The Perception of Infection Risks during the Early and Later Outbreak of COVID-19 in
Germany: Consequences and Recommendations

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Abstract

In three studies ($N = 1,055$), we investigated the determinants and consequences of the perception of infection risks during the early and later outbreak of COVID-19 in Germany. Individuals' perceived COVID-19 infection risk was reasonably in line with experts' assessment but changed over time. The probability of the rare event of becoming severely ill and hospitalized was overestimated. Overestimation increased in the exponential growth phase of the pandemic before decreasing at a later stage, thus indicating an inverse U-shaped pattern. Individuals showed biases in their risk perceptions concerning overconfidence and the underestimation of exponential growth of infection cases in the early phase of the pandemic. Forecasts were more accurate after the growth curve had flattened. Risk perceptions increased with perceived dread and tended to increase with perceived control over infection, the evaluation of scientific and one's own knowledge about the pandemic. Approval for the introduction of stricter governmental measures and acceptance of future vaccination measures was mainly influenced by rational utilitarian factors of risk perception (probabilities and utilities of outcomes). These rational influences were mediated by dread, but dread had an additional, potentially irrational effect. Adherence to governmental recommendations was mainly driven by dread and positive expected long-term consequences of the measures. To a smaller degree, adherence increased with perceived personal consequences of infection and decreased with negative expected short-term consequences of these measures. Implications for theory development are discussed and recommendations for dealing with virus outbreaks are derived.

Keywords

risk perception; overweighting of rare events; heuristics and biases; judgment; forecast; overconfidence; COVID-19

The outbreak of the COVID-19 pandemic starting in December 2019 has caused a global major economic and societal crisis. Countries applied various measures to address the threat. Most measures aimed at reducing the speed of the virus spread to avoid a potential overload and collapse of the health system. These “flatten the curve” measures involved governmental orders and recommendations including (a) reducing the number of direct contacts, (b) social distancing to avoid transmission in case of contact, (c) increased hygiene measures (e.g., hand washing, not touching the face, sufficient ventilation of rooms) and (d) various quarantine measures for infected persons, particularly vulnerable persons or even entire communities. Over time additional measures, for example to mitigate the consequences of quarantine (Brooks et al., 2020), also became increasingly important.

Investigations of previous outbreaks of infectious diseases such as H1N1 (swine flu) revealed that various factors influence the magnitude and speed of the spread of viruses (e.g., Poletti, Ajelli, & Merler, 2011; Rudisill, 2013). Some of these factors – such as characteristics of the pathogen as well as the sociodemographic structure of the population – must be taken as given. Behavioral factors, however, such as mobility patterns, adherence to governmental recommendations, and voluntary vaccination can be influenced. The behavioral and social sciences provide important insights for effective responses to induce large-scale behavior changes and to reduce the significant psychological burdens for individuals (Betsch, 2020; Chater, 2020; Van Bavel et al., 2020).

Of crucial importance in this context are individuals’ risk perception, which determines cognitive, affective, and behavioral responses (e.g., Brewer et al., 2007). Classic work on risk perception (Slovic, 1987) indicated that perceived risks are influenced by various characteristics (7 to 18 are considered by Slovic) that typically load on two main factors. Risk perception increases with perceived dread (the degree to which the negative consequences are dreaded “on the level of a gut reaction”) and lack of control about the consequences. Together with additional characteristics (i.e. catastrophic potential,

involuntariness, inequity, globality of the catastrophe, fatality of the consequences, risk to future generations, (unstoppable) increase of risk over time), these variables constitute the factor *dread risk*. Furthermore, risk perception increases with a second factor, *unknown risk*, which includes characteristics such as novelty and lack of scientific evidence as well as individual knowledge about the risk, non-observable risks, and risks with delayed effects.

Other decision-theoretical theories, such as the Conjoint Expected Risk model postulate that risk perceptions are determined by the probabilities of gains and losses, the status quo, and the utility of gains and losses (Luce & Weber, 1986). Hence, the Conjoint Expected Risk model postulates that individuals' risk perceptions are determined by the factors that are in line with normative standards of rationality (von Neumann & Morgenstern, 1947). In some contexts of health risks, the postulated factors by Slovic (1987; see above) did not have predictive power beyond the rational utilitarian factors postulated by the Conjoint Expected Risk model, whereas they did so in the financial domain (Holtgrave & Weber, 1993). Holtgrave and Weber (1993) suggest a hybrid model that takes into account rational factors and some risk factors suggested by Slovic (1987) such as dread. Other research identified general trust and general confidence as important predictors of perceived risk (Siegrist, Gutscher, & Earle, 2005). In the current research, we investigated (i) risk perceptions in a pandemic, including and combining influence factors identified in previous work as well as (ii) their connection with adherence to governmental recommendations, approval of governmental measures, and vaccination.

Risk perceptions have a substantial influence on behavior, particularly if individuals have a high self-efficacy and believe that the protective measures are effective (Maddux & Rogers, 1983; Rogers, 1975; Witte, 1994). Threatening communication and fear appeals that influence risk perception, for example, are particularly effective in changing behavior in combination with high efficacy (Peters, Ruiter, & Kok, 2013); in its absence, they may lead to defensive behavior (Witte & Allen, 2000). According to a meta-analysis (Brewer et al., 2007),

vaccination behavior increased with perceived probability of the negative outcome of the disease (likelihood of risk), a particular susceptibility of the individual, and assumed negative utility of consequences (severity). A second meta-analysis that contained various kinds of risk behavior found small to medium effects for experimental manipulations of risk perceptions on intentions and behavior (Sheeran, Harris, & Epton, 2014). Furthermore, risk perceptions (in the form of beliefs) have been shown to influence health behavior in reasoned action approaches (Ajzen, Albarracin, & Hornik, 2007). Thus, because risk perception is an important prerequisite for various health-related behaviors (including vaccination), it is important to better understand risk perception in respect to COVID-19 and investigate whether it is based on a rational decision process.

Persons' risk perceptions and responses to the COVID-19-pandemic have been investigated in various surveys. A study conducted in China (Li et al., 2020, February 28) found that the perceived severity of the COVID-19 outbreak was the risk factor that was most widely associated with emotional and behavioral reactions. Perceived controllability of the COVID-19 outbreak was the strongest protective factor against emotional problems. Self-assessed knowledge about COVID-19 was unrelated to emotional and behavioral changes, whereas social participation and precautionary measures increased with knowledge. A study in Hong Kong (Kwok et al., 2020, February 27) found that persons reacted to the first infection cases with an anxiety level that was borderline abnormal and that persons with a better understanding of COVID-19 and higher anxiety levels were more likely to follow social distancing measures. Wise et al. (2020, March 19) found that persons in the US had relatively high estimates concerning their risk of being infected with the novel coronavirus¹ (i.e., mean rating of 43 on an analog scale from 0 (very unlikely) to 100 (very likely), which implies a mean probabilities < .50). These estimates are, however, still substantially lower

¹ In the following, we will use the term coronavirus to refer to the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) that causes the coronavirus disease 2019 (COVID-19)

than leading experts' assessments at the time (i.e. .60 - .70; dpa, 2020, February 28).

Furthermore, people rated the infection risk for other persons (in their state) as substantially higher than their own risk, indicating overconfidence. The perceived likelihood of personally becoming infected and the perceived impact from global consequences were the only predictors for engagement in protective behaviors.

A comprehensive investigation of risk perception during the COVID-19 pandemic in Germany was conducted by Betsch and colleagues (Betsch, 2020; Betsch, Wieler, Bosnjak, et al., 2020; Betsch, Wieler, & Habersaat, 2020). In the project COSMO (COVID-19 Snapshot Monitoring), Betsch et al. (2020, April 11) found that the perceived probability of infection decreases with persons' self-efficacy and increases with perceived knowledge concerning COVID-19, perceived proximity of the virus and negative emotions with respect to the virus. Similarly, the expected severity of an infection increases with negative emotions (among further factors). Adherence towards the governmental measures increased (i.e., reactance decreased) with actual knowledge about COVID-19 protection measures, knowledge of effective protective measures, as well as trust in the government and the responsible governmental agency for disease control and prevention (i.e., Robert-Koch-Institute). In a later wave of the study conducted in May 2020 (05th – 06th), a declining perception of infection risks was observed (COSMO, 2020, May 8).

We conducted three studies (Figure 1), which were run in the early stage of the COVID-19 outbreak in Germany (from 17-03-2020 to 18-03-2020), during a steep exponential growth of infections cases (24-03-2020 to 31-03-2020), and after the curve had flattened (29-04-2020 to 04-05-2020). In these studies, we investigated rationalities and irrationalities of judgment and decision making with respect to the pandemic and tested the generalizability of previously established theories and findings to a global pandemic. Specifically, we were interested in whether risk perception and forecasts are influenced by rational or irrational (i.e., not in line with utilitarian standards of rationality) factors and also

investigated judgment biases.² We measured probabilities of risk perception (rather than verbal assessments of interval scaled risks), calculated expected utilities, and compared them with experts' estimates as well as within and between individuals to evaluate the extent to which individuals' perceptions of the situation can be seen as rational. Our work, therefore, has a different focus than the snapshot monitor approach used by COSMO (Betsch, Wieler, Bosnjak, et al., 2020; Betsch, Wieler, & Habersaat, 2020), which focused less on decision making and rationality and more on measured risk perceptions and attitudes towards public policy interventions.

More specifically, we were first interested in whether individuals show typical effects of risk perception and irrationalities in judgment and decision making in an acute involuntary risk situation. Classic work on risk perception typically concerns rare events (i.e., hazards with very small likelihoods of severe negative consequences) that are not very critical in terms of time (e.g., death from living close to a nuclear power plant, severe consequences from using Aspirin) (Holtgrave & Weber, 1993; Slovic, 1987). COVID-19, in contrast, involved acute threat and high risks of infection that go beyond rare events. Rare events are often treated qualitatively differently than events with higher likelihood (Hertwig & Erev, 2009; Kahneman & Tversky, 1979). Hence, it is unclear whether previous result generalize. According to standard models of risky choice, probability estimates for rare events, specifically for becoming severely ill and being hospitalized, are predicted to be overweighted, whereas larger probabilities should be underweighted (Kahneman & Lovallo, 1993; Kahneman & Tversky, 1979). Other work, in contrast, predicts that underweighting of rare events should appear and become more prevalent over time (Erev, Glozman, & Hertwig, 2008; Yechiam, Erev, & Barron, 2006). We investigated probability estimates for rare

² Here and in the following *irrational* refers to deviations from the standards of rationality defined by subjective expected utility theory (Edwards, 1954; von Neumann & Morgenstern, 1947). Furthermore, *irrational* is used to refer to contradictions to logic (i.e. overconfidence) and systematic deviations from true values (i.e. exponential-growth bias) as implied by judgment biases. Finally, *irrational* is used to refer to deviations from experts' assessments or probabilities derived from them (i.e. probability assessment of infection risks).

(becoming severely ill and being hospitalized) and frequent (being infected with COVID-19) hazards and their development over different stages of the pandemic.

Second, we addressed the question to which degree peoples' risk assessments are rational (i.e., precise and sufficiently close to experts assessments). We measured whether overconfidence bias (Dunning, Griffin, Milojkovic, & Ross, 1990) and exponential growth bias (Keren, 1983; Wagenaar & Sagaria, 1975) can be observed in an acute pandemic situation. Wise et al. (2020, March 19) provide first indications of overconfidence.

Slovic (1987) postulated that risk perceptions are influenced by experienced dread, control, and personal knowledge as well as the generally available scientific knowledge about the risk (among other factors). Results by COSMO (Betsch et al., 2020, April 11) indicate that not all of these factors (particularly own knowledge) might have the same influence in an ongoing pandemic. It must be noted, however, that work in the tradition of Slovic used global risk assessments as the dependent variable (how risky is the hazard?), whereas Betsch et al. used probability assessments (how high is the likelihood of infection?). We first followed the latter approach (but see also Study 3) and tested whether probabilistic risk assessment increases with perceived dread and decreases with perceived control over infection and perceived scientific knowledge about the virus (H1).

We were further interested in how well people are able to forecast aspects of the development of the pandemic over time, which is important for rational risk assessment. Individuals typically underestimate exponential growth substantially, referred to as exponential-growth bias (Keren, 1983; Wagenaar & Sagaria, 1975). We tested whether underestimation generalizes to an acute infection scenario and investigated the variation of forecasting accuracy over different stages of the pandemic. We were furthermore interested in whether the ability to forecast future COVID-19 infection numbers is related to various individual characteristics that have been shown to influence forecasts and judgments in general (Levy & Tasoff, 2017; Mellers et al., 2015; Musch, 2003; Toplak, West, & Stanovich,

2011). Specifically, we tested whether the accuracy of forecasts increases with intelligence, conscientiousness, and cognitive reflection and decreases with dread and overconfidence (H2).

Overconfidence has been defined as (i) overestimation of one's actual performance, (ii) overplacement of one's performance relative to others, and (iii) excessive precision in one's beliefs (Moore & Healy, 2008). Individuals place too much trust in their own judgments (Fischhoff, Slovic, & Lichtenstein, 1977), assume that they are better and more fortunate than others (Dunning et al., 1990; Moore & Cain, 2007; Weinstein, 1982, also referred to as unrealistic optimism or optimism bias), and overestimate the precision of their forecasts (Gort, Wang, & Siegrist, 2008; Towfigh & Glöckner, 2011). We investigated whether overconfidence also exists in an acute crisis with high involvement, high availability of information, and governmental campaigns attempting to reduce overconfidence particularly concerning infection risks. We were interested in whether overconfidence prevails similarly concerning multiple aspects of the crisis. Overconfidence (i.e. overplacement) was predicted to prevail concerning doing more than others to avoid infection and concerning the belief that negative consequences of infection would be less severe for oneself than for other persons (H3)³. Furthermore, there might also be overconfidence concerning the perceived risks of infection and hospitalization. Individuals might perceive their personal risk of infection to be lower than the risk for comparable others (Wise et al., 2020, March 19); and the same might hold for the risk of becoming severely ill and being hospitalized. We tested for these aspects of overconfidence, as well.

According to normative models of decision making (von Neumann & Morgenstern, 1947), individuals' approval of governmental actions in a pandemic as well as the acceptance of vaccination should increase with utilitarian factors of risk perception as described by the

³ Note that hypotheses are presented in a different order than in the pre-registration to improve comprehension.

Conjoint Expected Risk model (Luce & Weber, 1986). We investigated whether this is the case under acute threat of a pandemic. Specifically, we tested whether approval of more severe measures by the government increases with risk assessment and perceived consequences for the self in case of infection, higher assumed positive consequences following from these measures in the long run, and lower experienced current negative short-term consequences (H4).

Previous work on vaccination indicated that factors of rational risk assessment (i.e., probabilities and consequences) influence vaccination intentions (Brewer et al., 2007). We were interested in whether this also holds in an acute pandemic and whether perceived dread has an additional, potentially irrational effect in an acute crisis (cf. hybrid model, Holtgrave & Weber, 1993). We tested whether approval of COVID-19 vaccination increases with risk assessment, perceived consequences for self, and dread (H5) and investigated changes in the relative importance of these factors over time. Hypotheses were preregistered at:

<https://osf.io/j39rh>.

Study 1: Risk Perception in the Early Phase of the Pandemic

Method

Participants

Two hundred participants (141 female, mean age = 31 years) took part in the study, which was conducted online. Participants were mainly students (136) but also persons from the general public, recruited using the online recruitment system hroot (Bock, Baetge, & Nicklisch, 2014). Study completion took approx. 19 min. The study was administered in combination with a second study measuring social preferences towards persons with varying risk to suffer from severe COVID-19 symptoms. Participants received between 0 and 10 Euros (mean = 6.52 €, approx. USD 7.10) for their participation dependent on their, and an anonymous interaction partner's decisions in the other part of the study. They were informed about these outcomes only after the study was completed. The study was run from 17-03-

2020 8 pm to 18-03-2020 8 pm (CEST). The data of the study were matched with person characteristics data measured in a previous assessment using an anonymous code. We aimed for and collected 200 participants, since this would allow for the detection of small to medium sized effects for regression coefficients (assumed $f^2 = .055$, one-sided test) with power $1 - \beta = .95$.

13 (7%) participants indicated that they had been (or were currently) considered COVID-19 suspected cases based on the official criteria at that time (i.e., contact with infected persons or return from a risk area). 32 (16%) participants indicated that a close acquaintance was a suspected COVID-19 case according to those criteria. 90% of participants indicated that they informed themselves continually concerning current developments related to the coronavirus (60% indicating 4 and 30% 3 on the scale: *not at all* (1) to *continually* (4)).

Materials

Participants completed the online questionnaire that assessed all new measures and contained additional exploratory items as well as items from a second study (Dorrough, Hellmann, & Glöckner, 2020). The full materials and the data are available at OSF:

https://osf.io/2w58s/?view_only=465aa85be8b54295a8a070b0af4a857e

Risk assessment. The variable risk assessment was measured as the probabilities of (i) being infected with COVID-19 until the end of the year, and (ii) being infected and becoming seriously ill requiring hospitalization by the end of the year. Furthermore, we measured the negative consequences of both incidents. Persons indicated the expected severity of the consequences of being infected and of being infected and becoming seriously ill (scale: *no negative consequences* (0) to *maximum negative consequences* (10)). Negative expected utility scores for COVID-19 infections and becoming seriously ill were calculated by multiplying probabilities and consequences, respectively.

Accuracy of forecast. The accuracy of the forecasts concerning the development of COVID-19 infection cases in Germany was measured by asking participants to indicate how many people in Germany will be infected with COVID-19 in 3, 7, and 14 days. We additionally measured a peak assessment with two questions concerning time (“In how many weeks will the maximum number of COVID-19 infected persons in Germany be reached?”) and magnitude (“How many people will be infected by then?”). Finally, we asked for the number assumed deaths from COVID-19 by the end of the year. The forecasts were compared with the true numbers to determine accuracy in predictions. We were interested in the forecasts of the infection case count over time measured as average absolute deviation in percent.

Overconfidence. Four facets of overconfidence were recorded. Participants indicated the probability of being infected and becoming seriously ill not only for themselves but also for persons of their age and sex who live in the same area. A positive difference between both values (i.e., probability comparable other – probability self) indicates overconfidence. Furthermore, we used two Likert scale items (agreement: *not at all* (1) to *completely* (7)) to measure overconfidence (“I do more than the average participant of this study to protect myself against the coronavirus.”, and “In case of a corona infection, I expect to have more severe discomfort than the average participant of this study.”). Average values above and (for the second item) below the scale mean (4) would indicate overconfidence (i.e., overplacement).

Approval of more severe governmental measures and COVID-19 vaccination. Two three-item scales were used to measure approval of more severe governmental measures and COVID-19 vaccination. Participants indicated on 7-point Likert-scales their agreement with various statements (agreement: (1) *not at all* to (7) *completely*). Items, means, and scale reliabilities are provided in Table 1.

Additional predictors. The additional predictors control over infection risk, dread, and evaluation of scientific knowledge about COVID-19 were also measured using Likert-scales (Table 1). Dread and control, which belong to the factor dread risk (Slovic, 1987), were substantially correlated ($r = .35, p < .001$). Both predictors showed lower correlations with the evaluation of scientific knowledge, belonging to the second global factor unknown risk ($r = .18 / .17, p = .01 / .02$). As additional utilitarian risk measures, we assessed expected positive long-term consequences and experienced short-term negative consequences of the current governmental measures to reduce the spread of COVID-19 with 2-item scales each (Table 1). The reliability of the factor positive long-term consequences was relatively low; thus, results must be interpreted with caution.

Individual characteristics. General intelligence was measured with a 16-item, free, open access measure (ICAR16; $\alpha = .78$; Condon & Revelle, 2014). General personality factors including conscientiousness were measured using a six-factor personality inventory (HEXACO100; $\alpha = .77-.87$; Lee & Ashton, 2018). Cognitive reflection was measured using a 7-item version of the cognitive reflection test (CRT7; $\alpha = .75$; Toplak, West, & Stanovich, 2014).

Here and in the following studies, analyses were conducted in line with the pre-registration if not explicitly stated otherwise. Additional analyses are provided as robustness checks and if multiple ways of analyses were potentially possible. For directed hypotheses, we applied one-sided tests and explicitly noted those comparisons. For all other comparisons, we used two-sided tests.

Results

Accuracy of risk perception. Participants overall showed a large variation in their perceptions of COVID-19 risks (Figure 2). The estimated probabilities of infection by the end of the year vary over the full range of the scale ($M = .54, SE = .02, Md = .60$). The estimate was roughly in line with the risk communicated by the leading expert (Christian Drosten) at

the time of the survey in Germany, that is, 60 – 70% total infection rate indicated for an unknown time period (dpa, 2020, February 28). Probabilities for becoming severely ill and being hospitalized in the same time-period are considered rare events and estimated to be low ($M = .14$, $SE = .01$, $Med = .10$). Importantly, this estimate is higher than the maximum expected probability of becoming severely ill and hospitalized, which, according to our estimations⁴, ranges between $p = .014$ and $p = .0975$ (compared to the upper bound: $t(199) = 3.5$, $p < .001$). Hence, in line with classic work on risky choice, the rare event of becoming severely ill in the COVID-19 pandemic was overestimated in the early outbreak of the pandemic. This effect is especially remarkable as our sample was rather young (mean age = 31 years); thus, severe courses of a COVID-19 infection were especially unlikely for our participants. The assumed negative consequences vary considerably, as well, and are higher for becoming severely ill and being hospitalized ($M = 5.80$, $SE = 0.17$) compared to being infected ($M = 3.51$, $SE = 0.15$). When considering the overall risk, that is the negative expected utility of being infected (i.e., the product of probability and assumed consequences), the negative utility of becoming severely ill and being hospitalized ($M = 0.89$, $SE = 0.09$) is considerably lower than the overall negative utility of being infected ($M = 1.91$, $SE = 0.11$). This indicates some degree of rationality, since the former is a subset of the latter.

⁴ According to observed cases in Germany, 15% of the persons recorded as infected become severely ill and are hospitalized and 1.9% of the infected persons died (Robert-Koch-Institute, 2020, April 9). This results in an estimated maximum total probability of becoming severely ill and being hospitalized of: $p(\text{severe}) = \text{prob}(\text{infected}) * \text{prob}(\text{severe}|\text{infected}) = .65 * .15 = .0975$. It should be noted, however, that this number most likely grossly overestimates the risk, since the conditional probability will probably be lower, as mild cases often go unnoticed. Current estimates from a case-cluster study at the community Gangelt - one of the hotspots of the early COVID-19 outbreak in Germany - support this assumption (Streeck, Hartmann, Exner, & Schmid, 2020, April 9). They show infection rates (active and past) of $p = .15$. Many cases appear to go unnoticed. Taking these cases into account, the fatality rate of infected persons ($p(\text{fatality}|\text{infection})$) is much lower ($p = .0037$) than other estimates (e.g., $p = .019$, Robert-Koch-Institute, 2020, April 9). The fatality rate with respect to the total population in the community reported by Streeck et al. is even lower ($p = .0006$). Combining the estimate $p(\text{fatality}|\text{infection})$ with the relation of deaths to hospitalized cases reported by the Robert-Koch-Institute (1 : 5.8), another reasonable upper estimate might be: $p(\text{severe}) = \text{prob}(\text{infected}) * \text{prob}(\text{fatality}|\text{infected}) * 5.8 = .65 * .0037 * 5.8 = .014$.

Determinants of risk perception. To test our first hypothesis that risk assessment increases with perceived dread and decreases with perceived control over infection and evaluation of scientific knowledge about the virus, we regressed the probability (and the consequences) of being infected on these factors (Table 2). Only dread consistently predicted probability and consequences. In the univariate analyses, probability of infection increased with perceived control of being infected and the evaluation of scientific knowledge, which is opposite to the hypothesized effect. Similarly, of the investigated factors, only dread consistently predicted the expected negative utility of being infected and becoming severely ill and being hospitalized (Appendix, Table A1).

Accuracy in predictions of exponential growth. The participants' forecasts contained a small number of extreme outliers ($M \pm 3 SD$), which were excluded in line with our preregistration. The remaining estimates with case-numbers are provided in Table 4. Due to the (even after exclusion) highly skewed distributions, we report medians and interquartile ranges. The median for the current infection count was very close to the true number (8,000 vs. 8,198), indicating that persons were on average very well informed about the current situation. However, we observed a continuously increasing underestimation of the (roughly exponentially growing) infection case counts over time. For two weeks in the future, the true values were more than twice as large as the median prediction (i.e., $p50 = 50^{\text{th}}$ percentile).

Results concerning average prediction accuracy are presented in Table A2. We calculated a prediction accuracy index as average of the (absolute) deviations from the true values in percent (i.e., lower values indicating higher accuracy). To test our second hypothesis concerning interindividual differences in forecasting accuracy, this index was regressed on intelligence (ICAR16), conscientiousness (HEXACO), cognitive reflection (CRT7), dread, and an average overconfidence score (details below). Accuracy only increased with cognitive reflection ($b = -0.039$, $t = -1.83$, $p = .034$, one-sided test for directed hypothesis). This result

also held in univariate analyses and rank correlations (Spearman $r = -.21$, $p = 0.004$) as well as when excluding the exponential growth item included in the test (i.e., the item involves an estimate for lily pads doubling their size per day, Spearman $r = -.19$, $p = .006$). Intelligence showed an additional predicted effect in a univariate rank correlation (Spearman $r = -.16$, $p = 0.02$). We did not find support for the predicted effects of conscientiousness ($b = -0.01$, $t = -0.21$, $p = .83$), overconfidence ($b = .23$, $t = 1.38$, $p = .17$), and dread ($b = -0.02$, $t = -0.63$, $p = .53$) on forecasting accuracy. Further, exploratory analyses revealed that accuracy increased with higher values of neuroticism (HEXACO, Spearman $r = -.17$, $p = .016$). Only 16 days after data collection (03-04-2020), the real fatalities surpassed the median of the forecasted number of fatalities by the end of the year (Robert-Koch-Institute, 2020, April 3). Hence, fatalities were underestimated to a very large degree in the early phase of the pandemic. A brief discussion of the further forecasts is provided in the Appendix.

Overconfidence. We tested for (average) overconfidence of the participant concerning doing more against an infection and being less negatively affected by an infection than other participants. Participants, on average, indicated that they believed they protect themselves more against infection than the average participant ($M = 4.21$, $SE = 0.10$, $t(199) = 2.02$, $p = .045$). This indicates overconfidence; the effect (deviation from the mid-point of the scale of 4), however, was small. Substantially stronger overconfidence was observed for experiencing less severe consequences than the average participant (reversed item), $M = 2.51$, $SE = 0.10$, $t(199) = 14.2$, $p < .001$. In our data, there was no indication of overconfidence concerning the probability of becoming infected ($M = .01$, $SE = .01$, $t(199) = 0.87$, $p = .39$) but strong overconfidence concerning the probability of becoming severely ill and being hospitalized ($M = .06$, $SE = 0.01$, $t(199) = 4.22$, $p < .001$). Specifically, participants rated the probability of becoming severely ill themselves as being six percentage points lower than the probability of comparable others. Overall, the data mainly show overconfidence effects and, therefore, support our hypothesis. Of the four overconfidence measures, only the two probability-based

measures (probability of becoming infected and being hospitalized, respectively) showed reasonably high intercorrelations ($> |.3|$) and were included in an overconfidence score ($\alpha = .63$) – that is, they were used as predictor in the analysis on forecasting accuracy reported in the previous section.

Approval of more severe governmental measures. At this early time in the crisis, participants, on average, approved more severe governmental measures (Table 1), as indicated by a scale value above the average, $t(199) = 5.18, p < .001$. In a regression predicting approval of more severe measures simultaneously by all four hypothesized factors, we found support for our fourth hypothesis (Table 3, model 1). Approval increased with perceived infection probability, consequences of infection, and expected positive long-term consequences of governmental measures, and decreased with increasing negative short-term consequences of current governmental measures. Hence, interindividual differences in approval of more severe measures in the early pandemic were in line with rational prediction. Adding dread as a non-utilitarian factor that might drive irrational behavior to the regression substantially increased the explained variance, resulting in dread becoming the strongest predictor (Table 3, model 2), which is in line with various theoretical accounts (Holtgrave & Weber, 1993; Maddux & Rogers, 1983). The effects of probability and consequences of infection, as well as estimated long-term consequences, are substantially reduced. The decrease in coefficients between models 1 and 2 indicates that the effects of the rational factors are partially mediated by perceived dread, which is also confirmed by mediation analyses for probability and consequences of infection (both Sobel-Goodman $z > 3, p < .01$). The analysis overall indicates a mediating effect of dread for rational factors but also an irrational effect of dread on approval that goes beyond these rational factors.

Approval of COVID-19 vaccination. There was a high average approval of using COVID-19 vaccination for oneself and others already in this early phase of the outbreak

(Table 1). In a regression, we found support for our last hypothesis that approval of vaccination increases with probability and consequences of infection as well as dread (Table A3). The effect of consequences, was, however, not significant in the pre-registered analysis (model 2), since its influence appeared to be partially mediated by dread. Dread predicts approval of COVID-19 vaccination beyond rational utilitarian measures.

Exploratory analyses concerning the relation of personality and risk factors are provided in the appendix.

Discussion

This study conducted in the early stage of the pandemic shows strong influences of rational factors of risk perception (i.e. probability and consequences of infection) on approval of governmental measures and vaccination. These are partially mediated by dread; however, additional potentially irrational effects of dread also prevail. Risk perception, measured as probability of infection, is driven mainly by dread and not by controllability of or scientific knowledge about the risk. We observed considerable biases in risk perception concerning overconfidence and underestimation of exponential growth that are partially related to interindividual differences.

Study 2: Risk Perception in the Exponential Growth Phase

In a second study, we explored perceived probabilities of being infected and becoming severely ill and being hospitalized during the exponential growth phase of COVID-19 cases in Germany. The data was collected in combination with another study reported elsewhere (Dohle, Wingen, & Schreiber, 2020) that included our four core risk items at the end of the study. In the analysis, we followed an exploratory account and did not pre-register hypotheses. By doing so, we were able to join the other study and collect data also in the exponential growth phase of the pandemic (for the timing, see Figure 1).

Method

We received data from 737 participants, of which 661 met the inclusion criteria (18 years or older, permanent residency in Germany, and indicated no data quality issues) and were included in further analyses. Of these, 554 (83.8%) completed the questionnaire, indicating a dropout of 16.2% throughout the survey. The sample had similar demographics to Study 1 (77% female, 0.5% diverse, mean age = 35.2 years). Still, participants were more diverse and included substantially fewer students (less than 40% of persons in the category students, pupils, unemployed). The study measured probabilities and consequences of infection and becoming severely ill and being hospitalized with the same items as in study 1.⁵

Results

Results concerning probability assessment replicated the findings of Study 1. Probability estimates of being infected by the end of the year were relatively high and roughly in line with experts' estimations (see above), $M = .60$ (vs. $.54$ in Study 1), $SE = .01$, $Md = .63$. The probability estimation of the rare event of becoming severely ill and being hospitalized by the end of the year was again substantially overestimated and even more so than in Study 1, $M = .23$ (vs. $.14$ in Study 1), $SE = .01$, $Md = .15$. The consequences of infection were rated essentially the same as in Study 1, $M = 3.5$ (vs. 3.5), $SE = 0.11$. The consequences of becoming severely ill and being hospitalized were rated somewhat lower in Study 2, $M = 5.2$ (vs. 5.8), $SE = 0.12$. The negative expected utility of being infected ($M = 2.20$, $SE = 0.08$) and becoming severely ill ($M = 1.42$, $SE = .07$) were both somewhat higher than in Study 1. To test for potential changes over time, we conducted analyses using the pooled data of studies 1 and 2. Specifically, we regressed probabilities, outcomes, and utilities on a study

⁵ There was one minor deviation in that consequences were measured on a scale from 1 to 10 rather than 0 to 10. We rescaled the values to make them comparable to the other studies.

indicator variable controlling for age, gender, and a student status proxy variable⁶. We applied a Bonferroni corrected α error level of $\alpha = .05 / 6 = .008$ in the analyses to correct for multiple testing in the exploratory analyses. Only the perceived risk probability ($b = .08, t = 5.80, p < .001$) and utility ($b = .47, t = 3.90, p < .001$) for becoming severely ill and being hospitalized increased significantly between studies 1 and 2.

Discussion

The results replicate the observation from Study 1 that rare events such as becoming severely ill and being hospitalized are overestimated, while (higher) infection probabilities are estimated in a relatively rational manner. This overestimation of rare events appears to increase in a phase of exponential growth of infection rates. However, it must be acknowledged that we cannot control for all potential differences between samples, so that the latter result remains somewhat preliminary.

Study 3: Risk Perception in the Flattened Curve Phase

The third study was an improved replication of Study 1 conducted at a point in time when the infection curve had flattened (see Figure 1). For the study, we recruited a representative sample (according to age and gender) of the German adult population.

Method

Participants. The study was completed by 301 participants (156 female, 1 diverse, mean age = 50 years, $SD = 16$), recruited and incentivized by the online panel provider Toluna (<https://de.toluna.com/#/>). Income, occupation, and education were broadly distributed in the sample (Figure A1). Most of the participants lived in a relationship (63%) and had

⁶ Note that in Study 2, a student status was only measured as part of a socio-economic status scale in a category jointly with pupils, unemployed, and stay at home parents. Our proxy student indicator was set to 1 for persons in this category in the typical student age range (18 years < x < 30 years). Results, however, also hold if all people in the category are used.

children (60%). The study was part of the COVID-19 battery of the Social Cognition Center Cologne. The battery included six studies (Dohle et al., 2020; Dorrough et al., 2020; Glöckner, Dorrough, Michels, & Giersch, 2020, May 14; Imhoff & Lamberty, 2020, April 14; Schneider & Dorrough, 2020, May 14) that together took participants 25 minutes to complete. Of the participants, 5% indicated that they had been suspected of and tested for COVID-19. For 7 participants (2%), COVID-19 had been diagnosed. 3 participants (1%) indicated that they were active COVID-19 cases. 84% of the participants indicated that they continually inform themselves about COVID-19 (55% indicating 4 and 31% 3 on the scale: *not at all* (1) to *continually* (4)), which was similar to the value from the first study (90%). We aimed for 300 participants, since this would allow for detecting small effects for regression coefficients (assumed $f^2 = 0.036$, one-sided test) with power $1 - \beta = .95$.

Materials and procedure. Materials and procedure were essentially the same as in Study 1. We included a scale that measured subjectively assessed knowledge concerning COVID-19 to test a further component of the unknown risk factor (Slovic, 1987; see Table 1). Furthermore, we added an overall risk assessment item (“How high do you estimate the risk that you will be infected with the coronavirus?” rated on a 7-point Likert-scales (agreement: (1) *very low* to (7) *very high*), removed one no longer applicable question concerning governmental actions (see Table 1), and added more detailed demographic questions and exploratory questions concerning knowledge about various COVID-19 statistics. To be able to analyze effects of risk perception on individuals’ adherence to governmental recommendations, we used adherence scores from a 12-item scale of a further study in the battery, for which detailed results are reported elsewhere (Dohle et al., 2020) ($\alpha = .88$, example item: “When you think of the behavioral recommendations just mentioned, how often do you stick to them? Wash your hands regularly with soap.”). For the three scales that measured assessments of governmental actions, scale reliability decreased substantially at this later time point in the crisis, indicating more differentiated assessments (Table 1). For the

other factors, scale reliability was higher than in Study 1. Hypotheses were slightly modified and extended (<https://osf.io/xs6ru>). Materials and data are stored at OSF and will be made available after the further projects included in the battery by other authors have been finished or upon request.

Results and Discussion

Risk perception. We first compared results concerning risk perception with those in the early stage of the pandemic measured in Study 1. Due to the heterogeneity in samples, we estimated between-study differences in multiple regressions controlling for age, gender, and an indicator variable for student status (yes / no). The perceived probability of infection with COVID-19 was reduced by 15% points compared to Study 1, showing a bimodal distribution in the later phase of the crisis (Figure 2, bottom), $b = .15$, $t = 4.46$, $p < .001$. This perception was in line with a change in the leading experts' opinion concerning aiming for containing the virus rather than achieving herd immunity, which was broadly communicated in a joint statement of the four leading research organizations in Germany (Frauenhofer, Helmholtz, Leibniz, & Max Planck, 2020, April 28) at the time of the study.⁷ Interestingly, no reduction in risk perception was observed for the perceived risk of becoming severely ill and being hospitalized ($M_p = .15$, $SE = .01$ vs. $.14$ in Study 1 and $.23$ in Study 2). This rare event remained overestimated compared to the highest upper estimate (9.75%), $t(300) = 5.0$, $p < .001$, which in itself would need to be corrected downwards given the expert statement mentioned above. In line with our hypothesis, the perceived risk increased by 3.7% compared to the early stage of the crisis, $b = .037$, $t = 1.77$, $p = 0.039$ (one-sided test for directional hypothesis 7 in a regression model). Over the three studies, we observed an inverse U-shaped

⁷ Due to this change in expert opinions, it was not possible to test whether participants' perceptions of infection risk were in line with experts' opinion as stated in the second part of hypothesis 6. The observed rate was significantly below the standard of $p = .60$ used in Study 1.

pattern for both the perceived probability of infection and the risk of becoming severely ill and being hospitalized (Figure 1).

Determinants of Risk Perception. An investigation of the drivers of individual risk perception in multiple and univariate regressions revealed results mainly in line with Study 1 (Table 2, bottom). Risk perception was driven by dread. Control as well as scientific and one's own knowledge did not make an additional contribution. Risk perception again tended to increase with perceived control of infection in the univariate analysis. Finally, we regressed the additionally included overall risk assessment on the respective factors to connect our investigation to classic work on risk perception using such measures (Slovic, 1987). In contrast to theoretical predictions and previous findings, also for this risk measure, risk perception increased with control and one's own knowledge (additionally to the predicted effect of dread, Table A5).

Forecasting accuracy. Median forecasts of infection counts in the next 3, 7 and 14 days showed only a deviation of $\pm 2\%$ CHECK relative to the true values, which was considerably lower than the deviations in the early phase of the pandemic (Study 1: 39% and 62%), all $z > 5$, $p < .001$.⁸

Overconfidence. We again find overconfidence (i.e., deviations from the scale mean of 4) concerning doing more than others ($M = 4.5$, $SE = .09$, $t(300) = 5.4$, $p < .001$) and being less negatively affected by an infection than others ($M = 3.8$, $SE = .10$, $t(300) = 2.00$, $p = .02$). We find 1.7% point overconfidence for the probability estimations of becoming severely ill and

⁸ To compare the results between studies, we used ordered logit regressions comparing average absolute deviation scores (in %) between studies controlling for sex, age, and a student status indicator. A considerable proportion of participants (31%) indicated values in all three forecasts that were below their estimates for current infection counts. 25% indicated 14-day forecasts at or below 10,000 cases, which seem to refer to the additional numbers of cases rather than the cumulative number. Deviating from our pre-registration, we therefore excluded these participants from our analysis. When they are included in analyses, the results are nonsignificant.

being hospitalized compared to the probability of a similar other, $M = .017$, $SE = 0.01$, $t(300) = 1.87$, $p = .03$ (one-sided). All three effects replicated findings from Study 1. This convergence provides strong evidence for the existence of overconfidence. Even so, post-hoc Bayesian analyses revealed that some of the findings alone do not provide strong (if any) support for the alternative hypotheses. Surprisingly, for the probability of becoming infected with COVID-19 by the end of the year, the probability estimates for comparable others was 2.3 % lower than the estimate for persons themselves, indicating underconfidence, $M = -.023$, $SE = 0.01$, $t(300) = 2.5$, $p = .01$. In Study 1, no significant difference was observed. This indicates that overconfidence concerning probability of infection appears to vary between samples or over various phases of a pandemic.

Approval of More Severe Governmental Measures and Adherence to Recommendations. Approval of more severe governmental measures was driven by rational factors as hypothesized (Table 3, model 3). Only the effect for negative short-term consequences did not reach conventional significance levels. Again, dread mediated the influence of the rational effects but had an additional unique and strong effect. All coefficients were notably similar to the analysis in the early phase (Table 3, model 1), indicating no qualitative changes in the relation between risk perception and approval over time or between samples. In an exploratory analysis, we analyzed the effects of rational factors plus dread on adherence to governmental recommendations in a regression analysis using the average adherence scale from Dohle et al. (2020) (Table A4). Adherence was mainly driven by dread followed by expected positive long-term consequences of the current measures, which had a 43% smaller absolute effect than dread (Table A4). Adherence furthermore increased with the rational factors individual consequences of infection and decreases to a smaller degree with experienced negative short-term consequences of the governmental measures.

Approval of Vaccination. Approval of vaccination was also high in a later stage of the pandemic (Table 1). The effects of the rational factors probability of infection and consequences were substantially smaller than in Study 1, whereas the relative influence of dread was greater (Table A3).

General Discussion

We investigated the determinants and consequences of individuals' risk perceptions in three stages of the COVID-19-pandemic in Germany from a decision-theoretic perspective. We observed changes in risk perception between the early stage, an exponential growth stage, and a stage when the infection growth curve had flattened. Risk perceptions thereby roughly followed an inverse U-shaped pattern. Individuals were well informed about the crisis. Their probability assessments concerning the COVID-19 infection risk were high and roughly in line with experts' forecasts. Infection risk assessments were in the early stages substantially higher than in a US-based sample (Wise et al., 2020, March 19). This might potentially have been due to the high media coverage that communicated unequivocal statements of virologists concerning the risks of the pandemic in Germany. Furthermore, arguably, the smaller distance to Italy, the dreadful pictures from there, and potentially also *German Angst* (i.e. an increased level of anxiety and worries among Germans; Obschonka, Stuetzer, Rentfrow, Potter, & Gosling, 2017) might have helped individuals to take the risk seriously. This is also supported by our finding that probability of the rare event of becoming severely ill and being hospitalized was already substantially overestimated early on in the crisis and even increased in the exponential growth phase, which is in line with the most prominent models of decision making (Finucane, Alhakami, Slovic, & Johnson, 2000; Kahneman & Tversky, 1979). We see some indication that, after a peak in the exponential growth phase, this overestimation reduced in the flattened curve phase in line with some findings in decision from experience

showing underweighting of rare events (Barron & Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004; see also Yechiam et al., 2006).

Of the classic risk factors suggested by Slovic (1987), only dread consistently influenced risk perception. This is in line with affect heuristic, which predicts that people derive risk evaluations from affective reactions towards a stimulus (Finucane et al., 2000; Slovic, Finucane, Peters, & MacGregor, 2002). The risk factors suggested by Slovic (i.e., control and knowledge) in the context of rarer hazards did not generalize to the current pandemic situation as shown in Study 3. Specifically, risk perception measured with a global risk item even increased with control over infection and self-assessed knowledge. The reversed effect of knowledge is in line with results reported by Betsch et al. (2020, April 11), although they used probabilistic rather than global risk measures. A potential explanation for the partially reversed findings is that one's own knowledge and potentially also control are related to a more rational risk perception. In cases of typically overestimated rare risks such as a nuclear meltdown, effects of these factors are negative, leading to decreasing risk assessments. In situations of perceived high risks such as COVID-19 infections that are potentially underestimated, effects are positive, leading to higher risk assessments. A refinement of the theory in this respect might be considered.

Risk perception is largely dependent on rational forecasts concerning the development of infection cases. Forecasts in the early phase of the pandemic showed an exponential-growth bias – that is, an underestimation of the increase in infection rates. The accuracy of forecasts was higher after the curve had flattened. Furthermore, accuracy increased with cognitive reflection and intelligence (the latter only in a univariate analysis) but not with conscientiousness, dread, and overconfidence. In line with previous work on forecasting and judgment biases (e.g., Mellers et al., 2015; Toplak et al., 2011), cognitive reflection and intelligence appear to be the core determinants of accuracy in forecasts also in an acute risk

scenario. Dread does not harm forecasts also in a highly stressful situation of an ongoing pandemic in a phase of exponential growth of infection cases.

We observed overconfidence bias in three out of four measures; and the magnitude varied substantially across measures. Robust overconfidence was observed concerning (i) doing more than other to prevent infection, (ii) having less negative consequences in case of infection than others, and (iii) the probability of becoming severely ill and being hospitalized. No overconfidence was found concerning the infection risk with COVID-19. In Study 3, we even observed underconfidence concerning infection risks. This stands in contrast to a finding in the US (Wise et al., 2020, March 19), in which a lower likelihood for infection with respect to other comparable persons was observed. This deviation might be due to the fact that we used a more refined description of the other person (i.e. same age, same sex, living in the same area) and asked for probabilities or it might indicate a more successful information campaign concerning infection risks in Germany. We observed, however, that people assumed to have a 1.7 to 6 percentage points lower likelihood of becoming severely ill than other comparable persons. Given that the own risk of becoming severely ill was already substantially overestimated, the risk assessment for others becoming severely ill was even more irrational. Similarly, participants expected themselves to have substantially less severe consequences in case of a COVID-19 infection than other participants of the study and they assumed that they do more than others to avoid infection. Overall, our study shows that overconfidence prevails concerning various but not all aspects of risks perception and behavior.

The degree of approval of more severe governmental measures was mainly driven by the relevant normative factors (i.e., probabilities, consequences). The relative influence of these factors remained stable over the stages of the pandemic. Approval increased with perceived own infection risk, consequences of infection, and assumed positive long-term

consequences as well as decreasing negative short-term consequences. These findings are in line with social cognitive models (Rogers, 1983; Witte, 1994) that assume that health-related intentions and behaviors increase not only with risk perceptions but also with perceived outcome efficacy (i.e., assumed positive long-term consequences). These influences were partially mediated by dread; but dread had an additional strong direct effect. Similarly, the utilitarian factors perceived own infection risk and consequences of infection influenced persons' approval of using COVID-19 vaccination for themselves and others; and perceived dread had an additional effect, indicating some degree of irrational influences.

Finally, in exploratory analyses, we found that adherence to governmental recommendations in the flatten curve phase is mainly driven by dread and expected positive long-term consequences of the measures. Smaller effects for own consequences of infection and experienced short-term negative consequences due to the governmental measures were observed. Furthermore, experienced dread increased with neuroticism, which further adds to the notion that neuroticism is a central negative predictor of psychological well-being during the COVID-19 pandemic (Kroencke, Geukes, Utesch, Kuper, & Back, 2020, May 10).

Policy Implications

As a limitation, it must be acknowledged that our studies did not involve experimental manipulations. Therefore, the assumed causal direction of observed effects cannot be proven – this is a topic for further research. In combination with previous findings and theoretical considerations, our findings lead to the following policy implications:

- (1) Adherence to governmental recommendations depends strongly on perceived positive long-term consequences of the measures (i.e., outcome expectancies). Politicians and scientists must consistently and convincingly communicate and explain measures and their long-term aims to the public. Setting sub-goals and using adaptive regulations can be useful to support understanding and reinforce sustained adherence in the public.

- (2) The potential consequences for the persons themselves must be sufficiently explained; and short-term negative consequences of the measures must be alleviated. Still, our analysis of the factors driving adherence to governmental recommendations (Table A4) indicate that the public is not short-sighted and overly focused on these side effects. Citizens appear to be willing to bear the short-term costs, at least for some time.
- (3) Measures should be taken to educate people against underestimation of exponential growth of infection rates in an early phase of the pandemic and concerning overconfidence in all stages. An explicit (and, if possible, consistent) communication of risk probabilities by experts and politicians combined with stories and pictures from single cases (which can increase health risk perception, Evans et al., 2015; Slovic, 2010) is recommended to lead to proper risk assessments (and might have alleviated overconfidence concerning infection risks in the current situation). Further measures such as personalized information campaigns are recommended to reduce overconfidence also concerning doing more than others and concerning having less severe consequences than others.
- (4) The approval for introducing more severe governmental measures in the public is influenced by factors other than adherence to governmental measures after they have been introduced. Short-term negative consequences and probability of infection play a larger role for introducing new measures and should be taken particularly into account for that (whereas dread and positive long-term consequences are more important for adherence).
- (5) Perceived dread was confirmed to be the crucial factor in risk perception also in the COVID-19 pandemic. A combined presentation of rational arguments and pictures of single cases as described above might contribute to increased dread to a sufficiently high level. At the same time, based on theoretical considerations, it can be argued that efficacy expectations should be fostered and precautions should be taken to prevent defensive behavior and support individuals with handling the dread that suffer most.

Individualized support measures such as personality-based websites might contribute to provide individualized advice and contact information to psychological services (such as hotlines) for people with high values of neuroticism that feel particular dread according to our data (see also Kroencke et al., 2020).

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Figures

Figure 1. Risk perception (estimated probability of infection and probability to become severely ill and be hospitalized) plotted against the development of COVID-19 cases in Germany over time (source: Robert Koch Institute). Vertical lines indicate start and end dates of studies.

Figure 2. Corona risk assessment probabilities, consequences, and utilities of being infected and becoming severely ill and hospitalized by the end of the year, respectively, in Study 1 (top) and Study 3 (bottom).

Tables

	<i>Study1</i>		<i>Study3</i>	
factor / item	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
dread ($\alpha = .71 / .87$)	4.56	1.33	4.45	1.56
I experience the current Corona outbreak as threatening.	3.93	1.55	4.31	1.67
I experience the current Corona outbreak as threatening for persons around me.	5.19	1.48	4.58	1.65
control ($\alpha = .76 / .79$)	5.53	1.03	5.39	1.26
Through my own actions, I can influence whether I become infected with the coronavirus.	5.71	0.99	5.75	1.29
Through my own actions, I can influence whether persons around me become infected with the coronavirus.	5.74	1.16	5.50	1.44
Through my own actions, I can influence how strongly the coronavirus is spread in Germany.	5.14	1.62	4.92	1.74
scientific knowledge ($\alpha = .67 / .70$)	5.12	1.01	4.77	1.16
Science makes a decisive contribution to solving the corona crisis.	5.86	1.24	5.74	1.35
Scientists have extensive knowledge concerning the Corona virus and its spread.	4.34	1.44	4.82	1.5
I think the current knowledge about the coronavirus is not very reliable. (reversed)	3.52	1.42	4.20	1.65
The government should not rely so heavily on the opinion of scientists when making decisions. (reversed)	2.21	1.58	3.27	1.85
expected positive long-term consequences of government measures ($\alpha = .53 / .33$)	4.34	1.52	4.26	1.37
The current government measures will have negative long-term effects for me. (reversed)	3.75	1.84	3.75	1.81
The current measures of the government will have positive consequences for people in Germany in the long run.	4.44	1.83	4.27	1.72

approval of more severe government measures ($\alpha = .72$ / $.12$)	4.54	1.47	4.12	1.33
I think the current measures of the government to reduce the Corona infection risk are too strict. (reversed)	2.33	1.56	3.09	1.99
I think the government should do more to reduce the Corona infection risk.	3.63	1.83	3.33	1.91
Germany should immediately introduce a curfew to reduce the Corona infection risk.	4.32	2.10		
approval of Corona-vaccination ($\alpha = .83$ / $.87$)	4.89	1.62	5.04	1.82
I will have Corona vaccinated immediately if a vaccine is available.	4.66	1.85	5.00	2.00
I think it is not necessary for me to get vaccinated. (reversed)	2.78	1.83	2.83	2.05
I am in favor of obligatory vaccinations for all persons in Germany that are not yet resistant to the virus.	4.79	1.96	4.95	2.09
negative short-term consequences of governmental measures ($\alpha = .86$ / $.58$)	4.70	1.71	3.98	1.56
The current government measures to curb the corona epidemic have a short-term negative impact on me.	4.66	1.86	3.87	1.90
I am hardly negatively affected by the current government measures. (reversed)	3.27	1.79	3.92	1.82
subjective knowledge ($\alpha = .58$ / $.58$)			4.84	1.00
I know a lot about how the coronavirus spreads.			4.82	1.32
The consequences of a possible infection with the coronavirus are largely unknown to me. (reversed)			3.58	1.92
I know a lot about the consequences and course of more serious infections with the coronavirus.			4.79	1.42
I know a lot about how to protect myself against infection with the coronavirus.			5.34	1.26

Table 1. Factors and items scores for predictors and consequences of risk perception. All items are rated on a 7-point scale (agreement: not at all (1) to completely (7)). Cronbachs α values refer to Study 1 / Study 3.

Study 1	prob(infected)				consequ(infected)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dread	0.046** (2.90)	0.056*** (3.75)			0.744*** (6.21)	0.756*** (7.43)		
control	0.0247 (1.25)		0.0500* (2.49)		0.109 (0.67)		0.426** (2.68)	
scient. knowledge	0.0253 (1.39)			0.0405* (2.05)	-0.130 (-1.07)			0.0644 (0.46)
constant	0.0670 (0.52)	0.287*** (4.06)	0.267* (2.35)	0.337** (3.16)	0.177 (0.19)	0.0621 (0.14)	1.156 (1.28)	3.180*** (4.26)
<i>N</i>	200	200	200	200	200	200	200	200
adj. <i>R</i> ²	0.082	0.073	0.031	0.018	0.205	0.208	0.035	-0.004

Study 3	prob(infected)				consequ(infected)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dread	0.060*** (6.61)	0.060*** (6.46)			0.740*** (7.68)	0.754*** (7.81)		
control	0.00025 (0.02)		0.0236+ (1.88)		-0.0153 (-0.11)		0.321* (2.20)	
scientif. knowledge	-0.0080 (-0.54)			0.00604 (0.44)	0.0869 (0.60)			0.242 (1.56)
own knowledge	0.0105 (0.50)			<i>0.0219</i> <i>(1.47)</i>	0.0928 (0.56)			<i>0.300+</i> <i>(1.71)</i>
constant	0.0235 (0.31)	0.0361 (0.85)	0.177** (2.60)	0.276*** (4.10)	0.918 (0.83)	1.637*** (3.65)	3.261*** (4.12)	3.835*** (5.02)
<i>N</i>	301	301	301	301	301	301	301	301
adj. <i>R</i> ²	0.127	0.133	0.010	-0.003	0.199	0.204	0.021	0.008

Table 2. Factors predicting risk perception concerning probability and consequences of infection in Study 1 (top) and Study 3 (bottom). Multiple regressions (models 1 & 5) and simple regressions (other models) with Huber-White robust standard errors were used. Raw coefficients are reported. Coefficients for own knowledge displayed in italics were run in simple regressions and are displayed only for convenience in the same columns with the simple regression for scientific knowledge. *t* statistics in parentheses. All predictors ranged from 1 to 7.

+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

	approval of more severe government measures			
	Study1		Study 3	
	(1)	(2)	(3)	(4)
prob(infected) (0-1)	1.248*** (3.45)	0.798* (2.25)	1.105*** (3.50)	0.535+ (1.78)
conseq(infected) (0-10)	0.124** (2.91)	0.0276 (0.52)	0.0641+ (1.92)	-0.0174 (-0.54)
positive long-term consequences (1-7)	0.135+ (1.69)	0.0941 (1.25)	0.163* (2.39)	0.129* (2.00)
negative short-term consequences (1-7)	-0.155* (-2.35)	-0.185** (-2.94)	-0.106 (-1.63)	-0.163** (-2.67)
dread (1-7)		0.350*** (3.81)		0.347*** (6.02)
constant	3.565*** (6.31)	2.876*** (5.23)	3.187*** (6.21)	2.600*** (5.36)
<i>N</i>	200	200	301	301
<i>adj. R</i> ²	0.131	0.198	0.117	0.230

Table 3. Factors predicting approval of more severe government measures in Study 1 (models (1) and (2)) and Study 3 (models (3) and (4)). *t* statistics in parentheses.

+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

forecasted variables	N	p25	p50	p75	true value	true - p50	date
Study 1							
current infection count	198	7,000	8,000	9,200	8,198	198	18-03-2020
forecast infections 3 days	199	7,000	12,000	15,000	16,662	4,662	21-03-2020
forecast infections 7 days	196	12,000	19,500	30,000	31,554	12,054	25-03-2020
forecast infect. 14 days	199	16,000	30,000	60,000	67,366	37,366	01-04-2020
forecast weeks to peak	197	4	6	10	n/a		
#infected at peak	193	25,000	80,000	600,000	n/a		
forecast fatalities	198	200	1,000	6,000	n/a		
until 31-12-2020							
Study 3							
current infection count	297	150,000	160,000	162,000	159,119	-881	30-04-2020
forecast infections 3 days	300	3,000	160,000	170,000	162,496	2,496	03-05-2020
forecast infections 7 days	300	6,000	168,000	180,000	166,091	-1,909	07-05-2020
forecast infect. 14 days	299	10,000	175,000	200,000	172,239	-2,761	14-05-2020
forecast fatalities	293	7,000	10,000	20,000	n/a		
until 31-12-2020							

Table 4. Forecasts and true values for COVID-19 spread in Germany. True values are official number provided by the Robert-Koch-Institute. p25, p50 (median) and p75 refer to the respective percentiles of the distribution. Ns are below 200 due to exclusion of extreme outliers.

Appendix

	infection risk / neg. utility(infected)				hospitalization risk / neg. utility(hospitalized)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
dread (1-7)	0.468*** (5.72)	0.505*** (7.01)			0.330*** (4.95)	0.311*** (5.73)		
control (1-7)	0.181 (1.84)		0.380*** (4.03)		0.0380 (0.44)		0.152 (1.80)	
knowledge (1-7)	-0.0841 (-0.88)			0.0578 (0.53)	-0.213* (-2.02)			-0.129 (-1.13)
constant	-0.797 (-1.31)	-0.396 (-1.41)	-0.190 (-0.38)	1.613** (2.73)	0.270 (0.42)	-0.526** (-2.62)	0.0537 (0.11)	1.553* (2.51)
<i>N</i>	200	200	200	200	200	200	200	200
adj. <i>R</i> ²	0.190	0.184	0.058	-0.004	0.122	0.103	0.010	0.006

Table A1. Factors predicting risk perception concerning risk utility in multiple regressions (1 & 5) and simple regressions (other models). Raw coefficients are reported. *t* statistics in parentheses.

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

	<i>N</i>	min	max	p25	p50	p75
deviation forecast 3 days	199	0.02	2	0.16	0.34	0.64
deviation forecast 7 days	196	0.01	3.75	0.37	0.52	0.75
deviation forecast 14 days	199	0.04	73.22	0.41	0.64	0.84
average deviation	195	0.06	5.06	0.32	0.51	0.75

Table A2. Deviation of forecasts in proportions of the true value (absolute deviation) in study 1. Values > 1 indicate more than 100% deviation. p25, p50 (median) and p75 refer to the respective percentiles of the distribution. *N*s are below 200 due to extreme outlier exclusion.

	Study 1		Study 3	
	(1)	(2)	(3)	(4)
prob(infected)	1.246** (2.76)	0.956* (2.19)	0.543 (1.21)	0.0423 (0.10)
conseq(infected)	0.138** (2.70)	0.0796 (1.26)	0.157*** (3.51)	0.0886+ (1.77)
dread		0.210+ (1.85)		0.292** (3.12)
constant	3.726*** (11.25)	3.135*** (6.44)	4.091*** (15.09)	3.290*** (8.61)
<i>N</i>	200	200	301	301
adj. <i>R</i> ²	0.068	0.085	0.057	0.099

Table A3. Factors predicting approval of vaccination in Studies 1 and 3. *t* statistics are provided in parentheses

+ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

	adherence to government recommendations	
	(1)	(2)
prob(infected) (0-1)	0.125 (0.96)	-0.0958 (-0.78)
conseq(infected) (0-10)	0.0588*** (3.94)	0.0272* (2.07)
positive long-term consequences (1-7)	0.0898*** (3.72)	0.0766*** (3.64)
negative short-term consequences (1-7)	-0.0129 (-0.57)	-0.0352 ⁺ (-1.73)
dread (1-7)		0.134*** (5.47)
constant	3.681*** (18.24)	3.454*** (18.31)
<i>N</i>	301	301
<i>adj. R</i> ²	0.104	0.181

Table A4. Factors predicting adherence to government measures in the flattened curve phase of Study 3. *t* statistics in parentheses.

⁺ $p < .10$, * $p < .05$, *** $p < .001$

	(1)	(2)	(3)	(4)	(5)
dread	0.547*** (9.87)	0.547*** (10.03)			
control	-0.0164 (-0.21)		0.200* (2.49)		
scientif. knowledge	-0.0460 (-0.52)			0.0697 (0.77)	
own knowledge	0.0788 (0.78)				0.185* (2.00)
_cons	1.008* (2.43)	1.085*** (4.55)	2.437*** (5.58)	3.182*** (7.17)	2.619*** (5.97)
<i>N</i>	301	301	301	301	301
adj. <i>R</i> ²	0.276	0.281	0.021	-0.001	0.010

Table A5. Factors predicting overall risk assessment concerning COVID19 infection ((1) very low to (7) very high) in Study 3. *t* statistics in parentheses.

+ $p < .10$, * $p < .05$, *** $p < .001$

Study 1: Further Analyses

Forecasts of COVID-19 Peak

Information concerning the peak of the crisis are not yet available. A temporal peak has been observed on 07-04-2020. The number of active cases and total number of infections was 64,318 and 99,225, respectively (Robert-Koch-Institute, 2020, April 7). This preliminary peak was reached already 3 weeks after the survey and hence 3 weeks earlier than the median of the forecasts. The forecasted number of infection cases at peak ($Md = 80,000$) was roughly in line with the (preliminary) true number (81,771).⁹

Personality and risk / stress factors

⁹ Since our question remained ambiguous concerning whether we asked for the total number of infections or the number of active infections at peak, we use the average of both as the true value (81,771).

We conducted further exploratory analyses concerning the potential relations between personality and risk / stress factors measured in this study. We focused on relations predicted by standard models of personality that could potentially be used to provide individualized advice to handle this and future crises. Persons high in extraversion have more close contacts (face-to-face with more than 3 words spoken) than persons low in extraversion (Chan, Fu, & Hwang, 2015). Therefore, their risk of infection or at least becoming COVID-19 suspected cases should be higher. We indeed found that the likelihood of being a COVID-19 suspected case according to official criteria ($r = .16, p = .03$) and to have a close other that is COVID-19 suspected ($r = .17, p = .02$) increased with extraversion. The experienced dread due to the pandemic increased with neuroticism, $r = .22, p = .002$, but there was no effect of neuroticism on estimated infection probability and consequences of infection, both $r < .08, p > .28$. Hence, neuroticism appears to influence mainly the affective dread experience but not the utilitarian estimates. The evaluation of scientific knowledge about COVID-19 becomes more positive with increasing intelligence ($r = .24, p < .001$) and cognitive reflection ($r = .26, p < .001$).

Figure A1. Detailed socioeconomic sample background for Study 3. Measures were taken from prior work (Emrich, Hämmerle, Behrens, Meyer, & Pierdzioch, 2018). The full descriptions of the items for the occupation categories were: 1 = pupil, student, trainee, unskilled worker, housewife / husband, 2 = learned worker or skilled worker, self-employed, farmer / cooperative builder, cooperative farmer, 3 = foreman, master, polisher, employee with simple activity, official in simple service, 4 = employees, industry / works master or employee with qualified activity, civil servant in middle service, 5 = other self-employed with up to 9 employees / partners, 6 = employees with highly qualified activity or management function, official in the upscale service, freelance, self-employed academic, 7 = full-time employees with leadership and decision-making powers, civil servant in the higher service, self-employed with 10 and more employees