Relationship between perceived risk and compliance to infection control measures during the first year of a pandemic

Sebastian Bjørkheim[1], https://orcid.org/0000-0001-5182-098X

Sigurd Hystad[1], https://orcid.org/0000-0002-7245-9828

Bjørn Sætrevik[1], https://orcid.org/0000-0002-9367-6987

1: Operational psychology research group, Department for psychosocial science, Faculty of Psychology, University of Bergen

Abstract

The way people perceive health risks is often assumed to influence how they adopt precautionary measures. However, people's assessment of a given phenomenon's risk may vary over time, and the relationship between perceived risk and compliance with protective measures may be dynamic and bi-directional. We measured the perceived risk of COVID-19 and compliance with infection control measures for a large representative sample at four time-points during the first year of the COVID-19 pandemic in Norway. We employ a cross-lagged panel analysis to investigate both the cross-sectional and the temporal association between perceived risk and compliance. We [found / did not find] cross-sectional associations between perceived risk and compliance at [0-4] of the time points. The temporal associations showed that risk at [the first / the second / the third] time-points had [no / weak / strong / negative / positive] association with compliance at the subsequent time-point. Further, compliance at [the first / the second / the third] time-points had [no / weak / strong / negative / positive] association with risk at the subsequent time-point. The results suggest that the relationship between perceived risk and compliance with COVID-19 infection control measures is [bi-directional/unidirectional] and [stable/unstable] over time. A multiverse analysis showed that the relationships between perceived risk and compliance were [robust / not robust] to different operationalizations of perceived risk. -This highlights the need for a nuanced understanding of how risk perceptions impact behavior during a pandemic.

Keywords: Perceived risk; Compliance; COVID-19; Health protective behavior; Cross-lagged analysis; Registered report

1. Introduction

1.1. Background

Compliance with infection control measures may be decisive for determining the societal impact of a pandemic event. During the COVID-19 pandemic, public health authorities requested people to change their daily routines such as working from home, avoiding social gatherings, and limiting travel and the use of public transportation. People were also advised to take precautions such as wearing face masks, keeping physical distance from each other, and being careful about personal hygiene. While these measures are important to limit infection spread, their effectiveness depends on people's willingness to comply with them.

The theory of planned behavior (Ajzen, 1985, 1991) posits that attitudes, subjective norms, and perceived behavioral control shape behavioral intentions, which in turn determine behavior. Research on health-protective behavior typically places perceived risk as a core reason for compliance with health recommendations (Brewer et al., 2007). Over the course of a pandemic event, motivation to comply may fluctuate as infection risk varies, fatigue sets in, and people change their opinion of the precautionary advice. Compliance over an extended period can thus be viewed as a balancing act between protecting one's somatic health and maintaining one's mental health. This balancing act may lead to variations in how people see pandemic risks and their compliance with infection control measures, and priorities may change over time.

1.1.1. Perceived risk. Risk can be considered the product of two main factors: the probability of something occurring and the severity of the outcome. Typically, the term "risk" is used when the outcome is deemed to be negative or undesirable. While the objective probability of something occurring and its expected consequence can be calculated in some cases, people's perceptions of these two factors may deviate from the objective estimate (Mousavi & Gigerenzer, 2014; Tversky & Kahneman, 1979). Perceived risk may thus be considered a subjective evaluation of the probability and the consequence of an occurrence (Dowling & Staelin, 1994).

The psychological aspects of risk perception as a predictor of behavior can be complex and multifaceted. Several studies have examined the role of perceived risk on health-related compliance (Cori et al., 2020). This research suggests that when people perceive the risk of a negative health outcome as high, they may be more likely to take precautionary measures, whereas when the risk is perceived as low, compliance with those measures tends to be lower. Research on a variety of health-related behaviors has pointed to perceived risk as an important predictor of precautionary behavior such as wearing facemasks and taking vaccines (Brewer et al., 2007; Schwarzer, 2001; van der Pligt, 1998). The core assumption in this research has been that people are more motivated to adhere to infection control measures if they see themselves to be at risk. In a pandemic setting, the personal risk may correspond to how people assess the likelihood of being infected and the severity of contracting the disease. Research on the H1N1 pandemic in 2009 indicated that seeing the risk of infection as high was associated with taking precautionary measures against infection (Bults et al., 2011; Walter et al., 2012). More recent research on the COVID-19 pandemic has found a similar relationship between perceived risk and adherence to infection control measures (Webster et al., 2020). For instance, a study found that protective behavior such as hand washing and social distancing was associated with the perceived probability of being infected with COVID-19 during the first week of the outbreak in the US (Wise et al., 2020). A study during the lockdown in the UK found that seeing COVID-19 as a threat was a consistent predictor of several protective measures (Brown et al., 2021). Similar patterns of results have been shown across several countries and during different stages of the pandemic (e.g. Bruine de Bruin & Bennett, 2020, in the US; Ning et al., 2020, in China; Rattay et al., 2021, in Germany). A study comparing risk perceptions of COVID-19 in countries across Europe, America and Asia, found that higher risk perception was associated with the greater adoption of protective behavior in all countries (Dryhurst et al., 2020). The study also showed that having an individualistic worldview, prosocial intentions and personal experience with the virus were the strongest predictors of risk perception, but most studies used a cross sectional design. However, the motivation to comply with infection control measures may only partly be driven by people's self-interest in safeguarding their own health and partly driven by the desire to help or protect others (Aydinli et al., 2014). Studies on compliance to COVID-19 control measures has shown that prosocial concerns (being concerned about others health), and a sense of social responsibility predict engagement with infection control measures (Banker & Park, 2020; Böhm & Betsch, 2022; Zaki, 2020). ~~(Aydinli et al., 2014; Jordan et al., 2020)~~. This dual motivation to protect oneself and to protect others underscores how risk assessments also need to account for social considerations when shaping compliance to infection control measures.

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Cross-sectional data on perceived risk and compliance present limitations in establishing causal relationships and discerning the directional nature of the association between the variables. In one of few longitudinal studies on this, Schneider and colleagues (2021) measured risk perception of COVID-19 and health protective behaviors over a 10-month period in the UK through five nationally balanced cross-sectional surveys. The results revealed a consistent positive correlation between risk perception and adoption of protective health behaviors, where the strength of the relationship varied over time. They also found ~~that~~ psychological factors to be more predictive of risk perception than the objective measures such as the rate of new cases (Schneider et al., 2021). Lages and colleagues (2021) investigated this relationship during outbreaks of avian influenza, seasonal influenza and the common cold in Germany. They found that risk perceptions matched the relative level of risk associated with these diseases, and that during the period when influenza and the common cold were more prevalent, participants felt more at risk for these diseases compared to off-season times. However, this increase in perceived risk was more noticeable when considering others rather than themselves (Lages et al., 2021).This fits with a fallacy known as optimistic bias,~~-~~ whereby people systematically ascribe higher risks to others than they do to themselves across situations (Sharot, 2011; van der Pligt, 1998). While the authors found a relationship within each data collection round, panel data is needed to analyze for temporal relationships between risk perception and compliance during a pandemic event.

1.1.2. Compliance with infection control measures. Compliance with infection control measures is a key component of preventing the spread of infectious diseases. Measures such as hand hygiene, social distancing, and use of protective equipment, are essential for protecting society at large as well as individuals who are at particular risk. However, it may be challenging for individuals to comply with numerous measures to mitigate infection spread as it often requires individuals to change their behavior in inconvenient ways and adopt new habits. In the context of COVID-19, compliance with infection control measures and engagement in preventive behavior are intricately intertwined, often overlapping considerably. Both concepts entail actions aimed at reducing the spread of the virus and minimizing individual and collective risk. Compliance with measures such as wearing masks, practicing hand hygiene, and maintaining social distancing constitutes a proactive approach to preventing transmission, aligning closely with behaviors typically associated with preventive action. Consequently, in much of the research on COVID-19, these terms are frequently used interchangeably to represent the collective efforts individuals undertake to mitigate the impact of the pandemic (Brouard et al., 2020; Burton et al., 2021; Clark et al., 2020; Harper et al., 2021).

According to the health belief model (Janz & Becker, 1984), in order for health-related behavior change to happen, there must be a combination of health concern, perceived threat, perceived benefits of change, and an absence of perceived barriers or cost. The model suggests that individuals are more likely to engage in health protective behaviors when they believe they are at risk, when they perceive the health problem to be serious, and when they believe that acting will reduce the risk and it is feasible to do so. In a pandemic setting this may correspond to being more likely to comply with infection control measures if they have a high level of motivation to protect their health, perceive a considerable level of threat from the virus, and believe that following recommended measures will effectively reduce the threat. A systematic review found that using the health belief model was effective as a theoretical basis for designing interventions that increased adherence with health recommendations (Jones et al., 2014), and COVID-19 vaccination intention has been predicted by the model constructs (Wong et al., 2020).

Over the course of a pandemic, factors that affect compliance with infection control measures may shift. One such factor is motivation, which can be influenced by personal responsibility, belief in the effectiveness of measures, and positive reinforcement. Those who understand the importance of measures, such as wearing facemasks, and receive positive feedback may be more motivated to comply. ~~Previous~~ R~~r~~esearch on the H1N1 influenza showed that while knowledge about the disease increased, both perceived risk and intention to comply with control measures decreased over the first four months of the virus spread in the Netherlands (Bults et al., 2011). A study of self-reported compliance with COVID-19 social distancing measures over three months in the US, found that compliance was influenced by intrinsic motivation, capacity to comply, impulse control, social norms, and perceived duty to obey rules (Reinders Folmer et al., 2021). They also found that compliance declined over the course of the three months and that the decline was associated with people's threat perceptions, knowledge, and perceived social norms.

As the pandemic progressed, perceptions of risks related to COVID-19 may have changed for some individuals. Some may have become complacent about the situation, while others may have become more fearful as the number of cases rose and new variants of the virus emerged. Through the first year of the pandemic, new information and guidelines were periodically released, and this may have affected people's confidence in and motivation for complying with the infection control measures. On the other hand, people may have gained confidence in the control measures as it may have prevented them from getting infected with COVID-19, and they may have ascribed this to the effectiveness of precautionary behavior. As a consequence, compliance with infection control measures may contribute to perceiving less risk of getting infected with COVID-19. Understanding how perceptions of risk and compliance change over time may be crucial for developing interventions that will encourage compliance with infection control measures.

1.2. Knowledge gap

The majority of the studies on perceived risk and compliance during the first COVID-19 pandemic is based on cross-sectional surveys on convenience samples (Dryhurst et al., 2020), and a systematic review found that over 95% of studies about risk awareness in regard to containing COVID-19 used a cross-sectional design (Cipolletta et al., 2022). While cross-sectional studies are useful, it may be challenging to represent the motivations involved in a dynamic phenomenon such as a pandemic into an assessment on a single time-point. Particularly in a rapidly changing situation such as a global pandemic, it is important to investigate the stability of relationships over time, both from a theoretical and practical perspective. It has previously been argued that longitudinal studies on risk perception is necessary as cross-sectional studies can lead to wrong conclusion about the relationship between perceived risk and mitigation behaviors (Loewenstein & Mather, 1990; Siegrist, 2013). Also, the sampling bias involved in using convenience samples may create an inaccurate impression of how people perceive pandemic risks and their level of compliance, that may not hold for the population at large. The combination of perceived risk and compliance to health protective measures are rarely studied longitudinally, and the reverse relationship, with compliance as the predictor and risk as the outcome, is less documented still in the literature. While we should expect perceived risk to predict compliance, less is known about how past engagement with protective behavior may impact how people perceive of the risk scenario. -The current study may ~~help to~~ fill thise knowledge gap by investigating the relationship between perceived risk and compliance using longitudinal data from a representative sample.

1.3. Current study

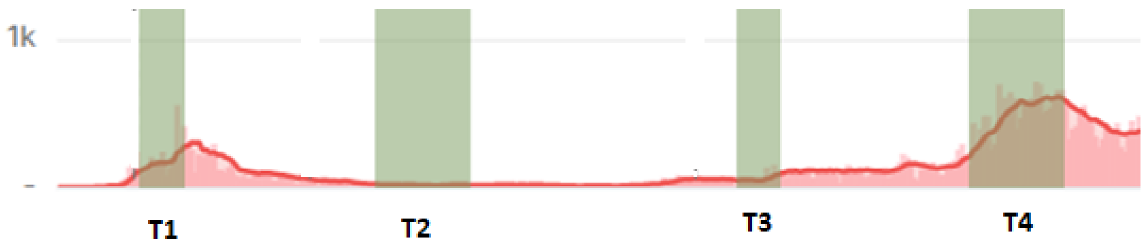
The current study was conducted as a part of the PANDRISK research project which aims to measure, track and predict the effect of perceived risk on compliance during the COVID-19 pandemic in Norway (see website: https://www.uib.no/en/pandrisk). The current study uses data from four nationally representative survey data collections collected between March 2020 and November 2020. Similar to Schneider and colleagues (2021), we measured the perceived risk of infection and compliance to infection control measures over the first year of the pandemic in Norway, but unlike the Schneider and colleagues (2021) we used a panel design that allows for temporal analyses between the variables. Longitudinal analysis will allow us to look for causal predominance between the variables and determine if the relationship changes over time. The current study used a registered report approach (Grand et al., 2018). ~~We will use a registered report publication process to enhance the transparency and rigor of our research methodology, study design and analysis plan. This approach ensures that the significance of our study is evaluated based on the research question and methodology, rather than the outcomes.~~

1.3.1. Timeline for COVID-19 spread and management of infection control measures in Norway.

Norway adopted a strategy of controlling the spread of COVID-19 through measures such as restrictions on public gatherings, border closures, quarantine requirements for travelers, and widespread testing and tracing. The Norwegian health authorities also prioritized protecting vulnerable groups and avoiding a complete lockdown, instead opting for targeted measures and temporary closures of specific sectors as needed (*NOU*, 2022). On March 12th, 2020, Norway closed its borders to travelers from abroad, except for those with a residence or work permit, and the Norwegian government recommended that people work from home if possible and that schools and universities switch to remote learning. Norwegians were advised to adopt a number of personal hygiene measures such as handwashing, avoiding touching public surfaces, and keeping physical distance from others. These efforts helped Norway maintain a relatively low number of cases and deaths compared to many other countries in the initial phase of the pandemic (Ursin et al., 2020). In addition to these measures, Norwegian authorities rolled out widespread testing and contact tracing efforts, and temporarily closed specific sectors, such as bars and restaurants, when outbreaks occurred.

Norway lifted many of its COVID-19 restrictions over time as the spread of the virus was brought under control. Starting in June 2020, the country lifted restrictions on social gatherings and allowed for some reopening of bars and restaurants, with restrictions on capacity and distancing measures in place (*NOU*, 2022). Throughout the rest of the year and into 2021, further easing of restrictions was carried out in a gradual manner, with close monitoring of the situation and adjustments made as needed.

Figure 1: Infection trendline during the data collection period.



Note: Red line indicates weekly average number of COVID-19 infections in Norway while the green columns indicate the data collection periods.

1.3.2. Research question and hypotheses. Based on previous research, there is reason to expect a positive association between "Perceived risk" and "Compliance". The analysis will first involve testing whether there is a positive association between perceived risk and compliance with infection control measures within each measurement point (H1). Note that the association between "Perceived risk" at T1 and "Compliance" at T1 will not be tested as a confirmatory hypothesis in the current model, as it has been tested conceptually in an earlier study (Sætrevik & Bjørkheim, 2022). Next, we will examine the temporal relationships between perceived risk and compliance with infection control measures to test whether perceived risk at the immediate prior measurement period, is positively associated with compliance at the subsequent measurement period (H2). This will be tested for all four data collection rounds. The same analyses will be run to test whether compliance at the immediate prior measurement point is associated (non-directional) perceived risk in the subsequent measurement point (H3).

H1: "Perceived risk" has a positive association with "Compliance" at each data collection.

~~a) "Perceived risk" at T1 will have a positive association with "Compliance" at T1.~~

~~b)~~a) "Perceived risk" at T2 will have a positive association with "Compliance" at T2.

~~c)~~b) "Perceived risk" at T3 will have a positive association with "Compliance" at T3.

~~d)~~c) "Perceived risk" at T4 will have a positive association with "Compliance" at T4.

H2: "Perceived risk" at a prior measurement point will predict "Compliance" at the subsequent measurement point.

a) "Perceived risk" at T1 will have a positive association with "Compliance" at T2.
b) "Perceived risk" at T2 will have a positive association with "Compliance" at T3.
c) "Perceived risk" at T3 will have a positive association with "Compliance" at T4.

H3: "Compliance" at a prior measurement point will predict "Perceived risk" at the subsequent point.

a) "Compliance" at T1 will be associated with "Perceived risk" at T2.
b) "Compliance" at T2 will be associated with "Perceived risk" at T3.
c) "Compliance" at T3 will be associated with "Perceived risk" at T4.

2. Methods

2.1. Participants

The data for this study are from the "Norwegian Citizen Panel" (https://www.uib.no/en/citizen), which is a continuously running online panel survey of Norwegians' opinions on social matters. Individuals randomly drawn from the Norwegian Tax Registry and invited to participate in the panel. The survey has been fielded two to three times a year since 2013. In 2020, two additional survey rounds were fielded with questions about the COVID-19 pandemic. The panel aims to be representative for adult (above the age of 18) Norwegians, with minor deviations from perfect representativity in terms of age, education level and geographical regions. Across survey rounds, the deviations from a perfectly representative sample of the Norwegian population remain stable and relatively small (see methodology reports: https://osf.io/drzck/). People over the age of 60 are overrepresented by a margin of 16%, whereas those under 29 years old are underrepresented by 13%. The overrepresentation of individuals with a university or college degree is modest at 29%, while those with upper secondary education are underrepresented by around 10%, as well as those with elementary education by 19%. Geographically, the sample displays a slight (3-5%) overrepresentation of individuals from urban areas in Oslo, Akershus and Western Norway. These stable deviations from representativity suggest that the sample remains reasonably representative of the Norwegian population across survey rounds but is slightly older and more educated.

An anonymized version of the dataset, devoid of personal identification codes, will be made available and disseminated via the project's Open Science Framework (OSF) page (https://osf.io/5k7qw/). Various precautions aimed at bolstering privacy are inherent in the dataset as all background demographic attributes are measured at a group level. A weighting variable for demographic deviations is provided in the dataset (https://osf.io/5k7qw/).~~https://osf.io/s46ax/~~).

Data for this study were collected in four rounds, in March (T1, n = 4083), June (T2, n = 2820), August-September (T3, n = 5541) and November (T4, n = 2533) in 2020. We assume that most (90%) of the participants remain from one round to the next based on prior tendencies in the Norwegian Citizen Panel data.~~The core panel sample size is around N ~ 2000~~. However, for rounds T1 and T3, the survey was fielded to a larger share of the Norwegian Citizen Panel, resulting in a sample size of 4083 and 5541 for these rounds respectively. -The model will be run on the participants who answered all the items in all rounds (complete cases). We expect that this approach will yield a panel of n ~ 2000. ~~Note that the model will use the participants who responded to all items in the four rounds (complete cases).~~We will compare the results of the complete case sample with different ways of handling missing data (both listwise deletion and pairwise deletion). ~~We expect a core panel sample size of around N ~ 2000.~~

2.2. Data collection

The University of Bergen serves as the governing body for the Norwegian Citizen Panel, while the company Ideas2evidence is responsible for recruiting participants, designing the survey, and documenting the data collection process. Prior to data collection, the Norwegian Citizen Panel obtained written informed consent from all panel members, and all ethical considerations regarding data collection and storage were approved by the Norwegian Centre for Research Data (reference number: 118868). Participants were invited to the data collection by email, with a reminder being sent out a week later to those who had not opened or completed the survey. A second reminder by email is typically sent out one week after the first reminder, and this is followed by a third reminder by sent out by SMS a few days later (see methodology reports for detailed description: https://osf.io/drzck/). Most participants (75%) typically respond within a week of receiving the survey. The panel data allows for analysis between data collection rounds. We assume an attrition rate from one round to the next of less than 5%, as this is the average wave-to-wave retention rate in the panel. No observations in the dataset will be excluded from the analysis. The Citizen Panel removes participants who have not responded to any of the last three survey rounds from the final datasets. These respondents will not be part of our analyses. The authors involved in this study did not have control over the data collection process (preempting the possibility of optional stopping).

2.3. Researchers' prior knowledge of data

The data has already been collected at the time of analysis planning, and the researchers have had access to the data. Some of the response distributions of items used in the current study have already examined and reported. Firstly, response distribution for perceived risk and compliance at T1 has been examined and reported (Sætrevik, 2021) and we have previously described the cross sectional association between perceived risk and compliance at T1 (Sætrevik & Bjørkheim, 2022). Contrary to our hypothesis, we found that those who perceive a higher risk are actually less likely to comply with safety measures. When we specifically looked at the risk of getting infected, we found a very small negative effect on compliance. However, when we asked about the perceived risk of infection for the general population, the effect on compliance was small and positive. Overall, our findings only weakly support the idea that seeing the pandemic as a threat leads to following safety measures, and only when considering the risk to the general population, not to oneself (Sætrevik & Bjørkheim, 2022). This association will not be considered among confirmatory hypotheses in the current study. ~~. The association we tested used an index of perceived risk and compliance items that we intend to use in H1a (but also included several other items~~

~~not included in the present analysis).~~ We have also calculated arithmetic means of the items suggested for this study at T1-T4, to report descriptive changes during the pandemic.

Note that in prior examination of the data we have not tested the relationship between perceived risk and compliance at any time points after T1, or tested associations between averages of the variables across T1-T4, or tested any cross-lagged associations (i.e., between time points). Despite being naïve to the answers of the ~~core~~ research questions, our prior knowledge of the data would be classified as a "level 1" submission in the PCI RR table for prior knowledge.

To combat the risk of bias associated with a "level 1" submission, a multiverse analysis will be performed by running the model with all possible combinations (except the option where none of the items are included) of items constituting the "perceived risk" variable. This leads to 15 different pathways of analysing the model (see script: https://osf.io/yvz87/). This approach will show if the results are robust towards different operationalizations of the "perceived risk" measure. The model will also be analysed with different ways of handling missing data by testing the model using either listwise or pairwise deletion to see if the results are robust towards selective attrition. In addition to the multiverse approach, a "blinded analyst" approach will be adopted. The second author will function as the blinded analyst, as they have not had previous access to the data and have not been part of the data curation process. In practice, the first author will do this by renaming the variables "perceived risk" and "compliance" to either "tango" and "foxtrot" for each time-point before transferring the dataset to the blinded analyst. The analyst can thus not know if the hypotheses are supported or not when reporting the analysis.~~To combat the risk of bias associated with a "level 1" submission, w the option where of the items are by testing the model using eitheror~~

2.4. Materials and variables

Two variables will be part of this analysis. The first variable, "Perceived risk" was measured with the average of four items asking about the risk of infection for self and others, risk of becoming seriously ill, and risk for changes to everyday life. The second variable, "Compliance" was measured with one item asking about the overall intention to follow the infection control measures. See Table 1 below for the phrasing of the items constituting the variables. The items were measured using a Likert-type scale with five response options for each statement. The perceived risk items asked participants to rate the level of risk and assigned numerical values between very low (1), somewhat low (2), medium (3), somewhat high (4), and very high (5). The compliance item was measured with five response options and assigned numerical values ranging from completely disagree (1), disagree (2), neither agree nor disagree (3), agree (4), and completely agree (5).

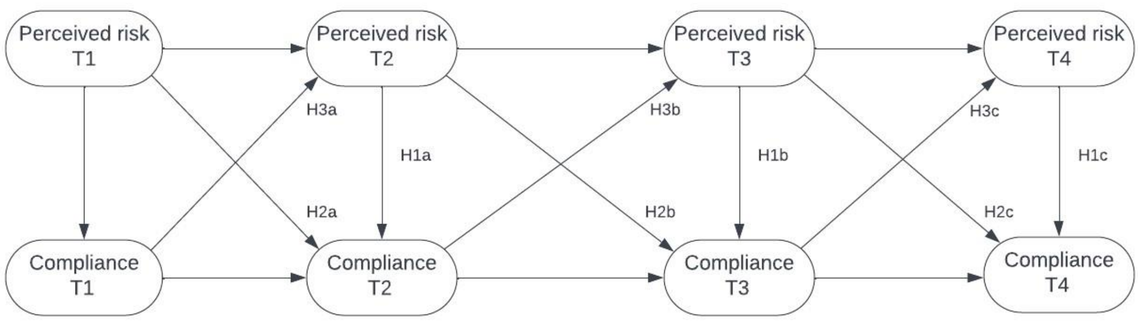
Table 2: List of items

Variable	Item text (translated to English)
Perceived risk	How high or low do you think the risk is that you will be infected by the coronavirus?
Perceived risk	How big do you consider the risk that an average adult will be infected by the coronavirus?
Perceived risk	How big do you consider the risk that you will become seriously ill from the coronavirus?
Perceived risk	How big do you consider the risk that your everyday life will change a lot due to the coronavirus?
Compliance	I do my best to follow the various advice from health authorities to limit the risk of infection (often washing hands, avoiding travel and situations with other people, keeping my distance and avoiding touching things)

2.5. Analysis plan

~~We will conduct a factor analysis on the four perceived risk items to establish an index for "Perceived risk". We will consider a RMSEA score equal to or below .08 and CFI equal to or above .95 for the factor analysis to be acceptable for indexing the perceived risk items. If the scores are below the acceptable level, we will remove the item with the lowest fit until we achieve an acceptable overall fit. If no acceptable fit can be reached, we will use the single item for perceived personal risk of infection ("How high or low do you think the risk is that you will be infected by the coronavirus?").~~ We will run a random intercept cross-lagged panel analysis on the data to test associations between perceived risk and compliance for the measurement points 1-4 (see Figure 1). We will also perform a multiverse analysis by testing the RI-CLPM model with different ways of combining the perceived risk items into an index. This will leave us with 15 possible combinations of the "perceived risk" variable (excluding the option where none of the items are counted towards the index), and will enable us to compare how robust the findings are to a particular operationalization of "Perceived risk".

Figure 1: Simplified representation of the hypotheses within the random intercept cross-lagged panel model (RI-CLPM) of perceived risk and compliance across the four measurement rounds.



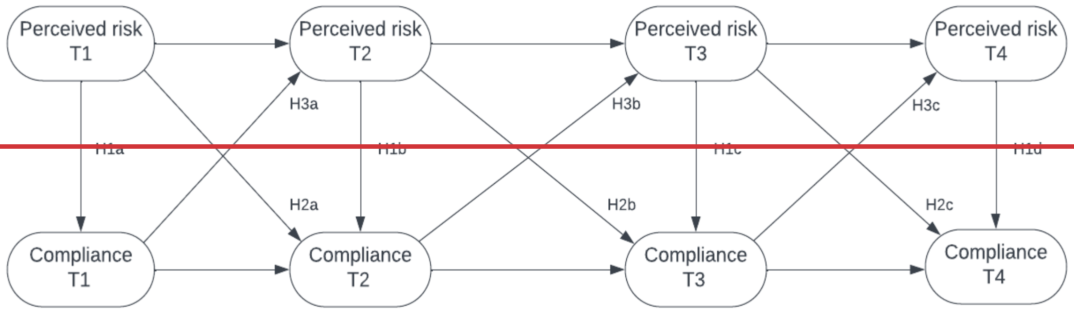

Perceived risk T1
Perceived risk T2
Perceived risk T3
Perceived risk T4
H3a
H3b
H3c
H1a
H1b
H1c
H1d
H2a
H2b
H2c
Compliance T1
Compliance T2
Compliance T3
Compliance T4

Table 3: Study design template

Question	Hypothesis	Sampling	Analysis Plan	The rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
Is "perceived risk" positively associated with "compliance" within each data collection round?	H1 a-c~~d~~ (see description in section 1.3.2)	Nationally representative panel data, with four data collections. We will only count participants who answered all the items in all the rounds towards the analysis (complete cases approach). We expect a panel sample of n ~ 2000. We will compare the results of this analysis to that of listwise deletion and pairwise deletion.~~:~~ ~~T1 n = 4083, T2 n = 2820, T3 n = 5541, T4 n = 2533.~~	We will conduct a factor analysis (across the four data collection rounds) on the items to establish indices for "Perceived risk". ~~We will consider a RMSEA score equal to or below .08 and CFI equal to or above .95 for the factor analysis to be acceptable for indexing the perceived risk items. If the scores are below the acceptable level, we will remove items until we achieve an acceptable fit.~~ We will run a random intercept cross-lagged panel analysis on the data to test if there is an association between perceived risk and compliance within each of the measurement points 1-4. We will test all the hypotheses against a p-value less than .01~~5~~. In accordance with Orth et al (2022), we will consider effect sizes of the RI-CLPM associations above 0.02 to be	Since the mechanisms work on a population level, public health interventions that have small effects on compliance may nevertheless have considerable impact for a large number of individual's health outcomes. Further, due to the potential for exponential growth in infection, small changes in compliance can have disproportionate effects on the population level. This leads us to accept small effect sizes as being relevant in this study.	Support for the H1 hypotheses will be taken to indicate that seeing a health crisis as a threat is associated with taking precautionary measures. Lack of support for H1 hypotheses will indicate that seeing the risk as high at a given time during the health crisis did not motivate people to take precautions at that time. The generalization of the interpretation of H1, H2 and H3 results may be limited to situations with similar pandemic severity, public knowledge, public health response and other cultural factors in Norway at the time of measurement.	If no relationships between perceived risk and compliance can be supported in the dataset, this could be discussed in light of the health belief model.

			meaningful in the predicted direction. We will also perform a multiverse analysis by testing the RI-CLPM model with different ways of combining the perceived risk items into an index. This will leave us with 15 possible combinations of the "perceived risk" variable (we have excluded the option where none of the items are counted), and will enable us to compare how robust the findings are to a particular operationalization of "perceived risk".			
Does "Perceived risk" at an earlier measurement point in the pandemic predict "compliance" at the subsequent measurement point?	H2 a-c (see description in section 1.3.2)		We will run a random intercept cross-lagged panel analysis on the data to test if there is an association between perceived risk at a measurement point and compliance at the immediate subsequent measurement point. Cut-offs for significance and effect size of interest as above.		Support for the H2 hypotheses will be taken to indicate that seeing the risk as high at one point leads to taking more precautions later in the health crisis. This could be due to being concerned lead to establishing attitudes and to form habits for being cautious that are still present at a later time. Lack of support for H2 hypotheses will indicate that perceived risk at an earlier stage does not impact behavior at a later stage. The inverse of H2 could also emerge, which would indicate that those who had been more concerned at an earlier stage were now fatigued or for other reasons less inclined to be cautious at a later stage.	

Does "Compliance" at an earlier point in the pandemic predict "Perceived risk" at a later point?	H3 a-c (see description in section 1.3.2)		We will run a random intercept cross-lagged panel analysis on the data to test if there is an association between compliance at a measurement point and perceived risk at the immediate subsequent measurement point. Cut-offs for significance and effect size of interest as above.		Support for the H3 hypotheses will be taken to indicate that being responsive to a health crisis at one point influences how the risk is viewed at a later time. A positive association could be due to a desire for current assessment to be consistent with previous behavior. A negative association could be due to disillusionment, after concluding that taking precautions about the risk in the past did not influence outcomes. Lack of support for H3 hypotheses can be interpreted to indicate that taking precautions in earlier stages have no prolonged effect on how people see the risk from health crises at a later time.	

3. References

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In J. Kuhl & J. Beckmann (Eds.), *Action Control: From Cognition to Behavior* (pp. 11–39). Springer. https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Aydinli, A., Bender, M., Chasiotis, A., Cemalcilar, Z., & van de Vijver, F. J. R. (2014). When does self-reported prosocial motivation predict helping? The moderating role of implicit prosocial motivation. *Motivation and Emotion*, *38*(5), 645–658. https://doi.org/10.1007/s11031-014-9411-8

Banker, S., & Park, J. (2020). *Evaluating Prosocial COVID-19 Messaging Frames: Evidence from a Field Study on Facebook* (SSRN Scholarly Paper ID 3684901). Social Science Research Network. https://doi.org/10.2139/ssrn.3684901

Böhm, R., & Betsch, C. (2022). Prosocial vaccination. *Current Opinion in Psychology*, *43*, 307–311. https://doi.org/10.1016/j.copsyc.2021.08.010

Brewer, N. T., Chapman, G. B., Gibbons, F. X., Gerrard, M., McCaul, K. D., & Weinstein, N. D. (2007). Meta-analysis of the relationship between risk perception and health behavior: The example of vaccination. *Health Psychology*, *26*(2), 136–145. https://doi.org/10.1037/0278-6133.26.2.136

Brouard, S., Vasilopoulos, P., & Becher, M. (2020). Sociodemographic and Psychological Correlates of Compliance with the COVID-19 Public Health Measures in France. *Canadian Journal of Political Science/Revue Canadienne de Science Politique*, *53*(2), 253–258. https://doi.org/10.1017/S0008423920000335

Brown, R., Coventry, L., & Pepper, G. (2021). COVID-19: The relationship between perceptions of risk and behaviours during lockdown. *Journal of Public Health*. https://doi.org/10.1007/s10389-021-01543-9

Bruine de Bruin, W., & Bennett, D. (2020). Relationships Between Initial COVID-19 Risk Perceptions and Protective Health Behaviors: A National Survey. *American Journal of Preventive Medicine*, *59*(2), 157–167. https://doi.org/10.1016/j.amepre.2020.05.001

Bults, M., Beaujean, D. J., de Zwart, O., Kok, G., van Empelen, P., van Steenbergen, J. E., Richardus, J. H., & Voeten, H. A. (2011). Perceived risk, anxiety, and behavioural responses of the general public during the early phase of the Influenza A (H1N1) pandemic in the Netherlands: Results of three consecutive online surveys. *BMC Public Health*, *11*(1), 2. https://doi.org/10.1186/1471-2458-11-2

Burton, A., McKinlay, A., Dawes, J., Roberts, A., Fynn, W., May, T., & Fancourt, D. (2021). *Understanding barriers and facilitators to compliance with UK social distancing guidelines during the COVID-19 pandemic: A qualitative interview study* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/k4wqh

Cipolletta, S., Andreghetti, G. R., & Mioni, G. (2022). Risk Perception towards COVID-19: A Systematic Review and Qualitative Synthesis. *International Journal of Environmental Research and Public Health*, *19*(8), Article 8. https://doi.org/10.3390/ijerph19084649

Clark, C., Davila, A., Regis, M., & Kraus, S. (2020). Predictors of COVID-19 voluntary compliance behaviors: An international investigation. *Global Transitions*, *2*, 76–82. https://doi.org/10.1016/j.glt.2020.06.003

Cori, L., Bianchi, F., Cadum, E., & Anthonj, C. (2020). Risk Perception and COVID-19. *International Journal of Environmental Research and Public Health*, *17*(9), Article 9. https://doi.org/10.3390/ijerph17093114

Dowling, G. R., & Staelin, R. (1994). A Model of Perceived Risk and Intended Risk-handling Activity. *Journal of Consumer Research*, *21*(1), 119–134. https://doi.org/10.1086/209386

Dryhurst, S., Schneider, C. R., Kerr, J., Freeman, A. L. J., Recchia, G., van der Bles, A. M., Spiegelhalter, D., & van der Linden, S. (2020). Risk perceptions of COVID-19 around the world. *Journal of Risk Research*, *23*(7–8), 994–1006. https://doi.org/10.1080/13669877.2020.1758193

Grand, J. A., Rogelberg, S. G., Banks, G. C., Landis, R. S., & Tonidandel, S. (2018). From Outcome to Process Focus: Fostering a More Robust Psychological Science Through Registered Reports and Results-Blind Reviewing. *Perspectives on Psychological Science*, *13*(4), 448–456. https://doi.org/10.1177/1745691618767883

Harper, C. A., Satchell, L. P., Fido, D., & Latzman, R. D. (2021). Functional Fear Predicts Public Health Compliance in the COVID-19 Pandemic. *International Journal of Mental Health and Addiction*, *19*(5), 1875–1888. https://doi.org/10.1007/s11469-020-00281-5

Janz, N. K., & Becker, M. H. (1984). The Health Belief Model: A Decade Later. *Health Education Quarterly*, *11*(1), 1–47. https://doi.org/10.1177/109019818401100101

Jones, C. J., Smith, H., & Llewellyn, C. (2014). Evaluating the effectiveness of health belief model interventions in improving adherence: A systematic review. *Health Psychology Review*, *8*(3), 253–269. https://doi.org/10.1080/17437199.2013.802623

Lages, N. C., Debbeler, L. J., Blumenschein, M., Kollmann, J., Szymczak, H., Keim, D. A., Schupp, H. T., & Renner, B. (2021). Dynamic Risk Perceptions in Times of Avian and Seasonal Influenza Epidemics: A Repeated Cross-Sectional Design. *Risk Analysis: An Official Publication of the Society for Risk Analysis*, *41*(11), 2016–2030. https://doi.org/10.1111/risa.13706

Loewenstein, G., & Mather, J. (1990). Dynamic processes in risk perception. *Journal of Risk and Uncertainty*, *3*(2), 155–175. https://doi.org/10.1007/BF00056370

Mousavi, S., & Gigerenzer, G. (2014). Risk, uncertainty, and heuristics. *Journal of Business Research*, *67*(8), 1671–1678. https://doi.org/10.1016/j.jbusres.2014.02.013

Ning, L., Niu, J., Bi, X., Yang, C., Liu, Z., Wu, Q., Ning, N., Liang, L., Liu, A., Hao, Y., Gao, L., & Liu, C. (2020). The impacts of knowledge, risk perception, emotion and information on citizens' protective behaviors during the outbreak of COVID-19: A cross-sectional study in China. *BMC Public Health*, *20*(1), 1751. https://doi.org/10.1186/s12889-020-09892-y

NOU 2022: 5. (2022, April 26). [NOU]. Government.No; regjeringen.no. https://www.regjeringen.no/en/dokumenter/nou-2022-5/id2910055/

Rattay, P., Michalski, N., Domanska, O. M., Kaltwasser, A., Bock, F. D., Wieler, L. H., & Jordan, S. (2021). Differences in risk perception, knowledge and protective behaviour regarding COVID-19 by education level among women and men in Germany. Results from the COVID-19 Snapshot Monitoring (COSMO) study. *PLOS ONE*, *16*(5), e0251694. https://doi.org/10.1371/journal.pone.0251694

Reinders Folmer, C. P., Brownlee, M. A., Fine, A. D., Kooistra, E. B., Kuiper, M. E., Olthuis, E. H., de Bruijn, A. L., & van Rooij, B. (2021). Social distancing in America: Understanding long-term adherence to COVID-19 mitigation recommendations. *PLOS ONE*, *16*(9), e0257945. https://doi.org/10.1371/journal.pone.0257945

Sætrevik, B. (2021). Realistic Expectations and Prosocial Behavioural Intentions to the Early Phase of the COVID-19 Pandemic in the Norwegian Population. *Collabra: Psychology*, *7*(18698). https://doi.org/10.1525/collabra.18698

Sætrevik, B., & Bjørkheim, S. B. (2022). Motivational factors were more important than perceived risk or optimism for compliance to infection control measures in the early stage of the COVID-19 pandemic. *PLOS ONE*, *17*(9), e0274812. https://doi.org/10.1371/journal.pone.0274812

Schneider, C. R., Dryhurst, S., Kerr, J., Freeman, A. L. J., Recchia, G., Spiegelhalter, D., & van der Linden, S. (2021). COVID-19 risk perception: A longitudinal analysis of its predictors and associations with health protective behaviours in the United Kingdom. *Journal of Risk Research*, *24*(3–4), 294–313. https://doi.org/10.1080/13669877.2021.1890637

Schwarzer, R. (2001). Social-Cognitive Factors in Changing Health-Related Behaviors. *Current Directions in Psychological Science*, *10*(2), 47–51. https://doi.org/10.1111/1467-8721.00112

Sharot, T. (2011). The optimism bias. *Current Biology*, *21*(23), R941–R945. https://doi.org/10.1016/j.cub.2011.10.030

Siegrist, M. (2013). The Necessity for Longitudinal Studies in Risk Perception Research. *Risk Analysis*, *33*(1), 50–51. https://doi.org/10.1111/j.1539-6924.2012.01941.x

Tversky, A., & Kahneman, D. (1979). Prospect Theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.1142/9789814417358_0006

Ursin, G., Skjesol, I., & Tritter, J. (2020). The COVID-19 pandemic in Norway: The dominance of social implications in framing the policy response. *Health Policy and Technology*, *9*(4), 663–672. https://doi.org/10.1016/j.hlpt.2020.08.004

van der Pligt, J. (1998). Perceived risk and vulnerability as predictors of precautionary behaviour. *British Journal of Health Psychology*, *3*(1), 1–14. https://doi.org/10.1111/j.2044-8287.1998.tb00551.x

Walter, D., Böhmer, M. M., Reiter, S., Krause, G., & Wichmann, O. (2012). Risk perception and information-seeking behaviour during the 2009/10 influenza A(H1N1)pdm09 pandemic in Germany. *Eurosurveillance*, *17*(13), 20131. https://doi.org/10.2807/ese.17.13.20131-en

Webster, R. K., Brooks, S. K., Smith, L. E., Woodland, L., Wessely, S., & Rubin, G. J. (2020). How to improve adherence with quarantine: Rapid review of the evidence. *Public Health*, *182*, 163–169. https://doi.org/10.1016/j.puhe.2020.03.007

Wise, T., Zbozinek, T. D., Michelini, G., Hagan, C. C., & Mobbs, D. (n.d.). Changes in risk perception and self-reported protective behaviour during the first week of the COVID-19 pandemic in the United States. *Royal Society Open Science*, *7*(9), 200742. https://doi.org/10.1098/rsos.200742

Wong, L. P., Alias, H., Wong, P.-F., Lee, H. Y., & AbuBakar, S. (2020). The use of the health belief model to assess predictors of intent to receive the COVID-19 vaccine and willingness to pay. *Human Vaccines & Immunotherapeutics*, *16*(9), 2204–2214. https://doi.org/10.1080/21645515.2020.1790279

Zaki, J. (2020). Catastrophe Compassion: Understanding and Extending Prosociality Under Crisis. *Trends in Cognitive Sciences*, *24*(8), 587–589. https://doi.org/10.1016/j.tics.2020.05.006