# Predicting attitudinal and behavioral responses to COVID-19 pandemic using machine learning

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Research Report

# Predicting attitudinal and behavioral responses to COVID-19 pandemic using machine learning

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## Abstract

At the beginning of 2020, COVID-19 became a global problem. Despite all the efforts to emphasize the relevance of preventive measures, not everyone adhered to them. Thus, learning more about the characteristics determining attitudinal and behavioral responses to the pandemic is crucial to improving future interventions. In this study, we applied machine learning on the multinational data collected by the International Collaboration on the Social and Moral Psychology of COVID-19 ($N = 51,404$) to test the predictive efficacy of constructs from social, moral, cognitive, and personality psychology, as well as socio-demographic factors, in the attitudinal and behavioral responses to the pandemic. The results point to several valuable insights. Internalized moral identity provided the most consistent predictive contribution—individuals perceiving moral traits as central to their self-concept reported higher adherence to preventive measures. Similar results were found for morality as cooperation, symbolized moral identity, self-control, open-mindedness, and collective narcissism, while the inverse relationship was evident for the endorsement of conspiracy theories. However, we also found a non-neglible variability in the explained variance and predictive contributions with respect to macro-level factors such as the pandemic stage or cultural region. Overall, the results underscore the importance of morality-related and contextual factors in understanding adherence to public health recommendations during the pandemic.

**Keywords:** COVID-19, social distancing, hygiene, policy support, public health measures

### Significance Statement:

Outcomes of this study suggest that morality-related factors, along with prosociality and individual characteristics related to information processing and self-control, play an important role in determining attitudinal and behavioral responses to the COVID-19 pandemic. However, a substantial variation in the predictive contribution of included variables was observed. Therefore, the role of context (both in terms of culture and stage of the pandemic) should not be underestimated. Nevertheless, this study highlighted multiple factors relevant to the prevention of COVID-19 in different stages of the pandemic and cultures, which makes it a good starting point for more complex and causal research designs.

## Introduction

The COVID-19 pandemic has caused significant loss of life, commodities, jobs, and disruption of communities worldwide. As of March 2022, over 450 million infections and more than 6 million deaths have been reported globally (1). As we write this paper, the daily number of new cases worldwide exceeds one million. Given the lack of vaccination and treatment options, controlling the spread of the SARS-CoV-2 virus in its early stages depended on preventive behaviors, such as physical distancing (2) or hand and object disinfection (3, 4). While governments across the globe rushed to implement the proposed measures, many citizens resisted such change (5, 6). This is indicative of the vital role of individual characteristics in the form of attitudes, abilities, traits, and perceptions in compliance with preventive measures. Thus, decision-makers may benefit from insights from the social and behavioral sciences that could explain who will adhere to or ignore advised measures (7).

Furthermore, nations vary in the strictness of preventive measures enacted by local governments and the severity of the consequences of COVID-19: some countries report more than 100 deaths (e.g. Croatia and the UK), while others count less than one death (e.g. Bhutan and China) per 100,000 citizens (8). A recent cross-national analysis suggests that many of these excess deaths in countries like the United States are the result of weak public health infrastructure and a decentralized, inconsistent response to the pandemic (9). This raises questions of how macro-level cultural variables might be associated with citizens' health attitudes and behaviors across nations.

The scientific community responded with numerous international research collaborations aimed at explaining adherence to preventive measures from different perspectives. One group of researchers (10) focused on cultural dimensions, self-awareness emotions, trust in governmental actions, and political orientation as predictors of compliance in the United States, Italy, and Korea. They found that horizontal collectivism was the only predictor of compliance significant in all three countries. Similarly, other scholars (11) identified collectivism's role in promoting preventive behaviors. In terms of adherence to preventive measures, prosocial tendencies emerged as a significant positive predictor, while perceiving others as violating preventive measures was the most consistent negative predictor (12). Results from another study across 70 countries showed that trust in government, conscientiousness, and agreeableness predicted engaging in preventive measures, with other variables having a negligible practical impact (13). As research accumulates, interpreting and integrating findings from diverse research streams with a variety of measures and samples presents another challenge for both scholars and practitioners.

Due to their freedom of theoretical constraints, data-driven approaches might offer solutions to "grand challenges" of existing theories, defined as complex problems with intertwined and evolving underlying mechanisms (14) as they allow the effective use of highly dimensional data (15). For instance, network analysis was used on data from the UK and the Netherlands to explore the relationship between multiple constructs relevant for COVID-19 attitudes and behaviors (16). The perceived level of adherence to norms and efficacy of preventive measures and support for these measures exhibited the strongest relationships with COVID-19 preventive behaviors. On the other hand, applying random forests on more than 100 potentially relevant variables established different descriptive and injunctive norms and prosociality as some of the most relevant predictors of behaviors (17). Overall, the relevance of prosociality and collectivism, both of which imply a willingness to make sacrifices for the benefit of the community, has been emphasized throughout the literature (10–12, 17–19). However, this does not eliminate the role of other individual differences and capacities in adherence to preventive measures (13, 17).

Our study expands on and contributes to the existing literature in three important ways. Firstly, we brought together a diverse team of experts to select several key constructs from social, moral, cognitive, and personality psychology that might be relevant to supporting public health recommendations. Despite a proliferation of studies on predictors of attitudinal and behavioral responses to the COVID-19 pandemic (see, for example, (20)), research in this field is still warranted. Hence, we sought to investigate attitudinal and behavioral responses in the first pandemic wave, when uncertainty regarding the spread of the virus dominated societies. In conjunction with the existing findings, our study provides valuable evidence which can be utilized to compare pandemic responses from different time points during the pandemic. Moreover, we sought to statistically test the association between the three related but distinct outcomes—maintaining physical hygiene, avoiding physical contact, and supporting governmental policies related to COVID-19. This distinguishes our approach from prior research that employed a general factor of preventive behaviors as it allowed us to gain insights both into attitudinal and behavioral responses to the measures aimed at mitigating the spread of the virus. Second, we consider potential cultural differences in the meaning of the studied constructs by establishing equivalence of factor scores through (partial) strong invariance (see (21)). Finally, to determine the efficacy of our independent variables in explaining contact avoidance, hygiene maintenance, and COVID-19 policy support in each country, we applied random forest-based regression algorithms appropriate for complex data sets with possible nonlinear and interactive relationships between variables (22, 23).

## Overview

We focused on two specific research questions utilizing a large international sample of 51,404 participants from 69 countries from all continents except Antarctica. First, we tested how precisely (in terms of the explained variance) avoiding contact, maintaining hygiene, and policy support could be predicted using a combination of variables from moral, social, personality, and cognitive psychology, as well as socio-demographic variables. Second, we tested which of the included variables provided a substantial contribution to the accuracy of our predictions. Descriptions of the expected effects (of all study variables) based on theories or earlier studies are available as Supplementary Materials A.(All supplementary files can be found online in the following OSF folder: https://osf.io/cvkyr/?view_only=c88c0431224c4f878750875e599d2983.) Additionally, to evaluate the robustness of our findings, we conducted additional analyses that took cultural differences and the pandemic stage during data collection into account.

## Materials and Methods

### International collaboration on the social and moral psychology of COVID-19 project

The aim of the International Collaboration on the Social and Moral Psychology of COVID-19 (ICSMP COVID-19) project is to examine and understand psychological factors related to the COVID-19 pandemic response. We launched the project in April 2020 via a social media call for national teams that could collect samples in their own country. Over 230 scholars responded to the call. The main questionnaire, created in English, was disseminated to each national team, responsible for translating it to their local language (using the standard forward–backwards method). Each team collected the data in their own country. The resulting datasets were then collated and analyzed altogether, and are available online (19, 24). The study received an umbrella ethics approval from the University of Kent.

## Participants

The analyzed sample consisted of 51,404 participants from 69 countries and territories, 25 of which collected samples representative of their respective nations regarding age and gender ($n = 22{,}064$). The remaining data were drawn from convenience samples. Following exclusion criteria set for the purposes of this study (we excluded participants providing inaccurate response to the attention check, participants who did not provide responses to more than one quarter of items, participants providing the same response more than ten times in a row on the items of our predictors, participants who chose "other" as their gender* and participants completing the questionnaire unusually fast or unusually slow, see Supplementary Materials B and C), 7,615 participants were removed, resulting in a sample of 43,789 ($M_{age} = 43$, $SD_{age} = 16$; 52% females) participants for our analyses (The number of participants who chose "other" as their gender was too low in the context of planned analyses).

## Measures

Unless otherwise indicated, participants responded on an 11-point scale with higher values indicating higher levels of the measured concepts (after reversing the appropriate items). Prior to conducting analyses that presumed grouping of participants, we achieved partial strong invariance for all of the included multi-item scales. This was important to ensure that we measured the same constructs with similar efficacy in each group (see (21)). Detailed output on how the fit was achieved can be found in Supplementary Material C.

### *Individual-level variables*

#### Criteria

Avoidance of physical contact during the coronavirus (COVID-19) pandemic was measured via five items. Adequate fit (CFI = 0.979, RMSEA (95% CI upper limit) = 0.086, SRMR = 0.024, and $\omega 2 = 0.69$) was achieved after correlating the residuals of the last two items (keeping distance and avoiding handshakes).

Maintaining physical hygiene was measured via five items related to washing hands and other behaviors related to personal hygiene. A single factor structure was retained (CFI = 0.999, RMSEA (95% CI upper limit) = 0.037, SRMR = 0.007, and $\omega 2 = 0.74$) with correlated residuals of the first two items (washing hands longer and more thoroughly).

Support for COVID-19-related policy decisions was measured with five items relating to restrictive policies affecting five areas of everyday life. A single factor structure was retained (CFI = 0.989, RMSEA (95% CI upper limit) = 0.098, SRMR = 0.016, and $\omega 2 = 0.86$) after correlating residuals of support for forbidding public gatherings and unnecessary travel, and closing parks.

### *Predictors*

#### Morality

Moral identity was measured using the 10-item moral identity scale (25). The original paper reports a two-factor model (Internalization and Symbolization), with acceptable internal consistency. The two-factor structure was confirmed in our study after correlating residuals of items 8 and 9, and 4 and 7 (CFI = 0.939, RMSEA (95% CI upper limit) = 0.084, SRMR = 0.067, $\omega 2_{\text{internalization}} = 0.68$, and $\omega 2_{\text{symbolization}} = 0.75$).

The moral circle scale (26) assesses the moral expansiveness across 16 different entities (human and nonhuman) deemed worthy of moral concern. Participants indicated the extent of their moral circle, i.e. the circle for which they are concerned about right and wrong done towards them, ranging from immediate family to all things in existence.

Morality as cooperation was measured using the Relevance subscale of the Morality-as-Cooperation Questionnaire (MAC-Q; (27)), which measures the extent to which each of the seven dimensions of cooperation is relevant when making moral judgments. One item per each of its seven dimensions was used in this study. After excluding the items of fairness and property and correlating residuals between *helping a family member* and *showing courage* and *helping a family member* and *uniting a community*, a general factor of the relevance of cooperation in morality (CFI = 0.991, RMSEA (95% CI upper limit) = 0.066, SRMR = 0.014, and $\omega 2 = 0.73$) was extracted.

#### (Pro)social identification and attitudes

National identity was assessed with two items combined into a scale: "I identify as [nationality]" (28) and "Being a [nationality] is an important reflection of who I am" (see (29)). The correlation among items was $r = 0.69$, and a single score was extracted using PAF.

Social belonging was measured using a four-item single-factor scale with excellent internal consistency (30). A single factor structure (CFI = 0.988, RMSEA (95% CI upper limit) = 0.115, SRMR = 0.017, and $\omega 2 = 0.78$) was confirmed in this study after correlating the residuals between first and third item.

Collective (national) narcissism was measured using three items of the original, single-factor Collective Narcissism scale (31). Invariance of this scale was tested along with the endorsement of COVID-19 conspiracy theories (32), which was measured using a single item for a denial conspiracy and three items for deflection conspiracies (e.g. "a hoax invented by interest groups for financial gains"). The three items related to collective narcissism and the four items related to belief in conspiracy theories were modeled together and yielded a clear two-factor structure (CFI = 0.988, RMSEA (95% CI upper limit) = 0.069, SRMR = 0.021, $\omega 2_{\text{Conspiracies}} = 0.92$, and $\omega 2_{\text{Collective narcissism}} = 0.87$).

Political orientation was measured using a single item, "Overall, what would be the best description of your political views?," on a scale ranging from very left-leaning ("0") to very right-leaning ("10").

COVID-19 risk perception was measured with two items asking participants to rate how likely it was for them and for the average person to get infected with COVID-19 by 2021 April 30, on a slider scale ranging from 0 ("impossible") to 100 ("certain"). Based on their high correlation ($r = 0.66$), a single component was extracted using PAF.

### Individual dispositions

Individual grandiose narcissism was measured using the brief version of the Narcissistic Admiration and Rivalry Questionnaire (33), comprising two subcomponents, rivalry (R) and admiration (A), which exhibited acceptable internal consistency. The scale achieved acceptable fit after correlating residuals between items 3 and 6 reflecting rivalry (CFI = 0.986, RMSEA (95% CI upper limit) = 0.068, SRMR = 0.020, $\omega 2 = 0.69$ for admiration, and $\omega 2 = 0.55$ for rivalry).

Trait self-control was measured as a single-factor four-item scale (34), with the last two items being negatively worded. However, an adequate fit was not obtained even after correlating residuals of the first two items (CFI = 0.988, RMSEA (95% CI upper limit) = 0.115, SRMR = 0.017, and $\omega^2 = 0.78$).

Self-esteem was measured using the Single-Item Self-Esteem-Scale (SISE), which achieved good test–retest reliability and was established as a viable alternative of longer self-esteem scales (35).

Trait optimism was measured using two items from the three-item optimism subscale of the Life Orientation Test-Revised (36). Based on their high correlation ($r = 0.71$), a single factor was retrieved using PAF.

Open-mindedness, reflecting the acceptance of limitation of one's knowledge and willingness to gain new knowledge, was measured with a six-item scale of the Multidimensional measure of intellectual humility (37). The originally proposed single-factor structure achieved an acceptable fit in our study (CFI = 0.998, RMSEA (95% CI upper limit) = 0.025, and SRMR = 0.007) and was retained. It exhibited questionable internal consistency ($\omega 2 = 0.50$).

Cognitive reflection was measured with a three-item test that measures the ability to inhibit intuitive answers and engage in reflection to provide correct ones, adapted from Frederick (38). Correct answers were coded as "1" and incorrect as "0," with a total scale ranging from 0 to 3.

### Demographic factors and experiences

The MacArthur Scale of Subjective Social Status (39) was used to measure subjective socio-economic status by asking participants to place themselves on an 11-rung ladder, with the top rung representing individuals who are best off (in terms of education, jobs, and wealth), and the bottom rung the ones worst off.

Participants were asked whether they had (coded as "1") tested positive for COVID-19 and/or had a close relative or acquaintance (friend, partner, family, colleague, and so on) who had tested positive for COVID-19 ("1") or not ("0") by the time of data collection.

Multiple demographic factors were also collected. Participants were asked to indicate whether they identify as "male," "female," or "other" and enter their age (in years). Additionally, participants' marital status had the following three options: married, single, in a relationship (recoded into married or in a relationship ("1") or other ("0")), after which they indicated the number of children they had. Participants were also asked to indicate their employment status (recoded into the employed, students, or retired ("1") or other ("0")). Finally, participants indicated whether they lived in an urban (coded as "1") or rural setting (coded as "0").

## Analytical procedure

This study was not preregistered. Our analytical approach consisted of multiple steps (see Supplementary Materials B–F) conducted in R (40). A detailed description of data cleaning is presented in Supplementary Material B, while used packages are listed at the beginning of every Supplementary Material in which they were used.

The psychometric properties of the applied measures were tested on the imputed data (see Supplementary Material C). We focused on testing the applied measures' factor structure and internal consistency. As the majority of the multi-item measures were taken from previously validated instruments, CFAs with robust maximum likelihood estimator (MLR; (41, 42)) and countries as clusters were applied using lavaan (43) to test whether the proposed structures fit to the overall data. Modification indices were consulted when theoretical models did not fit the data well.

We tested whether the obtained results were stable concerning the pandemic stage during data collection. In the absence of any specific criterion, we initially attempted to group countries according to the total number of COVID-19 cases per million inhabitants during the period of data collection, calculated as the average of the number of cases per million at the start date of data collection and the number of new cases per million at the end date of data collection.(https://github.com/CSSEGISandData/COVID-19.) In samples where only one date was provided, we used the available information for that date. However, we noticed an unwanted regularity in the grouping process—most countries with the total number of cases above the median were European countries, and no countries from Africa were in this group. Thus, to minimize potential cultural biases, we grouped the countries according to the Inglehart–Welzel cultural map (44) and selected the countries with the lowest and highest total number of cases per million from each cultural region (Orthodox European countries, Protestant European countries, Catholic European countries, English-Speaking countries, West and South Asian countries, Confucian countries, African–Islamic countries, and Latin American countries) as representative. This resulted in a group of countries in the early stage of the pandemic consisting of participants from Nigeria, Slovakia, Australia, Bulgaria, the Philippines, and Nepal. On the other hand, a group of countries in the advanced pandemic stage included participants from United Arab Emirates, Spain, Ireland, Serbia, Brazil, and Singapore. Regarding Latin American countries, we considered only countries with more than 150 participants as candidates, while no Protestant European countries were included due to all of them being in the advanced stage of the pandemic during the data collection period (with a total number of citizens infected per million exceeding 1,000). Our two groups were highly distinctive with respect to the total number of cases per million during the data collection ($M_{\text{early stage}} = 154.14$; $M_{\text{advanced stage}} = 3520.87$). In our attempt to further balance the analysis, we randomly selected the same number of participants from each selected country, equal to the size of the smallest included sample after the data cleaning ($n_{\text{UAE}} = 176$).

Then, we checked the cross-group invariance of our multi-item measures.(We also conducted analyses with groups reflecting regions of the Inglehart–Welzel cultural map (2020), which followed the described procedure. Due to space limitations, outputs of these analyses can be found in Supplementary Materials G.) After achieving an adequate fit by introducing changes suggested by modification indices, the cross-group invariance of each obtained theoretical model was tested. Stepwise tests were further conducted. First, configural models were formed for each construct, followed by models with constrained item loadings to test weak invariance, and ultimately models with constrained item loadings and intercepts to test strong invariance. If the configural model achieved adequate fit, successive changes in fit indices with respect to imposing restriction were used as a criterion for invariance. A CFI change of −0.015 accompanied by a change in RMSEA or SRMR of +0.015 was considered as an indication of achieving a higher level of invariance. If invariance was not achieved on the first attempt, modification indices were consulted to achieve partial invariance. Finally, we extracted factor scores from models reflecting strong invariance (where loadings and intercepts were constrained to form comparable scores across countries) using the ten Berge correction to use them in further analyses.

Because two-item measures cannot be tested using CFA, factor analyses using principal axis factoring were conducted to extract latent dimensions. In line with the factor scores based on strong invariance, the analyses were conducted on the entire dataset used in a specific analysis.

Socio-demographic characteristics and moral circle were not scaled. Variables absent from a specific national data set were replaced with a constant (i.e. the number of children in the Ghanaian data set was set to median of other countries, while the residence data was coded as urban for participants from Canada and Bulgaria).

The rest of the procedure was similar to the procedure applied by Van Lissa et al. (17). After data preparations, random forests were applied. Ranger function (45) was used to apply random forests that served as a basis for partial dependence plots and permutation importance metrics (see (46)), which were used to interpret the relationships (see Supplementary Material D). Regarding the hyperparameters, the number of trees was set to 1,000 and 2,000, $R^2$ was chosen as the accuracy metric, permutation importance metrics were extracted as estimated variable importance, the number of variables to test at each split ranged from five to twenty with an increment of one, splitting was based on variance, while the minimum node sizes ranged from 3 to 99 with an increment of three. Holdout sample was used to ensure the robustness of findings: 20% of the sample from each country formed a test set on which $R^2$ and variable importance metrics (see Supplementary Materials E and F) were calculated.

## Results

Obtained $R^2$ values of optimally tuned models were of weak to moderate magnitude both on the complete data ($R^2_{\text{contact}} = 0.134$, $R^2_{\text{hygiene}} = 0.200$, and $R^2_{\text{policy}} = 0.146$) and data consisting of samples nationally representative regarding age and gender ($R^2_{\text{contact}} = 0.172$, $R^2_{\text{hygiene}} = 0.256$, and $R^2_{\text{policy}} = 0.124$). In the early stage of the pandemic, prediction of contact avoidance was negligible ($R^2_{\text{contact}} = 0.045$, $R^2_{\text{hygiene}} = 0.272$, and $R^2_{\text{policy}} = 0.138$). On the other hand, in the advanced stage of the pandemic, our models led to a very imprecise prediction of maintaining hygiene ($R^2_{\text{contact}} = 0.129$, $R^2_{\text{hygiene}} = -0.043$, $R^2_{\text{policy}} = 0.173$). Therefore, we decided not to interpret the predictive contributions in models with maintaining hygiene as the criterion on the sample reflecting the advanced stage of the pandemic. Nevertheless, they are presented in the following paragraphs.

Results in Fig. 1 show the importance metrics based on the models that yielded the highest $R^2$ per analysis. As permutation importance reflects a reduction in error, these plots are not directly comparable. However, some common patterns can be observed.

In terms of avoiding contact (Fig. 2), internalized moral identity provided the most consistent contribution across analyses, followed by open-mindedness, collective narcissism, morality as cooperation, symbolized moral identity, and self-control. Endorsement of conspiracy theories seems to have exhibited a stronger relationship with our criteria in the early stage of the pandemic than in the advanced stage. In general, participants achieving higher scores on avoiding contact also achieved higher scores on internalized moral identity, morality as cooperation, self-control, and open-mindedness, respectively. These participants also exhibited lower endorsement of conspiracy theories. Regarding collective narcissism and symbolized moral identity, it seems that the individuals scoring around the midpoint reported higher contact avoidance compared to individuals scoring high and those scoring low on the scale.

Regarding hygiene maintenance (Fig. 3), the most invariable contribution was found for social belonging and morality as cooperation, followed by internalized and symbolized moral identity, collective narcissism, and self-control. Gender differences in hygiene maintenance found on the complete data and data based on representative samples were not detected in data organized according to the stage of pandemic. Participants scoring higher on social belonging, internalized and symbolized moral identity, collective narcissism, and self-control also scored higher on maintaining hygiene. However, only the relationship between belonging and hygiene maintenance seemed linear—all other lines reached a plateau at some point (usually around the midpoint), indicating participants achieving the lowest scores on these factors also achieved the lowest scores on maintaining hygiene. On the other hand, higher scores were related to higher reported hygiene maintenance among participants scoring above the mean of morality as cooperation.

The most invariable predictors of policy support (Fig. 4) were collective narcissism, internalized moral identity, and self-control. Endorsement of conspiracy theories, symbolized moral identity, possibly even morality as cooperation, and open-mindedness, seem to have exhibited a stronger relationship with policy support in the early stages of the pandemic compared to the advanced stage. Participants scoring higher on internalized moral identity and self-control generally were also more supportive of policy measures. However, the relationships were not linear in the early pandemic stage (and in the advanced stage in the context of self-control). The relationship between policy support and collective narcissism was also complex—it was close to linear and positive in the advanced pandemic stage, but in the early stages and on the complete data, it resembled an inverted-U-curve with a peak around the mean. This indicates that participants scoring around the mean were most supportive of restrictive policies, while those high and the ones low on collective narcissism were less supportive. Participants showing more endorsement for COVID-19 conspiracy theories were less supportive, while participants scoring higher on open-mindedness were more supportive of restrictive COVID-19 policies. The relationship between morality as cooperation and policy support was established only on the complete data and indicated that only among those above the mean higher morality as cooperation was related to higher policy support. The opposite was found for symbolized moral identity—only among those lowest on this trait, the relationship between morality as cooperation and policy support was linear and positive. No relationships were established around the mean or above the mean.

## Discussion

Taking the machine learning approach, we provided several insights into social, psychological, personality, and cognitive factors in predicting COVID-19 responses. Although the nature of the

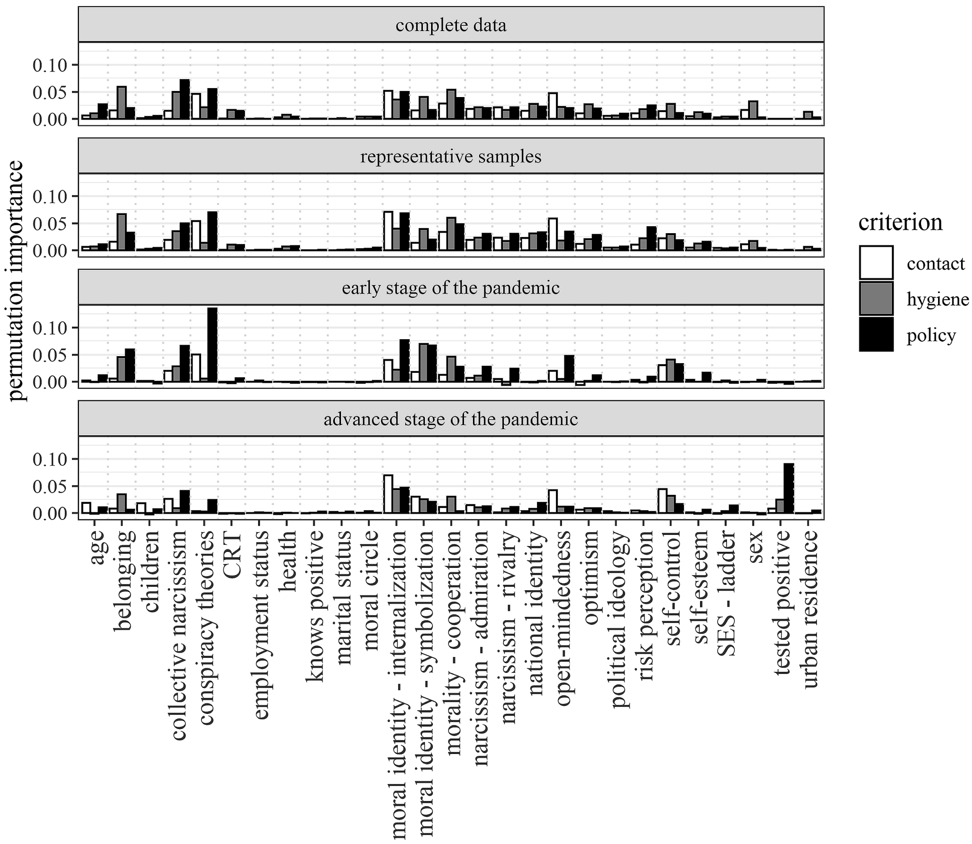


**Fig. 1.** Permutation variable importance calculated with respect to representativeness of the samples and stage of the pandemic.

analyses (i.e. the dependence of importance estimates on error estimates, which changes across models) prevents us from direct comparisons of results across models, some consistent patterns were observed.

Internalized moral identity was the most consistent predictor of COVID-19 attitudinal and behavioral responses—the extent to which people perceived moral traits as central to their self-concept was positively associated with their intentions to avoid physical contact, maintain hygiene, and support policy measures aimed at mitigating the spread of the virus. Morality-as-Cooperation was also associated with the attitudinal and behavioral responses, most consistently in predicting hygiene maintenance. These results suggest that maintaining hygiene, but also physical distancing and policy support, were perceived as collective actions that benefit the group more than they benefit the self. Symbolized moral identity was also associated with the criteria, but, interestingly, the relationship was nonlinear and strongest among participants scoring below the average of symbolized moral identity. These findings may reflect the fact that individuals characterized by moderate or high symbolization of moral identity prefer to be perceived as aligned with social norms, rather than actually adhering to them (47). However, the threshold at which the relationship becomes linear seems to change with respect to the pandemic stage and specific criteria, indicating the need for further research into these relationships.

Overall, these findings are in line with previous research suggesting that internalized moral identity is a relevant predictor of prosocial and cooperative intentions and behavior, with more inconsistent results when examining the symbolization dimension of moral identity (for a review, see (47, 48)). The only variable related to morality that did not substantially contribute to our criteria's prediction was the moral circle. Altogether, these results indicate that morality represents an important factor in adherence to preventive measures. Nevertheless, different aspects of morality provide different contributions to the prediction of adherence to these measures.

Open-mindedness and self-control were positively associated with avoiding contact and supporting policy, while self-control also exhibited a relatively steady, albeit weak, contribution to the prediction of hygiene maintenance. Open-mindedness was conceptualized as a part of cognitive humility, which reflects the virtue of being able to accept one's fallibility and the willingness to accept information contrary to one's initial beliefs (37, 49), with some authors treating it as a moral virtue (50, 51). Self-control is typically conceptualized as the capacity to work effectively to reach goals, resisting short-term temptations (34, 52). Some authors have suggested that self-control goals are often moralized (53). The relationship between open-mindedness and morality and between self-control and morality may underlie the predictive contribution of open-mindedness and self-control established in this study.

Social belonging was also established as a relevant predictor predominantly in terms of maintaining hygiene, while collective narcissism also provided a substantial contribution to predicting policy support and a less substantial contribution to predicting contact avoidance. On the one hand, ingroup identification promotes acceptance of group norms (54), implying that findings on social belonging could also reflect morality. On the other hand, the relationship between collective narcissism and our criteria seems to be more complex, in line with the mixed evidence of

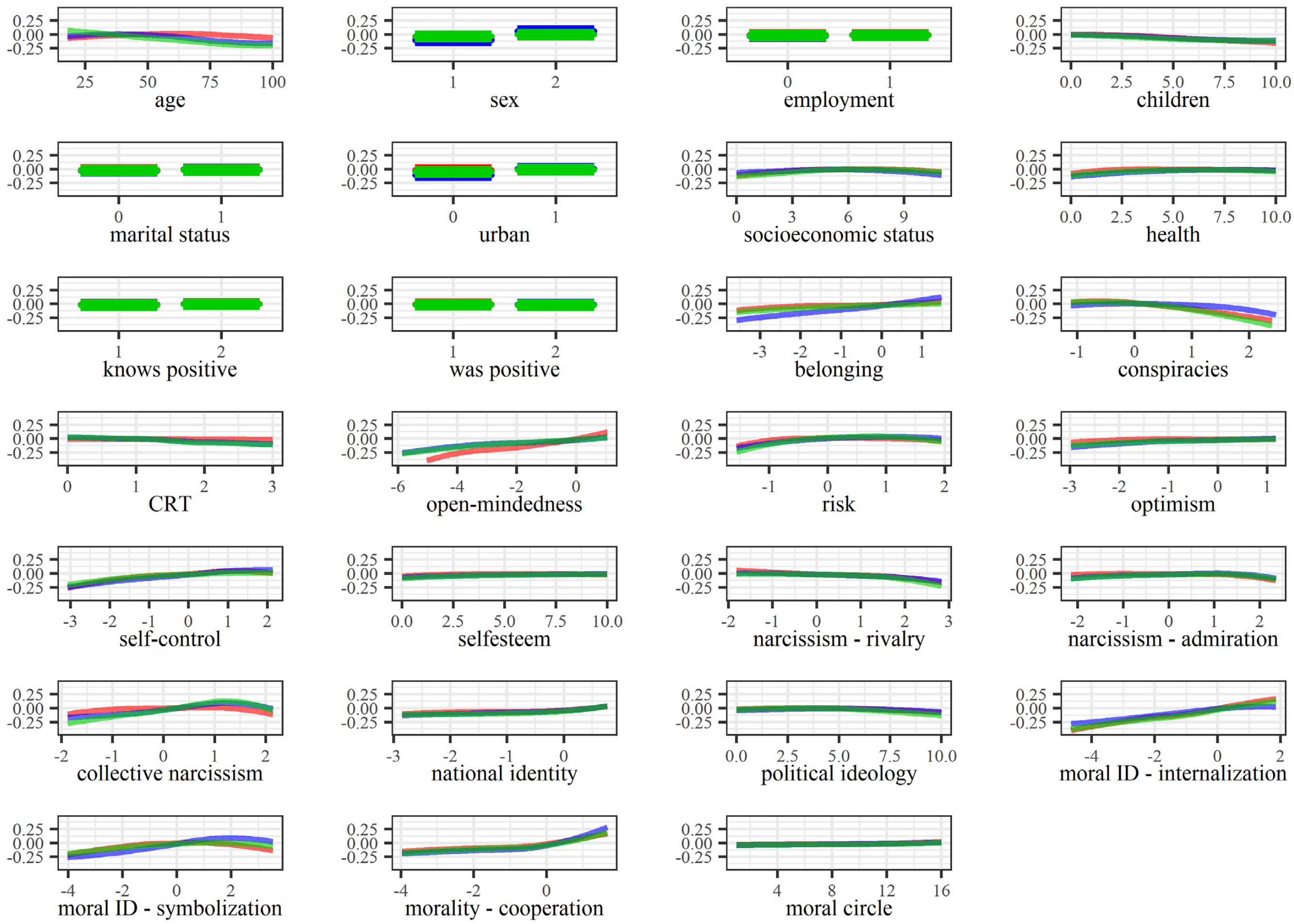


**Fig. 2.** Partial dependence plots depicting the relationships between our predictors and criteria based on the complete data.
Note: red, blue, and green represent avoiding contact, maintaining hygiene, and policy support, respectively.

previous studies on the role of collective narcissism concerning various types of preventive behaviors such as handwashing, physical distancing, and limiting leaving home (32, 55). Namely, the evidence of a curvilinear relationship between collective narcissism and contact avoidance and policy support might reflect the need of individuals high in collective narcissism to establish and maintain a positive national image for the outside world (e.g. as model citizens, or morally superior) (56, 57). However, at even higher levels of collective narcissism, the need to assert and signal grandiosity and superiority in relation to various threats (in this case, the virus) might manifest in lower support for restrictive preventive measures, even at the cost of possible negative consequences for ingroup members (58, 59). This is also evident from the inverted-U curve in the context of policy support, usually appearing slightly above the mean (except in the late stage of the pandemic, see Figs. 2 and 3). Overall, this suggests that while believing in ingroup potential may motivate individuals to adhere to prosocial norms, irrational belief in superiority can undermine the support for preventive measures that bring about short-term disturbance in the everyday ingroup dynamics.

Additionally, conspiracy beliefs seem to be linked to contact avoidance and policy support, especially in the early stage of the pandemic. Namely, endorsement of COVID-19 conspiracy theories was associated with lower intentions to engage in physical distancing and lower policy support. Given that conspiracy believers were found to be more self-centered (60) and less generous (61) during the COVID-19 pandemic, this finding speaks in favor of viewing contact avoidance as a form of prosocial action.

The presented findings suggest that prosociality and morality are relevant factors for understanding physical distancing. This is in line with previous work on the role of prosociality on physical distancing (e.g. (10, 12, 17); see (18) for a review) and with the idea that personal norms, internal standards on what is right or wrong in a given situation, play an important role in driving prosocial behavior ((62, 63); see (64), for a review). However, our results indicated a substantial contextual variability, as well. While we focused on several most dependable and most substantial predictors only to describe general patterns, it should be noted that multiple other factors provided a contribution limited to a specific stage of the pandemic or specific culture (see Supplementary Materials G). This also implies that campaigns for increasing compliance with preventive measures in future crises should be tailored to both the pandemic phase and the specifics of the culture in which they plan to be implemented. Additionally, the results of our study suggest that psychological factors are more relevant than demographics in the context of health-related crises and should not be neglected when tailoring preventive measures.

Generally, the obtained $R^2$ values were lower than those reported by Van Lissa et al. (17) in similar analyses. In their study, injunctive norms and support for COVID-19 restrictive measures

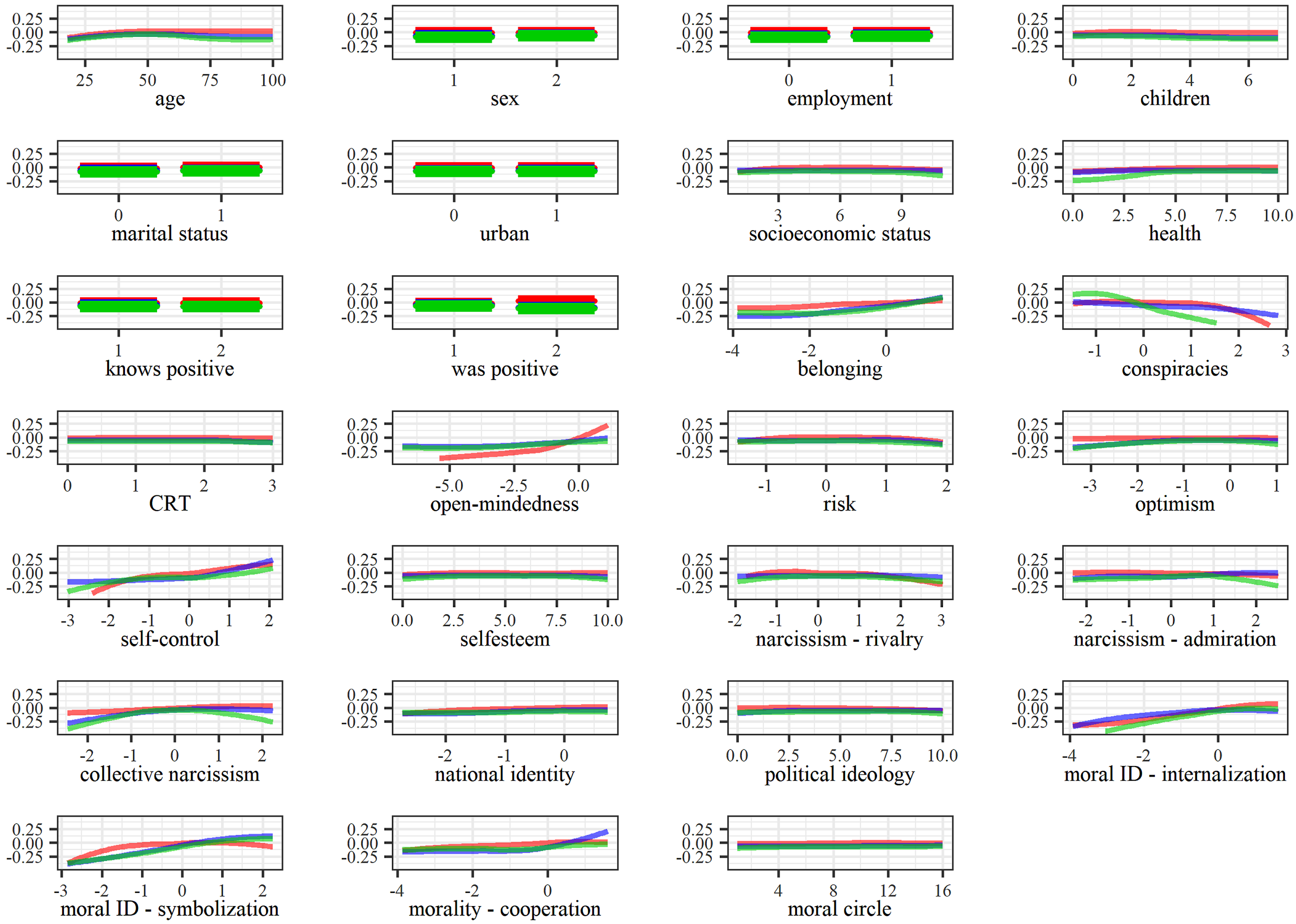


**Fig. 3.** Partial dependence plots based on the data reflecting the early stage of pandemic.
Note: red, blue, and green represent avoiding contact, maintaining hygiene, and policy support, respectively.

were found to be two clearly dominant predictors of preventive behaviors, which may roughly approximate two aspects of the Theory of Planned Behavior (65)—subjective norms and attitudes on the specific behavior. We did not include these variables in our study, although policy support could broadly be considered as attitudes regarding preventive measures. Conversely, we treated policy support as one of the criteria rather than as one of the predictors, with contact avoidance, hygiene maintenance, and policy support being moderately correlated ($r$ = approx. 0.40). Thus, the simplest explanation of the difference in the explained variance in our study compared to Van Lissa et al. (17) may reflect the difference in the extent to which the Theory of Planned Behavior has been represented among predictors. Considered together, the two studies provide evidence in favor of the Theory of Planned Behavior in the context of a global crisis.

Several limitations should be considered when interpreting our findings. First, not all the national samples were representative, and even the representative samples were not based on probabilistic sampling, and consequently, some segments of society may have been underrepresented. Furthermore, as the study was conducted online, our sample over-represents people with greater access to internet-enabled technology, which may be a particularly important consideration in less-developed countries (e.g. dissemination of conspiracy theories and fake news). Second, variability in our criteria was heavily skewed in many countries (i.e. the vast majority of participants reported high adherence to and support for preventive measures), which can be attributed to the first wave of the pandemic during which the data were collected. Nevertheless, in some countries, data collection was conducted during the peak of the first wave of the COVID-19 pandemic, while in other countries, it was carried out at its beginning. Although we tried to operationalize the pandemic stage according to the total number of infected individuals per million and took culture and sample size into account, even such operationalization may not have eliminated all the potential sources of bias. The rough similarity of the results based on representative and nonrepresentative data, as well as data from countries in different pandemic stages and data from countries grouped according to cultural zones (see Supplementary Materials G), provide arguments in favor of the validity of our findings; nevertheless, the robustness of these more specific findings needs to be corroborated utilizing different (i.e. longitudinal and nationally representative) samples. Furthermore, Morality-as-Cooperation had to be modeled differently than proposed in the original papers to achieve invariance. Additionally, as there are no conventional methods of testing the invariance of two-item and single-item measures across cultures, scores on such items may be less precisely calculated than in the case of multi-item measures. Finally, we focused on explaining variation in COVID-19 responses without testing causality. It should be noted that we used cross-sectional, self-reported data which may entail the desirability bias risk (66). However, there is evidence that such desirability bias does not play a key role,

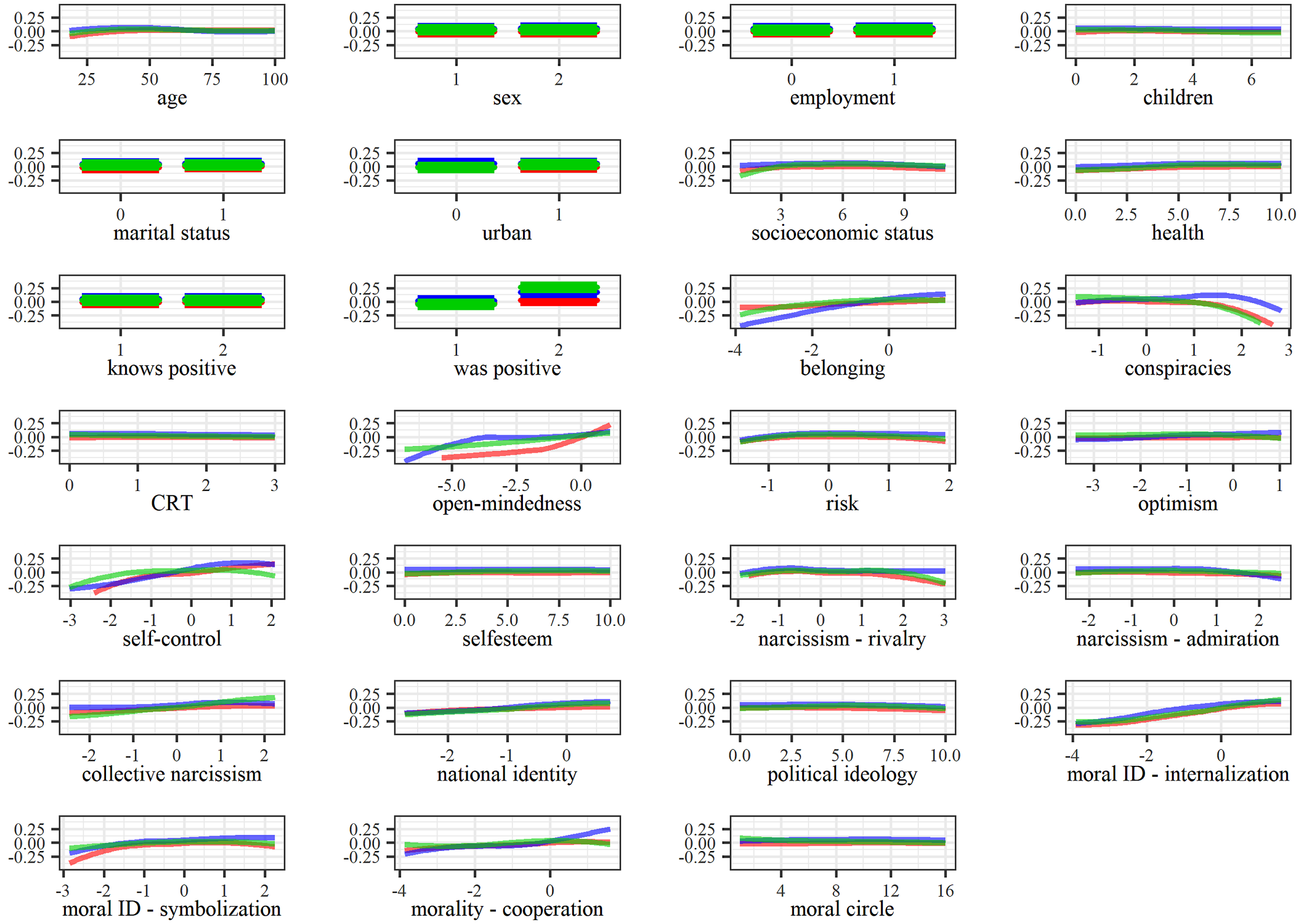


**Fig. 4.** Partial dependence plots based on the data reflecting the advanced stage of pandemic.
Note: red, blue, and green represent avoiding contact, maintaining hygiene, and policy support, respectively.

especially in self-reported measures like self-esteem, control, or optimism (67).

## Conclusion

Findings of our study indicate that the most effective predictors of COVID-19 responses, such as avoiding physical contact, maintaining hygiene, and supporting restrictive COVID-19 policies, were related to morality, prosociality, and traits and attitudes operationalizing self-control and information processing. However, the predictive contribution of even the most invariant predictors substantially varied with respect to the predicted type of response and cultural characteristics. While the research design of this study prevents any causal conclusions, the results suggest that the interplay between individual and contextual characteristics is relevant for understanding individual COVID-19 responses. Ultimately, our findings can serve as a starting point for future, more nuanced, research on the variables highlighted within our study. Hopefully, the growing body of research and accumulated insights should lead to informed and efficient prevention and intervention programs for health-related crises.

## Supplementary Material

Supplementary material is available at PNAS Nexus online.

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## Authors' Contributions

Conceptualization: T.P. and J.-v.B.; data curation: T.P., F.A., W.M.S., G.G.R., and P.S.B.; formal analysis: T.P., F.A., K.D., J.R.-M., M.M., P.D.K., C.P.-G., J.K., S.R., and E.H.; investigation (data collection): all authors; methodology: T.P. and J.K.; project administration: T.P.; software: T.P., F.A., K.D., J.R.-M., M.M., P.D.K., C.P.-G., J.K., S.R., and E.H.; supervision: T.P., M.M., M.D.B., and J.v.B.; validation: T.P.; visualization: T.P., J.K., and S.R.; writing—original draft: K.D., M.M., T.G., G.H., J.K., M.D.B., P.S., V.C., H.S.-G., M.Y., A.I., S.R., E.W., D.S., J.-W.v.P., E.H., C.T.E., R.F., Z.P., and P.M.; and writing—review and editing: all authors.

## Data Availability

The data that support the findings of this study are openly available in OSF at http://doi.org/10.17605/osf.io/tfsza. These data have been used in multiple other manuscripts, including the "National identity predicts public health support during a global pandemic" manuscript, where Professor John Nezlek conducted the main analyses.

## References

1. WHO. 2022. COVID-19 weekly epidemiological update. edn. 83. [accessed 2022 March 18]. https://www.who.int/docs/default-source/coronaviruse/situation-reports/20220315_weekly_epi_update_83.pdf?sfvrsn=194a6d66_4&download=true.
2. Thu TPB, Ngoc PNH, Hai NM, Tuan LA. 2020. Effect of the social distancing measures on the spread of COVID-19 in 10 highly infected countries. Sci Total Environ. 742:140430. DOI: 10.1016/j.scitotenv.2020.140430.
3. Alzyood M, Jackson D, Aveyard H, Brooke J. 2020. COVID-19 reinforces the importance of handwashing. J Clin Nurs. 29(15–16):2760–2761.
4. Meyers C, *et al.* 2021. Ethanol and isopropanol inactivation of human coronavirus on hard surfaces. J Hosp Infect. 107:45–49.

5. Ryu S, Hwang Y, Yoon H, Chun BC. 2020. Self-quarantine noncompliance during the COVID-19 pandemic in South Korea. Disaster Med Pub Health Prepare. 16:464–467.
6. van Zandwijk N, Rasko JEJ. 2020. The COVID-19 outbreak: a snapshot from down under. Expert Rev Anticancer Ther. 20(6):433–436.
7. Van Bavel JJ, *et al.* 2020. Using social and behavioural science to support COVID-19 pandemic response. Nat Hum Behav. 4(5):460–471.
8. Johns Hopkins Coronavirus Resource Center. 2022. Mortality analyses. [accessed 2022 March 7]. https://coronavirus.jhu.edu/data/mortality.
9. Bilinski A, Emanuel EJ. 2020. COVID-19 and excess all-cause mortality in the US and 18 comparison countries. JAMA. 324(20):2100.
10. Travaglino GA, Moon C. 2021. Compliance and self-reporting during the COVID-19 pandemic: a cross-cultural study of trust and self-conscious emotions in the United States, Italy, and South Korea. Front Psychol. 12:565845.
11. Biddlestone M, Green R, Douglas KM. 2020. Cultural orientation, power, belief in conspiracy theories, and intentions to reduce the spread of COVID-19. Br J Soc Psychol. 59(3):663–673.
12. Coroiu A, Moran C, Campbell T, Geller AC. 2020. Barriers and facilitators of adherence to social distancing recommendations during COVID-19 among a large international sample of adults. PLoS ONE. 15(10):e0239795.
13. Clark C, Davila A, Regis M, Kraus S. 2020. Predictors of COVID-19 voluntary compliance behaviors: an international investigation. Glob Transitions. 2:76–82.
14. Eisenhardt KM, Graebner ME, Sonenshein S. 2016. Grand challenges and inductive methods: rigor without rigor mortis. Acad Manag J. 59(4):1113–1123.
15. Igarashi Y, *et al.* 2016. Three levels of data-driven science. J Phys Conf Ser. 699:012001.
16. Chambon M, Dalege J, Elberse JE, van Harreveld F. 2021. A psychological network approach to attitudes and preventive behaviors during pandemics: a COVID-19 study in the United Kingdom and the Netherlands. Soc Psychol Person Sci. 13(1):233–245.
17. Van Lissa CJ, *et al.* 2022. Using machine learning to identify important predictors of COVID-19 infection prevention behaviors during the early phase of the pandemic. Patterns. 3:100482. DOI: 10.1016/j.patter.2022.100482.
18. Capraro V, Boggio P, Böhm R, Perc M, Sjåstad H. 2021. Cooperation and acting for the greater good during the COVID-19 pandemic. In: Miller MK, editor. The social science of the COVID-19 pandemic: a call to action for researchers. Oxford: Oxford University Press.
19. Van Bavel JJ, *et al.* 2022. National identity predicts public health support during a global pandemic. Nat Commun. 13:517.
20. Zettler I, Lilleholt L, Böhm R, Gondan M. 2021. Comparing responses in repeated cross-sectional and panel studies: results across eight weeks during the first COVID-19 lockdown in Denmark. Psychol Assess. 33(8):691–704.
21. Putnick DL, Bornstein MH. 2016. Measurement invariance conventions and reporting: the state of the art and future directions for psychological research. Dev Rev. 41:71–90.
22. Breiman L. 2001. Random forests. Mach Learn. 45(1):5–32.
23. Sage A. 2018. Random forest robustness, variable importance, and tree aggregation. [doctoral dissertation, Iowa State University]. [Ames, IA]: Iowa State University Digital Repository. DOI: 10.31274/etd-180810-6083.
24. Azevedo F, *et al.* 2022. Social and moral psychology of COVID-19 across 69 countries. PsyArXiv. DOI: 10.31234/osf.io/a3562.
25. Aquino K, Reed AII. 2002. The self-importance of moral identity. J Pers Soc Psychol. 83(6):1423–1440.
26. Waytz A, Iyer R, Young L, Haidt J, Graham J. 2019. Ideological differences in the expanse of the moral circle. Nat Commun. 10(1):4389.
27. Curry OS, Jones Chesters M, Van Lissa CJ. 2019. Mapping morality with a compass: testing the theory of 'morality-as-cooperation' with a new questionnaire. J Res Personal. 78: 106–124.
28. Postmes T, Haslam SA, Jans L. 2013. A single-item measure of social identification: reliability, validity, and utility. Br J Soc Psychol. 52(4):597–617.
29. Cameron JE. 2004. A three-factor model of social identity. Self Identity. 3(3):239–262.
30. Malone GP, Pillow DR, Osman A. 2012. The General Belongingness Scale (GBS): assessing achieved belongingness. Personal Ind Differ. 52(3):311–316.
31. Golec de Zavala A, Cichocka A, Eidelson R, Jayawickreme N. 2009. Collective narcissism and its social consequences. J Pers Soc Psychol. 97(6):1074–1096.
32. Sternisko A, Cichocka A, Cislak A, Van Bavel JJ. 2021. National narcissism predicts the belief in and the dissemination of conspiracy theories during the COVID-19 pandemic: evidence from 56 countries. Personal Soc Psychol Bull. 014616722110549. DOI: 10.1177/01461672211054947.
33. Back MD, *et al.* 2013. Narcissistic admiration and rivalry: disentangling the bright and dark sides of narcissism. J Pers Soc Psychol. 105(6):1013–1037.
34. Tangney JP, Baumeister RF, Boone AL. 2004. High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. J Pers. 72(2):271–324.
35. Robins RW, Hendin HM, Trzesniewski KH. 2001. Measuring global self-esteem: construct validation of a single-item measure and the Rosenberg self-esteem scale. Personal Soc Psychol Bull. 27(2):151–161.
36. Scheier MF, Carver CS, Bridges MW. 1994. Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): a reevaluation of the Life Orientation Test. J Pers Soc Psychol. 67(6):1063–1078.
37. Alfano M, *et al.* 2017. Development and validation of a multi-dimensional measure of intellectual humility. PLoS ONE. 12(8):e0182950.
38. Frederick S. 2005. Cognitive reflection and decision making. J Econ Perspect. 19(4):25–42.
39. Adler NE, Epel ES, Castellazzo G, Ickovics JR. 2000. Relationship of subjective and objective social status with psychological and physiological functioning: preliminary data in healthy, White women. Health Psychol. 19(6):586–592.
40. R Core Team. 2021. R: a language and environment for statistical computing. Vienna: R Foundation for Statistical Computing. [accessed 2021 December 12]. https://www.R-project.org/.
41. Brosseau-Liard PE, Savalei V. 2014. Adjusting incremental fit indices for nonnormality. Multivar Behav Res. 49(5): 460–470.
42. Brosseau-Liard PE, Savalei V, Li L. 2012. An investigation of the sample performance of two nonnormality corrections for RMSEA. Multivar Behav Res. 47(6):904–930.
43. Rosseel Y. 2012. lavaan: an R package for structural equation modeling. J Stat Softw. 48(1):1–36.
44. World Values Survey 7. 2020. The Inglehart-Welzel world cultural map 2020. [Provisional version]. [accessed 2022 February 24]. https://www.worldvaluessurvey.org/WVSContents.jsp?CMSID=findings&CMSID=findings.

45. Wright MN, Ziegler A. 2017. ranger: a fast implementation of random forests for high dimensional data in C++ and R. J Stat Softw. 77:1–17.
46. Altmann A, Toloşi L, Sander O, Lengauer T. 2010. Permutation importance: a corrected feature importance measure. Bioinformatics. 26(10):1340–1347.
47. Winterich KP, Aquino K, Mittal V, Swartz R. 2013. When moral identity symbolization motivates prosocial behavior: the role of recognition and moral identity internalization. J Appl Psychol. 98(5):759–770.
48. Jennings PL, Mitchell MS, Hannah ST. 2015. The moral self: a review and integration of the literature. J Organ Behav. 36(S1):S104–S168.
49. Spiegel JS. 2012. Open-mindedness and intellectual humility. Theory Res Educ. 10(1):27–38.
50. Arpaly N. 2011. Open-mindedness as a moral virtue. Am Philos Quart. 48(1):75–85.
51. Song Y. 2018. The moral virtue of open-mindedness. Canad J Philos. 48(1):65–84.
52. Fishbach A, Shah JY. 2006. Self-control in action: implicit dispositions toward goals and away from temptations. J Pers Soc Psychol. 90(5):820–832.
53. Hofmann W, Meindl P, Mooijman M, Graham J. 2018. Morality and self-control: how they are intertwined and where they differ. Curr Dir Psychol Sci. 27(4):286–291.
54. Livingstone AG, Haslam SA, Postmes T, Jetten J. 2011. "We Are, Therefore We Should": evidence that in-group identification mediates the acquisition of in-group norms1. J Appl Soc Psychol. 41(8):1857–1876.
55. Nowak B, *et al.* 2020. Adaptive and maladaptive behavior during the COVID-19 pandemic: the roles of Dark Triad traits, collective narcissism, and health beliefs. Personal Ind Differ. 167:110232.
56. Cichocka A. 2016. Understanding defensive and secure in-group positivity: the role of collective narcissism. Eur Rev Soc Psychol. 27(1):283–317.
57. Cichocka A, Cislak A. 2020. Nationalism as collective narcissism. Curr Opin Behav Sci. 34:69–74.
58. Cislak A, Wojcik AD, Cichocka A. 2018. Cutting the forest down to save your face: narcissistic national identification predicts support for anti-conservation policies. J Environ Psychol. 59: 65–73.
59. Marchlewska M, Cichocka A, Jaworska M, Golec de Zavala A, Bilewicz M. 2020. Superficial ingroup love? Collective narcissism predicts ingroup image defense, outgroup prejudice, and lower ingroup loyalty. Br J Soc Psychol. 59(4): 857–875.
60. Hornsey MJ, *et al.* 2021. To what extent are conspiracy theorists concerned for self versus others? A COVID-19 test case. Eur J Soc Psychol. 51(2):285–293.
61. Alper S, Douglas K, Capraro V. 2021. Conspiracy beliefs and generosity across 52 countries during the COVID-19 pandemic. PsyArXiv [preprint, version 2]. DOI: 10.31234/osf.io/fdyxr.
62. Capraro V, Rand DG. 2018. Do the right thing: experimental evidence that preferences for moral behavior, rather than equity or efficiency per se, drive human prosociality. Judg Decis Mak. 13(1):99–111.
63. Tappin BM, Capraro V. 2018. Doing good vs. avoiding bad in prosocial choice: a refined test and extension of the morality preference hypothesis. J Exp Soc Psychol. 79: 64–70.
64. Capraro V, Perc M. 2021. Mathematical foundations of moral preferences. J R Soc Interface. 18(175):20200880.
65. Ajzen I. 1991. The theory of planned behavior. Organ Behav Hum Decis Process. 50(2):179–211.
66. Graeff TR. 2005. Response bias. In: Kempf-Leonard K, editor. Encyclopedia of social measurement. Amsterdam: Elsevier Inc. pp. 411–418.
67. Caputo A. 2017. Social desirability bias in self-reported wellbeing measures: evidence from an online survey. Univ Psychol. 16(2):1–13.