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RESEARCH ARTICLE

Identifying important individual- and country-level predictors of conspiracy theorizing: A machine learning analysis

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Abstract

Psychological research on the predictors of conspiracy theorizing—explaining important social and political events or circumstances as secret plots by malevolent groups—has flourished in recent years. However, research has typically examined only a small number of predictors in one, or a small number of, national contexts. Such approaches make it difficult to examine the relative importance of predictors, and risk overlooking some potentially relevant variables altogether. To overcome this limitation, the present study used machine learning to rank-order the importance of 115 individual- and country-level variables in predicting conspiracy theorizing. Data were collected from 56,072 respondents across 28 countries during the early weeks of the COVID-19 pandemic. Echoing previous findings, important predictors at the individual level included societal discontent, paranoia, and personal struggle. Contrary to prior research, important country-level predictors included indicators of political stability and effective government COVID response, which suggests that conspiracy theorizing may thrive in relatively well-functioning democracies.

KEYWORDS
conspiracy theories, country-level variables, COVID-19, machine learning, individual-level variables

1 | INTRODUCTION

Societal polarization in the wake of the COVID-19 pandemic is a life-and-death example of the impact of conspiracy theories. Conspiracy theories contribute to many issues of existential importance including the erosion of democratic norms, vaccine hesitancy, and denial of climate change (Douglas, 2021; Uscinski & Parent, 2014). In order to address these negative impacts, it is crucial to have a comprehensive understanding of the predictors of conspiracy theorizing. A significant limitation of the existing literature is that researchers have typically examined only a small number of predictors at a time, within one or a small number of national contexts. This is largely because relevant theory tends to focus on low- to mid-level analyses, specifying only a small number of proximal predictors. This inevitably overlooks other possible predictors beyond the scope of these theoretical models (Douglas et al., 2019), and the relative importance of these predictors (Hornsey et al., 2023). Machine learning offers a complementary approach—a data-driven, exploratory analysis of many candidate predictors at different levels of analysis, which identifies the most important predictors of conspiracy theorizing and holds the potential to reveal overlooked factors at the individual and contextual (country) level, thus inspiring new hypotheses (Van Lissa, 2022a). In the present study, we conducted a machine learning analysis of 115 potential individual- and country-level predictors of conspiracy theorizing in a large international dataset collected during the early weeks of the COVID-19 pandemic.

1.1 | What are conspiracy theories and where might they thrive?

Conspiracy theorizing refers to a belief that two or more actors have coordinated in secret to achieve an outcome and that their conspiracy is of public interest but not public knowledge (Douglas & Sutton, 2023). In the past 15 years, research has focussed on the psychological determinants of conspiracy theorizing (see Douglas et al., 2017; Douglas et al., 2019 for reviews). In a review of the literature, Douglas et al. (2017) synthesised these psychological determinants into a framework of *epistemic factors* such as paranoia, *existential factors* such as feeling unsafe, and *social factors* such as perceptions of outgroup threat. Many of these same variables also predict conspiracy theorizing about the origins of COVID-19 (e.g., Bertin et al., 2020; Georgiou et al., 2020; Jolley & Paterson, 2020; Miller, 2020), suggesting that conspiracy theorizing about specific events (e.g., the origins of COVID-19) shares similar predictors with conspiracy theorizing about more general aspects of social and political circumstances (e.g., that politicians do not inform the public of the true motives behind their decisions).

Despite the abundance of prior research on individual-level predictors of conspiracy theorizing, each study has typically focussed on only a small number of predictors. For example, some studies have focussed on the relationship between individual differences in feelings of control and conspiracy theorizing (e.g., van Prooijen & Acker, 2015), whereas others have focussed on feelings of paranoia (e.g., Darwin et al., 2011). Different individual-level predictors are rarely combined within a single study, which precludes assessing their relative importance in predicting conspiracy theorizing. There are also doubts about the cross-national generalizability of individual-level predictors since research has generally studied these predictors in one national context (Hornsey et al., 2023). It therefore remains to be seen how frameworks such as the one proposed by Douglas et al. (2017) can explain conspiracy belief amidst a range of other (previously un-tested) variables, and across a wide range of national contexts.

Even less is known about potential contextual or country-level predictors of conspiracy theorizing. Conspiracy theorizing has typically been examined in smaller-scale studies conducted in one country (and typically in WEIRD samples) or has compared conspiracy theorizing across a limited number of countries (e.g., Adam-Troian et al., 2021; Stojanov & Douglas, 2022). Studies have yet to examine how conspiracy theorizing may vary from place to place according to country-level differences. These limitations of the literature pose a challenge when seeking to understand conspiracy theories in the context of a global threat like COVID-19.

There is some evidence at the within-country level suggesting that contextual factors may be important at the between-country level, too. Within countries, adverse socio-political circumstances such as low socio-economic status (Abalakina-Paap et al., 1999; Crocker et al., 1999; Goertzel, 1994; Uscinski & Parent, 2014), discrimination (Simmons & Parsons, 2005), discontent (Davis et al., 2018; Thomas & Quinn, 1991), and victimization (Parsons et al., 1999) are all associated with increased conspiracy theorizing. As countries typically differ in these contextual factors, we might expect conspiracy theorizing to be more prevalent in countries that have less well-functioning socio-political systems and where people have more reason to feel disillusioned. Following these findings, scholars have argued that conspiracy theorizing, and the deeper political and economic malaise they signify, could therefore be attenuated by increased societal equity and transparency (e.g., Douglas et al., 2015; Sobo, 2021).

There are, nonetheless, theoretical grounds to expect the opposite relationship between socio-political conditions and conspiracy theorizing. Conspiracy theories question and problematize power, and often refer to the actions of a powerful government and its agencies (Uscinski & Parent, 2014). Thus, they may flourish in countries with powerful and effective states, whose governments are seen as more capable of conspiring. There is also reason to think that conspiracy theories may flourish in democratic states. Specifically, conspiracy theorizing has been framed as a way to attack and delegitimize political opponents (Uscinski & Parent, 2014), allowing communities to construct alternative narratives to resist being erased or disempowered by those in power (e.g., Briggs, 2004; Sapountzis & Condor, 2013). Conspiracy theorizing provides a 'heuristically indispensable' reminder that political power is concealed and exercised secretly (Huntington, 1983, p. 78) and that in modern capitalist economies, 'corporations may make false claims; control certain markets unfairly; or manipulate Government support' (Sobo, 2021, p. 63). In sum, some scholars have argued that conspiracy theories may be a tenet of democracy.

There are therefore competing hypotheses about the societal conditions that foster conspiracy theories. According to some research, they thrive in brutal, dysfunctional, or unjust social conditions in which people are structurally disempowered and psychologically disillusioned (e.g., Douglas et al., 2015). On the other hand, they may prosper in more stable and democratic social conditions where states are strong and where politicians, journalists, opinion leaders, and the public have the political freedom and resources to express and disseminate their suspicion and criticism of powerful elites (Enders & Smallpage, 2018). Exploratory research using large-scale multinational data may determine which of these theoretical perspectives is most plausible.

1.2 | Methodological approaches

Existing research has largely been confirmatory, relying on theory to identify reliable predictors of conspiracy theorizing. Recently, it has been argued that machine learning analyses can complement existing theory by facilitating the rigorous exploration of large datasets, casting a broader net and identifying potentially overlooked relevant predictors (Van Lissa, 2022a, 2022b). In a recent analysis of this type, Brandenstein (2022) analysed several predictors of conspiracy theorizing based on Douglas et al.'s (2017) framework of epistemic, existential, and social needs. Brandenstein conducted a machine-learning analysis on a representative dataset of over 2000 UK citizens. This analysis revealed that the relationships between epistemic, existential, and social factors and conspiracy belief—which have been observed in previous research—were largely supported. Brandenstein (2022) therefore sets a precedent for using a machine-learning approach to study the predictors of conspiracy belief. In the current study, we go further by (a) examining a wider range of psychological predictors including many that have previously been untested, (b) examining a range of country-level predictors, and (c) including a wide range of national contexts. Multiple individual-level variables are tested simultaneously alongside multiple country-level factors to establish a picture of the most important predictors of conspiracy theorizing.

The machine learning algorithm *random forests* (Breiman, 2001) is particularly suited to this endeavour (see Brandmaier et al., 2016) because it can accommodate a large number of candidate predictors and performs variable selection, usually offers very good performance at low computational cost, and affords straightforward interpretation of variable importance and marginal effects of the predictors. The algorithm intrinsically accommodates non-linear associations and interactions between predictors, which is advantageous in the absence of a strong theory about the shape of associations. Random forests also curtail spurious results and maximize the generalizability of the findings by means of bootstrap aggregation. Specifically, many bootstrap samples are drawn from the original data, and a regression tree model is estimated on each bootstrapped dataset. The prediction error of this tree model is then estimated on cases not in the bootstrap sample, which provides an estimate of the model's generalizability. In model selection, this so-called 'out-of-bag' prediction error is minimized, thus ensuring a generalizable result. A further advantage of random forests is that it can accommodate both individual- and national-level predictors and is robust to measurement variance and cross-level interactions, where a given predictor has a different effect in different countries. In both cases (measurement variance or random effects), the model would include an interaction that accounts for different effects between countries. Random forests thus constitute a relatively flexible model that can identify potentially important predictors even in the presence of relationships of unknown complexity, while incorporating checks and balances to prevent false-positive findings and ensure generalizability (see Hastie et al., 2009).

1.3 | The present study

The present study used data collected by the PsyCorona consortium (see https://www.rug.nl/sustainable-society/research/previous-themes/psycorona/ for details), which was launched in 114 countries with over 60,000 participants in the weeks after the World Health Organization (WHO) declared COVID-19 a pandemic. A 20-min web-based survey, which was translated into 30 languages, investigated the psychological impact of the COVID-19 pandemic. Data were collected by a combination of convenience sampling, snowball sampling, and representative sampling by a professional service. Full details of the PsyCorona survey and all variables measured are available here: https://osf.io/qhyue.[1]

This study used data collected from 19 March to 17 May 2020. Individual-level variables included demographic factors (e.g., age, gender, education, religion) and shortened self-report measures of psychological factors, including some that pertain to the psychological needs associated with conspiracy theorizing (e.g., paranoia, feelings of struggle, migrant threat; Douglas et al., 2017). The survey was broad in scope and thus included many individual-level psychological variables not currently known to be relevant to conspiracy theorizing. From the PsyCorona survey, we included 80 individual-level variables, of which 16 were multi-item composites. The survey data were enriched with country-level factors (e.g., political stability, the effectiveness of government), some of which were matched to the date of participation in the survey (pandemic severity, government policy response to COVID-19). In total, 35 country-level variables were included. The dependent variable of interest was the extent to which participants engaged in conspiracy theorizing. A table of all variables and their descriptions is available in the project OSF repository: https://osf.io/ev24r/.

The present study is explicitly exploratory, and therefore no hypotheses are provided. Nevertheless, based on previous research we might expect some individual-level variables to emerge as important predictors (e.g., feelings of struggle, paranoia, migrant threat). Furthermore, as this analysis is one of the first studies on conspiracy theorizing to use a large multinational sample, we might expect results to shed light on the two contrasting perspectives we outlined earlier regarding country-level predictors. Specifically, if conspiracy theories are a consequence of poor socio-political conditions, then we would expect the machine learning results to show that conspiracy theorizing is related to country-level indices of negative life conditions including lower political stability and higher deaths from COVID-19. On the other hand, if conspiracy theorizing is more characteristic of relatively well-functioning societies with fewer social problems, we would expect it to be related to country-level indices of positive life conditions such as higher political stability and lower number of deaths from COVID-19.

[1] To date, several publications have been published or submitted which have utilized data from this large-scale cross-national longitudinal project. No project has investigated the individual- or country-level predictors of conspiracy theorizing.

2 | METHOD

All data files, analysis code and secondary data used in this study are available in the project OSF repository: https://osf.io/ev24r/.

2.1 | Participants

The cross-sectional PsyCorona survey was approved by the Ethics Committee of the University of Groningen (study code: PSY-1920-S-0390) and New York University Abu Dhabi (study code: HRPP-2020-42). All participants gave their informed consent before taking the survey. Of the 60,192 participants who completed the original survey, 61% were female, 38% were male and 0.5% indicated 'other' for their gender (0.5% were missing data). The majority of participants were between 25 and 34 years old (24.4%) with 22.2% aged 18–24, 19.2% 35–44, 14.3% 45–54, 11.4% 55–64, 6.9% 65–74, 0.9% 75–85 and 0.1% over 85 (0.6% were missing values). The majority of participants had a bachelor's degree education (30.1%), 1.5% had primary education, 13.2% secondary, 9.9% vocational, 22.9% higher, 16.5% has a master's degree and 5.3% had a PhD (0.7% were missing values).

2.2 | Conspiracy theorizing

The dependent variable was operationalized as a mean score of three items from the widely used conspiracy mentality questionnaire (CMQ; Bruder et al., 2013). These were 'Many very important things happen in the world, which the public is never informed about', 'Politicians usually do not tell us the true motives for their decisions' and 'Government agencies closely monitor all citizens' (0 = certainly not 0% to 5 = undecided 50% to 10 = certainly 100%, overall $\alpha = .73$; for reliability statistics per country, see Table S1). The CMQ is a measure of an individual's general tendency towards conspiracy theorizing. It does not refer to specific conspiracy theories (which vary widely across countries).

Note that random forests do not assume measurement invariance across countries for either the predictors or outcome variable. If measurement variance is present and causes heterogeneity in effects of other predictors across countries, the trees in the model accommodate this by first splitting on country and then splitting on the remaining predictors, effectively estimating country-specific models. Since country had low variable importance, however, there is little evidence that this is the case in our data. The full codebook for the survey is available here: https://osf.io/qhyue/. In most cases, brief or abbreviated measures (as was the case for the CMQ) were chosen to reduce the length of the survey and improve sample size and retention for subsequent waves.

2.3 | Data cleaning

As previously mentioned, we included 80 variables from the PsyCorona Survey. To ensure the stability of the modelling procedure and the performance of the model, we needed to exclude countries with very few participants. In particular, we sought to avoid imbalanced subgroups, which can lead to issues with reliability and robustness (Chawla et al., 2022). Countries constituting less than 1% of the total sample were therefore excluded. The final sample consisted of N = 56,072 respondents across 28 countries (all countries are listed in Table S1).

As our analyses required complete data and could not use multiple imputation, we used missForest, a single imputation method with comparable performance to multiple imputation, to impute missing data (Stekhoven & Bühlmann, 2012). Prior to imputation, we plotted the density of missing values by variable and by participant and observed that missingness in variables was mostly below 20%, and missingness in respondents was mostly below 28%. We excluded variables and participants with greater missingness than these subjective thresholds, which resulted in the exclusion of a number of variables that had been added or modified after data collection had started, and 1% of respondents. Third, we computed mean scores for multi-item scales using the tidySEM R-package (Van Lissa, 2021). Two scales were excluded because their reliability fell below acceptable standards. These were a three-item boredom scale, and an ad hoc 'Corona Reflection Task' where participants were asked to reason about epidemiological and policy dilemmas (Cronbach's alphas .53 and .27, respectively).

2.4 | Data enrichment

The PsyCorona data were enriched with country-level data from public sources. These sources were selected due to their international relevance for affording, shaping or guiding individual-level behavioural responses to COVID-19. They measured pandemic severity (as indicated by the number of cases, deaths and recovered patients), pandemic-related policies (including both pre-existing policies and ongoing governmental response to the COVID-19 pandemic) and pandemic preparedness. Table 1 presents an overview of the included databases. The time range in data collection afforded variability in the degree to which people in a given country were seeing cases and/or engaging in different containment policies. When applicable, respondents' country-level data were matched to their date of participation (e.g., confirmed cases, lockdown severity). After enrichment and data cleaning, there were 115 predictors (80 survey factors, 35 country-level factors).

2.5 | Data analytic plan

Prior to analysis, we used random sampling to construct a training dataset and test dataset consisting of 70% and 30% of the total sample, respectively. This ratio of training and test data is arbitrary, but conventional (Hastie et al., 2009). To avoid any cross-contamination between the training and test sample, this percentage and the random seed used to split the data were committed to the public GitHub repository before gaining access to the data (see the project OSF repository: https://osf.io/ev24r/). The training set was used for model building, and the test set was used exclusively for unbiased estimation of the final model's predictive performance (generalizability) after all other analyses were complete.

Random forest analyses were conducted using the ranger R-package (Wright & Ziegler, 2015). The forest consisted of 1000 trees. Two tuning parameters of random forests are the number of candidate variables to consider at each split of each tree, and the minimum node size resulting from a split. The optimal tuning parameters were selected by minimizing the out-of-bag mean squared error (MSE) using model-based optimization with the R-package tuneRanger; in large datasets, this approach is equivalent to cross-validation (Probst et al., 2019). The best model considered 30 candidate variables at each split, and a minimum of seven cases per terminal node. We report the results of this best model.

We report three types of output from the random forests analysis. The first are predictive performance metrics, which refer to the model's ability to accurately predict new data in the test dataset. As a standardized metric of predictive performance, we examine predictive R^2. It is a measure of explained variance analogous to the regular R^2, except that in the machine learning context, it is computed on the test dataset, which was not used to estimate the model. This estimate is unbiased, and always lower than the R^2 on the training data. Estimates of R^2 on the training sample should be interpreted as a measure of descriptive performance (i.e., how well the model describes the data at hand) and can be (severely) positively biased when used as an estimate of predictive performance in new data. Given that we also recruited an age-gender representative subsample across 20 countries, we were additionally able to compute predictive performance for the representative subsample of the test sample to better examine the generalizability of our findings to the target population.

The second outcome metric is variable importance, which reflects each predictor's relative contribution to prediction accuracy. Variable importance is estimated by randomly permuting (shuffling) the values of each predictor variable in turn, thus removing any meaningful association with the outcome. The model's predictive performance is then re-computed with one permuted variable, and the decrease in variable importance relative to the unpermuted model is taken to reflect the (inverse) importance of that variable (Breiman, 2001).

TABLE 1 Summary of country-level databases

Database	Description
1. Johns Hopkins University COVID-19 Data Repository Center for Systems Science and Engineering (CSSE)	Number of confirmed COVID-19 infections, deaths, and recoveries by date per country[a]
2. Global Health Security (GHS) Index	Country-level ratings of pandemic preparedness and general health security[b]
3. World Health Organization (WHO) and Organization for Economic Cooperation and Development (OECD)	Country-level health care resources and health infrastructure[c]
4. World Bank: Worldwide Governance Indicators (WGI)	Per-country data on aggregate ratings of: voice and accountability, regulatory quality, political stability and absence of violence, rule of law, government effectiveness and control of corruption[d]
5. Oxford COVID-19 Government Response Tracker (OxCGRT)	Governmental responses and policies with respect to COVID-19 by date per country[e]

a Available at https://github.com/CSSEGISandData/COVID-19.
b Available at https://www.ghsindex.org/
c Available at https://apps.who.int/gho/data/node.main.HWF and https://stats.oecd.org/index.aspx?queryid=30183
d Available at http://info.worldbank.org/governance/wgi/
e Available at https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

Note that, although random forests are robust to multicollinearity, multicollinearity does attenuate estimated variable importance.

The third type of output are partial dependence plots. These visualize the marginal bivariate association between each predictor and the outcome, while averaging over all other predictors. They are derived by computing predictions of the dependent variable across a range of values for each individual predictor, while averaging across all other predictors using Monte Carlo integration. They show the direction and (non)linearity of a specific marginal effect (Breiman, 2001). The partial dependence plots in this article are generated using the metaforest R-package (Van Lissa, 2018). Note that random forests are not the same as multiple linear regression (MLR). Whereas MLR is easier to interpret, random forests provide a better model. Other than identifying basic marginal associations, random forests are best suited to understand (1) how well an outcome can be predicted and (2) which variables are most important in predicting the outcome.

3 | RESULTS

3.1 | Predictors of conspiracy theorizing

The random forest model explained 26% of the variance in conspiracy theorizing in the testing sample, and 29% in the representative subsample of the testing sample. We tested alternative algorithms and found the predictive performance of the random forest approach to be superior (the results of these additional analyses are provided in Table S2). We report the top 30 predictors here due to space restrictions, but full results are available on the project OSF repository. Figure 1 displays the rank-ordered variable importance, along with an approximate indication of whether each predictor's effect is positively or negatively monotonous, or differently shaped (e.g., curvilinear). Table 2 provides a brief legend of the predictors and more detail is available on the project OSF repository. The partial dependence plots show the marginal bivariate association between each predictor and conspiracy theorizing, averaging over all other predictors (Figure 2).

Among the top 30 predictors of conspiracy theorizing were 15 individual-level factors and 14 country-level factors. The most important individual-level predictors were higher discontent with the direction of society, lower support for extraordinary government economic intervention and higher paranoia. Overall, these individual-level predictors are in line with prior theory and research. The most important country-level predictors were higher political stability, higher government effectiveness and lower deaths from COVID-19. Overall, they were objective indices of good life conditions.

4 | DISCUSSION

Research on the psychology of conspiracy theories has largely been biased towards the individual level of analysis and limited to theoretical frameworks that specify proximal causal relations between a small number of variables (Douglas et al., 2019). Using a machine-learning analysis, the present study sought to complement existing knowledge by providing a more comprehensive empirical overview of the associations between conspiracy theorizing and potentially relevant individual- and country-level predictors.

Our discussion of the results focusses on the 30 most important correlates of conspiracy theorizing, as identified by the analyses. Of these, 15 were individual-level factors. Conspiracy theorizing was correlated with—in descending order of magnitude—discontent with the direction of society, (low) support for extraordinary government intervention in the economy, paranoia, economic consequences, future focus, COVID-19 personal safety, (low) economic efficacy, perceptions of migrant threat, (low) online contact with immigrants, present focus, past focus, and (low) COVID-19 restrictive measures.

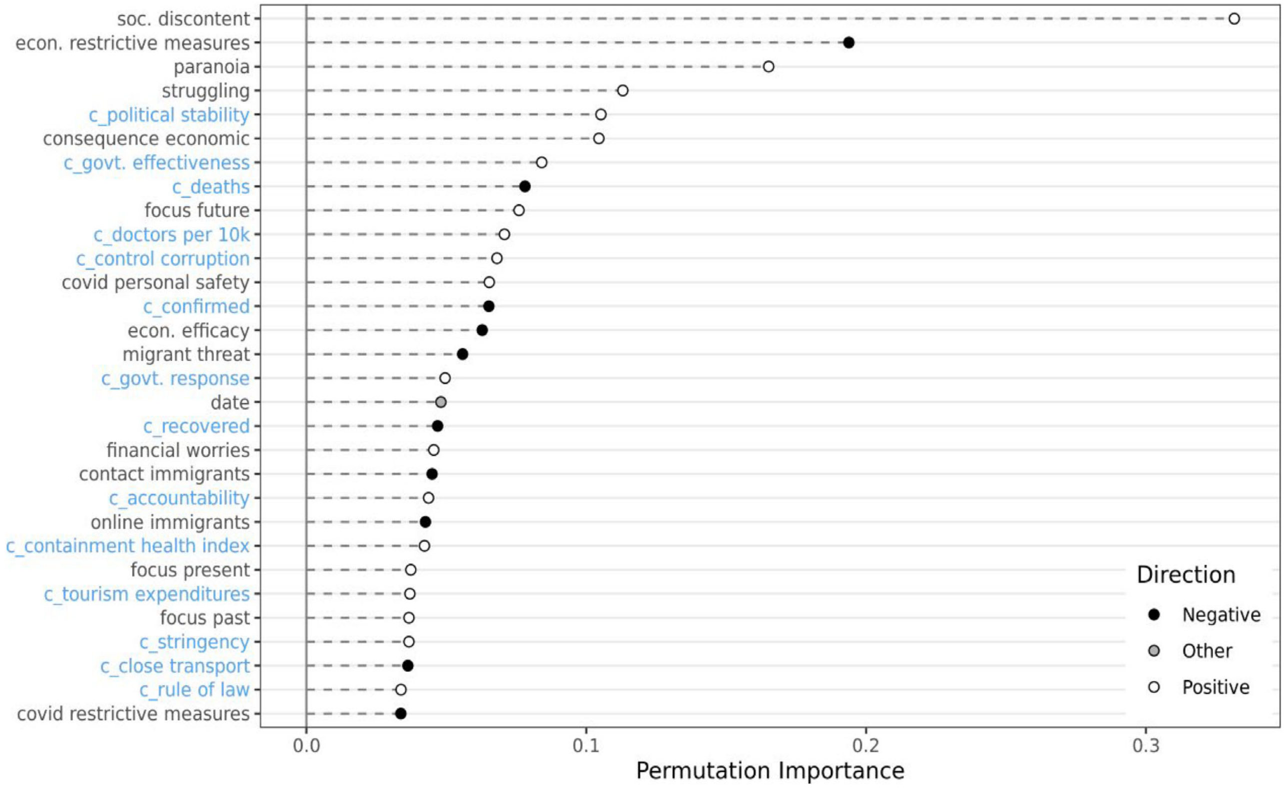

FIGURE 1 Rank-ordered variable importance. Permutation importance gives an indication of the relative importance for each predictor. It is based on the idea that if a predictor variable is important, then randomly permuting its values should have a large impact on the model's prediction accuracy. The colours give an approximate indication of whether the relationship is linearly positive or negative or whether the variable has a non-linear (i.e., 'other') relationship with conspiracy beliefs. For more information on the actual shape of the relationship see Figure 2. Table 2 provides a brief description of each variable.

The first four of these predictors were more powerful than any country-level predictors. For the most part, these individual-level predictors are in line with prior theory and research, including the results of a similar machine-learning analysis by Brandenstein (2022). Research has found that conspiracy theorizing is be associated with a negative view of elites, disillusionment with society, paranoia and frustrated psychological needs (Douglas et al., 2017, 2019). However, several important predictors have not been previously studied in conjunction with conspiracy theorizing, such as the variables related to temporal focus (future, present and past focus; Schipp et al., 2009). Future research might seek to explain why these variables are important predictors. For instance, perhaps temporal focus reflects a thinking style associated with a felt need to explain important events. Furthermore, several of the individual-level predictors that were positively associated with conspiracy theorizing were related to negative perceptions of society, especially of how society can meet individual needs. It is worth noting, however, that individuals' subjective perceptions of the overall welfare and direction of society can often be dissociated from objective reality (van der Bles et al., 2015). Experiencing societal discontent, therefore, does not mean that a society is indeed in decline. We therefore turn now to the associations between conspiracy theorizing and objective indicators of social conditions at the country level.

Fourteen of the 30 most important correlates of conspiracy theorizing were contextual (country-level) factors. These correlates had something clear and striking in common: they were objective indices of good life conditions. These were, in descending order: political stability, government effectiveness, (low) deaths, (low) confirmed cases of COVID-19, number of doctors per capita, control of corruption, government response to the pandemic, (low) number of recovered cases (entailing a low number of early cases), accountability, the containment health index, tourism expenditure, stringency, and rule of law. Conspiracy theorizing generally appeared to be higher in countries in which social, legal, and health conditions were favourable. Note, however, that the marginal associations for political stability, governmental effectiveness and corruption control suggest that the association between governmental effectiveness and conspiracy theorizing is positive and increasing for all but the most effectively governed countries. These consistently included Australia, Canada, Germany, Japan, the Netherlands and the United Kingdom. At very high levels of these indicators of governmental effectiveness, lower levels of conspiracy theorizing were observed (see Figure 2 and Figures S1 and S2). Furthermore, as was the case for individual predictors, important country-level variables emerged that have not previously been studied in conjunction with conspiracy theorizing, such as country-level tourism expenditure—arguably another indication of a

TABLE 2 Legend to the top 30 predictors of conspiracy theorizing listed in Figure 1

	Variable	Level	Brief description
1	soc. discontent	Individual	Concern about direction of society (Gootjes et al., 2021)
2	econ. restrictive measures	Individual	Support for extraordinary governmental intervention in economy (self-developed)
3	paranoia	Individual	State assessment of suspiciousness of other people (Schlier et al., 2016)
4	struggling	Individual	Disempowerment (Gootjes et al., 2021; Leander et al., 2019)
5	c_political stability	Country	Political stability and absence of violence/terrorism (World Governance Indicators)
6	consequence economic	Individual	How personally disturbing it would be to suffer economic consequences due to coronavirus (self-developed)
7	c_govt. effectiveness	Country	Government effectiveness (World Governance Indicators)
8	c_deaths	Country	Number of confirmed COVID-19 deaths (Johns Hopkins Center for Systems Science and Engineering)
9	focus future	Individual	Temporal focus on the future (Schipp et al., 2009).
10	c_doctors per 10k	Country	Number of doctors per 10,000 residents (Johns Hopkins Center for Systems Science and Engineering)
11	c_control corruption	Country	Control over corruption (World Governance Indicators)
12	covid personal safety	Individual	Engaging in infection prevention behaviours (e.g., handwashing) (self-developed)
13	c_confirmed	Country	Number of confirmed COVID-19 infections (Johns Hopkins Center for Systems Science and Engineering)
14	econ. efficacy	Individual	Belief that one's country is able to handle economic consequences of COVID (self-developed)
15	migrant threat	Individual	Perceived symbolic and realistic threats from migrants (based on American National Election Studies (2014) and European Social Survey (2014)). Note that higher values indicate lower migrant threat
16	c_govt. response	Country	Overall government response index-strong/weak (Oxford Policy Response Tracker)
17	date		Date of survey participation
18	c_recovered	Country	Number of confirmed COVID-19 recoveries (Johns Hopkins Center for Systems Science and Engineering)
19	financial worries	Individual	Perceived financial strain (Selenko & Batinic, 2011)
20	contact immigrants	Country	Days of in-person (face-to-face) contact with immigrants
21	c_accountability	Individual	Voice and accountability (World Governance Indicators)
22	online immigrants	Individual	Days of online (virtual) contact with immigrants in the past week
23	c_containment health index	Country	Containment and health index (Oxford Policy Response Tracker)
24	focus present	Individual	Temporal focus on the present moment (Schipp et al., 2009)
25	c_tourism expenditures	Country	Index of international tourism expenditure (The World Bank)
26	focus past	Individual	Temporal focus on the past (Schipp et al., 2009)
27	c_stringency	Country	Government COVID-19 response tracker, measured across 17 policy indicators (Oxford Government Response Tracker)
28	c_close transport	Country	Closure of public transport on day of survey (Oxford Government Response Tracker)
29	c_rule of law	Country	Confidence with, and abidance by the laws of society (country World Governance Indicators)
30	covid restrictive measures	Individual	Support for severe collective virus containment (self-developed)

well-functioning society. Future research might seek to further explore these associations.

In summary, our findings suggest that conspiracy theorizing may flourish more in effectively governed rather than dysfunctional societies, except in the most effectively governed societies. This does not negate the hypothesis that conspiracy theorizing is animated by adverse political developments including corporate and political corruption (Sobo, 2021), and government secrecy and surveillance (Enders & Smallpage, 2018; Huntington, 1983). Nor does it discount the role of collective or group-based adversities including poverty

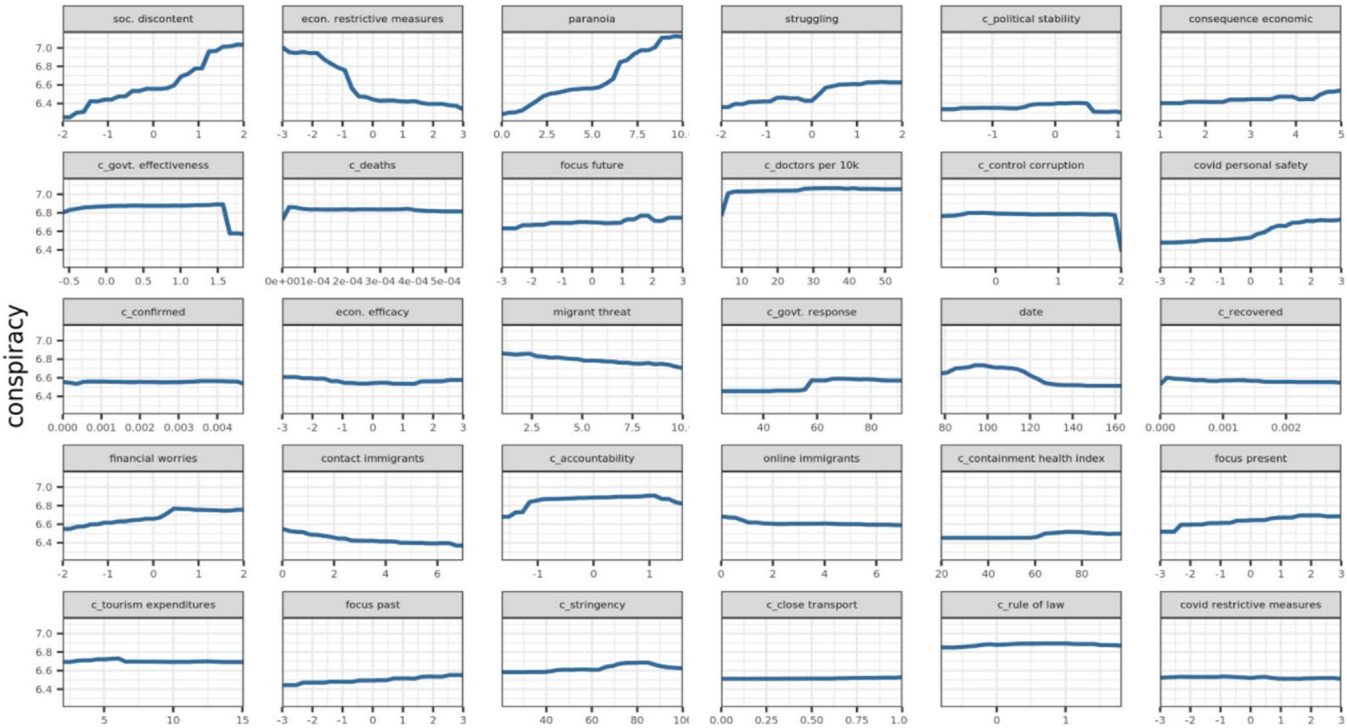

FIGURE 2 Partial dependence plots. Partial dependent plots offer a graphical representation of the marginal effect of the single predictor variable on the conspiracy outcome variable. The value of the individual predictor variable is varied over its full range while holding the values of all other predictor variables constant at their mean. The line indicates the predicted values at each level of the predictor variable for such a model.

(Abalakina-Paap et al., 1999; Crocker et al., 1999; Goertzel, 1994; Uscinski & Parent, 2014), discrimination (Simmons & Parsons, 2005), disadvantage (Davis et al., 2018; Thomas & Quinn, 1991), and victimization (Parsons et al., 1999). However, our findings are consistent with the perspective that conspiracy theorizing may play a corrective role in the functioning of effective societies where concerns about societal decline are possible (Briggs, 2004; Huntington, 1983; Sobo, 2021), and with the perspective that conspiracy theorizing is a privilege enjoyed in effectively governed societies where dissenters are sufficiently resourced to express and share their thoughts publicly (Douglas et al., 2019).

Our finding that conspiracy theorizing seems to thrive in effectively (but not the most effectively) functioning societies might at first glance appear to be at odds with prior literature on conspiracy theories (for reviews concluding that conspiracy theories, on balance, appear to be damaging to societies see Douglas et al., 2017, 2019). Specifically, conspiracy theorizing has been shown to predict political disengagement and anomie (Jolley & Douglas, 2014), endorsement of political violence (Jolley & Paterson, 2020), non-normative political action (Imhoff et al., 2021) and hatred of social and political outgroups (Kofta et al., 2020), none of which are necessarily hallmarks of effective societal functioning. It is important to note, however, that these findings have largely emerged from studies of the consequences of *individuals'* exposure to, or belief in, conspiracy theories. It is possible that the adverse effects of conspiracy theorizing on individual behaviour are countervailed by positive systemic effects of the sort identified by scholars (e.g., Briggs, 2004; Huntingdon, 1983; Sobo, 2021). Alternatively, conspiracy theorizing may flourish in well-functioning societies, while at the same time undermining their functioning. The present findings thus do not contradict previous findings but do indicate fruitful directions for future research. Future research should address whether these links are causal in nature, for example, by examining whether conspiracy theorizing is reduced when governments become more transparent and accountable (Jolley et al., 2018).

4.1 | Limitations and future research

One limitation of the present study is that our data are correlational. The exploratory findings resulting from machine learning analyses emphatically do not warrant causal conclusions, although they may give rise to causal hypotheses, which can be tested in future confirmatory research (Van Lissa, 2022a). A related limitation is that the results are conditional on the scope of the included predictors, as is the case in all quantitative research. We cannot exclude the possibility that an important predictor or confounder was omitted (e.g., political orientation, social media use), nor can we exclude the possibility that any of the predictors may be colliders.

Another limitation relates to the operationalization of conspiracy theorizing. We used three items from the CMQ, a scale intended to assess generalized political suspicions about authority that are associated with the endorsement of conspiracy theories. The CMQ does not assess the endorsement of *specific* conspiracy theories (e.g., about the moon landings or the death of Diana, Princess of Wales, COVID-19). The use of a more general measure like the CMQ may have some advantages—for example, it may be better suited for multinational research because it is not affected by cultural differences in familiarity with specific conspiracy theories, or impacted by culturally variant prejudices against specific alleged conspiratorial actors. However, some have argued that the CMQ assesses different aspects of conspiracy theorizing than other scales (Ståhl & van Prooijen, 2018; Sutton & Douglas, 2020), and some have questioned its validity (Swami et al., 2017). Another limitation related to the validity of the CMQ is that its items arguably refer to the effective functioning of a powerful state, one that is sufficiently resourced and organized to keep secrets and monitor its citizens. This may introduce confounding with objective between-country differences in functioning of the state, which may help explain some of the country-level effects we found. The CMQ items further reflect a sceptical and questioning attitude to political authority; although these attitudes are related to conspiracy theorizing, they can also be beneficial to societal functioning (e.g., Huntingdon, 1983; Sobo, 2021). Another advantage of the CMQ is that, compared to other scales, it does not reference implausible conspiracies (e.g., about aliens, secret societies of ethnic outgroups, or scientifically implausible events) to which people who are less educated or informed are more susceptible (Sutton & Douglas, 2020).

In sum, there are some unresolved conceptual issues in the literature about these different scales and the constructs they measure. Sometimes it is suggested they may address the same predisposition (Bruder et al., 2013), sometimes that they are substantively different (Sutton & Douglas, 2020), and sometimes the CMQ is treated as an antecedent of endorsement of specific conspiracy beliefs (Stojanov & Halberstadt, 2019). This uncertainty about the relation between conspiracy theorizing as measured by the CMQ and endorsement of specific conspiracy theories has important implications for the present results. Although the CMQ correlates with endorsement of specific conspiracy theories, we cannot conclude that factors predicting CMQ scores will also predict endorsement of specific (e.g., COVID-related) conspiracy theories. Further research is needed, therefore, before we can conclude that endorsement of specific conspiracy theories, as well as conspiracy theorizing generally, is associated with positive societal functioning.

Another potential limitation of the present study is that, in our interpretation of the results of the random forest analysis, we examined only bivariate marginal associations. This gives an impression of how each predictor is associated with conspiracy theorizing while averaging over all levels of all other predictors. This way of visualizing the results does not reveal potential interactions between predictors. However, several of the predictors did not show a clear association with the outcome on average, as indicated by relatively flat bivariate partial dependence plots, despite ranking high on variable importance. Although it is likely that such variables derive their importance from interaction effects, there is no straightforward way to know what these interactions are. Formulating and testing theoretically driven hypotheses about possible interactions with these variables could thus be an important avenue for future research. Relatedly, although our results suggest that some predictors have curvilinear associations with conspiracy theorizing, the present approach does not allow formal testing of the shape of this relationship. Future research ought to investigate this potential non-linearity using parametric models with more nuanced methods for cross-national comparisons.

We also need to acknowledge that the sample as a whole was not representative; for example, educated adults were overrepresented. Although biased sampling might pose a threat to generalizability, we can estimate generalizability on the representative subsample of the testing data. Our model achieved the highest predictive performance in this representative subsample, which suggests that the results are generalizable to the population. Furthermore, all participants took part voluntarily, so the possibility of self-selection bias should also be considered. A final limitation of this study is that the amount of variance in conspiracy theorizing that is explained is relatively small. One potential explanation may be that the CMQ has low reliability or validity. Another potential explanation is that important predictors may have been omitted. Although a consortium of scientists sought to include all scales relevant to their fields, our analyses cannot speak to potentially relevant predictors of conspiracy beliefs that were not included in the data. The same principle applies to the country-level predictors, with one major distinction. Specifically, as the variable 'country' was included as a predictor in the model as well, it should account for the effect of any unmeasured between-country differences. The fact that country did not rank highly among the important predictors indicates that there are no important omitted between-country differences.

5 | CONCLUSION

Research on the psychology of conspiracy theories has flourished in recent years and much has been learned about the antecedents and consequences of conspiracy theorizing. New technologies and computational power have made conspiracy theories much easier to disseminate during this time, and they also allow researchers to study them in new ways. The present study used a large cross-national survey to provide a unique insight into both individual- and country-level predictors of conspiracy theorizing, and used machine learning to complement existing theoretical knowledge of the relevant predictors of conspiracy theorizing. Many of the individual-level predictors identified as important in the analysis echo previous findings. However, we also identified a number of country-level predictors suggesting—contrary to existing research—that conspiracy theories may thrive the most in relatively well-functioning democratic countries.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ETHICS APPROVAL

The PsyCorona survey was approved by the Ethics Committee of the University of Groningen (study code: PSY-1920-S-0390) and New York University Abu Dhabi (study code: HRPP-2020-42).

DATA AVAILABILITY STATEMENT

All analysis code and secondary data used in this study are available at https://osf.io/ev24r/.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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