Risk as Feelings (with a moderate effect size). Affective Attitude became slightly more negative. Individualism modestly increased, while Hierarchy decreased somewhat. Social Norms declined over time. Social Distancing also decreased; however, the partial scalar model yielded smaller estimates than composite scores and full scalar models. Likewise, the partial scalar invariance model underestimated Hygiene & Cleaning's increase relative to composite scores analyses and the full scalar invariance model.

Next, we examined the predictive relationships among variables within each wave. The model tested on SW1 data ($\chi 2 = 3259.45$; df = 1104; $p < 0.001$) was an acceptable fit (CFI = 0.964; TLI = 0.962; RMSEA = 0.060; *p*-close = 0.000; SRMR = 0.73). It accounted for 21% and 31% of the Hygiene & Cleaning and Social Distancing variance, respectively (i.e., a moderate and large effect size according to R^2 standards); 53% and 27% in Risk as Feelings and Risk Analysis; 41% in Affective Attitude; and 26% in Social Norms. Social Norms and Risk as Feelings were associated with both Hygiene & Cleaning and Social Distancing. Risk Analysis was significant only with the latter class of protective behaviors (Fig. 3a). Hierarchy and Individualism were associated with a decreased perception of Social Norms. Cultural worldviews, especially Individualism, were also related to a less negative Affective Attitude. Higher Individualism was associated with lower Risk Analysis.

The same model tested on SW2 data ($\chi 2 = 3803.07$; df = 1104; $p < 0.001$) was a good fit (CFI = 0.956; TLI = 0.953; RMSEA = 0.067; *p*-close = 0.000; SRMR = 0.77). It accounted for 33% and 37% of the variance in Hygiene & Cleaning and Social Distancing, respectively (i.e., a large effect size); 46% and 25% in Risk as Feelings and Risk Analysis; 33% in Affective Attitude; and 18% in Social Norms. Like SW1, Indirect Experience was associated with Affective Attitude, and this latter with Risk as Feeling. Unlike SW1, Risk Analysis was no longer associated with Social Distancing and marginally significant with Hygiene & Cleaning (Fig. 3b). Moreover, Direct Experience of COVID 19 shaped participants' Risk Analysis at SW2. The social pathway remained the same at both

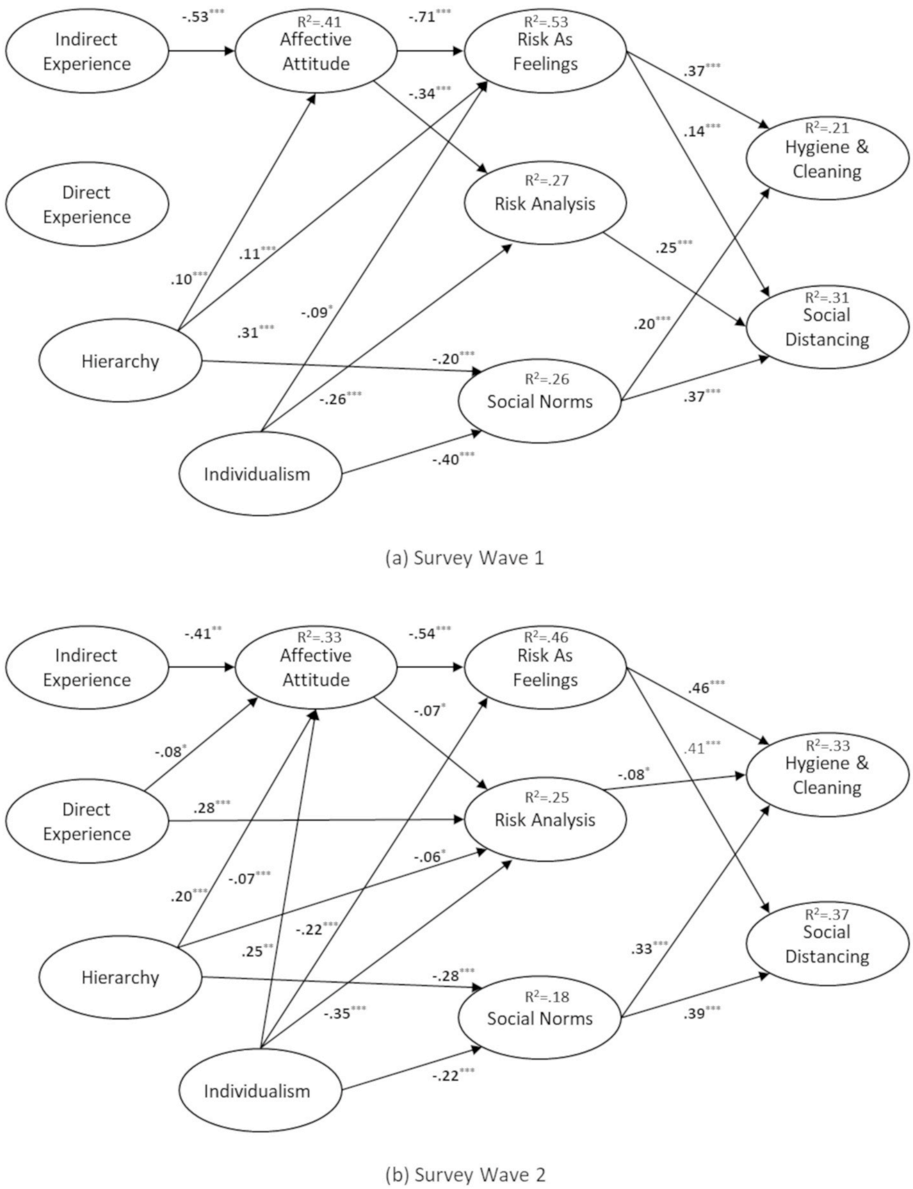

Fig. 3. The COVID-19 Risk Perception Model: Cross-sectional analysis of (a) Survey Wave 1 and (b) Survey Wave 2.
Standardized path coefficients are represented by straight single-headed arrows. Correlations among latent variables omitted. Coefficients flagged with asterisks are significantly different from zero, *p < 0.05, **p < 0.01, ***p < 0.001.

survey waves, with Hierarchy and Individualism predicting Social Norms, and the latter predicting the protective behaviors.

The models tested on SW1 and SW2 data posited two main pathways leading to protective behaviors (Fig. 2). As shown in Table 3, the *risk perception* pathway was significant at SW1 for three out of four tests of indirect effects. According to the completely standardized indirect effect metric, a large effect size was found from Indirect Experience to Hygiene & Cleaning through Affective Attitude and Risk as Feeling. Thus, 1 *SD* increase on Indirect Experience, produced an increase of 0.14 *SD* on Hygiene & Cleaning through Affective Attitude and Risk as Feeling changes. The remaining effects were small-moderate. The risk perception pathway at SW2 was significant only when Risk as Feeling was involved, and indirect effects through Risk Analysis were not significant. Again, the effect size from Indirect Experience to Hygiene & Cleaning through Affective Attitude and Risk as Feelings was large (Table 3).

The *social* pathway was significant at SW1 for all indirect effects tested. The effect size from Individualism to Social Distancing through Social Norms was large. Thus, 1 *SD* increase in Individualism produced a decrease of 0.15 *SD* in Social Distancing through the diminished perception of Social Norms. All indirect effects for the social pathway still were significant at SW2, and the effect sizes were overall in keeping with the analysis of SW1 data for Hierarchy. Individualism was more strongly associated with Hygiene & Cleaning at SW2 than at SW1, and conversely for Social Distancing (Table 3).

A longitudinal analysis tested the dependability of the relationship described above, controlling for the stability of the constructs across waves. Model fit was good ($\chi2 = 169725.82$; df = 4753; $p < 0.001$; CFI = 0.951; TLI = 0.95; RMSEA = 0.057; p-close = 0.000; SRMR = 0.73). The path coefficients in Fig. 4a were like those previously reported (Fig. 3a) except for the relation of Individualism with Affective Attitude (no longer significant in the longitudinal model) and Risk Analysis with promoting Hygiene & Cleaning (which became significant in the longitudinal model). The remaining coefficients were significant in both cross-sectional and longitudinal models (compare Figs. 3 and 4), and the absolute differences in the coefficients ranged between 0.00 and 0.13.

The longitudinal model showed that Direct Experience and

Table 3
Tests of indirect effects: Cross-sectional analysis of outbreak (SW1) and post-epidemic (SW2).

Indirect Effects	Model coefficients and Tests of Indirect Effects					
Risk Perception Pathway						
Survey Wave 1	*B*	*SE*	*z*	*p*	*95% CI*	*Beta*
Indirect Exp – Affect – Risk as Feelings – Hygiene & Cleaning	0.34	0.13	2.60	.009	[0.08, 0.60]	.14
Indirect Exp – Affect – Risk as Feelings – Social Distancing	0.12	0.06	2.20	.028	[0.01, 0.23]	.05
Indirect Exp – Affect – Risk Analysis – Hygiene & Cleaning	0.01	0.02	0.70	.482	[-0.02, 0.05]	.01
Indirect Exp – Affect – Risk Analysis – Social Distancing	0.10	0.05	2.26	.024	[0.01, 0.19]	.05
Survey Wave 2						
Indirect Exp – Affect – Risk as Feelings – Hygiene & Cleaning	0.12	0.02	5.24	.000	[0.08, 0.17]	.10
Indirect Exp – Affect – Risk as Feelings – Social Distancing	0.10	0.02	5.04	.000	[0.06, 0.14]	.09
Indirect Exp – Affect – Risk Analysis – Hygiene & Cleaning	0.00	0.00	−1.60	.111	[-0.01, 0.00]	.00
Indirect Exp – Affect – Risk Analysis – Social Distancing	0.00	0.00	−0.27	.790	[0.00, 0.00]	.00
Social Pathway						
Survey Wave 1						
Hierarchy – Social Norms – Hygiene & Cleaning	−0.03	0.00	−7.70	.000	[-0.04, −0.03]	-.04
Hierarchy – Social Norms – Social Distancing	−0.09	0.01	−10.24	.000	[-0.10, −0.07]	-.08
Individualism – Social Norms – Hygiene & Cleaning	−0.06	0.01	−8.71	.000	[-0.07, −0.04]	-.07
Individualism – Social Norms – Social Distancing	−0.15	0.01	−12.46	.000	[-0.17, −0.13]	-.15
Survey Wave 2						
Hierarchy – Social Norms – Hygiene & Cleaning	−0.08	0.01	−12.43	.000	[-0.09, −0.07]	-.09
Hierarchy – Social Norms – Social Distancing	−0.08	0.01	−10.64	.000	[-0.10, −0.07]	-.07
Individualism – Social Norms – Hygiene & Cleaning	−0.09	0.01	−12.40	.000	[-0.10, −0.07]	-.11
Individualism – Social Norms – Social Distancing	−0.09	0.01	−10.62	.000	[-0.10, −0.07]	-.09

Hierarchy were the latent variables with the greatest temporal stability. Social Norms, Social Distancing, and Risk Analysis were the most changeable (grey arrows in Fig. 4b). At SW2 (Fig. 4b), Risk as Feelings still was significantly associated with both types of protective behaviors controlling for the carryover effect that occurred between waves. Affective Attitude also remained a significant predictor of Risk as Feeling. At SW2, the paths from Affective Attitude to Risk Analysis and from the latter to both types of protective behaviors, although significant, were of modest size. The longitudinal model confirmed the role of Direct Experience as an antecedent of Risk Analysis so that at SW2, people who had personally known others suffering from or died of COVID-19 tended to judge an infection as more likely. At SW2, Hierarchy and Individualism still predicted Social Norms, and the latter still was significantly associated with Hygiene & Cleaning and Social Distancing controlling for carryover effects.

4. Discussion

The present study investigated how individual risk perceptions and socio-cultural factors influenced protective behaviors as the coronavirus epidemic progressed from its outbreak to the post-epidemic phase. In terms of mean level change, our findings revealed a decrease in social distancing and an increase in hygiene-cleanliness, corresponding to a reduction of risk perceptions and social norms and an increase in coronavirus experience. Concerning construct relationships, affective risk perceptions and social norms promoted behavior consistency regardless of epidemic contingencies. Analytic risk perceptions were linked to protective behaviors during the outbreak only.

4.1. Change in the average level of constructs

As the pandemic progressed, participants' direct experience of coronavirus increased according to cumulative COVID cases and fatalities, which jumped from 18,000 to 1300 at SW1 to 242,000 and 35,000 at SW2, respectively. Indirect experience grew as well, though to a lesser extent, probably due to the saturation of citizens' interest during the first week of the outbreak (Papapicco, 2020; Rovetta and Bhagavathula, 2020).

Affective attitude toward coronavirus remained stable, although slightly more negative in the post-epidemic period. Notably, this was the smallest change in our study. This finding matches the slight increment in indirect experience (indeed, the two domains were strongly associated in our study) and confirms the stability of emotional attitudes found in other risk perception studies (Lee and Tseng, 2015). Nevertheless, risk perceptions dropped over time. In the post-epidemic period, Italians were less afraid of coronavirus and perceived a lower probability of becoming infected. These findings are consistent with the reduction in risk perception, fear, and anxiety observed in other countries after the coronavirus outbreak (e.g., Wang et al., 2021).

In terms of subjective probability, the trend found in our study reflects the drop in the incidence of coronavirus cases between the two periods (Fig. 1). Notably, the drop in risk perception was larger for risk analysis than for risk as feelings. This result adds to prior findings and reinforces the view that the lower incidence of coronavirus when we administered the second survey might have primarily impacted the perceived likelihood of infection.

Hygiene and cleanliness had increased over time, while social distancing had decreased. It is worth emphasizing a severe scarcity of facemasks and disinfectants in Italy during the disease outbreak (Sossai et al., 2020). In the post-epidemic period, there was more availability of protective devices, and the usage of masks and hand sanitizers was enforced in venues accessible to the public. This contingency, we believe, aided compliance to hygiene and cleaning behaviors at SW2. As previously noted, social life returned to near normalcy during the post-epidemic period, making it more difficult to maintain social distance at this time. Furthermore, people were less compelled to curtail their sociability because the virus was less prevalent. Other interpretations are available, however.

Social norms were related to adherence to social distancing during the pandemic (Martínez et al., 2021). In our study, social pressure to prevent coronavirus infection declined over time. This finding might explain, at least in part, the observed decrease in social distancing, which, by definition, is influenced by the actions of others and what others would do or approve (Barbieri and Bonini, 2021). By contrast, promoting hygiene and cleaning depends on the person's will, can occur regardless of what others think or do, and was more enforced than social distancing in the post-epidemic period.

According to the cultural cognition theory (Kahan et al., 2011), individualism and hierarchy are stable individual attitudes. Confirming this view, they remained relatively consistent between epidemic periods

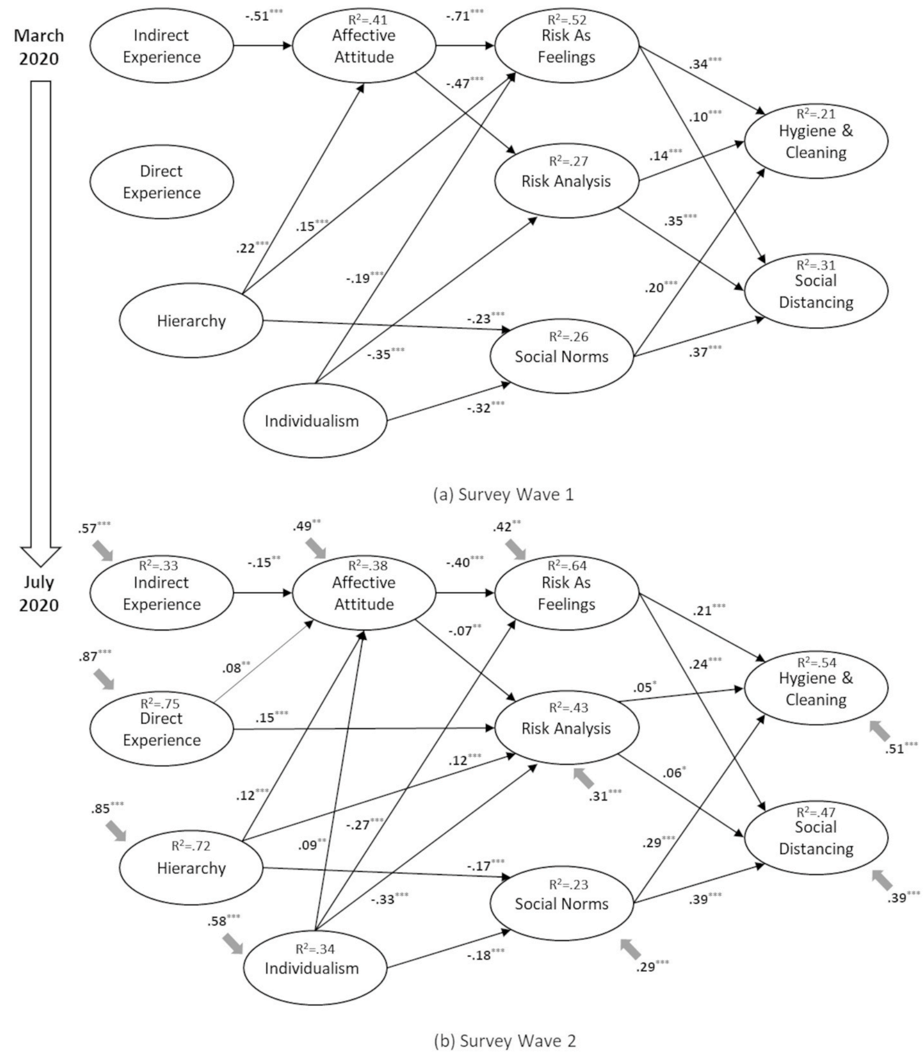

Fig. 4. The COVID-19 Risk Perception Model: Longitudinal analysis of (a) Survey Wave 1 and (b) Survey Wave 2.
Standardized path coefficients are represented by straight single-headed arrows. Grey arrows in (b) represent latent variable's temporal stability over time. Correlations among latent variables omitted. Coefficients flagged with asterisks are significantly different from zero, *p < 0.05, **p < 0.01, ***p < 0.001.

and were associated with risk perceptions.

4.2. Changes in construct relationships

The affect heuristic (Finucane et al., 2000; Slovic et al., 2004) maintains that the affective attitude, informed by experience, shapes risk perceptions. The cross-sectional and longitudinal analyses revealed a strong relationship between affective attitude and affective risk perception. During the outbreak, affective attitude was also moderately associated with the perceived likelihood of infection. In the post-epidemic, however, the latter relationship was negligible. These findings are compatible with the view that the epidemic surge triggered affective and analytic processes. In the post-epidemic period, however, only affective processes were activated.

We interpreted the dissociation of risk as feelings from risk as analysis in light of the two systems responsible for affective and deliberative reasoning, namely System 1 and System 2 (e.g., Evans and Stanovich, 2013). Our data are compatible with the view that System 1 was "always-on" during both epidemic periods, while System 2 was put in a sort of "stand-by" mode when the epidemic situation was less salient. One can consider System 1 as the default mode of thinking about coronavirus risk, producing intuitive feelings, which System 2 supervises and further elaborates when necessary (e.g., during the outbreak). This interpretation agrees with the view that affective reactions are needed to shift to an analytic processing mode (De Neys, 2012; Lench and Bench, 2015) and that affective risk perceptions are enduring, robust predictors of health behaviors (e.g., Janssen et al., 2014; Magnan et al., 2009).

Previous studies found that indirect experience fed risk perception and anxiety regardless of coronavirus incidence (Liu and Liu, 2020; Liu et al., 2020; Zeballos Rivas et al., 2021). Accordingly, people who reported to have often heard about coronavirus through the media had more negative attitudes and higher risk perceptions. These findings extend to the coronavirus context the conclusion that media exposure increases negative affect toward and perceived severity of respiratory infectious diseases (Tagini et al., 2021).

Research has shown that people with more direct encounters with coronavirus patients perceived a higher likelihood of infection than those with fewer or no direct contacts (e.g., Rosi et al., 2021). During the outbreak, the direct experience was unrelated to any other latent variable in the model, while we found the expected association in the post-epidemic period. We should mention that, while our sample covered the entire national territory, only northern Italy had a high enough number of coronavirus cases to warrant personal contact with sufferers during the disease outbreak. We believe that this contingency might explain the negative findings.

Personal experience of a life-threatening disease should make affective reactions more accessible to the individual, increasing one's perceived risk (Peters et al., 2006). The relation of direct experience with affective attitude, although significant, was marginal in the post-epidemic period. This could be due to the enduring strong relationship between indirect experience and affective attitude, which may have diluted the importance of direct experience.

Perceptions of risk are socially constructed (Kahan, 2012). Therefore, we hypothesized that individualism and hierarchy could influence risk perception and social norms. Individualism was associated with less perceived risk in both study periods, although these relationships were stronger in the post-epidemic. These findings are consistent with studies of cultural worldviews and COVID-19 risk perception (Dryhurst et al., 2020; Schneider et al., 2021; Siegrist and Bearth, 2021). In our study, individualism was also negatively associated with social norms. This finding resonates with previous research, which showed that people who live in individualistic cultures adhere to social standards less than those who live in collectivistic societies (Bond and Smith, 1996). No consistent or relevant patterns emerged for hierarchy with risk perception. Instead, hierarchy was associated with disregard for social norms. This is in line with cultural cognition theory (Kahan, 2012), which claims that low-hierarchical or egalitarian people are likely to define societal problems in terms of communal well-being (e.g., health). For instance, low-hierarchical individuals tended to support pro-environmental ideas by recognizing that unregulated industrial activities could threaten the common good for future generations (Xue et al., 2014).

Our study has a number of limitations. The first and most important caveat concerns the age of the sample, which was limited to 45 years due to a non-representative pool of respondents in the crowdsourcing platform used. This implies that our participants may have had a lower perceived risk of COVID-19 complications in terms of severity and mortality than older adults. Furthermore, there might be age-related variables that we missed as mediators or moderators in our model. Future research is needed to assess how chronic conditions that increase COVID-19 risks, perceived severity of COVID-19, and risk perceptions for others rather than themselves, could have influenced the average level of risk constructs and their relationships across waves. A second limitation is that our study lacks measures of traditional and social media coverage to confirm that media tone had changed the sentiment toward coronavirus between survey waves. Indeed, overall media exposure was linked with COVID-19 disease concern and preventive behaviors in a meta-analysis of 47 studies worldwide (Chu et al., 2022). However, there are no Italian studies on the impact of media exposure in the post-epidemic phase. Third, our measure of indirect experience has low reliability. This may limit the generalizability of the relationship between indirect experience and affective attitude but does not disqualify conclusions regarding model's fit and the risk perception pathway. Last, the affect heuristic framework, which inspired the model, does not clarify the relationships between the affective and analytical components of attitude, or how the cognitive components influence risk perceptions. Future studies should consider how cognitive factors could influence risk perception and protective behaviors.

5. Conclusions

Affective risk perceptions and social norms were crucial in sustaining protective health behaviors. We discussed how risk analysis was disengaged in the post-epidemic period. We want to emphasize here that exposure to a hazard is crucial for developing an emotional valence that drives health behaviors and judgments. This is the core of motivational salience, the force that drives choices by indicating whether something is good (or bad) through somatic markers (Bechara and Damasio, 2005). Our research found that indirect experience shaped feelings of risk through affective attitude. Considering the large effect size for this effect, our finding adds to the extant literature (Liu and Liu, 2020; Liu et al., 2020; Tagini et al., 2021) and suggests that the risk perception pathway was essential to sustain protective actions under varying epidemic conditions. People's perceptions of what others do or should do had a moderate effect on health behaviors and mediated the influence of individualism in both survey waves. Social norms have been thought to motivate protective actions during the COVID-19 outbreak. Our findings confirm these proposals. Italian citizens, especially individualistic and hierarchical ones, perceived less social pressure in the post-epidemic period to maintain the behaviors prescribed by the Government. Risk perception alone was not sufficient to motivate adherence to these behaviors.

Credit author statement

Lucia Savadori and Marco Lauriola: Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing. Marco Lauriola: Formal analysis.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.114949.

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