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Perceptions of behaviour efficacy, not perceptions of threat, are drivers of COVID-19 protective behaviour in Germany

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In the ongoing COVID-19 pandemic, non-pharmaceutical protective measures taken by individuals remain pivotal. This study aims to explore what motivates individuals to engage in such measures. Based on existing empirical findings as well as prominent behavioural theories, a partial least squares structural equation model (PLS-SEM) of predictors for pandemic protective behaviour was estimated using a representative German sample ($n = 437$). The study was preregistered at OSF. The model explains 69% of the variance for behavioural intention, which is strongly correlated with behaviour ($\rho = 0.84$). The most influential predictor for protective behaviour is its perceived efficacy, followed by normative beliefs and perceptions about costs for protective behaviour. Distrusting beliefs in science and scientists negatively predicted response perceptions and were also strongly and negatively correlated with behaviour. Knowledge about COVID-19 was weakly linked with perceived response efficacy, as well as with behaviour. These findings suggest that communication strategies surrounding COVID-19 should emphasise the efficacy of responses and foster a sense of responsibility.

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Introduction

As of January 2022, the COVID-19 pandemic has officially claimed more than 5 million lives worldwide (World Health Organization, 2021). Hailed as a positive example for its handling of the first wave (Stafford, 2020; Wieler et al., 2020), Germany began struggling to contain COVID-19 soon after (Lu et al., 2021; Robert Koch-Institut, 2022). With vaccination efforts—including booster vaccinations—ongoing, a rigorous testing strategy, the reduction of physical contacts at workplaces and schools, and non-pharmaceutical protective behaviour remain pivotal to combat the pandemic (Alwan et al., 2020; Bedford et al., 2020; European Centre for Disease Prevention and Control, 2021; Priesemann et al., 2021a, b).

In this preregistered study (https://osf.io/qds4a), we examine the determinants for individual protective behaviour in response to the COVID-19 pandemic. Our study contributes to the growing body of knowledge on predictors of behavioural change in the COVID-19 pandemic in three ways. Firstly, we integrate prominent behavioural models and findings from previous pandemics, allowing for a holistic view of what determines COVID-19 pandemic protective behaviour. Secondly, by using this holistic approach, our model was able to explain differences in behaviour better than many studies with a more singular focus. Thirdly, with our survey conducted in early 2021, we provide a perspective on a phase of the pandemic where individual protective behaviour has to be maintained rather than established.

We have organised and examined behavioural predictors for COVID-19 protective behaviour using partial least square structural equation modelling (PLS-SEM). Our research design also includes a parallel examination of climate protective behaviour. Not only is the actual change in individual behaviour insufficient for both these crises (Climate Action Tracker, 2019; World Health Organization, 2020), also, when trying to explain this insufficiency, many of the same behavioural determinants emerge, e.g., beliefs in the efficacy of the desired behaviours, normative beliefs, and gaps between intention and behaviour (Bavel et al., 2020; Gifford et al., 2011). While we will report only on the results pertaining to COVID-19 in this paper, the model of behavioural predictors we developed draws on research and behavioural models from both the environmental as well as the health context. There are different theoretical approaches to behaviour change, either in a continuum or in different stages or phases (Sutton, 2001). We use a continuum-based approach to model intention and behaviour. We assume that maintenance is more relevant than establishing protective behaviour as we examine high-frequency low-effort behaviours (e.g., mask-wearing).

Literature review

Early on in the COVID-19 pandemic, the importance of non-pharmaceutical individual protective measures became apparent (Dehning et al., 2020; Flaxman et al., 2020). Consequently, a lot of research has been published on correlates and predictors of such behaviour. In this section, we will give a short overview of the main findings, including some findings from previous pandemics.

Concerning socio-demographic characteristics, many studies suggest that women are more likely to engage in protective behaviour than men (Bish and Michie, 2010; Coroiu et al., 2020; Dai et al., 2020; Roozenbeek et al., 2020; Travis et al., 2021; Yíldírím et al., 2021; Zickfeld et al., 2020). It is also likely that higher age is associated with more protective behaviour (Bish and Michie, 2010; Dai et al., 2020; Travis et al., 2021), though there is some conflicting evidence (Barakat and Kasemy, 2020). The relationship between age and behaviour might be nonlinear (Honarvar et al., 2020; Zickfeld et al., 2020). Findings on the influence of lower or higher education are contradictory (Barakat and Kasemy, 2020; Bish and Michie, 2010; Dai et al., 2020; Nivette et al., 2021; Zickfeld et al., 2020). Lastly, people with a migratory background might be more likely to comply with protective measures (Nivette et al., 2021; Valsecchi and Durante, 2021).

In general, though, psychosocial factors have been found to be stronger predictors of protective behaviour than socio-demographic factors (Al-Rasheed, 2020; Batra et al., 2021; Yíldírím et al., 2021; Zickfeld et al., 2020). An early review also accounting for other pandemics indicated that worry and anxiety might play an important role in the adoption of protective behaviour (Usher et al., 2020). Findings on the relationship between fear—and similar affective factors—and behaviour or more cognitive factors like *perceived risk* and behaviour, however, are ambivalent. Mostly, the relationships between fear and protective behaviour (Harper et al., 2020, Qin et al., 2021) or perceived threat and protective behaviour (Barakat and Kasemy, 2020, Dai et al., 2020, Dryhurst et al., 2020, Harper et al., 2020, Qin et al., 2021, Stangier et al., 2021) are weak or even very weak, if significant. In a number of studies, however, a moderate to strong association between fear or perceived threat and protective behaviour was found (Ahmad et al., 2020, Barakat and Kasemy, 2020, Šuriņa et al., 2021, Yíldírím et al., 2021). Qin et al. (2021) explore how both the strength of perceived COVID-19 risk and protective behaviour, as well as the relationship between two those factors vary over time. They find that the relationship that is at times unidirectional, bidirectional, or insubstantial. Similarly, Zickfeld et al. (2020) observed that while reported pandemic protective behaviour increased, the perceived risk decreased. By contrast, in the study by Barakat and Kasemy (2020), the perceived threat increased over the 10 weeks studied.

Efficacy beliefs, both about the efficacy of protective behaviour and self-efficacy when engaging in protective behaviour, have been shown to be predictors of protective behaviour during other pandemics (Bish and Michie, 2010, Kim and Niederdeppe, 2012, Yoo et al., 2016). With this context and with many studies drawing on the *Theory of Planned Behaviour*, *Protection Motivation Theory*, or the *Health Belief Model*, the role of efficacy beliefs has also been frequently examined. Both *perceived self-efficacy* (Ahmad et al., 2020; Al-Rasheed, 2020; Bronfman et al., 2021; Lin et al., 2020) and the perceived efficacy of different types of protective behaviour—or *perceived response efficacy*—(Zickfeld et al., 2020) were found to be linked to protective behaviour. In some studies, however, the link between protective behaviour and perceived self-efficacy (Yíldírím et al., 2021), response efficacy (Al-Rasheed, 2020), or even both types of efficacy (Dai et al., 2020) was found to be very weak. The evidence is mixed for the influence of *perceived response costs* on protective behaviour during the H1N1 pandemic (Bish and Michie, 2010). For COVID-19, they have been found to have a negative influence (Barakat and Kasemy, 2020).

Another set of factors studied were normative beliefs. *Subjective norm*, i.e., normative pressure exerted by others, was found to have an effect of protective behaviour, though varied in strength (Ahmad et al., 2020; Bronfman et al., 2021; Lin et al., 2020). Social influences were important behavioural determinants in other pandemics, as well (Bish and Michie, 2010; Kim and Niederdeppe, 2012). The influence of moral norms was mostly found to be weak (Nivette et al., 2021) or not significant at all (Ahmad et al., 2020). However, there was a link found between *empathy* and compliance with protective measures (Miguel et al., 2021; Pfattheicher et al., 2020), as well as *prosocial attitudes* and compliance (Betsch et al., 2020; Coroiu et al., 2020).

Regarding the role of *knowledge* about COVID-19, the findings are also ambivalent. In some studies it has been linked to an increased likelihood of protective behaviour (Ahmad et al., 2020; Betsch, 2020; Bronfman et al., 2021). Most studies, however, found only a weak link or no significant relationship (Barakat and Kasemy, 2020; Batra et al., 2021; Honarvar et al., 2020; Stangier et al., 2021; Travis et al., 2021; Yíldírím et al., 2021; Zickfeld et al., 2020).

There is some evidence that institutional *trust* has a positive influence on protective behaviour (Al-Rasheed, 2020; Bish and Michie, 2010; Eitze et al., 2021; Šuriņa et al., 2021; Travis et al., 2021). Conversely, distrust or a lack of trust have been found to be negatively correlated with compliance with COVID-19 protective measures (Al-Rasheed, 2020; Betsch, 2020; Nivette et al., 2021).

Among other factors explored in relationship with protective behaviour are political orientation and moral foundations (Harper et al., 2020), mental health status (Yíldírím et al., 2021), and germ aversion (Stangier et al., 2021), for all of which correlations were found to be very weak at best. There is some evidence that personality factors like the *Big Five factors* (Costa and McCrae, 1992) or dark personality traits are weakly related with behaviour (Blagov, 2020; Miguel et al., 2021; Nivette et al., 2021). Further, conspiracy beliefs and trait reactance have been found to be weakly negatively correlated with behaviour (Resnicow et al., 2021), as have scepticism about the threat of COVID-19 (Filkuková et al., 2021), as well as risky decision-making and temporal discounting tendency (Byrne et al., 2021).

Theoretical background

To structure as well as supplement the existing empirical findings, we draw on six prominent behavioural models:

- *Theory of Planned Behaviour* (TPB) (Ajzen, 1991, 2011)
- *Protection Motivation Theory* (PMT) (Rogers, 1983; Rogers, 1975), originally developed to research the effects of fear appeals
- *Extended Parallel Process Model* (EPPM) (Witte, 1992), builds on the PMT
- *Model of Private Proactive Adaptation to Climate Change* (MPPACC) (Grothmann and Patt, 2005), also builds on the PMT, developed to explain adaption to climate change
- *Health Belief Model* (HBM) (Becker, 1974), developed in the context of health interventions
- *Value-Belief-Norm Theory* (VBN) (Stern, 2000), developed to explain pro-environmental behaviour

We further added elements of the trust/distrust model by McKnight et al. (McKnight and Chervany, 1996, 2001; McKnight et al., 2002). Figure 1 displays our theoretical model with its origins. The model with all hypothesised relationships is described in-depth in the "Methods" section.

Following, we discuss the theoretical frameworks for behaviour change integrated into our model.

The *Theory of Planned Behaviour* (TPB) (Ajzen, 1991, 2011) postulates that actual *Behaviour* is strongly predicted by *Behavioural Intention*. *Behavioural Intention*, in turn, has three predictors: *Attitude* toward the behaviour, *Subjective Norm*, and *Perceived Behavioural Control*. The sum of a person's salient positive and negative beliefs toward a behaviour constitutes their *Attitude* concerning behaviour. How an individual expects that significant others would evaluate the behaviour in question, and their own motivation to conform to these significant others form the *Subjective Norm*. *Perceived Behavioural Control* is similar to

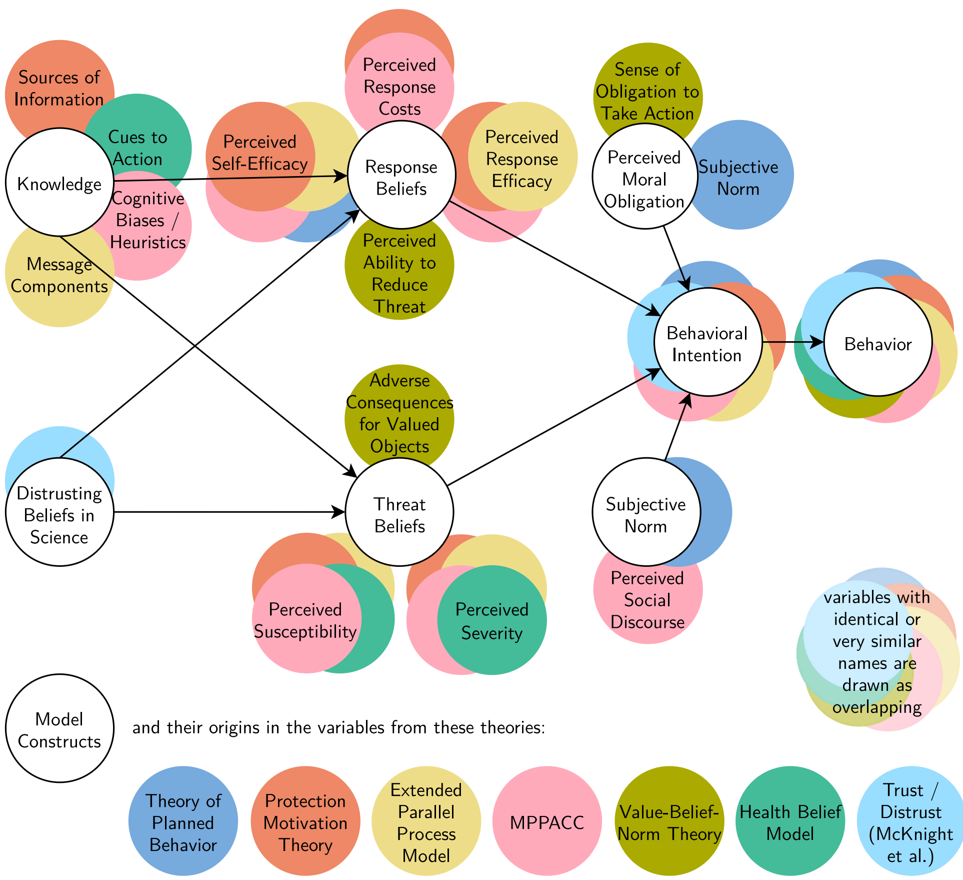

Fig. 1 Synthesised model of influence. The constructs in the theoretical model underlying this study with their origins in different existing behavioural models.

the concept of self-efficacy. It encompasses control beliefs and measures the amount of control the person believes they have over the behaviour in question. The TPB has been widely used in research on both pro-environmental behaviour (Gifford et al., 2011, Si et al., 2019) and health behaviour (Cheng and Ng, 2006; Godin and Kok, 1996).

The *Protection Motivation Theory* (PMT) (Rogers, 1983; Rogers, 1975) explains the cognitive processes triggered by so-called fear appeals, i.e., communication intended to dissuade an individual from a specific course of action. According to the theory, being confronted with such communication leads to two possible cognitive response pathways: the maladaptive and the adaptive response pathway. These response pathways, in turn, influence protection motivation and behavioural intention, which in turn leads to behaviour. Which pathway a person follows depends on their appraisal of threat and coping.

To appraise the threat, they consider if there are rewards for continuing the behaviour (*Maladaptive Response Rewards*) on the one hand; and the severity of the negative consequences (*Perceived Severity*) and their vulnerability to those consequences (*Perceived Susceptibility*) on the other hand. For the coping appraisal, they evaluate whether they feel that the proposed behaviour response is efficacious (*Perceived Response Efficacy*), whether they themselves are efficacious in regards to that response (*Perceived Self-Efficacy*) and what the *Response Costs* are. As the *Theory of Planned Behaviour*, the *Protection Motivation Theory* has been widely used in health contexts (Weinstein, 1993).

The *Extended Parallel Process Model* (EPPM) (Witte, 1992) explains different behavioural outcomes as reaction to fear appeals, specifically the difference in routes leading to no response and leading to maladaptive changes. As it is based on the PMT, the central variables are similar, i.e., *Perceived Self-Efficacy*, *Perceived Severity* and so on. By manipulating each of those variables, theoretically four different combinations emerge: High threat and high efficacy, high threat and low efficacy, low threat and low efficacy, and low threat and high efficacy.

One central advancement compared to the PMT is that Witte exactly describes which combination will to lead to which behavioural response. Like the PMT, the EPPM has mostly been used in the context of health-related messages (Popova, 2012).

The *Model of Private Proactive Adaptation to Climate Change* (MPPACC) (Grothmann and Patt, 2005) is another model based on the PMT which describes the psychological factors influencing climate change adaptation behaviour. It differs from the PMT mainly by the inclusion of more differentiated predictors, taking into account that behaviour might also be dependent on objective resources outside of attitudes and beliefs. Furthermore, it models *Avoidant Maladaptation* as a mediating variable instead of a parallel route. While this variable was originally part of our model, results from a pre-study did not support its further inclusion.

The *Health Belief Model* (HBM) (Becker, 1974; Janz and Becker, 1984) links a person's perceptions about a disease with their perceptions about the proposed health intervention, i.e., the behaviour. It also takes into account demographic variables, sociopsychological variables and different sources of information. Those in turn influence variables similar to those in the *Protection Motivation Theory*, i.e., perceptions about the threat and the behavioural response.

Stern's *Value-Belief-Norm Theory* (VBN) (Stern, 2000) postulates that a set of values, e.g., *Biospheric Values*, lead to a system of belief, e.g., an *Ecological Worldview*. Through these beliefs, pro-environmental personal norms are activated, what Stern calls a *Sense of Obligation to Take Pro-Environmental Actions*. The activation of these norms can lead to different kinds of environmentally significant *Behaviour*.

While *Trust* and the lack thereof, or *Distrust*, have been found to play an important role in determining health-related behaviour change (Floyd et al., 2000) and specifically COVID-19 pandemic protective behaviour (Al-Rasheed, 2020; Betsch, 2020; Nivette et al., 2021), none of the behavioural models examined thus far explicitly contains either as a variable. One influential conceptualisation of trust comes from McKnight et al. (McKnight and Chervany, 1996, 2001; McKnight et al., 2002). Drawing from an in-depth review of the existing trust literature, they developed a model of five trust-related constructs which reflects an interdisciplinary view on trust.

Broadly, they theorise that an individual's *Disposition to Trust* and their *Institution-Based Trust* predict their *Trusting Beliefs* and *Trusting Intentions*; and that *Trusting Intentions* predict *Trust-Related Behaviour*, which describes behaviour where one gives up control, even though that involves risk.

McKnight et al. argue further for a conceptualisation of *Distrust* not simply as the opposite of *Trust*, but as a distinct phenomenon (McKnight et al., 2002). Following Luhmann's (2014) characterisation of *Trust* as a mechanism functioning to reduce complexity, for *Distrust*, the reduction of complexity is then achieved by strategies like exertion of control. For *Distrust*, an analogous model of five related constructs is defined. The definitions are broadly similar, only that *Distrusting Behaviour* refers to an individual's refusal to depend on another person or party; and so on.

In our original model, we included both *Trusting* and *Distrusting Beliefs*. However, because of a lack of discriminant validity in the modelling process, our current model only includes *Distrusting Beliefs*.

Methods

In this section, we first describe the process of structural equation model estimation and evaluation. We then describe the additional analyses conducted. After outlining our measurement instrument, we close by characterising the process of data examination and preparation.

Partial least-squares structural equation modelling. As described by Hair et al. (2017), partial least-squares structural equation modelling (PLS-SEM) is a multivariate analysis technique that allows for the examination of two sets of relationships at the same time: First, the relationship between manifest, measured variables (*indicators*) and the unobservable, latent variables (*constructs*) derived therefrom; second, the relationships between those latent constructs. Consequently, a structural equation model (SEM) consists of a measurement—or outer—model and a structural—or inner—model. For our study, we follow the prevalent naming convention of the popular software *smartPLS* in calling correlation weight composites *reflective* constructs and regression weight composites *formative* constructs (Ringle et al., 2015). Additionally, we use higher-order constructs (HOC) as described by Sarstedt et al. (2019) and Becker et al. (2012). These are high-level constructs that condense a set of low-level constructs to which they relate in the same way that regular constructs relate to indicators.

The graphic representation of a structural equation model is called *path model* (Hair et al., 2017). In it, indicators are depicted as rectangles, constructs are depicted as ovals and the relationships between the model elements are shown with arrows. We depict lower-order constructs in higher-order models as ovals with a grey fill. Reflective measurement is indicated by the arrows pointing from the construct to the indicator. For formative measurement, it is the other way around. Structural relationships are signified by a path pointing from the exogenous construct to the endogenous construct.

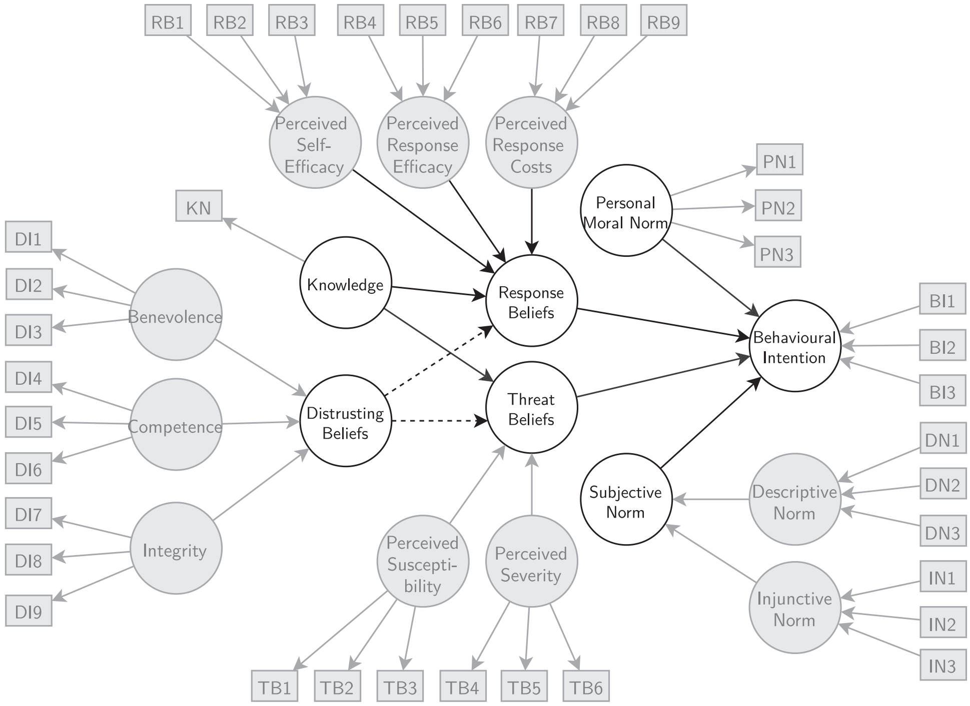

Fig. 2 Hypothesised structural equation model. Circles are drawn as constructs, indicators as rectangles, dashed paths signify a negative hypothesised influence.

Model specification. We synthesised the model from the behavioural theories discussed in the introduction. We further modified it based on the results of a pre-study conducted in the summer of 2020. Figure 2 shows the full hypothesised structural equation model.

We defined *Distrusting Beliefs in Science* (or *Distrusting Beliefs* for short) as the set of distrusting beliefs a person holds about virology and epidemiology. Following the theory by McKnight et al. (McKnight and Choudhury, 2006; McKnight and Chervany, 1996, 2001; McKnight et al., 2002), we hypothesised that these beliefs take on three dimensions. *Benevolence*: beliefs that science and scientists do not have one's best interest at heart; *Competence*: beliefs that the scientists are not capable to meet their responsibilities; and *Integrity*: beliefs that science and scientists are dishonest and unreliable. To represent these three dimensions, we conceptualised *Distrusting Beliefs* as a reflective-formative higher-order construct. We hypothesised that it has a negative influence on both *Response Beliefs* and *Threat Beliefs*.

We defined *Knowledge* as the sum of correct information known by a person about COVID-19. We hypothesised that *Knowledge* has a positive influence on both *Response Beliefs* and *Threat Beliefs*.

Response Beliefs were defined as the beliefs a person holds about the efficacy and feasibility of certain behavioural responses to the respective crisis (Grothmann and Patt, 2005; Rogers, 1975). We modelled them as a formative-formative higher-order construct comprised of three sets of perceptions. *Perceived Self-Efficacy*: a person's perception about their own ability to engage in certain behaviours (Ajzen, 1991; Grothmann and Patt, 2005; Rogers, 1975; Stern, 2000; Witte, 1992); *Perceived Response Efficacy*: a person's perception about the effectiveness of certain behaviours in attenuating the respective risk (Grothmann and Patt, 2005; Rogers, 1975; Stern, 2000; Witte, 1992); and *Perceived Response Costs*: a person's perception of costs associated with certain behaviours, be it monetary, psychological or temporal (Grothmann and Patt, 2005; Rogers, 1975). To ensure a uniform orientation of *Response Beliefs*, i.e., high values pointing to generally positive beliefs, we inverted *Perceived Response Costs*. We hypothesised that *Response Beliefs* have a positive influence on *Behavioural Intention*.

We defined *Threat Beliefs* as a person's beliefs about the degree of threat caused by COVID-19 to them, personally (Becker, 1974; Grothmann and Patt, 2005; Rogers, 1975; Stern, 2000). *Threat Beliefs* were modelled as a reflective-formative higher-order construct. *Perceived Susceptibility* refers to the perception a person has about the likelihood of the threat affecting them (Becker, 1974; Grothmann and Patt, 2005; Rogers, 1975; Witte, 1992). *Perceived Severity* denotes how severe a person perceives the threat to be (Becker, 1974; Grothmann and Patt, 2005; Rogers, 1975; Witte, 1992). We hypothesised that *Threat Beliefs* have a positive influence on *Behavioural Intention*.

In empirical research, the *Subjective Norm* variable has been extended and re-conceptualised to also include descriptive normative beliefs as well personal normative beliefs (Barbera and Ajzen, 2020; Chen, 2020; Niemiec et al., 2020; Rhodes and Courneya, 2003). Therefore, we defined *Personal Moral Norm* as the normative beliefs a person holds about a certain behaviour which are independent from normative pressure perceived to be exerted by others (Ajzen, 1991; Harrison, 1995; Niemiec et al., 2020; Stern, 2000) and hypothesised that it has a positive influence on *Behavioural Intention*.

We defined *Subjective Norm* as the normative pressure to engage in a certain behaviour a person feels from others that are important to them (e.g., friends, family and colleagues) (Ajzen, 1991, 2011). *Injunctive Norm* denotes what a person believes those important others want them to do (Barbera and Ajzen, 2020; Niemiec et al., 2020; Rhodes and Courneya, 2003). *Descriptive Norm* refers to normative pressure emerging because important others model a certain behaviour themselves (Barbera and Ajzen, 2020; Niemiec et al., 2020; Rhodes and Courneya, 2003). We hypothesised that *Subjective Norm* has a positive influence on *Behavioural Intention*.

Finally, *Behavioural Intention* refers to a person's intention to engage in certain pandemic protective protective behaviours

(Ajzen, 1991; Grothmann and Patt, 2005; McKnight and Choudhury, 2006; Rogers, 1975; Witte, 1992). It is the intermediate step between all the predictors discussed above and actual *Behaviour*.

To account for a possible time dependence of all predictors on *Behaviour*, we measured it in a separate time-lagged survey (Bubeck et al., 2012; Weinstein, 1993). We expected that a fraction of the original respondents would not participate in that follow-up survey. As we wanted to harness the largest possible sample size for the structural equation model, we decided to only include *Behavioural Intention* in the model. The relationship between *Behavioural Intention* and *Behaviour* was tested with Pearson correlation analysis (see the section "Additional analysis").

We implemented the model using the *SEMinR* package (Ray et al., 2021).

Model evaluation. To evaluate the measurement model and structural model, we followed the procedure described in Hair et al. (2019, 2017): For reflective (i.e., correlation weight) composites, the indicator loadings λ should be above 0.708; measures for internal consistency reliability are Cronbach's α, composite reliability ρ_C and ρ_A which all should be between 0.6 and 0.95; average variance extracted (AVE) as a measure for convergent validity should be larger than 0.50; and in order to establish discriminant validity, 1 should not be in the hetero-monotrait (HTMT) ratio bootstrap interval.

For formative (i.e., regression weight) composites, convergent validity was established using a redundancy analysis where the path coefficients β to the redundant reflective composite should be above 0.70; possible collinearity was measured using the variance inflation factor (VIF) which should be <5; and indicator weights w should be significant ($t \geq 1.65$ and no 0 in the bootstrap confidence interval), otherwise the indicator loadings should λ be significant and >0.50. We evaluated higher-order constructs according to Sarstedt et al. (2019). For structural model evaluation, we assessed possible collinearity analogous to the measurement model evaluation, the variance explained or in-sample explanatory power R^2 ($R^2 \geq 0.25$: weak, $R^2 \geq 0.5$: moderate, $R^2 \geq 0.75$: substantial) and effect size f^2 ($f^2 > 0.02$: small, $f^2 > 0.15$: medium, $f^2 > 0.15$: large), and relevance and significance of the path coefficients. For model predictivity, we used the PLSpredict metric instead of Q^2 and q^2 as discussed by Shmueli et al. (2016). We used *SEMinR* (Ray et al., 2021) for model evaluation and *htmltools* (Cheng et al., 2021), *DT* (Xie et al., 2021), and distill (Allaire et al., 2021) to publish evaluation results. The results of the iterative model evaluation can be found on the accompanying paper website: https://digitalemuendigkeit.github.io/covid-19-behaviour-sem/.

Robustness evaluation. We assessed potential nonlinear effects were assessed as described in Sarstedt et al. (2020) and Henseler et al. (2012). Potential hidden endogeneity was examined using the copula procedure by Hult et al. (2018). The results of the robustness evaluation can also be found on the paper website.

Additional analysis. To complement model estimation, we examined the correlation between *Behaviour* and *Behavioural Intention*. We posit that a large correlation between behaviour and intention indicates that the model can be used to predict pandemic protective behaviour.

Other than that, we explored whether there were influences on *Behavioural Intention* or *Behaviour* not hypothesised in the model. We tested for an influence of socio-demographic variables, specifically age, gender, education, occupation, household size and number of children in the household or income bracket. Additionally, we examined whether there was an influence of personality aspects operationalised through the *Big Five factors* (Costa and McCrae, 1992) and *internal-external control expectations*. We also tested for an influence of people's experiences with COVID-19 and the infection prevalence at their place of residence.

All additional statistical analyses were conducted in *R* (R Core Team, 2020; Wickham et al., 2019). As our data is non-parametric, we used Spearman's rank correlation coefficient ρ from the *RHMisc* package for all correlation tests (Harrell and Dupont, 2021; Hollander et al., 2015). For group comparisons, we used the Kruskal-Wallis rank sum test and the two-sided (pairwise) Wilcoxon rank sum test from the *stats* package (Hollander et al., 2015; R Core Team, 2020).

We specified variables used for the additional analysis differently than the model constructs: For variables measured by more than one survey items, we formed scales from the survey items for each variable. We evaluated scale reliability using Cronbach's α ($\alpha \geq 0.70$) (Gliem and Gliem, 2003). If a scale did not meet that standard, items were chosen on basis of item-total correlation or item content. As an exception to that, we disregarded Cronbach's α for the *Knowledge* variable as the different survey items were not supposed to measure the same concept (Taber, 2018). Instead, for the additional analysis we tallied up the number of correct, incorrect and 'do not know' answers.

Measurement Instrument and Sample. We conducted two surveys: The main survey (*survey 1*) and the follow-up survey (*survey 2*). For *survey 1*, participants were randomly assigned to one of two conditions: For one condition, respondents were mainly presented with COVID-19 pandemic items, for the other mainly with corresponding items for the climate crisis. As we will publish the results concerning the climate crisis at a later point, we focus on the COVID-19 items in the following sections. We describe the scales used, the implementation of the surveys, and the sample.

Survey Items. Firstly, participants were asked for demographic information as well as the degree to which they were affected by the COVID-19 pandemic. Apart from these items and the *Knowledge* items, all items were measured on a 6-point-Likert-scale, 1 signifying 'do not agree at all', 6 signifying 'completely agree'. Participants also answered personality questions using the *Big Five Inventory* (Rammstedt et al., 2014) and *IE-4 scale on control convictions* (Kovaleva et al., 2014).

Participants also answered behavioural questions. The main dependent variables (or endogenous constructs) of interest were *Behaviour* and *Behavioural Intention*. As discussed, we measured *Behaviour* only in the follow-up study to capture a possible time-dependence of the influence of beliefs, perceptions and *Behavioural Intention* on *Behaviour* (Bubeck et al., 2012; Weinstein, 1993).

The items for both *Behavioural Intention*, *Behaviour* and the different *Response Beliefs* lower-order constructs referred to a specific set of protective responses as well as protective behaviour in general to enable a redundancy analysis (Hair et al., 2017). We deducted this set of behaviours from German governmental recommendations active at the time of the surveys (Bundesregierung, 2020, 2021):

- Abiding by contact restrictions limiting private meetings
- Using the German corona warning app
- Wearing a mask in public

In *survey 1*, we asked respondents to rate their *Behavioural Intention* using the following items: "I plan to abide by the contact restrictions in place when meeting privately", "... to (continue to) use the Corona warning app", "... to (continue to) wear a mask in public", and "In general, I plan to (continue to) adhere to the Corona protection measures recommended by the government". In *survey 2*, we then asked respondents to rate their *Behaviour* in the time since *survey 1*: "I abode by the contact restrictions in place when meeting privately ", "I used the Corona warning app ", "I wore a mask in public ", and "In general, I adhered to the Corona protection measures recommended by the government ".

In *survey 1*, after the question block asking for *Behavioural Intention*, we first asked about the participants' *Response Beliefs*, with the item phrasing being adapted from Bubeck et al. (2018). For *Perceived Self-Efficacy*, the items were: "I have the ability to abide by the contact restrictions in place when meeting privately ", "... to use the Corona warning app ", "... to wear a mask in public", and "... to take protective measures against the coronavirus". For *Perceived Response Efficacy*, the following items were used: "Abiding by the contact restrictions in place when meeting privately is effective", "Using the Corona warning app is effective", "Wearing a mask in public is effective", and "Protective measures against the coronavirus are effective". The items for *Perceived Response Costs* read: "Abiding by the contact restrictions in place when meeting privately costs me much time, financial and/or emotional effort"and so on for all four kinds of behaviour.

We then asked about respondents normative beliefs. *Perceived Moral Obligation* was measured with three items, e.g., "I have a moral obligation to combat the spread of coronavirus" (adapted from Brody et al. (2012), Chen (2020)). *Subjective Norm* was measured with four items each for *Injunctive Norm* (e.g., "My friends think I should adhere to the Corona protection measures" and *Descriptive Norm* (e.g., "My friends adhere to the Corona protection measures") (adapted from Niemiec et al. (2020), Rhodes et al. (2006)). The respondents' *Threat Beliefs* were measured with three items each for *Perceived Susceptibility* (e.g., "I will probably get sick with the coronavirus (again)") and *Perceived Severity* (e.g., "I think that the coronavirus disease is dangerous") (items adapted from Abdelhafiz et al., 2020; Dryhurst et al., 2020; Ji et al., 2004; Tang and Wong, 2004).

We then asked about *Knowledge*. As mentioned above, this was not measured on a 6-point-Likert-scale. Instead, it was measured on a 3-point-scale with a 1 being assigned for incorrect answer, a 2 for 'don't know', and a 3 for the correct answer. In comparison to a dichotomous measurement, this reduces guessing and allows for a differentiation between respondents who are uninformed and respondents who are misinformed (Taddicken et al., 2018). *Knowledge* questions were adapted from Abdelhafiz et al. (2020), Roy et al. (2020), Zickfeld et al. (2020) and derived from findings by Rawat et al. (2021), Robert Koch-Institut (2021), and Sohrabi et al. (2020).

For *survey 2*, participants answered questions about their *Behaviour* since *survey 1* using the same specific set of behaviours as in *survey 1*. The items read: "I abided by the contact restrictions in place when meeting privately", "I used the Corona warning app", "I wore a mask in public", and "In general, I adhered to the Corona protection measures recommended by the government".

In the OSF repository, there is a survey table with a list of all constructs with their respective items and scales in German and a translation into English, as well as the sources used for the items.

Implementation. We conducted the surveys using the *Qualtrics* software (Qualtrics, 2021). Participants were recruited from the German population using a market research institute's panel. They were invited to the survey via e-mail.

We administered both surveys in German. *Survey 1* ran from January 12, 2021 until January 18, 2021. *Survey 2* ran from February 1, 2021 until February 8, 2021. Survey responses were matched using the id provided by the market research institute. PDFs of both surveys can be found in the OSF repository.

Sample. We aimed for a sample which was representative of the German population in terms of age and gender distribution. We aimed for a sample size of 500 respondents per condition so we could detect even small effect sizes ($f^2 \geq 0.02$) at a significance level of 10% with a statistical power of 80% (Faul et al., 2009).

Our full sample consists of $n = 869$ responses, with $n = 437$ responses for the COVID-19 condition and $n = 430$ responses for the climate crisis condition. Figure 3 depicts the age and gender distribution in our sample compared with the German population. Overall, our sample is representative in terms of gender (female: $n = 444$, male: $n = 424$, genderqueer: $n = 1$) and age ($M = 50.3$, SD $= 14.5$), but young male respondents and older female respondents are underrepresented. Our sample is slightly better educated than the German population at large, with less respondents having a secondary school leaving certificate (population: 58.8%, sample: 45.5%) and more respondents holding an university entrance qualification (population: 15.0%, sample: 19.9%) or an university degree (population: 17.3%, sample: 29.7%).

Data examination and preparation. We conducted the whole process of data examination and preparation with *R* (R Core Team, 2020). First, we filtered the data collected in the survey for speeders and for suspicious response patterns (e.g., straight-lining) using the *careless* package (Hair et al., 2017; Yentes and Wilhelm, 2018), as well as for implausible responses in text entry boxes, removing 86 out of 955 responses. Second, we examined each item for critical levels of skewness and kurtosis (Hair et al., 2017). As *PLS-SEM* generally does not assume normality of data distribution, we used a more liberal admissible interval of −5 to +5 for both metrics and discounted four items for the structural equation model estimation. Third, data was systematically missing for the items *COIN3* and *CODN3* asking for normative beliefs concerning colleagues as not every respondent had colleagues. As the amount of missing data was above the 15% threshold defined by Hair et al. (2017), we decided against data imputation and discounted the items in question for the structural equation model estimation. Last, we decided to include outliers for our analysis. While removing outliers can lead to better model fit, it might also exclude parts of the population studied and lead to skewed results (Hair et al., 2017).

Results

In this section, we first present the results of the partial least squares structural equation modelling (PLS-SEM). Afterwards, we complement the model with the results from additional statistical analysis.

PLS-SEM

Measurement model evaluation. Firstly, we describe the results of the measurement model evaluation. The quality criteria applied are described in the "Methods" section. In Table 1, we list the results of the measurement model evaluation. Internal consistency reliability and convergent validity is established for all constructs and indicators. *Knowledge* as a single-indicator construct is not subject to these quality criteria.

We evaluated discriminant validity using the bootstrapped hetero-monotrait (HTMT) ratio. The bootstrap confidence interval for all *Distrusting Beliefs* lower-order constructs contains

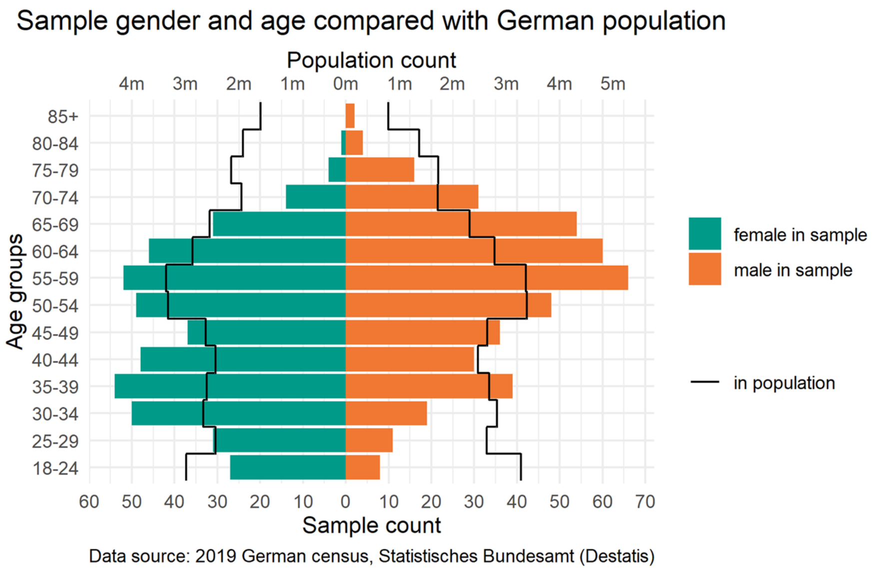

Fig. 3 Age and gender of the survey sample compared with the German population (Statistisches Bundesamt (Destatis), 2020). Men under 35 and women over 70 are underrepresented.

Table 1 Evaluation of the reflective measurement model: Loadings λ (original estimate), internal consistency reliability (α, ρ_C, ρ_A) and convergent validity (AVE).

Construct	Indicator	λ	α	ρ_C	ρ_A	AVE
Distrusting Beliefs: Benevolence	CODI1	0.89	0.84	0.91	0.85	0.76
	CODI2	0.86				
	CODI3	0.87				
Distrusting Beliefs: Competence	CODI4	0.82	0.83	0.90	0.83	0.74
	CODI5	0.86				
	CODI6	0.91				
Distrusting Beliefs: Integrity	CODI7	0.87	0.79	0.88	0.79	0.70
	CODI8	0.84				
	CODI9	0.81				
Personal Moral Norm	COPN1	0.96	0.90	0.95	0.90	0.91
	COPN3	0.96				

Table 2 Evaluation of the formative measurement model: Convergent validity (path coefficient β of redundancy analysis), collinearity (VIF), and indicator weights (original estimate w, bootstrap mean M and t statistic).

Construct	Indicator	β	VIF	Weight		
				w	M	$t(437)$
Perceived Response Efficacy	CORB4	0.76	2.19	0.48	0.48	7.14
	CORB5		1.44	0.23	0.22	4.22
	CORB6		2.24	0.44	0.44	6.93
Perceived Response Costs	CORB7	0.74	1.57	0.20	0.20	2.07
	CORB8		1.33	0.33	0.33	3.70
	CORB9		1.78	0.66	0.65	7.34
Descriptive Norm	CODN1	0.82	1.73	0.40	0.39	3.76
	CODN2		1.73	0.70	0.70	7.60
Behavioural Intention	COBI1	0.86	1.72	0.42	0.42	6.66
	COBI2		1.17	027	0.27	5.01
	COBI3		1.74	0.54	0.54	8.79

1, implying conceptual overlap. As these are all part of the same multi-level composite, this is permissible. For all other reflective inter-construct relationships, discriminant validity is established as there is no 1 in the bootstrap confidence interval.

The results of the formative measurement model are displayed in Table 2. Convergent validity is established for all constructs by means of redundancy analysis (β), there is no collinearity indicated by the variance inflation factor (VIF) and all weights are significant, both on the basis of the two-tailed t-tests and on the basis of the bootstrap confidence intervals not containing 0.

Distrusting Beliefs is the only higher-order construct to evaluate. As a reflective-formative (type II) higher-order construct, it is subject to the same quality criteria as a formative construct. While we could not evaluate convergent validity, we can rule out collinearity as no VIF is above 5. We can also establish significance and relevance: Even though the *Integrity* weight ($w = 0.18$, $t(437) = 1.90$) is non-significant on the basis of having a 0 in the bootstrap confidence interval, the loading ($\lambda = 0.91$) is sufficiently large for the construct to be retained. Both the *Benevolence* ($w = 0.42$, $t(437) = 3.41$) and *Competence* ($w = 0.46$, $t(437) = 5.00$) weights are significant based on the t-value and the bootstrap confidence interval.

As shown, the measurement model meets all quality criteria. Next, we introduce the results of the structural model evaluation.

Structural model evaluation. On the basis of the structural model quality criteria described in the Model Evaluation methods section, we identified two very similar possible models which can be found on the paper website: One with the *Response Beliefs* higher-order construct intact and one with it split up in its remaining lower-order constructs *Perceived Response Costs* and *Perceived Response Efficacy*. We chose the latter on the basis of a slightly larger R^2_{adj} of *Behavioural Intention*, In Table 3, we list the results of the respective structural model evaluation. Unfortunately, no value could be obtained for the *Distrusting Beliefs* and *Perceived Response Costs* VIF. Other than that, there is no collinearity as indicated by the VIF. The high VIF value for the *Perceived Response Efficacy* value is due to the inclusion of a copula to account for model endogeneity. The mean bootstrap path coefficients range in absolute values from 0.11 to 0.62. All are significant on the basis of both the bootstrap confidence interval and

Table 3 Evaluation of the structural model: Bootstrapped path coefficient β, effect size f^2 and collinearity (VIF); *VIF value for the model version without copula.

Exogenous construct	Endogenous construct	Path coefficient				f^2	VIF
		β	M	t(437)	p		
Distrusting Beliefs	Perceived Response Efficacy	−0.62	−0.62	16.40	<0.001	0.63	1.10
Distrusting Beliefs	Perceived Response Costs	−0.58	−0.59	14.25	<0.001	0.51	-
Knowledge	Perceived Response Efficacy	0.14	0.14	3.86	<0.001	0.03	1.10
Perceived Response Efficacy	Behavioural Intention	0.53	0.53	7.64	<0.001	0.18	4.98 (2.63)*
Copula Perceived Response Efficacy	Behavioural Intention	−0.07	−0.07	1.88	0.031	0.00	2.62
Perceived Response Costs	Behavioural Intention	0.11	0.11	2.34	0.010	0.03	1.33
Personal Moral Norm	Behavioural Intention	0.22	0.22	3.32	<0.001	0.05	3.11
Descriptive Norm	Behavioural Intention	0.14	0.14	2.36	0.009	0.03	2.02

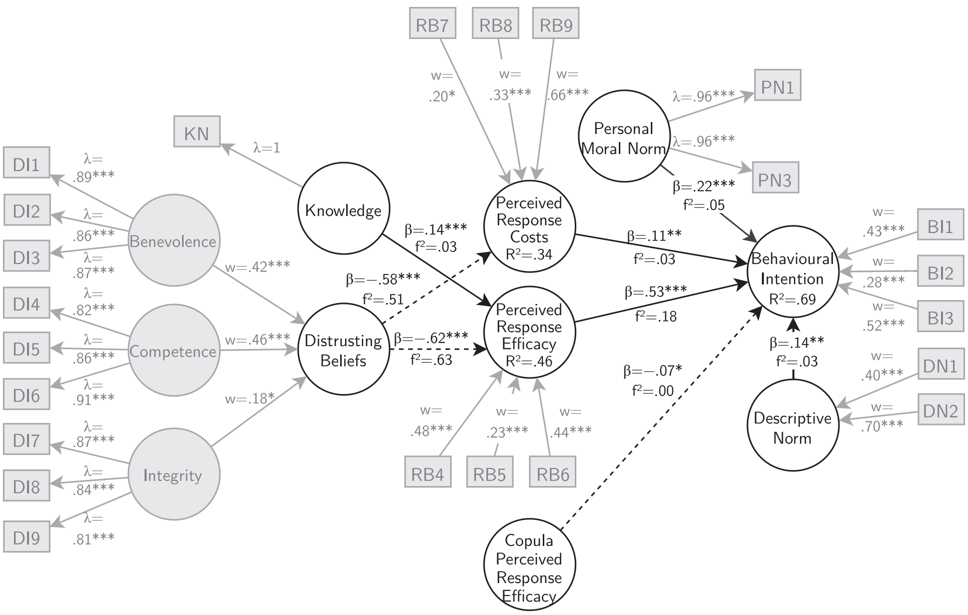

Fig. 4 Final structural equation model. Shown are original estimate loadings λ, weights w, and path coefficients β (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$), effect sizes f^2 and explained variance R^2; Dashed paths signify a negative path coefficient.

the t statistic at a level of at least 5% ($t(437) \geq 1.65$). Effect sizes range from small ($f^2 = 0.03$) to large ($f^2 = 0.63$).

The in-sample explanatory power is weak for *Perceived Response Efficacy* $R^2 = 0.46$ ($R^2_{adj} = 0.45$) and for *Perceived Response Costs* $R^2 = 0.34$ ($R^2_{adj} = 0.34$) and moderate for *Behavioural Intention* $R^2 = 0.69$ ($R^2_{adj} = 0.68$) (Sarstedt et al., 2019). To evaluate model predictivity, we applied the PLSpredict procedure (Shmueli et al., 2016). We found that the linear model predicted most indicators slightly to considerably better than our PLS model. This implies that our model, while moderate in explanatory power, might not serve as well as a predictive model.

Robustness evaluation. We did not find any indication for non-linear effects in our model. However, the copula procedure (Hult et al., 2018) pointed to endogeneity in the influence of *Perceived Response Efficacy* on *Response Beliefs*. Both constructs might be correlated with a third variable that is not part of our model. Therefore, the final model includes the *Perceived Response Efficacy* copula. By design, the copula is correlated with both *Behavioural Intention* and *Perceived Response Efficacy* (Hult et al., 2018). Consequently, the VIF increase for *Perceived Response Efficacy* to 4.98 is not surprising, nor does it imply problematic collinearity. We provide the full results of our robustness evaluation on the paper website.

Full model. In Fig. 4, the full structural equation model model is depicted. Compared to the hypothesised model (Fig. 2), we removed some constructs and paths. Specifically, we did not find a significant influence of *Threat Beliefs* concerning the pandemic, or of *Perceived Self-Efficacy*, or *Injunctive Norm* regarding pandemic protective behaviour, on the pandemic protective *Behavioural Intention*. Further, we found that *Knowledge* about the coronavirus only significantly influences *Perceived Response Efficacy*, but not *Perceived Response Costs*.

The model exhibits moderate in-sample predictive power for the main outcome variable *Behavioural Intention* ($R^2 = 0.69$). The strongest predictor for *Behavioural Intention* is *Perceived Response Efficacy* both in terms of the path coefficient and effect size, with a medium effect of $f^2 = 0.18$. All other predictors have only a small effect on *Behavioural Intention*. Among these, *Personal Moral Norm* exhibits the strongest and most significant path, and *Perceived Response Costs* and *Descriptive Norm* both have small and less significant path coefficients (around $\beta = 0.1$). As discussed, the robustness analysis suggested the existence of endogeneity in the influence of *Perceived Response Efficacy* on *Behavioural Intention*. Thus, we included a *Perceived Response Efficacy copula* in the model. Although the path coefficient and its effect are miniscule, the inclusion increases the effect size for *Perceived Response Efficacy*.

Table 4 Descriptive statistics for the variables considered in the additional analysis: Number of observations *n*, Cronbach's α, means *M* and standard deviation SD. All scales range from 1 to 6, with *Perceived Response Costs* inverted.

Variable	Items	*n*	α	*M*	SD
Behaviour	COB1, COB2, COB3, COB4	594	0.74	4.76	0.96
Behaviour Contact	COB1	594	-	5.40	1.05
Behaviour App	COB2	594	-	2.88	2.22
Behaviour Mask	COB3	594	-	5.37	1.11
Behaviour General	COB4	594	-	5.40	0.96
Behavioural Intention	COBI1, COBI2, COBI3, COBI4	869	0.82	4.67	1.13
Perceived Self-Efficacy	CORB1, CORB2, CORB3, CORB10	437	0.76	4.87	1.01
Perceived Response Efficacy	CORB4, CORB5, CORB6, CORB11	437	0.86	4.15	1.23
Perceived Response Costs	CORB7, CORB8, CORB9, CORB12	437	0.82	4.46	1.30
Distrusting Beliefs Benevolence	CODI1, CODI2, CODI3	437	0.84	2.51	1.18
Distrusting Beliefs Competence	CODI4, CODI5, CODI6	437	0.83	2.86	1.13
Distrusting Beliefs Integrity	CODI7, CODI8, CODI9	437	0.79	2.90	1.08
Perceived Susceptibility	COTB1, COTB2, COTB3	437	0.70	3.28	1.04
Perceived Severity	COTB4, COTB5, COTB6	437	0.85	4.99	1.03
Personal Moral Norm	COPN1, COPN2, COPN3	437	0.94	5.08	1.20
Descriptive Norm	CODN1, CODN2, CODN3, CODN4	437	0.86	4.89	0.99
Injunctive Norm	COIN1, COIN2, COIN3, COIN4	437	0.91	4.80	1.23
Subjective Knowledge	COSKN	437	-	4.13	0.97

Perceived Response Costs is strongly and negatively predicted by *Distrusting Beliefs* in science and scientists. *Perceived Response Efficacy* is also strongly and negatively predicted by *Distrusting Beliefs*. Additionally, there is a weak positive and significant influence of *Knowledge*. The model's explanatory power is weak for both *Perceived Response Efficacy* and *Perceived Response Costs*. This indicates that there are other influences we did not account for.

The only remaining higher-order construct in the final model is *Distrusting Beliefs*. All others, we removed or dissolved during model evaluation or dissolved because of a lack of significant influence on their descendant endogenous constructs. With the lower-order constructs of *Distrusting Beliefs*, beliefs in a lack of *Competence* of science and scientists have the strongest and most significant weight. This implies that those types of beliefs are the dominant component of respondents *Distrusting Beliefs* in science.

Additional analysis. In this section, we present descriptive findings as well as the results of the exploration of other potential influences on pandemic protective *Behaviour*.

Descriptive statistics. In Table 4, we depict the variables considered in the additional analyses. Both *Behavioural Intention* and actually reported pandemic protective *Behaviour* are, on average, high. Concerning the different protective behaviour types surveyed, the mean reported *Behaviour* for avoiding social *Contacts*, wearing a *Mask* and protective behaviour in *General* is very high. In contrast, respondents on average showed much less compliance concerning the usage of the German coronavirus warning *App*. However, this variable also has a high standard deviation.

Further, the average reported *Perceived Self-Efficacy* concerning pandemic protective measures is high, as is the *Perceived Response Efficacy* of those measures. Conversely, respondents perceive *Perceived Response Costs* (coded in reverse) to be low. *Distrusting Beliefs* in science and scientists are low to medium. Concerning the perceived threat exerted by the pandemic, the *Perceived Susceptibility* is noticeably lower than the *Perceived Severity*. This implies that respondents feel that while the pandemic itself is dangerous, the risk to themselves personally is rather low. All dimensions of normative beliefs are high. More extensive descriptive statistics can be found on the paper website.

Correlation between model variables and Behaviour. *Behavioural Intention* is strongly and significantly correlated with *Behaviour* ($\rho = 0.84$, $p < 0.001$). Thus, we argue that our model not only explains *Behavioural Intention*, but also sufficiently explains *Behaviour*. Apart from this correlation, most correlations found between model variables and *Behaviour* mirror model relationships between constructs and *Behavioural Intention*.

In addition, *Behaviour* is also correlated with *Perceived Self-Efficacy* ($\rho = 0.74$, $p < 0.001$), *Perceived Susceptibility* ($\rho = 0.35$, $p < 0.001$), *Perceived Severity* ($\rho = 0.56$, $p < 0.001$), *Injunctive Norm* ($\rho = 0.57$, $p < 0.001$), *Distrusting Beliefs Benevolence* ($\rho = -0.51$, $p < 0.001$), *Distrusting Beliefs Competence* ($\rho = -0.52$, $p < 0.001$), and *Distrusting Beliefs Integrity* ($\rho = -0.54$, $p < 0.001$), as well as with the number of correctly answered *Knowledge* questions ($\rho = 0.35$, $p < 0.001$). All those variables are similarly, if slightly stronger, correlated with *Behavioural Intention*.

With only few exceptions, all variables corresponding to model constructs are at least weakly and significantly correlated with each other. Among the *Threat Beliefs*, *Response Beliefs* and normative variables, the inter-correlations are strongest. Other than that there is a strong correlation between *Perceived Response Efficacy* and *Personal Moral Norm* ($\rho = 0.75$, $p < 0.001$) as well as between *Perceived Severity* and *Personal Moral Norm* ($\rho = 0.72$, $p < 0.001$). And while the count of *Knowledge* questions answered with 'don't know' is only very weakly correlated with other model variables, the correlations between the model variables and the count of correctly and incorrectly answered questions are slightly larger. For example, both *Perceived Severity* and *Personal Moral Norm* are positively correlated with the number of correct answers ($\rho \geq 0.39$, $p < 0.001$) and negatively correlated with the number of incorrect answers ($\rho \leq -0.32$, $p < 0.001$). The full correlation table can be found on the paper website.

Influence of other variables. For the following exploratory analysis, we only consider correlations $\rho \geq 0.3$. The full correlation analysis can be found at the paper website. We did not find a significant correlation of *Behaviour* or *Behavioural Intention* with any of the surveyed personality variables, age, household size, number of infected or hospitalised acquaintances or the COVID-19 count or incidence in the respondents' administrative district.

We also did not find a significant difference in *Behaviour* based on gender, education, occupation or income bracket. Concerning the respondents' own experience with COVID-19, people who are at risk for an especially severe COVID-19 infection show marginally more *Behaviour* ($M = 4.88$, Mdn = 4.75) than those who know they are not at risk ($M = 4.66$, Mdn = 4.75) ($Z = -2.35$, $p = 0.018$). Those who do not live with someone who is at risk report marginally less *Behaviour* ($M = 4.67$, Mdn = 4.75) than those who do ($M = 4.95$, Mdn = 4.75) ($Z = -2.63$, $p = 0.009$) or those who are unsure ($M = 5.20$, Mdn = 5.25) ($Z = -2.51$, $p = 0.012$). We did not find significant differences in *Behaviour* between respondents who had already been infected with COVID-19 and those who had not been infected or did not know, or between infected respondents who had been hospitalised or infected respondents who had not been. However, the lack of a significant difference in the latter comparison is likely due to a very limited sample size. There was also no significant difference in *Behaviour* between respondents who had to go to work or school outside home and those who did not.

Concerning the influence of *Knowledge*, we tested whether correct, incorrect or lack of knowledge for any question was associated with significantly higher *Behaviour* or *Subjective Knowledge*. Overall, *Subjective Knowledge* is very weakly correlated with the number of correct answers ($\rho = 0.24$, $p < 0.001$) and negatively correlated with the number of questions answered with 'don't know' ($\rho = -0.31$, $p < 0.001$). The full analysis can be found on the paper website.

The largest differences both in *Behaviour* and *Subjective Knowledge* can be found for the statement: "The disease could be transmitted from asymptomatic persons." Respondents who answered this correctly reported significantly more *Behaviour* ($M = 4.90$, Mdn = 4.75) than those who answered incorrectly ($M = 3.35$, Mdn = 3.00) ($Z = -3.32$, $p = 0.001$). Those who did not know the answer reported significantly less *Subjective Knowledge* ($M = 3.38$, Mdn = 3.00) than both those who answered incorrectly ($M = 4.57$, Mdn = 5.00) ($Z = -2.77$, $p = 0.006$) and those who answered correctly ($M = 4.15$, Mdn = 4.00) ($Z = -3.36$, $p = 0.001$).

Discussion

While we did not find evidence for all hypothesised paths of our structural equation model, the model performs well in explaining protective behavioural intention and protective behaviour. According to our model, the most important driver of COVID-19 protective behaviour and behavioural intention is a high perceived efficacy of the desired protective behaviour, confirming previous findings both in the context of COVID-19 (Zickfeld et al., 2020) and other pandemics (Bish and Michie, 2010; Kim and Niederdeppe, 2012; Yoo et al., 2016). Interestingly, an emphasis on the efficacy of protective measure was also central in the COVID-19 communication strategy of New Zealand, who, at the time of writing this paper, are among the countries boasting successes in fighting the pandemic (Hunt, 2021).

Although perceived self-efficacy was not a significant predictor of behavioural intention in our model, among all variables analysed in the correlation analysis, it showed the strongest correlation with protective behaviour. For one, this might be due to the different specification of the variables in the correlation analysis. For another, it matches the original conceptualisation of the TPB where *Perceived Behavioural Control*, a variable very similar to perceived self-efficacy, is posited to directly influence not only *Behavioural Intention*, but also *Behaviour* (Ajzen, 1991).

The existing evidence on the role of perceptions of self-efficacy and response efficacy in the determination of protective behaviour is somewhat conflicting (e.g., Al-Rasheed, 2020; Dai et al., 2020). Therefore, while our results indicate the importance of perceived efficacy in the determination of protective behaviour, they also underline the need that the exact influence be further explored. Possible explanations are differences in measurement, or that the influence varies with different types of protective behaviour.

Among perceptions and beliefs about the behavioural response itself, response costs play a subordinate role compared to efficacy belief which matches previous findings (Barakat and Kasemy, 2020). Their influence on behavioural intention is also smaller than that of normative beliefs. Admittedly, except for the restriction of private physical contacts, all behaviours surveyed are relatively easy to implement and therefore low in cost, both monetarily and psychologically. The mean reported response costs are rather low, supporting this assumption. In other contexts, response costs might be perceived to be prohibitive of behaviour, e.g., when implementing a certain behaviour threatens a person's ability to earn an income. This might also explain the previous mixed findings on the influence of response costs on H1N1 protective behaviour (Bish and Michie, 2010).

The two other behavioural predictors in our model are both normative beliefs. Personal moral norm is the second strongest influence after perceived response efficacy. The average perceived susceptibility, i.e., the sense of threat to oneself, is relatively low, while the average perceived severity is high. Therefore, it is plausible that behaviour is more strongly motivated by a sense of responsibility to others or to society in general (Miguel et al., 2021; Pfattheicher et al., 2020). Correspondingly, many of the prominent COVID-19 protective measures, e.g., wearing a mask, do not only or not even primarily protect the person engaging in the measure. Furthermore, if a person feels they are not at risk for a severe infection, they might seek to prevent an infection not for self-preservation, but to not transmit the disease to others. However, these findings are somewhat in conflict with previous findings where the influence of moral normative beliefs was generally weak or non-significant (Ahmad et al., 2020; Nivette et al., 2021). A notable difference between these studies and ours is that the samples questioned are (by design) much younger and the influence of moral beliefs might vary with age. Another possible explanation for the discrepancy are differences in measurement, as moral beliefs might encompass a range of different, possibly conflicting norms. By contrast, in the study by Harper et al. (2020) different moral foundations, i.e., varying facets of morality, where not substantially linked with protective behaviour. In any case, the role of moral beliefs in determining pandemic protective behaviour warrants further research.

Concerning normative pressure by others, descriptive norm, i.e., what kind of behaviour a person observes by others, also positively influences behaviour, though to a lesser extent than all other predictors (Ahmad et al., 2020; Lin et al., 2020). Similar influences have been observed in other pandemics (Bish and Michie, 2010; Kim and Niederdeppe, 2012). From the perspective of both injunctive and descriptive norm being facets of descriptive norm, this reaffirms findings that descriptive norm is a stronger predictor of behaviour than injunctive norm for the behaviours surveyed (Barbera and Ajzen, 2020; Rhodes and Courneya, 2003; Staudenmaier, 2012). By contrast, in their model based on the TPB, Bronfman et al. (2021) found injunctive norm to be the strongest behavioural predictor, overall. The difference might be due to the kind of behaviours measured. Bronfman et al. (2021) surveyed respondents on abstract prevention measures, while in our study, respondents were surveyed on specific behaviours. With this in mind, findings on the importance of subjective norm might be generally less transferable for different kinds of behaviour. Differences might also exist between the specific behaviours examined in our survey: Wearing a mask and using the warning app differ in visibility, therefore, descriptive norms are harder to derive. Further, compared to these two behaviours, the decision whether or not to meet people in private can be influenced much more directly by others.

Although beliefs and perceptions related to threat are major behavioural predictors in many of the theories underlying our model, they showed no influence on behaviour in our model. Still, perceived severity and perceived susceptibility are weakly to moderately correlated with behaviour. This is in line with previous studies that found only a weak relationship between perceived threat and protective behaviour (Barakat and Kasemy, 2020; Dai et al., 2020; Dryhurst et al., 2020; Harper et al., 2020; Qin et al., 2021; Stangier et al., 2021). For one, this might be due to the perceived susceptibility being on average, as discussed, rather low. If the personal threat by COVID-19 is perceived to be larger, it might still influence behavioural intention. In the future, we plan to further explore this in a multi-group analysis. That reported behaviour is, on average, still high even without an influence of threat-related beliefs, might be due to the impact of normative beliefs. As discussed above, respondents seem to be more worried for others than for themselves. By contrast, many of the health threats in the context of which the PMT and HBM were developed, e.g., smoking (Weinstein, 1993), mainly affect the person themselves. COVID-19, on the other hand, seems to be perceived mainly as a threat to others. This is also underlined by the fact that the COVID-19 case incidence at the time of either survey is not substantially correlated with behaviour. All this might indicate that people underestimate their personal risk, which should be further examined. This underestimation of risk might be also a function of time, as findings by Zickfeld et al. (2020) indicate. Qin et al. (2021) did a first longitudinal study on the development of perceived risk, protective behaviour, and the relationship between them, time which spanned spring and summer of 2020. Their results did not indicate a clear trend in a decoupling of risk perceptions and protective behaviour. The results from our survey which took place in early 2021 might indicate, however, that this decoupling takes place later in the progression of the pandemic. Further longitudinal studies on the relationship between risk perception and protective behaviour, as well as studies on the direction of that relationship, might provide more insight on the mechanics of the risk perception-behaviour link.

Further, distrusting beliefs in science are a significant negative predictor for response beliefs. In addition, those distrusting beliefs also strongly and negatively influence behaviour and behavioural intention, implying a direct influence as suggested by previous studies (Al-Rasheed, 2020; Betsch, 2020; Bish and Michie, 2010; Eitze et al., 2021; Nivette et al., 2021; Šuriņa et al., 2021; Travis et al., 2021). Distrusting beliefs are also related to threat beliefs as well as normative beliefs. If a person distrusts science and scientists and, consequently, their assertions and recommendations on COVID-19, this permeates all their beliefs and intentions surrounding COVID-19 and protective behaviour. Concerning the different dimensions of distrusting beliefs, i.e., distrusting beliefs in the benevolence, competence and integrity of science and scientists, model and correlation analysis differed: In the model, integrity contributes least to the higher-order construct and that constructs influence on its descendant endogenous constructs. By contrast, the trust dimensions are related similarly with behaviour and the all model variables are similar in magnitude. Future examinations should explore whether there are significant differences in the influences of these sub-dimensions of trust and distrust, or if this division is obsolete in the context of pandemic protective behavioural research.

The influence of knowledge, at least in the manner measured by us, is more ambivalent, with only a small effect size and path coefficient. This matches the majority of studies only finding a weak influence or no influence at all (Barakat and Kasemy, 2020; Batra et al., 2021; Honarvar et al., 2020; Stangier et al., 2021; Travis et al., 2021; Yíldírím et al., 2021; Zickfeld et al., 2020). In our exploratory analysis, the number of correctly answered questions is weakly correlated not only with behaviour and behavioural intention, but also with most model variables (negatively with distrusting beliefs). Even if knowledge overall does not strongly predict the types of behaviour surveyed in our study, there is a remarkable connection between subjective and actual knowledge. Namely, there is a significant negative correlation between subjective knowledge and the amount of questions answered with 'don't know', but no significant or substantial correlations with the amount of correctly or incorrectly answered questions. This implies that people who are not informed about COVID-19 are better at assessing their knowledge than those who are correctly informed or those who are misinformed. Similar to the climate protective behaviour context (Shi et al., 2016), the influence of knowledge on behaviour might also differ depending on the type of knowledge. For example, people who were misinformed about the possibility of transmission by asymptomatic persons showed significantly less protective behaviour than those who were correctly informed. It would be plausible that actionable knowledge about transmission routes has a larger impact on protective behaviour than knowledge about aspects like, e.g., case mortality, that an individual cannot influence with their behaviour. If so, people holding and acting on incorrect knowledge could have severe and detrimental consequences.

Apart from using the German corona warning app, our respondents reported an overall high level of compliance, mirroring findings from the *COSMO COVID-19 Snapshot Monitoring* project (Betsch, 2021) where compliance has remained stable and high throughout the course of the pandemic. This might not be wholly representative of the actual compliance in the German population due to the moderate validity of self-reported behavioural data (Kimberlin and Winterstein, 2008) as well as self-selection bias of respondents who are even willing to take part in a COVID-19 related survey. However, it also lends support to the assertion that protective measures taken on by individuals are, on their own, insufficient to end the pandemic. Wearing a mask in public, avoiding private contacts and using the tracking app cannot alone stifle an exponential infectious growth while transmission in production sites, offices, and schools is still unchecked (Bedford et al., 2020; Kriegel and Hartmann, 2021).

Further, a disproportionate regulation of private behaviour with a concurrent lack of workplace and school regulation is likely to lead to a further deterioration of trust and an increase in distrust in institutions. While trust in science remains relatively high and stable, a decline of trust in authorities and the government can already be observed (Betsch, 2021). Although our model focused on distrusting beliefs in science and scientists, an increase in distrust concerning authorities is likely to similarly lead to a reduction of compliance with protective measures on the individual level (Idoiaga Mondragon et al., 2021; Michie et al., 2020).

There are some limitations to the generalisability of our findings. As already outlined, self-reported behavioural data is prone to overstatements, especially in a context as strongly affected by normative beliefs as COVID-19 protective behaviour. In addition to the self-selection bias, there is also a selection bias for respondents who are high in technology competence and readily use the internet. This selection bias is also reflected in the fact that older and less-educated people, both groups who are less likely to use the internet (Initiative D21, 2021), are underrepresented in the sample. Further, predictors for COVID-19 protective behaviour might differ in other cultural contexts.

Aside from generalisability, the operationalisation of knowledge might be improved upon. We modelled it as a continuous variable (taking the mean of all knowledge question items with the levels *incorrect*, *don't know* and *correct*). However, results might be more nuanced if one examines each kind of question separately and compares the impact of correct, incorrect or missing knowledge by means of a multi-group analysis instead of modelling it as an exogenous variable.

Lastly, as we did not ask for respondents' migratory background, we were unable to explore the relationship between migratory background, health protective behaviour and COVID-19 risk. Given the cruel juxtaposition that people with a migratory background are likely more compliant with protective measures (Nivette et al., 2021; Valsecchi and Durante, 2021) and, at the same time, at increased risk of COVID-19 (Hayward et al., 2021), this is an important topic that future work should explore further.

Overall, even though not all hypothesised paths in our model could be supported, it still has moderate explanatory power. More important, the beliefs included in our model predict behavioural intention and behaviour considerably better than the alternate factors examined in our exploratory analysis. For example, contrary to previous studies (Barakat and Kasemy, 2020; Betsch, 2020; Coroiu et al., 2020; Travis et al., 2021; Yíldírím et al., 2021), we could not find a significant relationship between behaviour and either gender or age. Furthermore, we did not find substantial significant relationships between behaviour and personality traits, or between behaviour and a person's personal experience with COVID-19.

Based on our findings, we propose that communication aimed at improving behavioural compliance with COVID-19 protective measures should emphasise the efficacy and effectiveness of proposed measures as well as imposed rules and restrictions. Furthermore, appeals should aim to activate normative moral beliefs and foster a sense of empowerment concerning one's ability to protect others. Concerning the role of fear, it might be necessary to examine whether people tend to underestimate their own risk for an infection or severe consequences of an infection. If so, communication should aim to illustrate the actual risk for different sections of the population.

Data availability

The data used to estimate the model is available in an OSF repository: https://osf.io/kt9wp/.

Code availability

The full code for all analyses is available at GitHub: https://github.com/digitalemuendigkeit/covid-19-behavior-sem.

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Author contributions

All authors designed the theoretical model and planned and conducted the survey. LK analysed the results and estimated the models. LK and LB drafted the manuscript. ACV and LK prepared the supplementary website and the OSF and GitHub repositories. All authors revised and reviewed the manuscript.

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Competing interests

The authors declare no competing interests.

Ethical approval

For our survey, we have obtained ethical approval from the empirical social research ethics committee of the RWTH Aachen University philosophical faculty (ethics approval number: 2020_023_FB7_RWTHAACHEN). All research was performed in accordance with the relevant guidelines and regulations and in accordance with the Declaration of Helsinki.

Informed consent

All participants were informed about the purpose of the study as well as the ways the data would be used and were required to consent to participate in the study.

Additional information

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