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Social Psychological Bulletin
Psychologia Społeczna

Determinants of Adoption and Rejection of Protective Measures During the SARS-CoV-2 Pandemic: A Longitudinal Study in Germany's Second Wave

Pia Ochel [1], Sarah Eitze [1,2], Regina Siegers [1], Cornelia Betsch [1,2], Anna Seufert [1]

[1] *Department of Health Communication, Media and Communication Sciences, University of Erfurt, Erfurt, Germany.*
[2] *Health Communication, Bernhard Nocht Institute for Tropical Medicine, Hamburg, Germany.*

Social Psychological Bulletin, 2022, Vol. 17, Article e7515, https://doi.org/10.32872/spb.7515

Received: 2021-09-17 • **Accepted:** 2022-03-23 • **Published (VoR):** 2022-07-04

Handling Editor: Tomasz Besta, University of Gdansk, Gdansk, Poland

Corresponding Author: Sarah Eitze, University of Erfurt, Nordhäuser Straße 63, 99089 Erfurt, Germany. E-mail: sarah.eitze@uni-erfurt.de

Supplementary Materials: Data, Materials [see Index of Supplementary Materials]

Abstract

The adoption and acceptance of protective measures are crucial for containing the ongoing coronavirus disease (COVID-19) pandemic. In a recent article in this journal, Dohle et al. (https://doi.org/10.32872/spb.4315) investigated the influence of risk perceptions and trust in politics and science on those constructs in March/April 2020. Since then, the pandemic has undergone several dynamic changes. We analyzed longitudinal data (N = 800) to investigate whether trust and risk were relevant predictors for pandemic measures at a later stage (October 2020/January 2021). The concept of risk perception was supplemented by risk attitude and affective risk to produce a more comprehensive picture of the risk component. We found that greater trust in science at time point 1 predicted less rejection and more adoption of measures at time point 2. Moreover, trust in politics predicted less rejection of measures. From all aspects of cognitive risk perception, only higher severity predicted lower rejection. All other cognitive aspects were non-significant. However, affective risk was shown to be a major predictor: the more the coronavirus was perceived as frightening and worrisome, the lower the rejection and more frequent the adoption of measures. Also, the higher the risk attitude related to health topics, the less frequent the implementation of measures. We replicated the analysis with predictors from time point 2 and deviations are discussed. Our results indicate that affective risk and general attitude toward health risk are more predictive of taking up measures in the context of COVID-19 than cognitive risk.

Keywords

COVID-19, protective measures, trust, risk attitude, affective risk, health communication

Highlights

- Longitudinal data from two time points, before and during a peak in the incidence of COVID-19 infections in Germany, were analyzed.
- Affective risk and risk attitude toward health were more predictive of taking up measures in the context of COVID-19 than cognitive risk.
- Higher trust in science at time 1 predicted less rejection and more adoption of measures at time 2, and higher trust in politics predicted less rejection.
- Analyses were replicated with cross-sectional data, it was shown that the estimators at time 1 provided reliable results in a longitudinal analysis, which is an important finding for addressing health crises.

The rejection (or disapproval) of policies and the adoption (or uptake) of protective behaviors determine the transmission and containment of severe acute respiratory syndrome coronavirus type 2 (SARS-CoV-2). Various studies have addressed the potential influence of different factors on the implementation of protective measures, such as social distancing and good hand hygiene (Scholz & Freund, 2021; Stroebe et al., 2021; Vacondio et al., 2021). At the beginning of the pandemic, in March and April 2020, Dohle et al. (2020) aimed to identify whether sociodemographic variables, risk perception, and trust are important factors influencing the acceptance and implementation of protective measures. In two studies (Study 1: explorative, convenience sample; Study 2: confirmatory, representative sample), it was found that older and female individuals showed greater adoption and acceptance of measures. In terms of risk perception, it was shown that a higher perceived susceptibility (risk of becoming infected in comparison to another person of the same age and same gender) to the coronavirus disease (COVID-19) significantly predicted more frequent adoption of measures. However, the perceived risk of infection (conceptualized as the product of the subdimensions probability of getting infected and anticipated severity of consequences) did not turn out to be significant in either of their studies. Finally, a higher level of trust in science predicted higher adoption as well as higher acceptance; trust in politics, in contrast, predicted both variables in Study 1 but had no influence in Study 2. This work aims to delineate on why the perceived risk of infection—usually a key element in theories of health behavior—do not seem to play a consistent role in this context. One possible explanation could be that only one of the two subdimensions (probability of infection or severity of the disease) is particularly important. Other studies also point in this direction: different dimensions of cognitive risk perceptions are mostly unrelated to the intention and actual behavior of protective measures as Scholz and Freund (2021) showed. We will examine the longitudinal impact of probability, severity, and susceptibility to further investigate these diverse effects.

Since the beginning of the pandemic, restrictive policies have repeatedly been changed (Hale et al., 2020). As the study by Dohle et al. (2020) took place at the beginning of the pandemic, it remains unclear to what extent trust, risk, and sociodemographic factors can still explain the acceptance and adoption of protective measures at a later stage of the pandemic. Our data allow us to look at those aspects in October 2020 and January 2021. Second, in contrast to the cross-sectional design of Dohle et al. (2020), the panel design of the current study allows us to estimate the effect of individuals' attitudes and behaviors over time. Moreover, additional factors such as affective risk (Loewenstein et al., 2001; Slovic et al., 2004) and risk attitude (E. U. Weber et al., 2002) are added herein to the predictors investigated by Dohle et al. (2020) to further explain behavior.

Often, affective risk perceptions are even more strongly associated with preventive behaviors than cognitive risk perceptions (Dillard et al., 2012; Janssen et al., 2014; Loewenstein et al., 2001). Affective risk was shown to be correlated with different protective behaviors during the swine flu (A/H1N1) pandemic in 2009 (Goodwin et al., 2011; Renner & Reuter, 2012; Setbon & Raude, 2010). Recently, Vacondio et al. (2021) also found that a higher level of worry was associated with higher engagement in protective COVID-19 behaviors. Loewenstein et al. (2001) argued that there is often a discrepancy between the cognitive evaluation of a threat and the fear experienced in connection with that risk. As such, this study aims to investigate whether affective risk is of greater importance than cognitive risk in association with COVID-19.

The second additional predictor evaluated in this study is risk attitude in the context of health and safety. Several authors have argued that risk-taking behavior is not a stable personality trait but is rather domain-specific (Hanoch et al., 2006; E. U. Weber et al., 2002). The Domain-Specific Risk-Taking (DOSPERT) scale (Blais & Weber, 2006; E. U. Weber et al., 2002) measures risk attitudes in five subdomains. The subscale of health and safety assesses willingness to engage in health-related risks such as "driving a car without wearing a seat belt" (Blais & Weber, 2006). Keinan et al. (2021) found that the health subscale was highly correlated with showing risky COVID-19-related behaviors. We presume that a higher health-related risk attitude will be related to lower adoption and acceptance of COVID-19 measures.

Data from the COVID-19 Snapshot Monitoring in Thuringia (COSMO-T) allow us to investigate the research question—that is, why risk perception does not seem to play a definite role in the context of COVID-19—and to analyze the stability of effect sizes in the risk–behavior relationship during the first winter of the pandemic. The study was designed as a longitudinal online survey with two measurement points. Data collection took place in October 2020 (T1) and January 2021 (T2). During the first data collection T1, the 7-day incidence increased from 16.3 (10/15/2020) to 43.1 (10/27/2020) per 100,000. At this time, there was no lockdown, but restrictions came into effect (e.g., restriction of large events and festivities when the 7-day-incidence reached 35 per 100,000). During the second data collection T2, the 7-day incidence increased from 251 (01/04/2021) to 326 (01/12/2021) per 100,000 (Robert Koch-Institut, 2021). Since November 2, 2020, contact restrictions, closure of restaurants, entertainment establishments and sports facilities were established and labeled as “lockdown light”. On December 16, the measures restricted non-essential retail and private gatherings of more than 5 people from two households. Schools and kindergartens were closed. A detailed overview with numbers of deaths, new cases per day and intensive care unit cases can be found in the Supplementary Materials. The contents of the questionnaires largely resemble those of the national COSMO and include various psychosocial constructs, COVID-19-specific queries, and sociodemographic items (Betsch et al., 2020).

Method

Participants and Design

The collected data are part of a longitudinal online survey with two survey periods (Survey 1 [T1]: October 15–27, 2020; Survey 2 [T2]: January 4–12, 2021). Non-probability quota samples were used for the first survey, representing the distribution of age × gender of the adult population of the German federal state of Thuringia, according to the German census. Final analyses were conducted with n = 721 cases for the investigation of rejection and n = 669 cases for adoption (differences due to missing values). We did not exclude or run a further analysis with people who were or had been infected with COVID-19 as the size of the group was too small (1% at T1, 3.3% at T2). Sociodemographic distribution, survey drop-out rates, and trial reports are shown in a CONSORT flow chart in the supplement (Supplementary Materials File 1: Consort Flow Chart.docx). The study was approved by the institutional review board at the University of Erfurt (#20200724), and all participants provided informed consent prior to entering the study.

Measures

Detailed information about the scales, answer options, and recoding of all variables are given in the supplement (Supplementary Materials File 2: Codebook.xlsx). For the adoption of protective measures, a mean score of 5 items was calculated (using a mask; washing hands for 20 seconds; keeping a distance of 1.5 meters in public spaces; avoiding social gatherings; and reducing social contacts to a minimum; Cronbach’s α = .88). Answers were given on a 5-point scale (1 = “never” to 5 = “always”). Participants who indicated the answer option “does not apply” for at least 1 of the items at T2 were excluded (n = 49). Excluding these participants did not change the reported patterns of results. The rejection of measures was assessed using 1 item (“I think the measures being taken to contain the pandemic are greatly exaggerated”; 7-point scale: 1 = “disagree completely" to 7 = "agree completely"). The sociodemographic information assessed was related to age, gender, education, employment, having children under 18 years old, and having a chronic condition.

Cognitive risk perceptions were assessed as perceived susceptibility to and probability of an infection with SARS-CoV-2, and as the perceived severity of COVID-19 for oneself. Each was assessed with one item (7-point scales, with higher values indicating higher perceived risk). Affective risk was assessed with two items, measuring how frightening and worrying the coronavirus was perceived to be. A mean score was computed (Cronbach's α = .87), with higher scores showing a higher perceived affective risk. Risk attitude toward health and safety issues was assessed using the safety and health items of the DOSPERT scale (E. U. Weber et al., 2002). A mean value of the 8 items was computed (Cronbach's α = .78), with higher levels indicating a greater willingness to engage in risky behaviors in the subdomain (5-point scale).

Trust in science was assessed with 1 item, while trust in politics was assessed with 4 items. Participants were asked to indicate their level of trust in the institutions mentioned in handling the COVID-19 pandemic well. All answers were given on 7-point scales, with higher values indicating greater trust. Participants specifying that they could not make a statement were coded as missing values. A mean score across all 4 items measuring trust in politics was computed (Cronbach's α = .93), excluding all participants with at least one missing value (n = 43). Excluding these participants did not change the reported patterns of results.

Statistical Analysis

Paired t-tests (n = 639) were calculated to test for changes in the mean values over time both for dependent and independent variables (except risk attitude). Hierarchical regressions predicted a) the adoption of protective measures and b) the rejection of measures assessed at T2. The following predictors assessed at T1 were included (stepwise) in accordance with the procedure of Dohle et al. (2020): 1) demographic variables, 2) the subdimensions of risk: susceptibility, severity, and probability, 3) trust in science and politics, and additionally in step 4) affective risk and risk attitude. Heteroskedasticity-consistent estimators were calculated using the HC4 method to address heteroskedasticity and the non-normal distribution of residuals in the dataset (Hayes & Cai, 2007). All materials, data, and code, including the version numbers of the software used, are available through the Open Science Framework (see Supplementary Materials).

Results

Changes Over Time

Both the adoption of protective measures, $t(638) = 8.120$, $p < .001$, $M = .18$, $SD = .57$, 95% CI [.138, .225], and the rejection of measures increased significantly over time, $t(638) = 1.965$, $p = .049$, $M = .14$, $SD = 1.79$, 95% CI [.000, .278]. None of the cognitive risk perceptions (i.e., perceived severity, susceptibility, and probability) changed over time ($p_s > .05$). Affective risk increased over time, with the coronavirus being seen as more frightening and worrisome at T2 than at T1, $t(638) = 4.431$, $p < .001$, $M = 0.24$, $SD = 1.36$, 95% CI [.133, .344]. Trust in politics decreased significantly over time, $t(638) = -3.813$, $p < .001$, $M = -.18$, $SD = 1.20$, 95% CI [−.275, −.088], whereas trust in science remained stable ($p > .05$).

Adoption of Protective Measures

As can be seen in Table 1, the final model with all predictors explained 33.1% of the variance in the adoption of protective behavior at T2, $R^2 = .331$, $F(14,654) = 16.04$, $p < .001$. Significant predictors as measured at T1 were being male ($\beta = -.11$, $p = .001$) and not having children under 18 years of age ($\beta = .10$, $p = .021$). None of the cognitive risk perceptions at T1 predicted the adoption of protective measures at T2. Affective risk, in contrast, had a positive influence on adoption ($\beta = .18$, $p < .001$); the more the coronavirus was perceived as frightening and worrisome, the more frequently protective measures were implemented. Also, the higher the willingness to engage in risky behaviors in the health domain, the less frequently protective measures were adopted ($\beta = -.30$, $p < .001$). Both predictors—risk attitude and affective risk—had the greatest relative impact on protective behavior, $\Delta R^2 = .103$, $\Delta F(2,654) = 43.30$, $p < .001$. Finally, while greater trust in science predicted more adoption ($\beta = .11$, $p = .013$), trust in politics was not a significant predictor ($p = .126$).

https://doi.org/10.32872/spb.7515

Table 1

Regression Coefficients (Assessed at T1) on Adoption of Protective Measures (Assessed at T2)

	Step 1				Step 2				Step 3				Step 4			
Predictor variable	***B***	***SE B* HC**	**β**	***p* HC**	***B***	***SE B* HC**	**β**	***p* HC**	***B***	***SE B* HC**	**β**	***p* HC**	***B***	***SE B* HC**	**β**	***p* HC**
Intercept	3.84	.14		< .001	3.40	.16		< .001	3.18	.17		< .001	3.89	.20		< .001
Age	0.01	.002	.23	< .001	0.01	.002	.18	< .001	0.01	.002	.19	< .001	0.004	.002	.08	.089
Gender male (vs. female)	-0.23	.05	-.17	< .001	-0.25	.05	-.18	< .001	-0.28	.05	-.20	< .001	-0.15	.05	-.11	.001
Children under 18 no (vs. yes)	0.20	.08	.13	.011	0.17	.07	.11	.020	0.14	.07	.09	.046	0.16	.07	.10	.021
Chronic condition yes (vs. no)	-0.003	.06	-.002	.963	-0.10	.06	-.08	.059	-0.09	.05	-.07	.087	-0.04	.05	-.03	.388
Education: low (vs. high)	-0.04	.13	-.01	.763	-0.02	.12	-.01	.862	0.07	.11	.02	.548	0.08	.12	.02	.497
Education: middle (vs. high)	-0.09	.05	-.07	.079	-0.08	.05	-.06	.131	-0.04	.05	-.03	.423	-0.03	.05	-.03	.458
Employment yes (vs. no)	-0.11	.06	-.08	.049	-0.03	.05	-.02	.606	-0.03	.05	-.02	.596	-0.03	.05	-.02	.514
Susceptibility					0.03	.02	.07	.154	0.03	.02	.08	.143	0.02	.02	.03	.479
Severity					0.11	.02	.25	< .001	0.09	.02	.21	< .001	0.04	.02	.09	.070
Probability					-0.01	.02	-.02	.609	-0.02	.02	-.04	.333	-0.02	.02	-.04	.355
Trust in Science									0.04	.02	.10	.037	0.04	.02	.11	.013
Trust in Politics									0.03	.02	.08	.055	0.03	.02	.06	.126
Affective Risk													0.08	.02	.18	< .001
Risk Attitude													-0.31	.04	-.30	< .001
ΔR^2						.067, $p < .001$				.022, $p < .001$				.103, $p < .001$		
R^2		.139, $p < .001$				.206, $p < .001$				.228, $p < .001$				.331, $p < .001$		

Note. N = 669. Included as predictors (assessed in October 2020): age, gender (0 = female, 1 = male), having children under 18 years (0 = yes, 1 = no), chronic disease (0 = no, 1 = yes), education, employment (0 = no, 1 = yes), risk, trust, affective risk, and risk attitude. Dependent variable was assessed in January 2021. *SE B* HC = heteroscedasticity-consistent standard errors. *p* HC = heteroscedasticity-consistent *p*-values.

Rejection of Measures

The overall model explained 37.9% of the variance in the rejection of measures at T2, $R^2 = .379$, $F(14,706) = 43,625$, $p < .001$ (see Table 2). None of the sociodemographic variables emerged as significant for the rejection of measures ($p_s > .05$). Severity had a negative influence on rejection ($\beta = -.17$, $p = .001$). The more dangerous COVID-19 as an illness was perceived to be, the less people rejected the measures. Neither probability nor susceptibility predicted the rejection at T2 ($p_s > .05$). Affective risk had a negative influence ($\beta = -.21$, $p < .001$): the more the coronavirus was perceived as frightening and worrisome, the less likely it was that people would reject the measures. Risk attitude was found to be non-significant ($p = .106$). In terms of trust in politics ($\beta = -.23$, $p < .001$) and trust in science ($\beta = -.14$, $p = .002$), a negative influence was found, in which the higher the level of trust, the lower the rejection of measures.

Analyses of Stability Over Time

Because we are interested in the stability of predictions over time, we computed in-depth analyses by comparing longitudinal to cross-sectional data. For this we compared for each, adoption and rejection, a longitudinal model (Model 1)—consisting of independent variables assessed at T1 and a dependent variable assessed at T2—with a cross-sectional model (Model 2), which consisted of independent and dependent variables assessed at T2. As predictors we included the variables used in the final step of the earlier hierarchical regressions. We then compared the standardized beta weights between longitudinal and cross-sectional regressions to analyze the extent to which the effect sizes for predictors change over time. Consistency suggests that predictors are reliable over time, inconsistency suggests that predictors may vary over time in their importance and may not be useful for recommendations about long-term interventions.

Figure 1 shows the results of the differences in the standardized beta coefficients and the significance levels. For the adoption of measures, it was shown that the cognitive risk variables severity and susceptibility lead to inconclusive significance levels—the two factors were significant in the cross-sectional model (T2-T2) but non-significant in the longitudinal model (T1-T2). For all other variables, the predictions were consistent. For the rejection of measures, the data showed inconclusive significance levels for the medium level of education and susceptibility. Again, the two factors were significant for the cross-sectional model but non-significant for the longitudinal model. For all other variables, the predictions were consistent. Moreover, the difference in standardized beta coefficients (Model 1 - Model 2) did not exceed ± 0.1, except for susceptibility in terms of adoption. The minimal difference between the beta weights speaks for reliable estimations and therefore, their usefulness in long-term recommendations.

https://doi.org/10.32872/spb.7515

Table 2

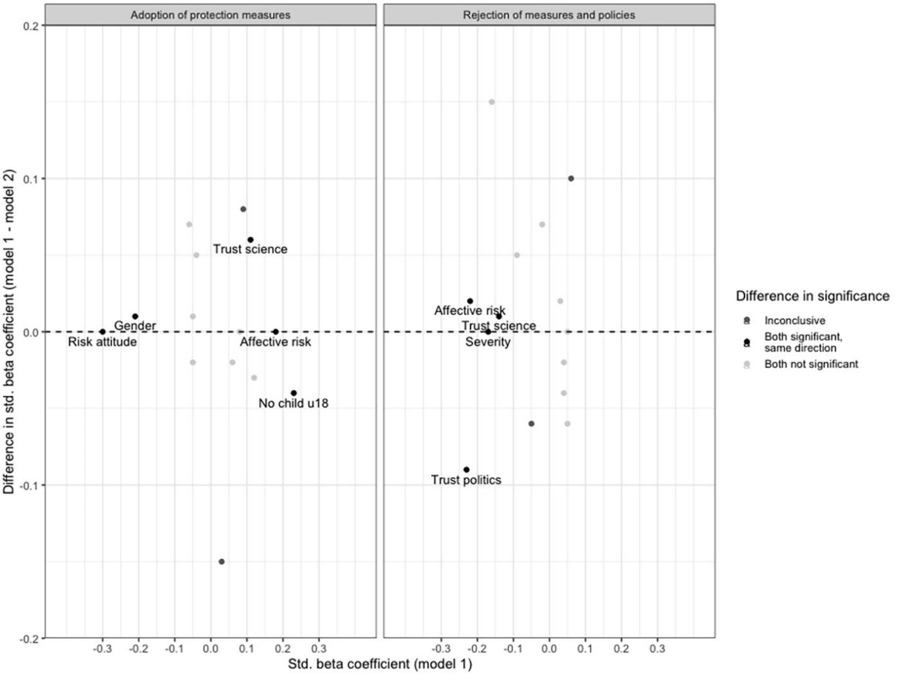
Regression Coefficients (Assessed at T1) on Rejection of Measures (Assessed at T2)

Predictor variable	Step 1 *B*	Step 1 *SE B* HC	Step 1 β	Step 1 *p* HC	Step 2 *B*	Step 2 *SE B* HC	Step 2 β	Step 2 *p* HC	Step 3 *B*	Step 3 *SE B* HC	Step 3 β	Step 3 *p* HC	Step 4 *B*	Step 4 *SE B* HC	Step 4 β	Step 4 *p* HC
Intercept	3.45	.41		< .001	6.16	.42		< .001	7.45	.41		< .001	7.35	.51		< .001
Age	-0.004	.01	-.03	.555	0.004	.01	.03	.467	0.002	.005	.01	.690	0.01	.01	.04	.226
Gender male (vs. female)	0.30	.17	.01	.878	0.07	.15	.02	.657	0.25	.14	.06	.071	0.07	.14	.02	.636
Children under 18 no (vs. yes)	-0.49	.20	-.10	.015	-0.36	.18	-.07	.043	-0.19	.17	-.04	.287	-.19	.17	-.04	.249
Chronic Condition yes (vs. no)	-0.18	.18	-.04	.318	0.27	.17	.06	.107	0.18	.16	.04	.258	0.09	.15	.02	.553
Education: low (vs. high)	0.41	.47	.04	.38	0.20	.38	.02	.589	-0.30	.34	-.03	.375	-.35	.34	-.03	.297
Education: middle (vs. high)	0.46	.17	.10	.008	0.36	.15	.08	.019	0.15	.15	.03	.324	0.12	.14	.03	.383
Employment yes (vs. no)	0.47	.21	.10	.024	0.08	.18	.02	.677	0.11	.17	.02	.513	0.12	.17	.03	.485
Susceptibility					-0.15	.08	-.10	.056	-0.13	.07	-.09	.073	-0.07	.07	-.05	.351
Severity					-0.48	.07	-.36	< .001	-0.34	.06	-.25	< .001	-0.23	.07	-.17	.001
Probability					-0.14	.07	-.09	.040	-0.07	.06	-.04	.286	-0.02	.06	-.02	.686
Trust in Science									-0.20	.06	-.16	.001	-0.17	.05	-.14	.002
Trust in Politics									-0.31	.06	-.23	< .001	-0.30	.06	-.23	< .001
Affective Risk													-0.30	.06	-.21	< .001
Risk Attitude													0.17	.11	.05	.106
ΔR^2						.203, p < .001				.102, p < .001				.034, p < .001		
R^2		.041 p < .001				.244, p < .001				.346, p < .001				.379, p < .001		

Note. N = 721. Included as predictors (assessed in October 2020): age, gender (0 = female, 1 = male), having children under 18 years (0 = yes, 1 = no), chronic disease (0 = no, 1 = yes), education, employment (0 = no, 1 = yes), risk, trust, affective risk, and risk attitude. Dependent variable was assessed in January 2021. *SE B* HC = heteroscedasticity-consistent standard errors. *p* HC = heteroscedasticity-consistent *p*-values.

Figure 1

Scatterplot Depicting Standardized Beta Coefficients at T1, the Difference in Standardized Beta Coefficients Model 1 - Model 2, and the Difference in Significance



Note. On the left side of the graph the beta weights regarding the adoption of protective measures are shown and on the right side of the graph for rejection of measures. The x-axis shows the magnitude of the beta coefficients from Model 1 (predictors assessed at T1) while the y-axis represents the deviation from these coefficients in Model 2 (predictors assessed at T2). The dashed line indicates no deviation between the two models while positive values on the y-axis indicate higher beta values in longitudinal model T1-T2 (e.g., Trust in Science) and negative values indicate higher beta values in cross-sectional model T2-T2 (e.g., Trust in Politics) of the respective variables. The color of the dots represents whether each variable was significant in both models and maintained the direction of prediction (dark gray), whether the direction or significance differed between the two models (gray), or whether the variable was not significant in either model (light gray). Risk attitude was only assessed at T1, which is why there is no difference between Model 1 and Model 2.

Next, we examined the difference in distribution of the predicted and actual data (mean squared prediction errors, MSPE). For both dependent variables it was shown that the squared residuals of the longitudinal analysis (Model 1) were, on average, not significantly different from those of the cross-sectional (Model 2) analysis (adoption: $p = .439$; rejection: $p = .276$). The Kolmogorov-Smirnov test similarly confirmed no significant difference between the predicted and the empirical distribution (adoption: $p = .833$; rejection: $p = .517$). Thus, the effects within the adoption model as well as in the rejection model were consistently estimated over time – the estimators at T1 produced reliable results in a longitudinal analysis. The results suggest that the adoption and rejection of protective measures can be predicted by past data.

Discussion

The present longitudinal data contribute to identifying predictors of the adoption and rejection of protective measures over the first winter months in the COVID-19 pandemic. Earlier studies (Scholz & Freund, 2021; Vacondio et al., 2021), including the study by Dohle et al. (2020), were conducted cross-sectionally at a time when the pandemic was beginning to unfold on an international scale. Our data were collected at a later point in the pandemic when the situation was not as new as it had been.

Further, cross-sectional studies do not allow for causal inferences (Caruana et al., 2015). With our longitudinal study design, it is still not possible to draw causal conclusions, but we can observe how perceptions identified at the beginning of the study are related to subsequent behavior. Finally, we added the risk attitude and a second dimension of risk perception to the predictors of protective measures. This complements the previous research and gives insights into evidence-based behavioral intervention planning based on psychological research.

It was shown that cognitive risk perceptions are not the major factors predicting the behavior under consideration, both short term and over time. Apart from severity, which predicted rejection, the other cognitive risk perceptions proved to be irrelevant for the two outcome variables in the present longitudinal study. For the cross-sectional analyses susceptibility and severity were significant. The lack of explanatory power of probability here shows that it is advisable to look at subdimensions of risk.

Within our longitudinal analyses, predictors other than cognitive risk have been shown to be relevant in explaining behavior. In terms of trust in politics, mixed results were found. Initial political trust had no influence on the adoption of protective measures three months later but turned out to be the greatest predictor of rejection. High levels of trust in institutions and support for politicians are of great importance in the context of a health crisis (Bish & Michie, 2010; Blair et al., 2017; Han et al., 2020; Rubin et al., 2009), because trust can legitimate decisions by authorities (Bennett et al., 2010). However, Dohle et al. (2020) did not find any influence of trust in politics on the adoption or acceptance of measures in their second, representative study, and in the present study, it only predicted the rejection of measures.

One reason for this contrasting result could be that trust in politics was of great importance at the beginning of the pandemic. Several authors described a "rally 'round the flag" effect in the period from January to May 2020 (Baekgaard et al., 2020; Sibley et al., 2020; Yam et al., 2020). These studies showed an increase of support for national leaders across culturally diverse countries. However, our longitudinal data, which show

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(1) a general decline of trust in politics as well as (2) that trust becomes less important in predicting behavior and attitudes over time, suggest that this importance has vanished over time. The fact that then new behaviors have become routine may also make trust less important. Cross-sectional data of the national COSMO (Betsch et al., 2020) also show a decline of trust in the federal government from a rather moderate level at the beginning of the pandemic (April 2020) to a lower level, indicating rather little trust, one year later (April 2021).

More trust in science to deal well with COVID-19 was reflected in more frequent adoption as well as less rejection of protective measures. Average trust in science also remained constant, at a high level, over time. Trusted communicators should be involved in the process and should be considered providers of important information. This is of particular interest after vaccination—the most effective protective measure—has become available. As it is voluntary in most countries, it is important to increase the population's confidence and to use trusted sources of information in vaccination campaigns.

Risk attitude and affective risk were the strongest longitudinal predictors of the adoption of protective measures: those who were generally more willing to take health risks adopted protective measures less frequently. This speaks for a differentiated targeting of risk-seeking people in this domain. The same was true when the virus was seen as non-frightening and non-worrisome. In terms of the rejection of measures, it was shown that the more the coronavirus was seen as frightening and worrisome, the smaller the level of rejection three months later. Risk attitude, however, did not predict rejection. According to the present data, emotional risk perception is of higher importance than cognitive risk perception when it comes to the personal risk assessment of COVID-19 and the related behavior. This is in line with other studies investigating different protective behaviors (Dillard et al., 2012; Janssen et al., 2014; Loewenstein et al., 2001; Renner & Reuter, 2012). In the present study the average cognitive risk assessment remained constant over time—even though the number of infections increased tenfold (Robert Koch-Institut, 2021). A possible reason might be the habituation of risk (Slovic, 1987). The ongoing exposure to the pandemic could have created a sense of familiarity and the risk is attenuated by habituation. Dryhurst et al. (2020) showed that the risk perception was high in ten different countries at the beginning of the pandemic in mid-March to mid-April. This is not applicable to our data at a later date, where risk perception was on a rather low to medium level. The level of risk perception may have come to a plateau. Further longitudinal research is needed to investigate the cognitive underpinnings of risk perception during the pandemic over time.

Furthermore, there was a difference between the predictors of adoption and rejection. On the one hand, personal aspects such as risk attitude were important for the adoption of protective measures—primarily a process that one undertakes for one's own protection. On the other hand, trust in policy—a process involving others—was most important for rejection. Rejection appears to be more of an attitudinal than a behavioral characteristic. Additionally, the two strongest factors were not important to the respective other.

Our analyses of the stability of effects over time have shown that our longitudinal analyses do not differ significantly from cross-sectional analyses—cross-sectional data are thus well suited to predict future behavior and to make stable recommendations for behavioral interventions. This is important in the context of the ongoing pandemic and can be considered when planning and implementing policies. It was shown that in cross-sectional analyses, cognitive risk perception became important for behavior. Affective risk perception, however, had an impact in both models.

Our results come with some limitations. First, the adoption of measures was self-reported and could be overestimated due to a social-desirability bias. Second, cognitive risk was measured with fewer items and rejection was measured via a single survey item asking whether the participant felt that the measures taken to manage the COVID-19 pandemic were exaggerated, and not how reasonable each protective measure is, as Dohle et al. (2020) did. Therefore, the results for this construct can only be seen as conceptual and not as a direct replication of the original results by Dohle et al. (2020). Nevertheless, our results show similar patterns, and we therefore conclude that the item is suitable to gain further insights. Third, even though the sample of the initial study was representative of the age × gender distribution of the Thuringian population, it was not representative in terms of education level. Furthermore, the analysis sample was not representative of the age × gender of the population because of the drop-out rate (see Supplementary Materials File 3: Drop Out Analyses.docx). The age range from 18 to 74 years was chosen because online surveys tend to show a self-selection bias, which may be more pronounced among the older age group (W. Weber et al., 2020). Last, the results may be restricted to Western societies and should be interpreted within its cultural–psychological perspective.

Conclusion

In this longitudinal study, it was shown that various determinants measured in October 2020 predicted the adoption and rejection of protective measures in January 2021. Affective risk and risk attitude were of great importance, with health-specific risk attitude being the strongest predictor of adoption. Affective risk was a reliable risk dimension for predicting behavior over a longer period. For cognitive risk dimensions, only severity had a significant effect on rejection; both other cognitive risk dimensions (probability and susceptibility) were non-significant for both rejection and adoption. Additionally, cognitive risk remained unaffected by increased disease dynamics. The study shows that people’s perceptions of a pandemic should be monitored multidimensionally to detect estimates of sufficient behavioral change motivation and to support communication measures complementing restrictions to effectively control the pandemic.

Funding: This work was supported by the University of Erfurt and the State Chancellery of Thuringia (no funding numbers). The authors alone are responsible for the views expressed in this manuscript and they do not necessarily represent the views, decisions, or policies of the institutions with which they are affiliated.

Acknowledgments: The authors have no additional (i.e., non-financial) support to report.

Competing Interests: The authors have declared that no competing interests exist.

Data Availability: For this article, data is freely available (for access see Index of Supplementary Materials below).

Supplementary Materials

For this article, the following Supplementary Materials are available (for access see Index of Supplementary Materials below):

- Cases and incidences during T1 and T2: Table with COVID-19 cases and incidences during data collection.
- Codebook_After_Rev: Codebook for all variables collected.
- Consort Flow Chart_After_Review: Flow chart for sample with missing values, drop-outs, and demographics for analysis sample.
- Covid cases with Mean of Adoption and Rejection: Figure showing the average adoption of measures in relation to COVID-cases in Thuringia.
- DATA_RAW_After_REV: Raw data set.
- DATA_RECODED_After_Rev: Recoded data set.
- Drop Out Analyses: Analysis of the drop out.
- Figure 1 Scatterplot: Scatterplot depicting standardized beta coefficients at T1, the difference in standardized beta coefficients Model 1 - Model 2, and the difference in significance.
- Intercorrelations_Adoption: Table showing intercorrelations between independent variables (T1) and adoption of protective measures (T2).
- Intercorrelations_Rejection: Table showing intercorrelations between independent variables (T1) and rejection of protective measures (T2).
- Means And Standard Deviations: Table showing means and standard deviations of independent and dependent variables.
- Protective Measures Output: Output of the R-markdown file.
- Protective Measures Code Rmd: R-markdown file including all analysis and figures.
- Syntax Comment Analyses: SPSS syntax file for the analysis.
- Syntax Comment Data Preparation: SPSS Syntax file for the preparation of the data set.
- Thulong: Data set for R-analysis.

Index of Supplementary Materials

Ochel, P., Eitze, S., Siegers, R., Betsch, C., & Seufert, A. (2022). *Supplementary materials to "Determinants of adoption and rejection of protective measures during the SARS-CoV-2 pandemic:*

A longitudinal study in Germany's second wave" [Data, Codebook, Code, Materials]. OSF. https://doi.org/10.17605/OSF.IO/E2Y5P

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PSPS Polish Social Psychological Society

Social Psychological Bulletin (SPB) is an official journal of the Polish Social Psychological Society (PSPS).

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