Exploring the Association between Compliance with Measures to Prevent the Spread of COVID-19 and Big Five Traits with Bayesian Generalized Linear Model

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Abstract

Research has examined the association between people's compliance with measures to prevent the spread of COVID-19 and personality traits. However, previous studies were conducted with relatively small-size datasets and employed frequentist analysis that does not allow data-driven model exploration. To address the limitations, a large-scale international dataset, COVIDiSTRESS Global Survey dataset, was explored with Bayesian generalized linear model that enables identification of the best regression model. The best regression models predicting participants' compliance with Big Five traits were explored. The findings demonstrated first, all Big Five traits, except extroversion, were positively associated with compliance with general measures and distancing. Second, neuroticism, extroversion, and agreeableness were positively associated with the perceived cost of complying with the measures while conscientiousness showed negative association. The findings and the implications of the present study were discussed.

Keywords: COVID-19; preventive measures; physical distancing; social distancing; Big Five; big data; Bayesian analysis; data-driven analysis

1. Introduction

Research has found that implementation of preventive measures, such as social and physical distancing, significantly decreases the spread of COVID-19 (Thu et al., 2020). Unfortunately, implementing such measures can negatively influence economy and well-being, and be perceived as costly efforts (Atalan, 2020). Thus, people's intent to comply with the measures is necessary for effective containment of COVID-19. Given compliance has become a

significant factor in efforts to deal with COVID-19 (Chang et al., 2020), it would be informative to examine the association between people's personality traits and compliance to better understand the mechanisms of spread prevention from the perspective of personality psychology.

Personality psychologists have examined whether and how personality traits are associated with compliance in diverse domains of human lives. In previous studies, the association between the Big Five personality traits and compliance in general has been investigated in diverse contexts (Allen & Walter, 2018; Clarke & Robertson, 2005). Given compliance motivation is considered to emerge from risk aversion and prosocial tendency (D'Attoma et al., 2020; Eisenhauer, 2008), we may consider how personality traits are associated with the aforementioned two factors to better understand the relationship between the traits and compliance.

First, researchers have suggested that the Big Five personality traits are related to one's tendency to avoid risk by not involving in risky behaviors. In the domain of potentially risky sexual behavior, a previous empirical study and meta-analysis reported that high extroversion showed a significant positive association with risk taking while agreeableness, openness, and conscientiousness showed a negative association (Allen & Walter, 2018; Ingledew & Ferguson, 2007). The similar pattern was found in risky driving. A meta-analysis showed that risky driving is positively associated with extroversion and negatively associated with agreeableness and conscientiousness (Clarke & Robertson, 2005). Given these previous studies, we can expect that risk aversion would be negatively associated with extroversion, so it would also be negatively associated with compliance motivation to avoid potential risks. On the other hand, agreeableness, openness, and conscientiousness can be considered as traits positively associated with compliance.

Second, we can also consider the possible association between personality traits, prosocial tendency, and compliance. Several previous studies have examined how Big Five personality traits and prosocial tendency, such as prosocial and moral motivation, ethical leadership, are related. At the conceptual level, Roberts et al. (2014) proposed that conscientiousness is fundamentally related with rule abiding tendency, self-control, and finally, morality and virtue. An empirical study also demonstrated that conscientiousness was significantly associated with ethical leadership (Kalshoven et al., 2011). Moreover, other studies have reported that agreeableness and openness were also commonly related to prosocial motivation and behavior (e.g., Carlo et al., 2005; Kline et al., 2019). These previous studies suggest that agreeableness, openness, and conscientiousness that significantly predict prosocial tendency. Given that prosocial tendency becomes a source of compliance (D'Attoma et al., 2020; Eisenhauer, 2008), we may assume that the aforementioned traits would be significantly associated with compliance.

Recent studies have examined how personality traits in terms of the Big Five personality traits were associated with compliance with preventive measures during the pandemic. Carvalho, Pianowski, and Gonçalves (2020) demonstrated that low extroversion was associated with stronger compliance with social distancing while low conscientiousness was associated with weaker compliance with containment measures among 715 Brazilians. Ebrahimi, Hoffart, and Johnson (2020) found that low extroversion and high conscientiousness were positively associated with voluntary social distancing among 4,158 Norwegians. One study conducted with 8,548 Japanese participants reported that compliance was positively associated with agreeableness, conscientiousness, and openness, while negatively associated with extroversion (Nofal et al., 2020). In general, extroversion showed a negative association with compliance with

containment measures while conscientiousness, agreeableness, and openness showed a positive association. These findings are consistent with the aforementioned associations between personality traits and compliance in general reported in the previous studies conducted before the pandemic.

However, limitations in the previous studies warrant further research. First, they recruited a relatively small size of participants within one country. Given the pandemic has widely affected countries on the globe, it is necessary to examine a large-scale dataset for better generalization. Second, related to the analysis method, use of frequentist ANOVA or regression analysis cannot inform us which regression model is the best model to explain compliance among all possible models (Han & Dawson, 2021). The previous studies entered trait scores into their analysis model and examined their significant with p -values. However, $p < .05$ is only about a null hypothesis, not an alternative hypothesis (Han et al., 2018). Also, testing the regression model with multiple trait scores entered does not inform us whether the tested model is the best model; instead, the model is only being compared with a null model (Han & Dawson, 2021).

To address the issues, a large-scale international survey dataset, COVIDiSTRESS Global Survey dataset (Yamada et al., 2021), was analyzed with Bayesian generalized linear model (GLM). The best model explaining compliance with Big Five trait scores among international participants was examined from Bayesian perspective that enables exploration the best model in a data-driven manner. It allows us to explore which model is the best model among all possible candidate in terms of all possible combinations of candidate predictors (Wagenmakers et al., 2018). Also, the best model identified by Bayesian method is more stringent than the ordinary regression model in frequentist analysis. Consequently, the identified model is less likely to

commit overfitting caused by an unnecessarily complicated model (Han & Dawson, 2021).

Bayesian GLM was employed in this study given these methodological merits.

2. Methods

All data and R source code files for the present study are available via the Open Science Framework project page at <https://osf.io/5jgbu/>.

2.1. Dataset

In this study, a large-scale international dataset, COVIDiSTRESS Global Survey dataset (Yamada et al., in press), was analyzed. This dataset was initially collected from 173,426 participants across 179 countries. The project was conducted to examine the relationship between participants' psychological and behavioral responses to COVID-19. The cleaned data file available for public (<https://osf.io/f8h9w/>) contained responses from 125,306 participants across 177 countries (see Lieberoth et al. (2021) and Yamada et al. (2021) for demographics and cleaning procedures). After performing pre-process procedures (described in supplementary methods), responses from 61,889 participants across 19 countries were used for further analyses. Tables S1 and S2 present demographical information of the whole dataset and samples in each, respectively.

2.2. Measures

The full survey form used for COVIDiSTRESS Global Survey is available at <https://osf.io/mhszp/>. It has been translated into different languages by international collaborators who participated in the project.

2.2.1. Big Five Inventory

To measure participants' personality traits, the Short 15-item Big Five Inventory (BFI-S) with 15 items was used (Lang et al., 2011). Each subscale in Big Five traits, neuroticism,

extroversion, openness, agreeableness, and conscientiousness, was measured with three items. Responses were anchored to a six-point Likert scale (“Strongly disagree”—“Strongly agree”).

2.2.2. Compliance with Preventive Measures

In this study, three items about compliance were employed to measure three dependent variables. For general compliance with preventive measures, “I have done everything I could possibly do as an individual to reduce the spread of Coronavirus” was presented. To assess compliance with distancing, “I have done everything I could possibly do to keep physical distance to others” was used. These items were selected as they were directly related to one’s tendency to abide by prevented measures. In addition to the first item about general compliance, the second item about distancing was included because distancing measures were found to be particularly influential on people’s economic status and wellbeing (Tull et al., 2020).

In addition, “I feel that keeping a physical distance from others would have a high personal cost to me,” was employed to assess the perceived personal cost to abide by distancing measures. Responses were anchored to a six-point Likert scale (“Strongly disagree”—“Strongly agree”). The item about the perceived cost was included in the analyses for additional evidence on behavioral tendency. In fact, previous research about how people behave when they are presented with guidelines for desirable actions (e.g., Han et al., 2017) suggests why such an item can provide additional evidence. The perceived cost and difficulty to follow such guidelines better predicted actual behavioral outcomes compared with self-reported intent to follow the guidelines (Han et al., 2017). Given intent to comply with guidelines asked by explicit questions is likely to be susceptible to social desirability bias particularly during the pandemic (Daoust et al., 2020), use of an item inquiring about the perceived cost would provide a better proxy for actual behavioral tendency as shown in the prior research.

Although a total of six items were employed to assess compliance in the original COVIDiSTRESS Global Survey, only three items were analyzed in the present study. The other three items were excluded from the analyses because they were deemed to be irrelevant to the main focus of the present study, one's own compliance. The first excluded item was more about one's knowledge about preventive measures instead of behavior ("I feel well informed about steps I can take, to help reduce the spread of Coronavirus"). The second excluded item asked whether one felt that other people were following measures well ("I trust others around me to follow guidelines to stop the spread of Coronavirus"). The third excluded item was primarily about one's preparedness for quarantine and isolation instead of compliance ("I have bought large extra supplies of food or grocery items").

2.2.3. Demographical Information

Following a previous study that examined COVIDiSTRESS Global Survey dataset (Lieberoth et al., accepted in principle), three demographics variables, participant' age, gender, and educational level, were employed as covariates. These variables were also employed in the previous studies examining compliance and beliefs on preventive measures (Alper et al., 2020; Daoust, 2020; Lüdecke & von dem Knesebeck, 2020). The studies reported that the aforementioned demographical factors were significantly associated with behavioral and psychological responses to preventive measures, such as protective behavior, distancing, and COVID-19 conspiracy theories. Given the findings from the previous studies, the three demographical variables were employed as covariates in the present study as were in Lieberoth et al. (2021).

2.3. Analysis Plan

The dataset was first preprocessed to exclude inappropriate responses and outliers. Then, the reliability and validity of the BFI-S were tested. Measurement alignment was also performed to enable appropriate analyses of the multi-country dataset. Further details about the procedures are described in supplementary methods. After completing measurement alignment, correlation analysis was performed to examine the correlations between the Big Five personality traits and compliance variables.

Bayesian GLM implemented in *BayesFactor* package was performed with adjusted BFI-S factor scores to explore the best model for each of three dependent variables. Five adjusted BFI-S subscale scores were entered as predictors, participants' age, gender, and educational level as covariates, and their country as a random effect. Frequentist and Bayesian GLM with *lmerTest* and *brms* packages were conducted with the identified best model reporting the greatest Bayes factor (BF) (vs. null model) to estimate the coefficient, *p*-value, and BF (vs. null hypothesis) of each predictor. For *brms*, the default Cauchy prior, Cauchy (0, 1) (Rouder & Morey, 2012).

BF indicates to what extent observed data supports a specific model over another. If two models, Models A vs. B, are compared, BF_{AB} means to what extent evidence favors Model A over B (Wagenmakers et al., 2018). $BF_{AB} \geq 3$, which is a widely used cutoff, suggests that evidence positively supports Model A over B (Han, 2020). In this study, BF was calculated for each candidate model in terms of BF against the null model only with intercepts. A model reporting the greatest BF in Bayesian GLM was identified as the best model. Similarly, for each estimated coefficient (e.g., *B*), BF indicating to what extent data supports an alternative hypothesis, $B \neq 0$, was also calculated with *brms* (threshold: $BF \geq 3$).

Because there have been concerns regarding whether excluding outliers significantly alters analysis results (Aguinis et al., 2013), Bayesian GLM was performed once again with the

dataset that was not screened for outliers. The results from Bayesian GLM with the dataset with outliers were compared with those from Bayesian GLM with the dataset without outliers.

3. Results

3.1. Descriptive Statistics

Table S3 presents descriptive statistics, including mean and standard deviations values for the whole dataset and each country, of each predictor and dependent. Correlations between the Big Five personality trait and compliance variables are reported in Table S4. In supplementary materials, the correlation between two compliance items, which demonstrated a large effect, $r = .65$, was discussed in “About compliance items” section.

3.2. Reliability and Validity Check, and Measurement Alignment

Cronbach α s of the BFI-S were reported in Table S3. After excluding data from 29 countries with $\alpha < .55$, data from 19 countries were used for further analyses ($N = 61,889$). The whole sample α values were at least .60 in all five subscales.

When measurement invariance was tested, even configural invariance without any model constraints was not achieved, RMSEA = .072, SRMR = .056, CFI = .811, TLI = .752. Thus, measurement alignment was performed to adjust factor loadings for further analyses. Resultant R^2 values demonstrated that for all five subscales, non-invariance was well absorbed during alignment, $R^2 > .95$ (see Table S5).

3.3. Bayesian GLM

The result of model comparison with Bayesian GLM are presented in Table S6. Table 1 presents the result of frequentist and Bayesian GLM for each dependent variable with estimated coefficients. First, when general compliance tendency was examined, the model with all five subscale scores reported the greatest BF, $6.87e+2364$. All subscales, except extroversion, were

positively associated with the dependent variable. All estimated coefficients were significantly different from zero.

Second, when compliance with distancing was a dependent variable, the model with all five subscale scores was identified as the best model, $BF = 1.82e+2487$. All subscales, except extroversion, showed positive association. All estimated coefficients significantly differ from zero.

Third, when perceived personal cost to comply with distancing was tested, the model without openness showed the greatest BF, $2.08e+1022$. All included predictors (i.e., neuroticism, extroversion, agreeableness) except conscientiousness were positively associated with the perceived personal cost. All estimated coefficients were significantly different from zero.

When these results were compared with the results from Bayesian GLM with the dataset containing outliers, there were no significant differences in the identified best models. The three identified best models were identical across the two different conditions. Further details are described in “Whether outlier exclusion based on Mahalanobis distance significantly influenced Bayesian GLM outcomes” section in supplementary materials.

<Place Table 1 about here>

4. Discussion

In this study, the best regression models explaining three different types of compliance with measures to contain COVID-19 were identified by Bayesian GLM with a large-scale international dataset. Compliance with preventive measures were positively associated with all Big Five traits except extroversion that showed negative association. These results are consistent with previous studies that examined the relationship between Big Five traits and compliance during the pandemic with relatively small-scale datasets. Extrovert people might experience

more difficulties with distancing measures because they strongly prefer social activities (Nofal et al., 2020). Neuroticism is perhaps associated with increased concern of being contracted COVID-19 so with compliance (Qian & Yahara, 2020). Agreeable, open-minded, and conscientious people might comply with the measures perhaps because they tend to value communal goals and harmony (agreeable), be more opened to the new social norms (open-minded) and adhere to regulations and rules consistently (conscientious) (Abdelrahman, 2020; Nofal et al., 2020; Zajenkowski et al., 2020).

Interestingly, the perceived personal cost to comply with preventive measures, which has not been well examined in the previous studies, were positively associated with neuroticism, extroversion, and agreeableness while only negatively associated with conscientiousness. It is well expected to see the positive association with extroversion and negative association with conscientiousness because extroverted people might experience more difficulties to be isolated from others while conscientious people might perceive doing so is consistent with their own personality (Carvalho et al., 2020; Liu et al., 2021; Nofal et al., 2020). In general, these findings are consistent with the previous studies that examined the associations between Big Five personality traits, risk aversion and prosocial tendency, and compliance.

Then, why were neuroticism and agreeableness positively associated with the perceived cost while also being positively associated with compliance? People with high neuroticism scores might comply preventive measures due to their strong concerns over COVID-19, but the strong concern would also make them feel more negative about their behavior (Liu et al., 2021). In fact, the negative impact of neuroticism on mental health during the pandemic period has been reported (Qian & Yahara, 2020). Agreeable people might also experience negative sentiments perhaps because they tend to emphasize with and help others in so they might be uncomfortable

with being separated with social interactions with such others (Abdelrahman, 2020; Graziano et al., 2007).

We can also consider the association between conscientiousness, morality, and virtue. Previous studies suggested that conscientious traits are significantly associated with morality and virtue (Kalshoven et al., 2011; Roberts et al., 2014). Moral philosophers have argued that virtuous people do not feel that moral actions are burdensome because they have internalized and habituated morality and virtue into themselves (Han, 2015; Sanderse, 2014). So, conscientious people may be less likely to feel that complying preventive measures, particularly social distancing, are very demanding to do in their everyday lives. On the other hand, although agreeableness and openness are positively associated with prosocial tendency (Carlo et al., 2005; Kline et al., 2019), they are not deemed to be associated with morality or virtue (Kalshoven et al., 2011; Roberts et al., 2014). Perhaps people possessing prosocial motivation do not necessarily be conscientious or virtuous. In the cases of such people, prosocial motivation might originate from sources external from themselves, such as social norms, conventions, or relationships (Choi et al., 2020), instead of internalized morality and virtue possessed by virtuous people. Hence, people who are not conscientious might experience more difficulties and struggles while complying with preventive measures compared with conscientious people.

One interesting point is that openness, which is positively associated with prosociality similar to agreeableness (Kline et al., 2019), was not significantly negatively associated with the perceived personal cost of compliance. It might be explained by a negative association between openness and (right-wing) authoritarianism perspective (Hodson et al., 2009; Manson, 2020). Hodson et al. (2009) reported that within the context of intergroup threat, only openness among the Big Five personality traits negatively predicted right-wing authoritarianism perspective,

which was significantly associated with perceived intergroup threat and prejudice. This finding may suggest that compared with agreeableness, openness is more likely to work as a buffering factor while coping with hostile external situations. In fact, Manson (2020) showed that extreme right-wing authoritarianism negatively predicted willingness to comply with distancing measures during the pandemic. Hence, it would be possible to say that openness would positively predict one's willingness to follow distancing measures, and finally, did not show a significant positive association with the perceived cost.

Findings from the present study will be able to provide useful theoretical insights about research on the relationship between personality traits and compliance. First, in the present study, large-scale data collected from diverse countries were analyzed. The majority of previous studies that examined the aforementioned relationship were conducted with relatively small-scale data collected from a single country. Thus, the present study contributes to the generalization of the theory across different countries and cultural backgrounds. Second, a relatively less studied aspect, the perceived personal cost of compliance, was examined. Given the perceived cost and difficulty well predicts actual behavioral tendency to follow guidelines and is robust against social desirability bias (Han et al., 2017), the analysis of the perceived cost in the present study would provide additional evidence regarding the relationship between personality traits and complying behavioral tendency.

Moreover, one methodological contribution of the present study is that it employed Bayesian GLM to explore the large-scale international dataset. By utilizing the data-driven method, it was possible to explore the regression models that best predicted compliance-related variables with the least model complexity with big data. Given these, findings from the present

study will provide useful insights to researchers who are interested in the relationship between compliance with measures to contain COVID-19 and various personality traits.

However, several limitations warrant further research. First, although one item inquired about participants' compliance tendency in an indirect way, the two other items explicitly inquired about compliance behavior. The two items might not be ideal to assess participants' actual compliance behavior due to possible social desirability bias. Thus, future studies may need to employ more direct measures for compliance behavior other than self-report to better examine actual behavior. Second, the BFI-S instead of its full version was used, so it might result in limited measurement reliability and validity. In fact, Hahn et al. (2012) reported that the reliability of the BFI-S was inferior to that of a longer measure, such as the NEO-PI-R. Hence, it would be possible to consider employing a longer measure to examine personality traits in a more reliable way.

5. References

- Abdelrahman, M. (2020). Personality Traits, Risk Perception, and Protective Behaviors of Arab Residents of Qatar During the COVID-19 Pandemic. *International Journal of Mental Health and Addiction*. <https://doi.org/10.1007/s11469-020-00352-7>
- Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-Practice Recommendations for Defining, Identifying, and Handling Outliers. *Organizational Research Methods*, 16(2), 270–301. <https://doi.org/10.1177/1094428112470848>
- Allen, M. S., & Walter, E. E. (2018). Linking big five personality traits to sexuality and sexual health: A meta-analytic review. *Psychological Bulletin*, 144(10), 1081–1110. <https://doi.org/10.1037/bul0000157>
- Alper, S., Bayrak, F., & Yilmaz, O. (2020). Psychological correlates of COVID-19 conspiracy

beliefs and preventive measures: Evidence from Turkey. *Current Psychology*.

<https://doi.org/10.1007/s12144-020-00903-0>

Atalan, A. (2020). Is the lockdown important to prevent the COVID-19 pandemic? Effects on psychology, environment and economy-perspective. *Annals of Medicine and Surgery*, 56, 38–42. <https://doi.org/10.1016/j.amsu.2020.06.010>

Carlo, G., Okun, M. A., Knight, G. P., & de Guzman, M. R. T. (2005). The interplay of traits and motives on volunteering: agreeableness, extraversion and prosocial value motivation. *Personality and Individual Differences*, 38(6), 1293–1305.

<https://doi.org/10.1016/j.paid.2004.08.012>

Carvalho, L. de F., Pianowski, G., & Gonçalves, A. P. (2020). Personality differences and COVID-19: are extroversion and conscientiousness personality traits associated with engagement with containment measures? *Trends in Psychiatry and Psychotherapy*, 42(2), 179–184. <https://doi.org/10.1590/2237-6089-2020-0029>

Chang, S. L., Harding, N., Zachreson, C., Cliff, O. M., & Prokopenko, M. (2020). Modelling transmission and control of the COVID-19 pandemic in Australia. *Nature Communications*, 11(1), 5710. <https://doi.org/10.1038/s41467-020-19393-6>

Choi, Y.-J., Han, H., Bankhead, M., & Thoma, S. J. (2020). Validity study using factor analyses on the Defining Issues Test-2 in undergraduate populations. *PLOS ONE*, 15(8), e0238110. <https://doi.org/10.1371/journal.pone.0238110>

Clarke, S., & Robertson, I. (2005). A meta-analytic review of the Big Five personality factors and accident involvement in occupational and non-occupational settings. *Journal of Occupational and Organizational Psychology*, 78(3), 355–376. <https://doi.org/10.1348/096317905X26183>

- D'Attoma, J. W., Volintiru, C., & Malézieux, A. (2020). Gender, Social Value Orientation, and Tax Compliance. *CESifo Economic Studies*, 66(3), 265–284.
<https://doi.org/10.1093/cesifo/ifz016>
- Daoust, J.-F. (2020). Elderly people and responses to COVID-19 in 27 Countries. *PLOS ONE*, 15(7), e0235590. <https://doi.org/10.1371/journal.pone.0235590>
- Daoust, J.-F., Nadeau, R., Dassonneville, R., Lachapelle, E., Bélanger, É., Savoie, J., & van der Linden, C. (2020). How to Survey Citizens' Compliance with COVID-19 Public Health Measures: Evidence from Three Survey Experiments. *Journal of Experimental Political Science*, 1–8. <https://doi.org/10.1017/XPS.2020.25>
- Ebrahimi, O., Hoffart, A., & Johnson, S. (2020). Factors associated with Adherence to Social Distancing Protocols and Hygienic Behavior during the COVID-19 Pandemic. *PsyArXiv Preprints*. <https://doi.org/10.31234/osf.io/h7wmj>
- Eisenhauer, J. G. (2008). Ethical preferences, risk aversion, and taxpayer behavior. *The Journal of Socio-Economics*, 37(1), 45–63. <https://doi.org/10.1016/j.socec.2007.01.030>
- Graziano, W. G., Habashi, M. M., Sheese, B. E., & Tobin, R. M. (2007). Agreeableness, empathy, and helping: A person $\times$ situation perspective. *Journal of Personality and Social Psychology*, 93(4), 583–599. <https://doi.org/10.1037/0022-3514.93.4.583>
- Hahn, E., Gottschling, J., & Spinath, F. M. (2012). Short measurements of personality – Validity and reliability of the GSOEP Big Five Inventory (BFI-S). *Journal of Research in Personality*, 46(3), 355–359. <https://doi.org/10.1016/j.jrp.2012.03.008>
- Han, H. (2015). Purpose as a moral virtue for flourishing. *Journal of Moral Education*, 44(3), 291–309. <https://doi.org/10.1080/03057240.2015.1040383>
- Han, H. (2020). Implementation of Bayesian multiple comparison correction in the second-level

analysis of fMRI data: With pilot analyses of simulation and real fMRI datasets based on voxelwise inference. *Cognitive Neuroscience*, 11(3), 157–169.

<https://doi.org/10.1080/17588928.2019.1700222>

Han, H., & Dawson, K. J. (2021). Improved model exploration for the relationship between moral foundations and moral judgment development using Bayesian Model Averaging. *Journal of Moral Education*. <https://doi.org/10.1080/03057240.2020.1863774>

Han, H., Kim, J., Jeong, C., & Cohen, G. L. (2017). Attainable and Relevant Moral Exemplars Are More Effective than Extraordinary Exemplars in Promoting Voluntary Service Engagement. *Frontiers in Psychology*, 8, 283. <https://doi.org/10.3389/fpsyg.2017.00283>

Han, H., Park, J., & Thoma, S. J. (2018). Why do we need to employ Bayesian statistics and how can we employ it in studies of moral education?: With practical guidelines to use JASP for educators and researchers. *Journal of Moral Education*, 47(4), 519–537. <https://doi.org/10.1080/03057240.2018.1463204>

Hodson, G., Hogg, S. M., & MacInnis, C. C. (2009). The role of “dark personalities” (narcissism, Machiavellianism, psychopathy), Big Five personality factors, and ideology in explaining prejudice. *Journal of Research in Personality*, 43(4), 686–690. <https://doi.org/10.1016/j.jrp.2009.02.005>

Ingledeu, D. K., & Ferguson, E. (2007). Personality and riskier sexual behaviour: Motivational mediators. *Psychology & Health*, 22(3), 291–315. <https://doi.org/10.1080/14768320600941004>

Kalshoven, K., Den Hartog, D. N., & De Hoogh, A. H. B. (2011). Ethical Leader Behavior and Big Five Factors of Personality. *Journal of Business Ethics*, 100(2), 349–366. <https://doi.org/10.1007/s10551-010-0685-9>

- Kline, R., Bankert, A., Levitan, L., & Kraft, P. (2019). Personality and Prosocial Behavior: A Multilevel Meta-Analysis. *Political Science Research and Methods*, 7(1), 125–142.
<https://doi.org/10.1017/psrm.2017.14>
- Lang, F. R., John, D., Lüdtke, O., Schupp, J., & Wagner, G. G. (2011). Short assessment of the Big Five: robust across survey methods except telephone interviewing. *Behavior Research Methods*, 43(2), 548–567. <https://doi.org/10.3758/s13428-011-0066-z>
- Lieberoth, A., Lin, S.-Y., Stöckli, S., Han, H., Kowal, M., Chrona, S., Gelpi, R., Tran, T. P., Jeftić, A., Rasmussen, J., Cakal, H., & Milfont, T. (2021). Stress and worry in the 2020 coronavirus pandemic: Relationships to trust and compliance with preventive measures across 48 countries. *Royal Society Open Science*, 8(2), 200589.
<https://doi.org/10.1098/rsos.200589>
- Liu, S., Lithopoulos, A., Zhang, C.-Q., Garcia-Barrera, M. A., & Rhodes, R. E. (2021). Personality and perceived stress during COVID-19 pandemic: Testing the mediating role of perceived threat and efficacy. *Personality and Individual Differences*, 168, 110351.
<https://doi.org/10.1016/j.paid.2020.110351>
- Lüdecke, D., & von dem Knesebeck, O. (2020). Protective Behavior in Course of the COVID-19 Outbreak—Survey Results From Germany. *Frontiers in Public Health*, 8.
<https://doi.org/10.3389/fpubh.2020.572561>
- Manson, J. H. (2020). Right-wing Authoritarianism, Left-wing Authoritarianism, and pandemic-mitigation authoritarianism. *Personality and Individual Differences*, 167, 110251.
<https://doi.org/10.1016/j.paid.2020.110251>
- Nofal, A. M., Cacciotti, G., & Lee, N. (2020). Who complies with COVID-19 transmission mitigation behavioral guidelines? *PLOS ONE*, 15(10), e0240396.

<https://doi.org/10.1371/journal.pone.0240396>

Qian, K., & Yahara, T. (2020). Mentality and behavior in COVID-19 emergency status in Japan:

Influence of personality, morality and ideology. *PLOS ONE*, 15(7), e0235883.

<https://doi.org/10.1371/journal.pone.0235883>

Roberts, B. W., Lejuez, C., Krueger, R. F., Richards, J. M., & Hill, P. L. (2014). What is

conscientiousness and how can it be assessed? *Developmental Psychology*, 50(5), 1315–

1330. <https://doi.org/10.1037/a0031109>

Rouder, J. N., & Morey, R. D. (2012). Default Bayes Factors for Model Selection in Regression.

Multivariate Behavioral Research, 47(6), 877–903.

<https://doi.org/10.1080/00273171.2012.734737>

Sanderse, W. (2014). An Aristotelian Model of Moral Development. *Journal of Philosophy of*

Education. <https://doi.org/10.1111/1467-9752.12109>

Thu, T. P. B., Ngoc, P. N. H., Hai, N. M., & Tuan, L. A. (2020). Effect of the social distancing

measures on the spread of COVID-19 in 10 highly infected countries. *Science of The Total*

Environment, 742, 140430. <https://doi.org/10.1016/j.scitotenv.2020.140430>

Tull, M. T., Edmonds, K. A., Scamaldo, K. M., Richmond, J. R., Rose, J. P., & Gratz, K. L.

(2020). Psychological Outcomes Associated with Stay-at-Home Orders and the Perceived

Impact of COVID-19 on Daily Life. *Psychiatry Research*, 289, 113098.

<https://doi.org/10.1016/j.psychres.2020.113098>

Wagenmakers, E.-J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Selker, R., Gronau,

Q. F., Dropmann, D., Boutin, B., Meerhoff, F., Knight, P., Raj, A., van Kesteren, E.-J., van

Doorn, J., Šmíra, M., Epskamp, S., Etz, A., Matzke, D., ... Morey, R. D. (2018). Bayesian

inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin &*

Review, 25(1), 58–76. <https://doi.org/10.3758/s13423-017-1323-7>

Yamada, Y., Čepulić, D.-B., Coll-Martín, T., Debove, S., Gautreau, G., Han, H., Rasmussen, J.,

Tran, T. P., Travaglino, G. A., & Lieberoth, A. (2021). COVIDiSTRESS Global Survey dataset on psychological and behavioural consequences of the COVID-19 outbreak.

Scientific Data, 8(1), 3. <https://doi.org/10.1038/s41597-020-00784-9>

Zajenkowski, M., Jonason, P. K., Leniarska, M., & Kozakiewicz, Z. (2020). Who complies with

the restrictions to reduce the spread of COVID-19?: Personality and perceptions of the COVID-19 situation. *Personality and Individual Differences*, 166, 110199.

<https://doi.org/10.1016/j.paid.2020.110199>

Table 1

Frequentist and Bayesian GLM results with the best model for each dependent variable

	<i>B</i>	<i>SE</i>	β	Standardized <i>SE</i>	<i>df</i>	<i>t</i>	<i>p</i>	Bayes factor (vs. <i>B</i> = 0)
DV: "I have done everything I could possibly do as an individual to reduce the spread of Coronavirus" (overall compliance)								
Neuroticism	.01	.00	.03	.00	61,220.00	5.75	< .001	Infinite
Extroversion	-.01	.00	-.03	.00	61,490.00	-6.23	< .001	Infinite
Openness	.03	.00	.10	.00	61,470.00	23.88	< .001	Infinite
Agreeableness	.04	.00	.12	.00	61,450.00	28.67	< .001	Infinite
Conscientiousness	.05	.00	.17	.00	60,590.00	34.32	< .001	Infinite
DV: "I have done everything I could possibly do to keep physical distance to others" (compliance with distancing)								
Neuroticism	.01	.00	.03	.00	61,380.00	7.58	< .001	Infinite
Extroversion	-.01	.00	-.05	.00	61,490.00	-11.98	< .001	Infinite
Openness	.04	.00	.10	.00	61,490.00	24.01	< .001	Infinite
Agreeableness	.03	.00	.09	.00	61,480.00	22.51	< .001	Infinite
Conscientiousness	.04	.00	.12	.00	61,080.00	25.35	< .001	Infinite
DV: "I feel that keeping a physical distance from others would have a high personal cost to me" (perceived personal cost of distancing)								
Neuroticism	.06	.00	.16	.00	61,100.00	33.86	< .001	Infinite
Extroversion	.07	.00	.20	.00	61,480.00	45.82	< .001	Infinite
Agreeableness	.01	.00	.02	.00	61,420.00	4.85	< .001	Infinite
Conscientiousness	-.01	.00	-.02	.00	60,200.00	-4.51	< .001	Infinite

Note. Only BFI-S predictors of interest were included. Full results with covariates are presented in Table S7.

Supplementary Materials

Supplementary Methods

Preprocessing Procedures

First, responses from a country, “other,” were excluded ($n = 232$).

Second, responses from participants who spent less than 132 seconds, which was 10% of the estimated time to complete the whole survey, were filtered out ($n = 1,243$). The response time information was automatically recorded by Qualtrics upon the completion of the survey. In Lieberoth et al. (2021) that applied the same screening procedure based on response time, the top 1% participants in terms of their survey completion speed were filtered out. Given the extremity of such cases (top 1% survey completion speed), the criterion is deemed to be appropriate to filter out insincere responses (e.g., responses provided without careful considerations, randomly marked responses, etc.).

Third, for measurement invariance test, responses from countries where less than 100 participants who completed the survey were screened out ($n = 21,286$) following Lieberoth et al. (2021). In this process, only the items related to the present study, the Big Five personality trait, compliance, and demographical information items were examined to be as inclusive as possible. Participants who completed the aforementioned items were not screened out even they did not complete the whole survey.

Fourth, to exclude outliers, Mahalanobis distance was used and participants with $p < .001$ in χ^2 test were excluded ($n = 3,020$). Since there have been concerns regarding whether excluding outliers significantly alters analysis outcomes (Aguinis et al., 2013), the results of Bayesian GLM with versus without with outlier exclusion were compared.

Reliability and validity check, and measurement alignment

The internal consistency of the BFI-S across different countries were tested with Cronbach α . To assure at least acceptable consistency ($\geq .60$), data collected from countries where the BFI-S showed $\alpha < .55$ was excluded from further analyses. The validity was tested through measurement invariance test implemented in *cfa* in *lavaan* R package. A robust estimator, WLSMV, was used given responses to the BFI-S were ordinal. If scalar invariance, which assumes that factor loadings and intercepts are equal across countries, was not achieved, measurement alignment implemented in *sirt* package was performed to adjust factor loadings to address measurement non-invariance as recommended for cross-cultural studies (Fischer & Karl, 2019). We examined whether the alignment process successfully addressed non-invariance by checking the resultant for loadings and intercepts, the amount of non-invariance absorbed during alignment. R^2 closer to 1.00 indicates successful alignment (Asparouhov & Muthén, 2014).

Supplementary Analyses and Results

About compliance items

From the correlation analysis (see Table S4), we can find that overall compliance and compliance with distancing measures were significantly correlated and the effect size was large ($r = .65$). It would be possible to consider that the two items assessing the two aforementioned aspects of compliance tendency would significantly overlap with each other, so only one of them shall be employed to avoid redundancy. To test whether it is the case, additional exploratory analysis was conducted.

For the exploration, discriminant validity was examined with an R function, *discriminantValidity*, implemented in *semTools* package (Jorgensen et al., 2021). Discriminant validity was examined whether the two constructs, overall compliance and compliance with distancing measures, were distinguishable from each other. If a significant outcome results from

χ^2 test, then discriminant validity between the tested constructs is supported, so the constructs are deemed to be distinct from each other (Jorgensen et al., 2021; Rönkkö & Cho, 2020). On the other hand, a non-significant outcome suggests that discriminant validity could not be supported, so it is impossible to distinguish the two constructs.

The result of χ^2 test indicated that discriminant validity was supported, $\chi^2 (1) = 968.82, p < .001$. Thus, although the two tested constructs, overall compliance and compliance with distancing measure, were significantly correlated with each other, they shall be treated as two distinguishable and independent constructs. It may suggest that the two items assess two unique and distinct constructs, so they could not be collapsed into one.

Whether outlier exclusion based on Mahalanobis distance significantly influenced Bayesian GLM outcomes

To examine whether outlier exclusion significantly altered Bayesian GLM outcomes, we performed Bayesian GLM with a dataset that did not pass the outlier exclusion process. Then, the results were compared with those from Bayesian GLM performed without outliers.

First, when overall compliance was examined, two best candidate models were identified. The first model included extroversion, openness, agreeableness, and conscientiousness, $BF = 8.65e+1236$, and the second model included all five Big Five personality trait variables, $BF = 7.42e+1236$. Because the BF difference between the two models was 1.22 (< 3.00), evidence did not significantly prefer one model over the other. Thus, these two models equivalently well predicted the dependent variable. Second, when compliance with distancing measures was analyzed, the best regression model contained all five Big Five personality trait variables, $BF = 1.81e+1277$. Third, in the examination of the perceived personal cost, the identified best model included neuroticism, extroversion, agreeableness, and conscientiousness, $BF = 2.18e+944$.

The best models identified from Bayesian GLM with the pre-outlier-exclusion dataset were identical to the best models identified from the main analyses, Bayesian GLM with the post-outlier-exclusion dataset. Hence, it would be possible to conclude that the outlier exclusion procedure performed in the present study did not significantly alter the analysis results.

Table S1
Demographical information presented in raw numbers

	N	Age		Gender			Education level						
		Mean (years)	SD (years)	Female	Male	Other/ would rather not say	PhD, doctorate	College degree, bachelor, master	Some college, short continuing education or equivalent	Up to 12 years of school	Up to 9 years of school	Up to 6 years of school	None
All	61,889	39.38	13.93	43,344	17,587	836	6,681	33,527	10,878	7,060	1,038	1,495	951
Per country													
Australia	273	43.19	14.13	207	63	3	44	158	50	18	2	0	1
Belgium	526	36.49	12.74	303	220	1	36	312	120	44	8	4	1
Bosnia and Herzegovina	1,029	36.74	11.57	769	251	6	55	619	185	157	3	1	3
Canada	386	41.28	13.95	252	122	10	54	221	88	16	1	3	3
Croatia	2,473	35.60	12.35	1,949	510	7	130	1,518	400	395	11	4	5
Finland	19,882	43.56	14.09	16,134	3,354	364	840	9,827	4,085	2,640	616	1,310	425
France	11,427	33.08	12.60	5,898	5,328	177	1,131	6,610	2,439	892	79	140	106
Germany	1,217	36.88	12.09	839	358	18	132	688	241	141	8	1	1
Japan	4,579	44.53	11.28	2,017	2,503	57	119	2,261	565	1,095	156	14	355
Mexico	7,497	37.49	13.72	5,405	2,014	43	2,317	4,009	701	386	38	4	24
Poland	2,506	31.28	7.80	2,172	317	17	127	1,378	575	388	17	0	8
Russia	114	32.77	11.96	83	31	0	18	81	6	1	7	0	0
Slovakia	735	41.87	13.11	557	174	4	89	425	127	72	2	7	6
South Africa	108	41.18	10.52	79	27	2	11	72	18	7	0	0	0
Sweden	2,614	46.43	12.24	1,979	604	26	218	1,438	453	446	46	3	4
Switzerland	1,015	43.26	17.54	624	381	4	87	587	168	130	30	2	6
Taiwan	2,336	33.17	11.35	1,653	630	52	707	1,438	81	102	5	1	0
United Kingdom	1,206	39.88	12.78	922	275	8	160	761	212	67	5	1	0
United States	1,966	42.99	14.79	1,502	425	37	406	1,124	364	63	4	0	3

Table S2
Demographical information presented in percentage values

	N	Gender		Education level							
		Female	Male	Other/ would rather not say	PhD, doctorate	College degree, bachelor, master	Some college, short continuing education or equivalent	Up to 12 years of school	Up to 9 years of school	Up to 6 years of school	None
All	61,889	70.04%	28.42%	1.35%	10.80%	54.17%	17.58%	11.41%	1.68%	2.42%	1.54%
Per country											
Australia	273	75.82%	23.08%	1.10%	16.12%	57.88%	18.32%	6.59%	0.73%	0.00%	0.37%
Belgium	526	57.60%	41.83%	0.19%	6.84%	59.32%	22.81%	8.37%	1.52%	0.76%	0.19%
Bosnia and Herzegovina	1,029	74.73%	24.39%	0.58%	5.34%	60.16%	17.98%	15.26%	0.29%	0.10%	0.29%
Canada	386	65.28%	31.61%	2.59%	13.99%	57.25%	22.80%	4.15%	0.26%	0.78%	0.78%
Croatia	2,473	78.81%	20.62%	0.28%	5.26%	61.38%	16.17%	15.97%	0.44%	0.16%	0.20%
Finland	19,882	81.15%	16.87%	1.83%	4.22%	49.43%	20.55%	13.28%	3.10%	6.59%	2.14%
France	11,427	51.61%	46.63%	1.55%	9.90%	57.85%	21.34%	7.81%	0.69%	1.23%	0.93%
Germany	1,217	68.94%	29.42%	1.48%	10.85%	56.53%	19.80%	11.59%	0.66%	0.08%	0.08%
Japan	4,579	44.05%	54.66%	1.24%	2.60%	49.38%	12.34%	23.91%	3.41%	0.31%	7.75%
Mexico	7,497	72.10%	26.86%	0.57%	30.91%	53.47%	9.35%	5.15%	0.51%	0.05%	0.32%
Poland	2,506	86.67%	12.65%	0.68%	5.07%	54.99%	22.94%	15.48%	0.68%	0.00%	0.32%
Russia	114	72.81%	27.19%	0.00%	15.79%	71.05%	5.26%	0.88%	6.14%	0.00%	0.00%
Slovakia	735	75.78%	23.67%	0.54%	12.11%	57.82%	17.28%	9.80%	0.27%	0.95%	0.82%
South Africa	108	73.15%	25.00%	1.85%	10.19%	66.67%	16.67%	6.48%	0.00%	0.00%	0.00%
Sweden	2,614	75.71%	23.11%	0.99%	8.34%	55.01%	17.33%	17.06%	1.76%	0.11%	0.15%
Switzerland	1,015	61.48%	37.54%	0.39%	8.57%	57.83%	16.55%	12.81%	2.96%	0.20%	0.59%
Taiwan	2,336	70.76%	26.97%	2.23%	30.27%	61.56%	3.47%	4.37%	0.21%	0.04%	0.00%
United Kingdom	1,206	76.45%	22.80%	0.66%	13.27%	63.10%	17.58%	5.56%	0.41%	0.08%	0.00%
United States	1,966	76.40%	21.62%	1.88%	20.65%	57.17%	18.51%	3.20%	0.20%	0.00%	0.15%

Table S3
Descriptive statistics of compliance and BFI-S variables

	Compliance						BFI-S														
	Comp_1		Comp_2		Comp_3		Neuroticism			Extroversion			Openness			Agreeableness			Conscientiousness		
	Mean	SD	Mean	SD	Mean	SD	α	Mean	SD	α	Mean	SD	α	Mean	SD	α	Mean	SD	α	Mean	SD
All	5.02	.96	4.97	1.02	2.74	1.47	.71	5.40	3.69	.79	6.12	4.26	.69	12.66	2.75	.60	7.46	2.90	.63	5.26	3.22
Per country																					
Australia	5.13	.90	5.15	.83	2.84	1.50	.71	7.27	4.29	.82	7.42	4.33	.62	12.16	2.46	.59	7.83	2.94	.56	5.63	2.57
Belgium	5.24	.85	5.33	.80	2.74	1.52	.67	5.93	3.56	.79	3.96	4.38	.62	12.50	2.66	.57	9.01	2.83	.58	3.86	2.72
Bosnia and Herzegovina	5.27	.83	5.09	.95	2.35	1.22	.65	6.67	3.76	.77	7.69	3.37	.60	12.49	2.34	.57	7.54	2.76	.64	5.27	2.32
Canada	5.21	.83	5.29	.87	2.67	1.52	.74	4.41	3.14	.82	5.01	4.13	.63	13.07	2.59	.58	7.46	2.83	.65	5.45	2.76
Croatia	5.27	.75	5.16	.84	2.28	1.22	.71	8.99	4.34	.79	7.28	3.39	.63	12.74	2.35	.58	7.43	1.92	.66	6.01	2.57
Finland	4.97	.94	4.84	1.03	2.95	1.53	.73	4.82	3.40	.83	6.42	3.98	.66	12.83	2.48	.62	7.48	2.72	.63	5.15	2.64
France	5.20	.89	5.33	.85	2.55	1.49	.74	3.88	3.19	.83	6.51	4.63	.64	12.67	2.82	.58	7.37	2.92	.59	3.83	2.88
Germany	5.00	.88	5.05	.92	2.91	1.49	.74	5.13	3.36	.79	5.83	4.18	.65	12.70	2.39	.56	6.99	2.49	.61	5.08	2.67
Japan	4.13	1.03	3.96	1.06	2.87	1.18	.77	6.36	2.77	.69	3.49	3.51	.74	10.38	2.90	.59	4.96	2.76	.55	2.07	2.26
Mexico	5.27	.92	5.23	.98	2.54	1.48	.65	6.94	3.54	.77	5.19	4.14	.63	14.50	2.42	.57	8.16	3.05	.63	7.93	2.71
Poland	5.05	.91	5.07	.95	2.89	1.41	.66	4.54	2.75	.71	8.37	4.10	.63	12.42	2.52	.57	7.84	2.62	.59	7.41	2.90
Russia	4.74	1.14	4.86	1.14	3.01	1.39	.67	8.53	3.58	.80	5.75	3.80	.59	12.32	2.61	.60	6.38	2.47	.63	3.61	2.61
Slovakia	5.14	.91	5.01	1.01	3.22	1.45	.77	6.02	2.89	.76	5.36	3.61	.64	12.57	2.18	.61	8.54	2.51	.63	4.75	2.48
South Africa	5.33	.79	5.38	.78	2.71	1.57	.71	4.05	3.21	.77	6.63	3.60	.63	13.01	2.66	.68	7.55	2.85	.61	7.06	2.43
Sweden	4.94	.91	4.84	.96	2.71	1.39	.78	2.68	2.86	.81	7.28	4.03	.66	12.92	2.70	.61	6.99	2.18	.62	5.30	2.39
Switzerland	5.02	.86	5.07	.87	2.85	1.53	.71	4.78	3.81	.81	6.39	3.46	.60	11.69	2.21	.56	6.95	2.65	.61	6.28	2.60
Taiwan	4.88	.82	4.78	.88	2.47	1.26	.69	9.08	3.56	.86	3.86	4.03	.67	11.16	2.33	.66	7.28	3.05	.56	2.71	2.54
United Kingdom	5.18	.87	5.25	.87	2.85	1.51	.70	5.63	2.78	.77	7.75	3.24	.61	13.65	2.60	.56	10.57	2.31	.60	7.37	1.91
United States	5.12	.96	5.17	.95	2.62	1.49	.70	6.92	3.59	.83	6.40	5.08	.62	10.82	2.00	.60	9.05	2.48	.59	10.15	2.69

Note. Comp_1: “I have done everything I could possibly do as an individual to reduce the spread of Coronavirus” (overall compliance). Comp_2: “I have done everything I could possibly do to keep physical distance to others” (compliance with distancing). Comp_3: “I feel that keeping a physical distance from others would have a high personal cost to me” (perceived personal cost of distancing).

Table S4
Correlation between Big Five personality traits and compliance

	1	2	3	4	5	6	7
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1. Neuroticism							
2. Extroversion	-.21						
3. Openness	-.05	.21					
4. Agreeableness	-.14	.27	.18				
5. Conscientiousness	-.09	.21	.23	.30			
6. Overall compliance	-.04	.11	.20	.22	.26		
7. Compliance with distancing	-.04	.07	.19	.19	.22	.65	
8. Perceived personal cost of distancing	.09	.15	.02	.02	-.02	-.09	-.11

Note. All correlations reported $p < .05$.

Table S5

R² values resulting from measurement alignment

	Factor loadings	Intercepts
Neuroticism	.95	1.00
Extroversion	.98	1.00
Openness	.99	1.00
Agreeableness	.96	1.00
Conscientiousness	.97	1.00

Table S6

Results from Bayesian GLM for best model search

	Included predictors	Bayes factor (vs. null model)	Bayes factor (vs. best model)
DV: "I have done everything I could possibly do as an individual to reduce the spread of Coronavirus" (overall compliance)			
Best	neuroticism, extroversion, openness, agreeableness, conscientiousness	6.87E+2364	1.00
2nd best	extroversion, openness, agreeableness, conscientiousness	2.05E+2359	2.98E-06
3rd best	neuroticism, openness, agreeableness, conscientiousness	1.28E+2358	1.86E-07
4th best	openness, agreeableness, conscientiousness	2.64E+2350	3.84E-15
5th best	neuroticism, extroversion, agreeableness, conscientiousness	9.00E+2243	1.31E-121

DV: "I have done everything I could possibly do to keep physical distance to others" (compliance with distancing)

Best	neuroticism, extroversion, openness, agreeableness, conscientiousness	1.82E+2487	1.00
2nd best	extroversion, openness, agreeableness, conscientiousness	2.59E+2476	1.42E-11
3rd best	neuroticism, openness, agreeableness, conscientiousness	6.23E+2457	3.42E-30
4th best	openness, agreeableness, conscientiousness	2.73E+2441	1.50E-46
5th best	neuroticism, extroversion, openness, conscientiousness	3.51E+2379	1.92E-108

DV: “I feel that keeping a physical distance from others would have a high personal cost to me” (perceived personal cost of distancing)

Best	neuroticism, extroversion, agreeableness, conscientiousness	2.08E+1022	1.00
2nd best	neuroticism, extroversion, openness, agreeableness, conscientiousness	5.21E+1020	2.50E-02
3rd best	neuroticism, extroversion, agreeableness	3.77E+1019	1.81E-03
4th best	neuroticism, extroversion, conscientiousness	7.83E+1018	3.76E-04
5th best	neuroticism, extroversion, openness, agreeableness	1.27E+1018	6.14E-05

Note. Null model: model only with intercepts. For each dependent variable, the best model was bolded.

Table S7

Frequentist and Bayesian GLM results with the best model for each dependent variable (including covariates)

	<i>B</i>	<i>SE</i>	β	Standardized <i>SE</i>	<i>df</i>	<i>t</i>	<i>p</i>	Bayes factor (vs. <i>B</i> = 0)
DV: “I have done everything I could possibly do as an individual to reduce the spread of Coronavirus” (overall compliance)								
Neuroticism	.01	.00	.03	.00	61,220.00	5.75	< .001	Infinite
Extroversion	-.01	.00	-.03	.00	61,490.00	-6.23	< .001	Infinite
Openness	.03	.00	.10	.00	61,470.00	23.88	< .001	Infinite
Agreeableness	.04	.00	.12	.00	61,450.00	28.67	< .001	Infinite
Conscientiousness	.05	.00	.17	.00	60,590.00	34.32	< .001	Infinite
Age	.01	.00	.12	.00	64,170.00	29.01	< .001	Infinite
Gender (vs. female)								
Male	-.19	.01	-.09	.00	61,490.00	-21.98	< .001	Infinite
Other, etc.	-.02	.03	.00	.00	61,480.00	-.06	.54	.07
Education (vs. college, bachelor, etc.)								
PhD/Doctorate	.01	.01	.00	.00	61,490.00	.75	.46	.03
Some college, etc.	.02	.01	.01	.00	61,490.00	2.09	.04	.14

12 yrs of school	.02	.01	.01	.00	61,490.00	1.53	.13	.07
9 yrs of school	.07	.03	.01	.00	61,480.00	2.53	.01	1.12
6 yrs of school	.01	.02	.00	.00	61,480.00	.38	.70	.05
None	.03	.03	.00	.00	61,490.00	.96	.34	.08

DV: "I have done everything I could possibly do to keep physical distance to others" (compliance with distancing)

Neuroticism	.01	.00	.03	.00	61,380.00	7.58	< .001	Infinite
Extroversion	-.01	.00	-.05	.00	61,490.00	-11.98	< .001	Infinite
Openness	.04	.00	.10	.00	61,490.00	24.01	< .001	Infinite
Agreeableness	.03	.00	.09	.00	61,480.00	22.51	< .001	Infinite
Conscientiousness	.04	.00	.12	.00	61,080.00	25.35	< .001	Infinite
Age	.01	.00	.12	.00	61,490.00	29.57	< .001	Infinite
Gender (vs. female)								
Male	-.16	.01	-.07	.00	61,490.00	-17.44	< .001	Infinite
Other, etc.	.04	.03	.00	.00	61,480.00	1.16	.25	.12

Education (vs. college, bachelor, etc.)

PhD/Doctorate	.02	.01	.00	.00	61,490.00	1.17	.24	.03
Some college, etc.	.00	.01	.00	.00	61,490.00	-.19	.85	.02
12 yrs of school	-.04	.01	-.01	.00	61,490.00	-3.29	< .01	5.99
9 yrs of school	.02	.03	.00	.00	61,480.00	.58	.56	.06
6 yrs of school	-.02	.03	.00	.00	61,480.00	-.92	.36	.07
None	-.09	.03	-.01	.00	61,480.00	-2.85	< .01	4.01

DV: "I feel that keeping a physical distance from others would have a high personal cost to me" (perceived personal cost of distancing)

Neuroticism	.06	.00	.16	.00	61,100.00	33.86	< .001	Infinite
Extroversion	.07	.00	.20	.00	61,480.00	45.82	< .001	Infinite
Agreeableness	.01	.00	.02	.00	61,420.00	4.85	< .001	Infinite
Conscientiousness	-.01	.00	-.02	.00	60,200.00	-4.51	< .001	Infinite
Age	-.01	.00	-.08	.00	61,450.00	-18.50	< .001	Infinite
Gender (vs. female)								
Male	.02	.01	.01	.00	61,490.00	1.40	.16	.10

Other, etc.	.07	.05	.01	.00	61,480.00	1.39	.16	.37
Education (vs. college, bachelor, etc.)								
PhD/Doctorate	-.02	.02	-.01	.00	61,490.00	-1.24	.22	.12
Some college, etc.	-.07	.02	-.02	.00	61,490.00	-4.72	<.001	Infinite
12 yrs of school	-.09	.02	-.02	.00	61,490.00	-4.93	<.001	Infinite
9 yrs of school	-.09	.04	-.01	.00	61,490.00	-1.89	.06	.73
6 yrs of school	-.21	.04	-.02	.00	61,490.00	-5.43	<.001	Infinite
None	-.01	.05	.00	.00	61,490.00	-.20	.84	.14

Note. Reference group for gender: female. Reference group for educational level: College degree, bachelor, master. *p*-values < .05 and Bayes factors ≥ 3 were bolded.

Supplementary References

- Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-Practice Recommendations for Defining, Identifying, and Handling Outliers. *Organizational Research Methods*, 16(2), 270–301.
<https://doi.org/10.1177/1094428112470848>
- Asparouhov, T., & Muthén, B. (2014). Multiple-Group Factor Analysis Alignment. *Structural Equation Modeling: A Multidisciplinary Journal*, 21(4), 495–508.
<https://doi.org/10.1080/10705511.2014.919210>
- Fischer, R., & Karl, J. A. (2019). A Primer to (Cross-Cultural) Multi-Group Invariance Testing Possibilities in R. *Frontiers in Psychology*, 10. <https://doi.org/10.3389/fpsyg.2019.01507>
- Jorgensen, T. D., Pornprasertmanit, S., Schoemann, A. M., Rosseel, Y., Miller, P., Quick, C., Garnier-Villareal, M., Selig, J., Boulton, A., Preacher, K., Coffman, D., Rhemtulla, M., Robitzsch, A., Enders, C., Arslan, R., Clinton, B., Panko, P., Merkle, E., Chesnut, S., ... Rönkkö, M. (2021). *Package ‘semTools.’*
<http://ftp5.gwdg.de/pub/misc/cran/web/packages/semTools/semTools.pdf>
- Lieberoth, A., Lin, S.-Y., Stöckli, S., Han, H., Kowal, M., Chrona, S., Gelpi, R., Tran, T. P., Jeftić, A., Rasmussen, J., Cakal, H., & Milfont, T. (2021). Stress and worry in the 2020 coronavirus pandemic: Relationships to trust and compliance with preventive measures across 48 countries. *Royal Society Open Science*, 8(2), 200589.
<https://doi.org/10.1098/rsos.200589>
- Rönkkö, M., & Cho, E. (2020). An Updated Guideline for Assessing Discriminant Validity. *Organizational Research Methods*, 109442812096861.
<https://doi.org/10.1177/1094428120968614>