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Going beyond simplicity: Using machine learning to predict belief in conspiracy theories

Nils Brandenstein

Department of Psychology
Heidelberg University, Heidelberg, Germany

Correspondence

Nils Brandenstein, Heidelberg University, Hauptstr. 47–51, D-69117 Heidelberg, Germany.

E-Mail: nils.brandenstein@psychologie.uni-heidelberg.de

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Abstract:

Public and scientific interest in why people believe in conspiracy theories (CT) surged in the past years. To come up with a theoretical explanation, researchers investigated relationships of CT belief with psychological factors such as political attitudes, emotions, or personality. However, recent studies have put the robustness of these relationships into question. In the present study, a prediction-based analysis approach and machine learning models are deployed to detect and remedy poor replicability of CT belief associations. The analysis of a representative dataset with 2025 UK citizens supports the assumption that the current simplicity of the field's analysis routine, exhibiting high sample-specificity and neglecting complex associations of psychological factors with CT belief, may obscure important relationships. The results further point towards key components of conspiratorial mindsets like general distrust and low socio-political control. Important implications for building a coherent theory of CT belief are derived.

Keywords:

conspiracy; belief; prediction; machine learning; social psychology; political attitudes

Introduction

In light of the recent COVID-19 pandemic, Conspiracy Theories (CTs) and their proponents have gained a lot of public and scientific attention. CTs are usually defined as a set of narratives that contradicts an official explanation for a given event, causally blaming a small special interest group with a malevolent plot for its occurrence (e.g. Douglas et al., 2016; Swami et al., 2011). Since CTs permeate through countries and social classes (e.g., Oliver & Wood, 2014) and can crucially influence our way of thinking (e.g., Douglas & Sutton, 2008; Lewandowsky, Oberauer, et al., 2013) as well as our behavior (e.g., Imhoff & Lamberty, 2020), their investigation is also of applied socio-political relevance. Although many CTs contain radical views regarding the causes for certain events, believing in CTs seems to be a general human phenomenon (Miller et al., 2016). As a result, scholars have tried to understand what makes people susceptible to CT belief. Douglas et al. (2017) argued that CTs appeal to people when they promise to satisfy psychological needs, which can be classified into epistemic motives (e.g., the need for understanding, sense-making), existential motives (e.g., need for security and having control over one's environment) and social motives (e.g., the need of belongingness and maintaining a positive self and group image). Especially in comparison to non-conspiratorial explanations for given events, CTs can serve as a simple and consistent set of causal explanations, which arguably satisfy these psychological needs. Since not all people adhere to CT belief to the same extent, researchers investigated a variety of psychological factors like socio-political attitudes and personality factors which may account for individual differences in susceptibility and motive satisfaction. Resultingly, robust associations between CT belief and psychological factors should be found that are directly linked to epistemic, existential, and social motives. Upon closer inspection of previous studies, however, the result pattern is not as clear-cut as one may expect.

Epistemic motives in relation to CT belief

First turning to studies on epistemic motives, a host of previous research has shown that belief in CTs is higher among people experiencing feelings of uncertainty and/or showing little dispositional tolerance for uncertainty (e.g., Maftai & Holman, 2020; Van Prooijen & Jostmann, 2013). Feelings of uncertainty are directly linked to the epistemic motive and sense-making process and CT belief adaptation may serve as a mean to reduce them. However, some studies did not find an association between dispositional uncertainty and CT belief (e.g., Moulding et al., 2016).

Furthermore, scholars have argued that low levels of education and impoverished analytical thinking styles should increase belief in CTs (e.g., Douglas et al., 2016; van Prooijen, 2017). Since CTs deliver overly simplified explanation of complex events, they often have an intuitive appeal. Thus, people with lower cognitive abilities and less analytical thinking may be more likely to accept CTs at face value. On the other hand, higher levels of education and analytical thinking style should lead to more skepticism and scrutiny of CTs, which should reduce belief in them. Although empirical studies generally support this theoretical notion (Douglas et al., 2016; Swami et al., 2014; van Prooijen, 2017), Ståhl and Van Prooijen (2018) showed that high levels of analytical thinking only reduce belief in CTs, if people also value epistemic rationality, that is the motivation to form beliefs on rational grounds.

High levels of religious denomination have also been shown to be positively associated with belief in CTs. Scholars expected this relationship because coincidental events can also be seen as deliberately caused by a powerful agent (i.e., God, influential groups), a feature that both CT belief and religious belief share (e.g. Newheiser et al., 2011). Upon further investigation, however, Jasinskaja-Lahti and Jetten (2019) were able to show that this positive association of religiosity and CT belief is alleviated when accounting for trust in official institutions and that religious and non-religious people adhere to CTs to the same extent.

More general personality traits like the Big Five have also been linked to epistemic motives and increased CT belief in the past. In this regard, CTs may, for instance, satisfy curiosity for people high in Openness (Swami et al., 2013), help individuals with high levels of Neuroticism to reduce uncertainty (Hollander, 2018) or bolster suspicion and antagonism towards others for people low in Agreeableness (Swami & Furnham, 2012). In a recent meta-analysis, Goreis and Voracek (2019) further investigated these proposed relationships. They were, however, unable to find evidence for a substantial linkage between any of the Big Five personality traits and CT belief. Summarizing previous study results on epistemic motives, psychological factors like analytical thinking style and (to some extent) uncertainty seem to be the more robust correlates of CT belief, while general personality traits or religious denomination may be far less suited to explain individual belief differences.

Existential motives in relation to CT belief

Turning to existential motives, a host of studies have shown that people are more likely to adapt CT belief when they experience a lack of control over their life and what is happening in the world (e.g. Abalakina-Paap et al., 1999; Imhoff, 2015; van Prooijen & Acker, 2015), which directly triggers the existential motive to feel safe and secure. In a recent study, Stojanov et al. (2020) conducted six experiments on the relationship of perceived lack of control and CT belief and showed the constructs to be correlated in general. However, they did not find a substantial effect of experimentally manipulated lack of control on CT belief adaptation, which indicates trait rather than state lack of control to be associated with CT belief. Experiencing a stable, continuous lack of control in everyday life might thus be more relevant for CT belief adaptation than a temporary, situationally triggered lack of control. Furthermore, this linkage seems to depend on the type of control beliefs: While socio-political control (i.e., perceived influence in political decision making

process) seems to be robustly associated with CT belief, results regarding the relationship between personal control (i.e., achieving goals) or interpersonal control (i.e., control over social situations) and CT belief are mixed (Imhoff & Lamberty, 2018). Somewhat similar to control beliefs, researchers investigated the disposition to perceive structure in random and unrelated events as a predictor of CT belief. While some studies found evidence for these dispositional “nothing happens by accident” beliefs to be positively related to CT belief (e.g., Moulding et al., 2016; Van Prooijen et al., 2018), others found no difference between individuals with high and low priors for randomness (Dieguez et al., 2015).

Further, low self-esteem has been linked to higher CT endorsement in the past (e.g., Swami et al., 2011). Arguably, individuals with low self-esteem may be more likely to belief CTs since holding these beliefs enable them to blame others for their personal problems (Abalakina-Paap et al., 1999). This external attribution may then help to deal with feelings of insecurity arising from personal problems. However, this linkage does not seem to be very robust either (cf. Cichocka et al., 2016).

The same holds true for the construct of death anxiety (i.e., dispositional fear of death and its consequences), which arguably triggers the existential motive of feeling safe and secure the most. People high in death anxiety are assumed to be more susceptible to CTs, since holding these beliefs may alleviate feelings of existential threat by making the future more predictable and help individuals to understand the root cause of their feelings (van Prooijen, 2019). Although a study by Newheiser et al. (2011) found a positive relationship between death anxiety and endorsement of a specific CT belief, others did not (e.g. Bruder et al., 2013).

Recent preliminary findings also suggest low dispositional resilience (i.e., the ability to bounce back from stress) to increase CT belief adaptation (Miller, 2020). Individual differences in dispositional resilience are assumed to be related to the coping strategies used to deal with stressful

life events (e.g., Wood & Bhatnagar, 2015). People low in resilience often use passive, dysfunctional coping strategies like avoidance and blaming others (Yi et al., 2005). As a result, vulnerable individuals may be more inclined to belief CTs as a coping strategy to reduce feelings of existential threat and making sense of the stressful situation (see van Prooijen, 2019 for a discussion on existential motives and sense-making processes). However, more research is needed to support this idea and clarify the functional basis of this relationship.

In summary, research on existential motives indicate that dispositional control beliefs (especially socio-political control) might be a key component of CT belief, while other psychological factors like self-esteem and death-anxiety seem to be less relevant.

Social motives in relation to CT belief

Finally, research on psychological factors fueling social motives for CT belief adaptation involve group memberships, socio-political attitudes, and trust. A fair number of previous studies focused on the relationship of Right-Wing-Authoritarianism (*RWA*) and Social Dominance Orientation (*SDO*) with CT belief. Although being markedly different constructs, both *RWA* and *SDO* correspond to generalized attitudes and prejudice towards distinct groups (Imhoff & Bruder, 2014) which in turn may increase susceptibility to CT beliefs. More specifically, people high in *RWA* exhibit negative attitudes towards nonconforming, potentially dangerous individuals, while people high in *SDO* show negative attitudes towards derogated, low status groups (e.g., Asbrock et al., 2010). In this regard, CTs may be used to further bolster these generalized attitudes and satisfy the social motive of belongingness and positive in-group evaluation. Consistent with this idea, most researchers found *RWA* and *SDO* to be positively correlated with CT belief (e.g. Grzesiak-Feldman & Irzycka, 2009; Kofta et al., 2020; Swami, 2012). However, the association of *RWA* and/or *SDO* with greater CT endorsement does not always seem to arise (e.g., Imhoff & Bruder,

2014; Oliver & Wood, 2014). Similar to these group perceptions, narcissism and collective narcissism have been proposed to be associated with CT belief adaptation fueled by defensive motives (defending the view of oneself or one's in-group). In general, studies seem to support this assumption (e.g., Cichocka et al., 2016; Golec de Zavala & Federico, 2018; Kay, 2021).

Moreover, different forms of institutional trust (e.g., trust in government, parties, science) as well as interpersonal trust have been the focus of investigation in many previous studies. The overwhelming majority supports the idea that lower trust in these entities is associated with stronger CT belief (e.g. Bruder & Kunert, 2021; Einstein & Glick, 2015; Lewandowsky, Gignac, et al., 2013). In a nationwide study conducted by Miller et al. (2016) in the US, trust in government and interpersonal trust functioned as a moderator of the relationship between political ideology, knowledge, and CT beliefs. Therefore, trust may also be a more complex psychological factor, influencing the relationship of other psychological factors with CT belief (cf. Mari et al., 2021; Miller et al., 2016).

Somewhat similar to interpersonal trust, the concept of subclinical paranoid ideation, that is being suspicious of other people's behaviors and intentions in general (Van Prooijen & Van Lange, 2014, p. 240), has recently been gaining much attention in the CT belief literature. Studies have shown that paranoid ideation seems to be closely related to CT belief (e.g., Darwin et al., 2011; Grzesiak-Feldman & Ejsmont, 2008). However, since paranoid ideation and conspiracy belief share the same notion of assuming people to pursue malicious plans, their construct independency has been questioned. In a recent meta-analysis, Imhoff and Lamberty (2018) found further empirical support for their association but also showed that they indeed seem to be different constructs. However, the functional basis of their relationship may still be open to debate.

Consistent with the social motive of the desire to belong, research has shown that people generally exhibit higher levels of CT belief if they feel ostracized and isolated from the society

(e.g. Leman & Cinnirella, 2013; Moulding et al., 2016; Poon et al., 2020). In this regard, CT belief allegedly help individuals to deal with their loneliness and feel connected again (Douglas et al., 2017). In conclusion, social motives seem to be highly interwoven with CT beliefs. More specifically, distrust in other people and official institutions, generalized social attitudes as well as feelings of isolation seem to go hand in hand with heightened CT belief susceptibility.

Structural factors in relation to CT belief

On top of psychological motives, structural factors like age, gender, living area and socioeconomic status (*SES*) have also been investigated in CT belief research. The general line of reasoning to expect differences between these factors revolves around members of marginalized groups (e.g., minorities, low SES, women and youth), who, for instance, exhibit less perceived control or adhere more to paranoid thinking styles due to their social standing (cf., Darwin et al., 2011; Stempel et al., 2007). However, studies have yielded mixed results. Differences between genders remain highly obscure with no real observable trend (cf., Dyrendal et al., 2021; Marques et al., 2021; Swami et al., 2011). Similarly, studies reported CT belief to be positively related to age (van Prooijen, 2017), negatively related (Jensen et al., 2021; Marques et al., 2021) or not related at all (Douglas et al., 2016). Differences in living areas which cause individuals to be more or less physically isolated from others have also been proposed to be predictive of CT belief. Again, some studies found individuals living in remote or rural areas to adhere more to CT beliefs (Marques et al., 2021; Siddiqui, 2020), while others did not (Stoica & Umbreş, 2021). Socio-economic factors like income and – more generally – SES may also serve as potential predictors of CT belief. Indeed, stigmatization and feelings of permanent insecurity through material strain (i.e. precarity) associated with low income and SES has been shown to increase CT belief susceptibility (Adam-

Troian et al., 2021). Nevertheless, a clear-cut relationship between income and SES with CT belief does not seem to arise (cf., Douglas et al., 2016; Douglas et al., 2019; Freeman et al., 2020).

In general, the mixed pattern of relationships between structural factors and CT belief seems to suggest that there may be little to no differences between groups in general. Positive findings in previous literature might also be attributable to study sample characteristics or psychological factors that may mediate the relationship (e.g., existential threats, perceived control, or trust). However, there is still more research needed on structural factors to draw a conclusion.

Quo vadis? – The current state of conspiracy theory research

Although this overview is non-exhaustive (see Table 1 for a more detailed report), it yet shows that several psychological factors are associated with individual CT belief susceptibility to different extents. Still, as indicated by the numerous contradicting findings, many of these associations seem to be inconsistent or obscure. However, obtaining robust relationships of psychological factors with CT belief tendencies is crucial in the current state of research, as a coherent theoretical framework is still lacking (van Prooijen & Douglas, 2018). Addressing this issue, Stojanov and Halberstadt (2020) argued that these inconsistencies result from the field's discord over how to measure belief in CTs in the first place. Over the years, different CT belief scales and singular items with varying degrees of specificity have been used (e.g., Brotherton et al., 2013; Bruder et al., 2013). Consequently, study results may differ as a function of CT belief measurement. Although measurement plurality can certainly explain some of the inconsistencies in the literature, it does not explain why associations between psychological factors and CT belief differ between studies using identical assessment instruments or experimental and correlational designs. This is true for several of the previously mentioned psychological factors, like intolerance for uncertainty (cf. Maftai & Holman, 2020; Moulding et al., 2016), the Big Five (see Goreis & Voracek, 2019), self-

esteem (see Cichocka et al., 2016) or internal control (see Stojanov et al., 2020), to just mention a few.

One way to deal with inconsistencies is certainly to explicitly consider measurement and design plurality as boundary conditions in current theorizing. However, I argue that inconsistencies in CT belief associations with psychological factors can also be tackled from another angle -- namely by overcoming the simplicity of current analysis routines.

First, researchers regularly do not conduct cross-validation of their model results. This is problematic due to a phenomenon called *bias-variance-tradeoff*: In most cases when fitting an explanatory model, we are trying to reduce *bias*, so that the parameter estimates of the model fit the true parameter values most closely. Bias is contrasted by *variance*, describing a model's sensitivity to small changes in the dataset. Now, if researchers are only concerned about finding the best fit for one particular dataset (reducing bias) they will produce models that cannot be generalized to new data, as their variance increase drastically (Yarkoni & Westfall, 2017). Additionally, the regular use of frequentist statistics like NHST and p (e.g., Bakker et al., 2012) in combination with small sample sizes can cause further generalization problems, as Stojanov et al. (2020) and OpenScienceCollaboration (2015) illustrated.

Second, most researchers assume linear relationships between psychological factors and CT belief, while many studies in psychology – even in CT research itself – show much more complex associations. Van Prooijen et al. (2015) and Imhoff et al. (2022), for instance, showed that the relationship between political ideology and CT belief follows a quadratic U-shape with the political extremes being more prone to CT belief. Finally, most studies only test single candidate factors for CT belief at a time, ignoring interactions and covariates. This can be problematic since complex psychological phenomena likely have many interplaying small-effect causes rather than few big ones (Götz et al., 2021). Goreis and Voracek (2019) argued that belief in CTs falls into this

area, since individual beliefs can be influenced by a variety of proximal and distal factors and their interactions. Some of the previously stated exemplary findings on psychological factors support this notion empirically, like the findings that analytical thinking is only negatively associated with CT belief if people also value rationality (Ståhl & Van Prooijen, 2018), the moderating role of knowledge and trust on the relation between political attitude and CT endorsement (Miller et al., 2016) or vanishing relationships between CT belief and psychological factors, when accounting for covariates like paranoid ideation (Imhoff & Lamberty, 2018). Thus, current practice in CT research can lead to an overestimation of the impact of single predictors. Apparent from these problems, contradicting results may be elicited by a misfit between the current theoretical standing of the field and the study design typically used by researchers.

The present research

In the present study, I suggest using a predictive analysis approach and machine learning models (ML) to address the discord of CT belief correlates in previous studies. A predictive approach aims to find the ratio between bias and variance that minimizes the prediction error on unseen data. In turn, models are obtained that replicate well and whose results are more trustworthy. This is achieved by using cross-validation and model regularization. The former allows to estimate how well results replicate and the latter renders them better replicable by tuning the model fit (often by introducing bias, see above). Therefore, if our goal is to find robust associations between potential psychological factors and CT belief, a predictive approach will be arguably better suited for this purpose than just evaluating the model fit on one dataset, as has been done in most previous studies. On top of this, using ML models can help identify robust correlates of CT belief. Since many ML models are flexible and non-linear approximators, they can find the optimal bias-variance-ratio

more easily and generally obtain better replicability than traditional methods (Hindman, 2015). Plus, ML models can account for all possible predictor relationships and interactions in the data. Recently, researchers in the social sciences have acknowledged these advantages and started using ML models in research areas in which clear theoretical assumptions not yet exist, prior findings fail to generalize or when predictor variables and their relationships with a criterion are manifold (e.g., Walsh et al., 2017). Since this is arguably the case for CT research, ML models represent a promising option to alleviate inconsistent results and extract how psychological factors are associated with CT belief. In this study, I will use the popular *Random Forest (RF)* Machine Learning algorithm (Breiman, 2001) to predict belief in CTs based on a variety of previously investigated psychological factors, which all have been linked to CT belief in the past. Further, I will render support to the interpretability of the RF results and compare the performance to linear models on the same dataset by using a predictive modeling approach.

[INSERT TABLE 1 HERE]

Methods

Dataset overview

The dataset used in the present work is part of a panel study conducted by the COVID-19 Psychological Research Consortium (McBride et al., 2021), in which the authors collected data on several topics over multiple representative waves in the UK, including CT belief. Representativeness of the study sample was assured by defining strata for age, sex and household income for the UK prior to sampling. Target quotas for each stratum were obtained from Eurostat population estimates (Eurostat, 2020) and the Office for National Statistics (2017). The final

sample quotas for age, sex and household incomes were met within 1% deviation of the representative UK target quotas. The dataset contains $N = 2025$ adults (1047 female, $M_{age} = 45.4$ years, $SD = 15.9$), all of which were residents of the UK. The complete dataset, information about the panel study, quotas, as well as design and conduct can be found in McBride et al. (2021) and the corresponding OSF repository.

Measures and data preprocessing

Belief in CTs was measured using the Conspiracy Mentality Questionnaire (CMQ) by Bruder et al. (2013), a validated scale to assess a person's general tendency (i.e. mindset) to belief in CTs. This measurement was chosen due to its beneficial features of being independent of events and societal contexts while still exhibiting high correlations with belief in more specific CTs (Bruder et al., 2013; Stojanov et al., 2020). The dataset further contains all previously investigated psychological factors listed in Table 1 (except from Narcissism and Need for Uniqueness), which were used as *features* (i.e., predictors) to predict belief in CTs. The inclusion of predictors was based on the literature review described in the Introduction but limited to data availability. Caveats to the generalizability of the findings due to missing factors in the current dataset will be addressed in the Discussion.

Due to the big number of predictors investigated in the present study, all information regarding their measurement (including operationalization and scale reliability scores) are mainly presented in a tabular form (see Table 2). In the following, the characteristics of the used measurements will be presented in an abbreviated form. Structural factors (e.g., age, gender) as well as political ideology, self-esteem, and trust in different entities (i.e., people, government, parties, scientists) were assessed with single item questions. The Big Five personality factors,

control beliefs, paranoid ideation and uncertainty were assessed using subscales of existing instruments. More specifically, facets of the Big Five personality factors (i.e., Extraversion, Openness, Agreeableness, Neuroticism, Conscientiousness), were assessed using the respective two item subscales of the Short Big Five Inventory by Rammstedt and John (2007). Similarly, the different types of control beliefs (i.e., internal, randomness and socio-political, see Table 1) were measured using the three item control belief subscales *internal*, *chance* and *powerful others* of the Locus of Control scale by Sapp and Harrod (1993). Paranoid ideation was assessed using the five item *Persecution* subscale of the Persecution and Deservedness Scale by Melo et al. (2009). The 12 item subscale *Uncertainty is stressful and upsetting* of the Intolerance of Uncertainty scale by Buhr and Dugas (2002) was deployed to measure uncertainty. Analytical thinking was measured using the total sum of right answers to the Cognitive Reflection Task by Frederick (2005) with five questions. All other psychological factors in the present study (RWA, SDO, Resilience, Death-Anxiety, and Loneliness) were measured using the entirety of existing, validated scales for each respective construct. In other words, all item responses in these scales were averaged (including subscales), resulting in total scale means.

Prior to model building, the dataset was preprocessed. At first, missing values on the features were imputed using the mean across participants for each feature (< 10% of total values). The responses of six participants were excluded from the analysis (each representing a unique level in the gender variable) since model prediction on unseen data can fail, if a predictor level only occurs in one data subset. All categorical features were *one-hot-encoded* (i.e., dummy-coded), the dependent variable and numerical features were standardized.

[INSERT TABLE 2 HERE]

Model Selection

Representing the current approach, I modeled a standard ordinary least squares regression model (*OLS*). Following the predictive approach, I also deployed a regularized *linear Ridge Regression* (*RR*), which penalizes the size of the parameter estimates (contingent on the number of features in the model) and shrinking them towards zero, leading to a more biased model compared to *OLS* (Hoerl & Kennard, 1970). This regularization technique is also known as “L2 regularization” and was chosen over stepwise procedures, as either retaining or dropping variables exhibits high variance and is often ineffective (e.g., Hastie et al., 2009, p. 93ff). The last deployed ML model, a Random Forest Regressor (*RF*), was chosen, since it can cope with smaller datasets and many predictors, account for complex interactions and non-linear relationships. *RFs* can be best described as types of non-linear models, based on the idea of *decision trees*. These trees learn input-output relationships by iteratively splitting the so-called “predictor space” in distinct, non-overlapping regions. Due to its non-linear approximation, a decision tree can obtain a perfect prediction on the training data if grown deep enough, which can lead to overfitting. Tackling this problem, *RFs* comprise an ensemble of single decision trees. For every decision tree in the *RF*, a random subsample of predictors as well as a random bootstrap subsample of participants is drawn. Consequently, the single trees are decorrelated and the overall *RF* is regularized. In the end, the outputs of the single trees are aggregated to retrieve one final prediction for each sample in the *RF*. For more information, see Breiman (2001).

Analytical procedure

All analysis steps were performed in a *Jupyter Notebook* (Kluyver et al., 2016) using the Python programming language version 3.8, the *numpy* (Van Der Walt et al., 2011) and *pandas* (McKinney, 2011) library for data management as well as the *scikit-learn* library (Pedregosa et al., 2011) for model building and data preprocessing. The full analysis code can be found in the corresponding OSF project (see Appendix). For all models, the available features indicated in Table 1 were entered as independent variables and the conspiracy mentality (CMQ) as the dependent variable.

To assess and compare model performance (i.e., capability to generalize to unseen data) of the RF, RR and OLS, cross-validation (*CV*) was used. Note that although a designated held-out test set is often more desirable to test model generalizability, CV yields a robust estimate of prediction performance and is even preferable when working with small to medium sized datasets (cf. Raschka, 2018). Therefore, CV represents a great option for CT belief research, since researchers do not need to extensively collect data and can work with smaller datasets at their disposal while still being able to estimate generalization performance of modeled associations between psychological factors and CT belief, as well as compare competing models. CV works by splitting the entire dataset into k groups (folds), each unique group once functioning as the test fold (out-of-sample) and the remaining $k-1$ groups functioning as the training data (in-sample) in k rounds. The final generalization performance is obtained by averaging the prediction error over the k test folds.

However, this procedure is sensitive to the composition of the k training folds and the partitioning scheme (Rodriguez et al., 2009). In other words, the number of folds chosen and specific train fold characteristics (e.g., extreme cases or outliers) can lead to a noisy estimate of the model's capability to generalize to new data, especially when dealing with small samples.

Consequently, it has been suggested to repeat the CV procedure to account for small perturbations in the single folds, thereby stabilizing the estimation of a given model's capability to generalize to new data (e.g. Krstajic et al., 2014; Rodriguez et al., 2009). Thus, the present study conducted a 10x5 repeated CV. Five folds have been selected, as this number generally results in models with neither excessively high bias nor high variance (other things being equal), leading to realistic replicability estimates (James et al., 2013, p. 184). Resultingly, each of the training folds contained $N = 1616$ observations and each of the test folds contained $N = 403$ observations.

In “flexible” models like the RR and RF, the researcher must fine tune the so-called *hyperparameters*, which control the amount of regularization in the model. Fine tuning these hyperparameters was achieved by automatically finding the best settings using a *GridSearch* algorithm (Pedregosa et al., 2011). Hereby, the researcher must only define a potential grid of potential hyperparameters, and the algorithm automatically selects the best combination. This procedure was built into the CV: Before training and validating the model on the five test sets (outer-loop), each training set was split into five additional folds (inner-loop) and the best hyperparameters were selected in this inner loop, before completing the outer loop. In other words, the tuning procedure was *nested* into the cross-validation procedure, carried out by a search algorithm. In doing so, the risk of obtaining overfitted, high variance models is further reduced, yielding a more realistic picture of out-of-sample prediction performance, since finding the best hyperparameters and evaluating model performance in the outer loop are not mixed.

After retrieving the optimal hyperparameters in the inner-loop, the RF as well as both linear models were iteratively trained on the five training folds and tested on the corresponding five test folds (outer-loop) to get an average prediction performance. Note that the inner loop was not applied to the OLS model, as there are no hyperparameters to be tuned. The whole nested CV procedure was repeated ten times to get the final generalization performance, as previously

described. Studies have shown that this (repeated) nested cross-validation is an essential method for reliable model assessment (He & Chalise, 2020; Krstajic et al., 2014; Varma & Simon, 2006). Figure 4 in the appendix presents an illustrative overview of the repeated nested cross-validation.

Performance validation

To compare the linear models and the RF regarding their generalization performance to unseen data, the root mean squared error (*RMSE*) as well as the explained variance R^2 were calculated. Further, the *permutation feature importance (PFI)* as well as the *Accumulated Local Effects* plots (*ALE*) (Altmann et al., 2010; Apley & Zhu, 2020) were calculated for the RF. These metrics enable deep insights into variable relationships in a ML model (i.e., RF) and will be briefly explained.

The permutation feature importance measures how much a particular predictor contributes to the overall performance in the model. It is obtained by iteratively shuffling the rows of each feature, thereby removing its information (i.e., signal). In each step, the model is run again with one permuted feature, the new prediction performance is obtained and compared to the unpermuted, original model. This procedure is repeatedly applied (here: ten times) for each feature at a time to get an average estimate of the importance. In short, the values we obtain for each predictor expresses the average decrease explained variance R^2 when the information of this feature is removed from the model. Note that this importance measure is relative and that the values should not be interpreted in an absolute manner, similar to standard parameter estimates of linear models. Also note that the relative importance of a feature also takes interaction effects with other features in the model into account, meaning that the interaction effect between two features is present in both importance measures (i.e., the features main and interaction effects). Therefore, the PFI values do not add up to the total amount of explained variance, but a larger sum (Molnar, 2020). For more information on permutation-based feature importance, see Altmann et al. (2010) or Molnar (2020).

ALE plots go a step further than permutation importance. First, we choose a feature for which we want to know how it affects CT belief prediction on average. Now, for each possible value v of our feature, we calculate the change in prediction by looking at a small “window” of values around v and calculating the difference in prediction between the upper and lower window which embeds our value of interest. To illustrate this method, let us say we want to predict the price of a house based on several features, like living area in m^2 , neighborhood, year of built etc. We now want to know, how each value v of the feature “living area” influences our price prediction. “For the effect of living area at $30 m^2$, the ALE method uses all houses with about $30 m^2$, gets the model predictions pretending these houses were $31 m^2$ minus the prediction pretending they were $29 m^2$. This gives us the pure effect of the living area and is not mixing the effect with the effects of correlated features.” (Molnar, 2020). These calculated differences are then accumulated and centered to obtain the ALE curves. Resultingly, ALE values can be interpreted as a simple main effect of a feature at different values v in comparison to the average effect of the predictor values (centered at zero). Put simply, the ALE curves show us how our features are associated with the outcome prediction. Note however that ALE values are not the same as, for instance, linear regression coefficients and cannot be compared one-to-one, since they are calculated differently. For more information, see Molnar (2020).

Results

Prior to model building and evaluation, Pearson correlations between all continuous variables were calculated (Table 3, Appendix). The strongest associations with CT belief were obtained with interpersonal trust ($r = .25, p < .001$), trust in government ($r = .21, p < .001$), locus of control: powerful others ($r = .24, p < .001$) and paranoid ideation ($r = .19, p < .001$). On the other hand,

psychological factors like self-esteem ($r = -.05, p > .99$), SDO ($r = -.07, p > .99$) or the Big Five personality traits ($ps > .99$) except Neuroticism ($r = .10, p = .01$), were not substantially correlated to CT belief. In general, these observed correlations of psychological factors with CT belief are mostly in line with the results pattern of previous research (cf., Table 1). Some of the predictors were intercorrelated to a mentionable degree, for example resilience and neuroticism ($r = -.69, p < .001$), the subjective control dimensions “chance” and “powerful others” ($r = .69, p < .001$) and trust in government and trust in parties ($r = .62, p < .001$). Expectedly, most of the medium to medium-high correlations were found in context of different subscales of the same or theoretically linked constructs. Note that these potential multicollinearities only pose a problem to the interpretability of linear regression model coefficients but not to their overall prediction performance on unseen data per se (Harrell Jr, 2015, p. 105). Following Jacobucci and Grimm (2020) suggestions when comparing linear and ML models in psychological research, reliability of predictors and outcome were inspected using Cronbach’s alpha. All scales obtained high to sufficient scores ($\alpha > .70$) with one exception: The two-item subscales of the short Big Five scale yielded reliability scores below .70 (tested with the Spearman-Brown Coefficient), although the authors of the short Big Five scale Rammstedt and John (2007) reported sufficient reliability in their validation study. An overview over the reliability scores can be found in Table 2.

Cross-validation results

Figure 1 shows the prediction performance of the linear regression (OLS), ridge regression (RR) and Random Forest (RF) obtained in the cross-validation procedure. Notably, this analysis estimates how good and consistent (on average) our models predict CT belief on unseen data (test folds), which gives us an estimate for their generalization performance, if we were to apply them on further, unseen data. Along with the mean prediction performance, the standard error across the

ten repeated CVs is reported. This metric can be used as an estimate of the uncertainty around the generalization estimate (i.e. prediction variance) to compare model stability (Krstajic et al., 2014). Therefore, both the average prediction performance estimate and the standard error can be used to make an informed decision about which model (i.e., OLS, RR, RF) is best suited to robustly capture the associations between personal factors and CT belief.

Looking at the prediction error, the OLS performed the worst out of all three models, $RMSE_{OLS} = 0.921$ ($SE = 0.58^{-3}$). In contrast, regularizing a linear model helped to improve the average prediction error as well as model stability, as shown by the results of the RR, $RMSE_{RR} = 0.917$ ($SE = 0.45^{-3}$). In comparison to both linear models, the RF delivered the lowest prediction error overall, $RMSE_{RF} = 0.911$ ($SE = 0.50^{-3}$), only exhibiting a slightly higher standard error than the RR across the CV runs. Looking at the explained variance R^2 , the results paint a similar picture: The ranking of all three models remained the same with the OLS showing the lowest average R^2 value and highest standard error, $R^2_{OLS} = 14.87\%$ ($SE = 0.11\%$). Again, the RF performed the best $R^2_{RF} = 16.80\%$ ($SE = 0.08$) and the RR explained more variance than the OLS, $R^2_{RR} = 15.54\%$ ($SE = 0.08$). Figure 1 graphically illustrates these differences in model performance, averaged over all ten CV repetitions. Overall, the results indicate that the OLS performs the worst when predicting CT belief on out-of-sample data. In comparison, the RR showed higher performance overall, indicating that regularization of a linear model helped to predict CT belief more robustly and accurately. This pattern illustrates that even when dealing with medium sized dataset like the present study, low-capacity linear models can capture a non-negligible amount of noise in the data, yielding models with higher variance. Furthermore, associations of personal factors and CT belief might not be limited to singular, linear relationships, since a non-linear, flexible RF showed the best generalization performance to unseen data with comparatively stable performance across different test sets. Further, the mean prediction error and explained variance in the RF did not fall

within the respective 1 SE range of the RR or OLS (see Figure 1), providing further argument for its superiority to linear models. In the next step, the importance of personal factors for CT belief prediction in the RF, as well as their associations will be analyzed.

[INSERT FIGURE 1 HERE]

Feature relationship and importance

Before calculating the permutation feature importance, the RF was fitted on the complete dataset, again using a Grid Search algorithm (Pedregosa et al., 2011) to find the best hyperparameters. Looking at the importance plot (Figure 2), the most relevant feature for prediction performance in the RF turned out to be the belief in powerful others controlling people's lives (socio-political control). When the information of this feature was removed, the average explained variance decreased by more than 10%. Decrease in explained variance of the second most important feature, trust in the government, is almost on par with belief in powerful others. The third highest scoring feature, interpersonal trust, turned out to be less important for the overall model performance, although still exhibiting 8% average decrease in variance, when information on this feature is removed. All following features are trailing in comparison to the three mentioned ones with less than 6% average decrease in explained variance. Nevertheless, the RF attributed them incremental importance, showing that most of the features still contain relevant information for CT belief prediction. Furthermore, the estimation error of feature importance throughout permutations seems to be relatively low for most features, as seen in the lower and upper boxplot bounds.

[INSERT FIGURE 2 HERE]

To investigate the association of the top three features with belief in CTs, ALE plots were calculated (Figure 3), which reveal linear as well as non-linear trends. Starting with the most relevant feature, belief in powerful others, a value of + 1 standard deviation from the sample mean increased predicted CT belief by 0.10 compared to the prediction when using the average of the feature. In other words, the function of belief in powerful others and belief in CTs shows a positive slope (i.e., coefficient) of $\sim .10$. Note however, that the function is not perfectly linear, as we can see the slope to ramp up significantly for people reporting values between $\frac{1}{2}$ SD to 1 SD from the mean. For all other features, the change in slopes seems to be even more pronounced: We can observe a steeper, almost exponential slope of the functions for values above the feature means than for values below the feature means. More precisely, 1 SD increase in distrust in information from government or trust in people leads to higher amount of CT belief than a 1 SD decrease lowers the amount of CT belief. In summary, the plots illustrate non-linear associations between psychological factors and belief in CTs.

[INSERT FIGURE 3 HERE]

Discussion

Belief in CTs and its determinants have gained much scientific interest in the past decade. Although numerous studies have investigated the relationship of psychological factors with belief in CTs, recent studies have put many of the proposed associations into question (e.g., Goreis & Voracek, 2019). The present study argues that methodological problems like high sample-specificity, a focus on binary linear relationships and the neglect of predictor interactions may have contributed to these inconsistencies in the literature. As a partial solution to these problems, a predictive analysis approach (cross-validation and regularization) and machine learning algorithms were proposed and applied to a recently collected, openly available large data set (McBride et al., 2021).

Methodological insights for studies on conspiracy theory belief

As expected, the present results show that CT belief prediction performance of a standard linear model (OLS) is low and model variance seems to be an issue, as seen in direct performance comparison to a regularized linear regression. Already from a mere methodological view, it is thus not surprising that associations between psychological factors and CT belief are inconsistent across difference studies, since researchers who follow the current analysis approach may end up with vastly divergent coefficients on small datasets. Reducing model variance by using a regularized linear regression (ridge regression, RR) helped alleviating these issues and improve performance. Therefore, future research should incorporate cross-validation and model comparison techniques when defaulting to linear models before interpreting potential associations of personal factors and CT belief, since they might be inflated. Furthermore, the chosen non-linear Random Forest outperformed both linear models in the cross-validation, yielding more accurate CT belief predictions. Most importantly, this surplus in performance and generalization capability supports the existence of more complex interactions and non-linear relationships between predictors of CT

belief than many previous study designs accounted for. This notion is further supported by the accumulated local effects (ALE) plots indicating non-linear relationships, which draws on similar findings in this research area (e.g. Van Prooijen et al., 2015). Adding to this point, the permutation feature importance revealed multiple psychological factors to be relevant for CT belief prediction, supporting the existence of interplaying effects as noted in Götz et al. (2021).

Comparing the prediction performance in the present study ($R^2_{\text{RF CV}} \sim 17\%$) with previous research is not an easy task, since previous studies neither reported generalization performance on (big) unseen datasets nor conducted any kind of cross-validation techniques (to the author's knowledge). Furthermore, several previous studies did not employ linear prediction models of CT belief or report effect sizes, rendering comparisons between previous and the present findings even more difficult. Studies that did, report effect sizes ranging from $R^2 = 10\%$ (Cichocka et al., 2016), up to $R^2 = 40\%$ (Galliford & Furnham, 2017), putting the results of the present study somewhere in the middle of previously reported effect sizes. Nevertheless, belief in CTs could be predicted to a mentionable degree, which arguably represents a more reasonable estimate, considering the limitations of other studies mentioned before. In sum, the present results advocate the use of extensive analysis strategies in CT research, such as cross-validation, model comparison, inclusion of multiple predictors and their interactions, as well as accounting for non-linear relationships.

Theoretical and practical implications of the current research

Apart from conceptual findings, the present study also delivers concrete theoretical insights. Looking at the relative importance of psychological factors for predicting CT belief, striking similarities to previous research can be observed: The most important predictor in the Random Forest turned out to be socio-political control (locus of control – powerful others). This result is in line with previous research on socio-political control, since the belief in powerful others controlling

one's environment seems to be one of the most robust and strong correlates of CT belief (see Table 1). Furthermore, socio-political control was a strong predictor of CT belief, regardless of other covariates in the model, which largely rules out other potential explanations for their association raised in the past, like spurious relationships (cf. Stojanov et al., 2020). Theoretical considerations also speak for the strong association of socio-political control and CT belief, since a perceived lack of control is directly tied to social motives and e.g. the tendency to detect agency of powerful actors in random events (van Prooijen, 2019). Although the causal direction of this relationship is still debated (cf. Jolley & Douglas, 2014; Stojanov et al., 2020) belief in socio-political control seem to be deeply interwoven with a conspiratorial mindset.

The same applies to dimensions of distrust in official institutions and people in general: Especially for levels of distrust above average, the probability of CT belief seems to increase almost exponentially (see Figure 3). Again, this finding is supported by previous literature, showing comparatively robust relationships between trust and CT belief. Since official institutions like the government or parties are generally seen as high power groups (e.g. Imhoff & Bruder, 2014) potentially being orchestrators of societal events, this relationship between distrust and conspiracy mentality becomes apparent. Similarly, interpersonal trust was often associated with heightened CT endorsement (e.g. Imhoff & Lamberty, 2018). Van Prooijen et al. (2021) state multiple potential reasons for this linkage: If those in power are unwilling to protect the ordinary citizen against malevolent intentions of others, people may be less likely to risk being exploited by others leading to more distrust. People high in conspiracy mentality also showed reduced investments in a behavioral trust board game, independent of interpersonal trust cues. Thus, high levels of distrust in official institutions and society seem to go hand in hand with conspiracy mentality.

Although still being important for CT belief prediction, all other predictors are trailing in comparison to the aforementioned ones. This might be due to several reasons. First, most of the

remaining predictors showed much less clear and strong associations in previous literature, like self-esteem, the Big Five and internal locus of control (see Table 1). Thus, their low importance might arise due to their inherent low association with CT belief in the first place. However, other predictors showed comparatively high associations with CT belief in the past. This finding might be explained due to shared variance with other constructs in the model or the predictors solely being moderators of (and/or being moderated by) other constructs, as already shown for e.g. ideology (Miller et al., 2016), analytical thinking style (Ståhl & Van Prooijen, 2018) or neuroticism (Imhoff & Lamberty, 2018). Consequently, these constructs might still be associated with CT belief but, when accounting for other predictors, their share in explained variance shrinks. Recent studies on feature importance in ML models indicate that the importance of highly correlated predictors (in comparison to uncorrelated predictors) might be slightly overestimated in the permutation, which could have influenced their relative position in the estimation (Wei, 2015)¹. Nevertheless, the relative order of predictors falls in line with the general result patterns of previous research. For instance, CT belief associations with paranoid ideation, authoritarianism and uncertainty seem to be much stronger and robust than with e.g., self-esteem or the Big Five, which is mostly in line with their relative rank in the feature importance plot (see Figure 2). In sum, researchers may especially focus on psychological factors like control beliefs, trust and generalized attitudes to understand why some people are more susceptible to CT belief than others.

On top of these theoretical insights, practical implications for dealing with CT belief arise. Building bridges between citizens and (local) governments may not only be helpful for a stable society but also for potential CT belief reduction through increased trust. Although others did not

¹ Note that this only affects predictors that are at least to some extent related to the outcome. The feature importance in the RF were also calculated using *Shapley Values* (Lundberg et al., 2018), which are not influenced by the presence of correlated features. The results revealed a similar picture to the permutation importance with trust in government, interpersonal control and socio-political control being the most important predictors. The summary plot can be found in Figure 5 in the supporting information or in the linked OSF project.

find manipulated individual control to be associated with reduced CT belief (Stojanov et al., 2020), empowering individuals' perception of socio-political control may still be a promising approach. Based on previous research in this area, both increasing trust and perceived socio-political control may best be tackled from regulatory angles, that is by increasing involvement of individuals in political decision-making processes (Parent et al., 2005). Studies in this area have shown that increasing government responsiveness (Kahne & Westheimer, 2006), in-person and online interaction with citizens (Arshad & Khurram, 2020) or e-government initiatives (Parent et al., 2005) can be fruitful strategies to deal with political distrust and efficacy, which may then lead to lower CT belief susceptibility.

Limitations of the current research

Naturally, the present study has its limitations. First, some potentially important variables which have been shown to be related to CT beliefs in previous research, like for example need for uniqueness (Imhoff & Lamberty, 2017), ostracism (Poon et al., 2020) or narcissism (Cichocka et al., 2016) were not available in the data set analyzed here (see Table 1). Although exhibiting a fair amount of explained variance, the prediction performance of the models in the present study could potentially be improved by including these missing variables. However, even though they might account for some unexplained variance or share variance with other constructs (e.g., loneliness, self-esteem) the present results and previous studies still point towards key components of a conspiratorial mindset like trust, socio-political control or generalized attitudes.

Second, the measurement of constructs must be addressed. Although the used locus of control scale by Sapp and Harrod (1993) shows good internal consistency and construct validity, it has not been as widely used in CT research as other measures. This leads to comparability limitations for the association of CT belief, especially for the control dimension *chance*. Adding to

that, the control subscale *powerful others* (socio-political control) and *chance* were highly correlated ($r = .69$, Table 3, Appendix), which could also explain the relatively high feature importance of control subscale chance in the Random Forest, as mentioned earlier. Further, there seems to be an overlap between item formulations of socio-political control and the conspiracy mentality questionnaire CMQ (e.g., “My life is chiefly controlled by powerful others” vs. “I think that there are secret organizations that greatly influence political decisions”). Although this semantic overlap could cast doubt in their construct independency, both constructs were only correlated to a small degree ($r = .24$) and have multiple distinct correlates (Table 3, Appendix). Adding to that, robust associations between similar measurements of socio-political control and CT belief across studies further support the significance of their relationship (see Table 1).

Even though the used cross-validation procedure has been shown to deliver robust generalization estimation performance, the final models fitted on the whole dataset may not perform as precisely on a newly-collected, designated test set (cf. Bates et al., 2021). Since the Random Forest also exhibited a non-negligible amount of variance in the cross-validation, it is unclear if it would consistently outperform linear models in other CT belief conceptualizations. Note however that Krstajic et al. (2014) argued that the use of standard errors to assess model performance and variance needs to be redefined in the repeated cross-validation context and thus may not be as informative in the present study. Speaking of CT measurement, the current study used the CMQ (Bruder et al., 2013) to assess people’s general conspiracy mentality and not belief in specific CTs. This measurement of CT belief was chosen, since specific CTs limit the generalizability of findings to specific socio-political events which are heavily influenced by cultural context and situational variables and do not reflect the underlying mentality or belief readiness (Stojanov et al., 2020). Therefore, numerous studies have used the CMQ to measure CT belief in the past and have also shown general conspiracy mentality to be a direct predictor of belief

in more specific CTs (e.g., Bruder et al., 2013; Dyrendal et al., 2021; Swami et al., 2010). These features combined made the CMQ a well-suited option for the present research question. Nevertheless, the results of the present study may not be directly translated to belief in other, more specific CTs. While being comparably large and representative, the dataset exclusively consisted of UK residents and the transferability of results to other cultures and countries is pending. Finally, since analyzing concrete predictor interactions was beyond the scope of the present study, future research on CT belief should investigate these relationships more thoroughly. In summary, the proposed approach should be extended to other datasets, operationalizing CT belief in different ways, include a variety of potential predictors and analyze their interactions.

General conclusion

Investigating CTs and why people are drawn to them is more than just an end-in-itself. However, we must be aware of potential pitfalls in our research approach. The present study showed that cross-validation and replication efforts are warranted in CT belief research. Arguably, this emerging research area can accumulate knowledge at a higher rate if correlational results are robust and generalizable, especially when inductively building theories on these findings. Otherwise, we end up in the current situation of contradicting and inconsistent results, ultimately leading to confusion and hindering progress. Moreover, ML models can be a fruitful alternative to standard linear models. Using them, we gain insights about complex associations and interactions of psychological factors with CT belief that go beyond the simplicity of current findings. Adopting all these practices, we can focus our research efforts and built on solid foundation to ultimately progress in establishing a comprehensive CT belief framework.

Conflict of interest

This manuscript has not been published (except from a PrePrint on PsychArchive) and is not under consideration for publication elsewhere. There are no conflicts of interest and funding to disclose.

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Footnotes

¹ Note that this only affects predictors that are at least to some extent related to the outcome. The feature importance in the RF were also calculated using *Shapley Values* (Lundberg et al., 2018), which are not influenced by the presence of correlated features. The results revealed a similar picture to the permutation importance with trust in government, interpersonal control and socio-political control being the most important predictors. The summary plot can be found in Figure 5 in the supporting information or in the linked OSF project.

4. Tables

Table 1

Table 1. Overview of variable relationships with belief in conspiracy theories in previous studies.

Variable	Author	Direction and strength of relationship with CT belief
Age	1. Imhoff et al. (2022)	[O] +, $b = .00$, $b = 0.34^*$
	2. Douglas et al. (2016)	[-] -, $b = -0.16^*$, $b = 0.01$
	3. Van Prooijen (2017)	[+], $b = 0.15^{***}$
Gender	1. Dyrendal, Kennai & Bendixen (2021)	[O] +, $t = -1.74$, $t = 2.88^*$ [male more CT belief]
	2. Imhoff et al. (2022)	[O] +, $b = 0.05$, $b = 0.34^*$ [male more CT belief]
	3. Swami et al. (2011)	[+], $t = 2.62^*$ [women more CT belief]
Living Area	1. Siddiqui (2020)	[-] -, $r = -.23^*$, $r = -.30^*$, $r = -.28^*$, $r = -.005$
	2. Marques et al. (2020)	[O] -, $b = 0.04$, $b = 0.02$, $b = 0.06^{**}$, $b = 0.04^*$
	3. Stoica & Umbres (2020)	[O], $r = .003$, $r = .03$
Education	1. Douglas et al. (2016)	[O] -, $r = -.13$, $r = -.26^{**}$
	2. Van Prooijen (2017)	[-], $r = -.15^{***}$; $r = -.26^{***}$
	3. Van Prooijen & Acker (2015)	[O] -, $r = -.21^{***}$, $r = -.11^{***}$, $r = -.13^{***}$, $r = -.16^{***}$, $r = -.02$
Social economical status (SES) / Income	1. Adam-Troijan et al. (2021)	[-], $r = -.25^{***}$ [precarity]
	2. Freeman et al. (2020)	[O], $r = .02$, $r = -.02$ [income]
	3. Douglas et al. (2016)	[O] -, $r = -.13$, $r = -.12^*$ [income], $r = -.06$, $r = -.16$ [SES]
Religion	1. Oliver & Wood (2014)	[O] +, $r = .36^{***}$, $r = .10^{***}$, $r = .19^{***}$, $r = .00$, $r = .11^{***}$ [importance of religion]
	2. Jasinskaja-Lahti & Jetten (2019)	[+], $r = .25^*$, $r = .04^*$ [importance of religion; when accounting for trust: negative]
	3. Newheiser, Farias & Tausch (2012)	[-], $r = -.49^{***}$ [religiosity belief inventory]
Ideology	1. Imhoff et al. (2022)	[+], $b = 0.10^{***}$, $b = 0.19^{***}$ [quadratic effect], $b = 0.14^{**}$, $b = 0.12$ [linear effect]
	2. Imhoff & Bruder (2014)	[O], $r = .07$
	3. Van prooijen et al. (2015)	[+], $b = -0.32^*$, quadratic: $b = 0.35^*$ [Study2a]
Right-Wing Authoritarianism (RWA)	1. Imhoff & Bruder (2014)	[O] +, $r = .05$, $r = .16$, $r = .29^{***}$ [Study 4]
	2. Bruder et al. (2013)	[+], $r = .28^{***}$
	3. Imhoff & Lamberty (2018)	[+], $r = .21^{**}$
Social Dominance Orientation (SDO)	1. Imhoff & Bruder (2014)	[O], $r = .03$, $r = -.05$, $r = .14$
	2. Bruder et al. (2013)	[+], $r = .16^*$
	3. Dyrendal, Kennair & Bendixen (2021)	[+], $r = .24^{***}$, $r = .12^{**}$ [SEM paths]
Self esteem	1. Swami (2012)	[O], $r = -.03$
	2. Cichoka et al. (2016)	[O], $r = -.08$, $r = .05$
	3. Swami & Furnham (2012)	[-], $r = -.16^{**}$
Paranoid ideation	1. Bruder et al. (2013)	[+], $r = .45^{***}$
	2. Darwin et al. (2011)	[+], $r = .47^{**}$
	3. Imhoff & Lamberty (2018)	[+], $z = .38^{***}$ [meta analysis]
Resilience	1. Miller (2020)	[-], $b = -0.19^*$ [supplementary section C]
Death anxiety	1. Imhoff & Bruder (2014)	[O], $r = .08$
	2. Newheiser et al. (2011)	[+], $r = .32^{***}$
	3. Bruder et al. (2013)	[O], $r = .10$
Control: Internal	1. Bruder et al. (2013)	[O], $r = .03$
	2. Imhoff & Lamberty (2018)	[O], $r = -.13$, $r = .06$
	3. Kofta et al. (2020)	[-], $r = .14^{**}$ [study 4]
Control: Perception of randomness	1. Moulding et al. (2015)	[+], $r = .26^{**}$ [World assumption scale: Randomness]
	2. Van Prooijen et al. (2017)	[+], $r = .37^{***}$, $r = .23^{**}$ [illusory pattern perception]
	3. Dieguez et al. (2015)	[O], $r = .13$, $r = -.04$, $r = -.10$ [prior subjective randomness]
Control: Socio-political	1. Bruder et al. (2013)	[-], $r = -.22^{***}$
	2. Imhoff & Bruder (2014)	[-], $r = -.23^{***}$
	3. Imhoff & Lamberty (2018)	[-], $r = -.19^{**}$, $r = -.22^{**}$
Uncertainty	1. Moulding et al. (2015)	[O] -, $r = .09$, $r = .16$, $r = .09$, $r = .13$, $r = .30^{**}$
	2. Kofta et al. (2020)	[-], $r = .13^{**}$ [study 4]
	3. Miller (2020)	[-], $b = .22^{***}$ [supplementary section C]
Interpersonal trust	1. Green & Douglas (2018)	[-], $b = -0.24^{**}$
	2. Imhoff & Lamberty (2018)	[-], $r = -.16^{**}$
	3. Goertzel (1994)	[-], $r = -.37^*$
Trust in government	1. Bruder & Kunert (2021)	[-], $b = -0.48^{***}$
	2. Mari et al. (2021)	[-], $r = -.22^{***}$
	3. Imhoff & Lamberty (2018)	[-], $r = -.53^{***}$, $r = -.28^{**}$
Trust in political parties	1. Krouwel et al. (2017)	[-], $r = -.27^{**}$
	2. Leiser, Duani & Wagner-Egger (2017)	[-], $r = .46^*$
Trust in scientists	1. Bruder & Kunert (2021)	[-], $b = -0.42^*$
	2. Rothmund et al. (2022)	[-], $r = -.45^{**}$
Extraversion	1. Goreis & Voracek (2019)	[O], $r = .01$ [meta analysis]
	2. Swami & Furnham (2012)	[O], $r = .03$
	3. Imhoff & Lamberty (2018)	[O], $r = -.012$, $r = -.006$
Openness	1. Goreis & Voracek (2019)	[O], $r = .02$ [meta analysis]
	2. Imhoff & Lamberty (2018)	[O], $r = .01$, $r = -.04$
	3. Swami et al. (2010)	[+], $r = .23^{***}$
Agreeableness	1. Goreis & Voracek (2019)	[O], $r = -.02$ [meta analysis]
	2. Brotherton et al. (2013)	[O], $r = .11$
	3. Swami et al. (2011)	[-], $r = -.07^*$
Neuroticism	1. Goreis & Voracek (2019)	[O], $r = .03$ [meta analysis]
	2. Imhoff & Lamberty (2018)	[+], $r = .13^*$, $r = .14$ [accounting for paranoia]
	3. Hollander (2018)	[+], $r = .03^*$, $r = -.08^{***}$, $r = .09^{***}$, $r = .08^{***}$
Conscientiousness	1. Goreis & Voracek (2019)	[O], $r = .01$ [meta analysis]
	2. Imhoff & Lamberty (2018)	[O], $r = -.05$, $r = -.02$
	3. Swami & Furnham (2012)	[+], $r = .12^{**}$
Analytical thinking	1. Swami et al. (2014)	[-], $r = -.25^{***}$
	2. Swami & Furnham (2012)	[-], $r = -.17^{***}$
	3. Stahl & van Prooijen (2018)	[O], $b = -0.07$ [accounting for rationality]
Isolation/Ostracism	1. Poon et al. (2020)	[+], $b = .35^{***}$ [ostracism]
	2. Graepner & Coman (2017)	[+], $r = .19^*$ [social exclusion]
	3. Moulding et al. (2016)	[+], $r = .34^{**}$ [sense of isolation]
Need for Uniqueness	1. Imhoff & Lamberty (2017)	[+], $r = .128^*$, $r = .203^{**}$, $r = .139^*$
	2. Kay (2021)	[+], $r = .11^*$
	3. Lantian et al. (2017)	[+], $r = .17^*$ [Study 2]
Narcissism	1. Cichoka et al. (2016)	[+], $r = .24^{***}$ [collective narcissism]
	2. Sternisko et al. (2020)	[+], $r = .30^*$, $r = .48^*$ [collective narcissism]
	3. Kay (2021)	[+], $r = .23^*$ [Narcissistic Personality Inventory]

Note. Exemplary studies limited to three for each variable (if available). Indication of direction: [+] significant positive relationship found, [-] significant negative relationship found, [O] no significant relationship found. Coefficients displayed as found in original study, rounded to two decimal places, * $p < .05$, ** $p < 0.01$, *** $p < 0.001$. All listed variables are also available in the present study's dataset (except from Need for Uniqueness and Narcissism). More information on measurements used in the present study can be found in Table 2.

Table 2

Table 2. Overview of variables, operationalization and scale reliability coefficients in the present study.

Variable	Description, source and example item	Number of items, response format	Reliability (Cronbach's α)
Outcome			
Conspiracy Mentality	Mean CMQ Score (Conspiracy Mentality Scale, Bruder et al., 2013) "I think that politicians usually do not tell us the true motives for their decisions"	5 items, 11-point scale (Certainly not - Certainly)	.85
Features (Predictors)			
Age	Age of participant in years	1 item, open text	-
Gender	Gender of participant	1 item, categorical (male; female; other: open field)	-
Living Area	Area of living	1 item, categorical (city; suburb; town; rural area)	-
Education	Highest qualification	1 item, categorical (no qualifications; O-level/GCSE or similar; A-level or similar; diploma; undergraduate degree; postgraduate degree; technical qualification; other)	-
Income	Approximate annual household income	1 item, categorical (1: £0 - 15,490; 2: £15,491 - £25,340; 3: £25,341 - £38,740; 4: £38,741 - £57,930; 5: >= £57,931)	-
Religion	Religion of participant	1 item, categorical (Christian; Muslim; Jewish; Buddhist; Sikh; Atheist; Agnostic; or other)	-
Ideology	Self reported rating on 10-point political ideology scale	1 item, 10-point scale (left - right)	-
Right Wing Authoritarianism	Total scale mean score: Right Wing Authoritarianism (Short Authoritarianism Scale, Bizumic & Duckitt, 2018) "What our country needs most is discipline, with everyone following our leaders in unity"	6 items, 5-point scale (Strongly disagree - Strongly agree)	.73
Social Dominance Orientation	Total scale mean score: Social Dominance Orientation (Social Dominance Scale; Ho et al., 2015) "An ideal society requires some groups to be on top and others to be on the bottom"	8 items, 5-points scale (Strongly oppose - Strongly favour)	.84
Self-esteem	Single-item Self-esteem Scale (SISES) (Robins, Hendin, & Trzesniewski, 2001) "I have high self esteem"	1 item, 7-point scale (Not very true of me - Very true of me)	-
Paranoid ideation	Mean score of subscale "Persecution", Persecution and Deservedness Scale (Persecution and Deservedness Scale; Melo, Corcoran, Shryane, & Bentall, 2009) "I'm often suspicious of other people's intentions towards me"	5 items, 5-point scale (Strongly disagree - Strongly agree)	.86
Resilience	Total scale mean score: Resilience (Brief Resilience Scale; Smith et al., 2008) "I tend to take a long time to get over set-backs in my life"	6 items, 5-point scale (Strongly disagree - Strongly agree)	.88
Death anxiety	Total scale mean score: Death Anxiety (Death Anxiety Inventory; TomásSábado, Gómez-Benito, & Limonero, 2005) "I find it difficult to accept the idea that it all finishes with death"	17 items, 5-point scale (Totally disagree - Totally agree)	.94
Control: Internal	Mean score of subscale "Internal", Locus of control (Locus of Control Scale; Sapp & Harrod, 1993) "My life is determined by my own actions"	3 items, 7-point scale (Strongly disagree - Strongly agree)	.71
Control: Chance [Randomness]	Mean score of subscale "Chance", Locus of control (Locus of Control Scale; Sapp & Harrod, 1993) "To a great extent, my life is controlled by accidental happenings"	3 items, 7-point scale (Strongly disagree - Strongly agree)	.70
Control: Powerful others [Socio-political]	Mean score of subscale "Powerful others", Locus of control (Locus of Control Scale; Sapp & Harrod, 1993) "Getting what I want requires pleasing those people above me"	3 items, 7-point scale (Strongly disagree - Strongly agree)	.85
Uncertainty-Intolerance	Mean score of subscale "Uncertainty is stressful and upsetting", Intolerance of uncertainty (Intolerance of Uncertainty Scale, Buhr & Dugas, 2002) "I always want to know what the future has in store for me"	12 items, 5-point scale (Not characteristic of me at all - Entirely characteristic of me)	.90
Interpersonal trust	Trust in people ("Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?")	1 item, 5-point scale (Mostly people can be trusted - Need to be very careful)	-
Trust in government	Trust in government ("Could you indicate how much trust you have in the government")	1 item, 5-point scale (Completely trust - Do not trust at all)	-
Trust in political parties	Trust in political parties ("Could you indicate how much trust you have in political parties")	1 item, 5-point scale (Completely trust - Do not trust at all)	-
Trust in scientists	Trust in scientists ("Could you indicate how much trust you have in scientists")	1 item, 5-point scale (Completely trust - Do not trust at all)	-
Extraversion	Mean score of subscale "Extraversion", Big Five personality factors (Short Big Five Inventory; Rammstedt & John, 2007) "I see myself as someone who is reserved"	2 items, 5-point scale (Disagree strongly - Agree strongly)	.57 (Spearman-Brown)
Openness	Mean score of subscale "Openness", Big Five personality factors (Short Big Five Inventory; Rammstedt & John, 2007) "I see myself as someone who has an active imagination"	2 items, 5-point scale (Disagree strongly - Agree strongly)	.13 (Spearman-Brown)
Agreeableness	Mean score of subscale "Agreeableness", Big Five personality factors (Short Big Five Inventory; Rammstedt & John, 2007) "I see myself as someone who is generally trusting"	2 items, 5-point scale (Disagree strongly - Agree strongly)	.27 (Spearman-Brown)
Neuroticism	Mean score of subscale "Neuroticism", Big Five personality factors (Short Big Five Inventory; Rammstedt & John, 2007) "I see myself as someone who get nervous easily"	2 items, 5-point scale (Disagree strongly - Agree strongly)	.65 (Spearman-Brown)
Conscientiousness	Mean score of subscale "Conscientiousness", Big Five personality factors (Short Big Five Inventory; Rammstedt & John, 2007) "I see myself as someone who does a thorough job"	2 items, 5-point scale (Disagree strongly - Agree strongly)	.51 (Spearman-Brown)
Analytical thinking	Total sum of right answers: Cognitive Reflection Task (Frederick, 2005) "If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?"	5 items, multiple choice with 4 answer options	-
Loneliness [Isolation/Ostracism]	Total scale mean score: Loneliness (Three item Loneliness Scale; Hughes, Waite, Hawley, & Cacioppo, 2004) "I lack companionship"	3 items, 3-point scale (Hardly ever, Some of the time, Often)	.88

Note. Variable names describe investigated construct, brackets indicate construct description in previous studies (cf. Table 1). Reliability scores only calculated for (sub-)scales with at least two continuous items. Further information regarding variable measurement in the present study can also be retrieved from the codebook of the original dataset (McBride et al., 2021).

5. Figures

Figure 1. Graphical illustration of model cross-validation performance (out-of-sample).

Note. Black dots represent average RSME and explained variance R^2 , respectively. Error bars indicate ± 1 SE from the mean over all ten test folds in the repeated cross-validation.

Figure 2. Permutation feature importance (PFI) of RF model features.

Note. Permutation feature importance calculated using ten permutations per feature on the full dataset. Upper and lower box-plot bounds indicate ± 1.5 IQR, outliers represented as circles.

Figure 3. Accumulated-local-effects plots (ALE) of the three most important features in the RF.

Note. Features are negatively coded, higher values indicate more distrust/less control. Values for predicted CT belief and features are standardized. Gray lines indicate single Monte Carlo simulations for the dataset, solid black line represents the average accumulated local effect (see Molnar, 2020).

6. Appendix

Data Availability

All materials, data and analysis code used in the present study can be found in the corresponding OSF repository:

https://osf.io/ckjyp/?view_only=fcd99a9d7e634a7ebfd442ba8b4272e9

Table 3

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Self esteem	4.09	1.58	-																						
2. Ideology	5.32	1.86	0.22***	-																					
3. Paranoid Ideation	2.49	1.00	-0.22***	0.01	-																				
4. SDO	2.40	0.69	0.15***	0.44***	0.19***	-																			
5. RWA	3.03	0.67	0.06	0.38***	0.04	0.33***	-																		
6. Loneliness	1.59	0.62	-0.36***	-0.10***	-0.02	-0.07	-0.07	-																	
7. Control: Internal	4.89	1.07	0.33***	0.13***	-0.04	0.05	0.01	0.35***	-0.18***	-															
8. Control: Powerful others	3.37	1.41	-0.16***	-0.03	0.06	0.02	0.01	0.36***	-0.12***	0.10***	-														
9. Control: Chance	2.67	1.53	0.22***	0.05	0.06	0.04	0.04	0.35***	-0.12***	0.12***	0.18***	-													
10. External locus of control	2.61	0.96	0.14***	0.07	-0.20***	0.04	0.04	0.24***	0.18***	0.13***	0.13***	-0.13***	-												
11. Agreeableness	3.37	0.80	0.15***	-0.04	-0.38***	-0.19***	0.01	-0.23***	0.15***	-0.21***	-0.19***	-0.15***	0.18***	-											
12. Conscientiousness	3.72	0.87	0.20***	0.08*	-0.26***	-0.07	0.18***	-0.19***	0.22***	-0.24***	-0.24***	-0.17***	0.23***	-0.23***	-										
13. Neuroticism	2.85	1.05	-0.51***	-0.11***	0.40***	-0.04	-0.03	0.42***	-0.30***	0.34***	0.34***	0.17***	0.23***	-0.25***	0.07	-									
14. Openness	3.25	0.83	0.03	-0.07	-0.02	-0.15***	-0.11***	0.07	0.02	-0.02	0.02	0.07	0.05	0.10***	0.07	-									
15. Death anxiety	2.58	0.88	-0.11***	0.07	0.46***	0.19***	0.07	0.28***	-0.12***	0.42***	0.37***	-0.07	-0.17***	-0.25***	-0.39***	0.00	-								
16. Resilience	3.27	0.84	0.50***	0.13***	-0.43***	0.03	0.07	-0.44***	0.36***	-0.38***	-0.39***	0.35***	0.26***	0.30***	-0.69***	0.00	-0.39***	-							
17. Uncertainty	2.93	0.76	-0.25***	-0.03	0.50***	0.03	0.01	0.38***	-0.14***	0.45***	0.42***	-0.26***	-0.26***	-0.2***	0.52***	0.04	0.54***	-0.51***	-						
18. Interpersonal trust	3.29	1.02	-0.10*	0.15***	0.38***	0.15***	0.22***	0.16***	-0.10***	0.21***	0.20***	-0.09*	-0.28***	-0.05	0.15***	-0.06	0.22***	-0.16***	0.21***	-					
19. Trust: government	3.41	1.10	-0.20***	-0.32***	0.09*	-0.24***	-0.25***	0.09*	-0.12***	0.09**	0.10*	-0.09*	-0.09*	-0.06	0.13***	0.07	.00	-0.14***	0.06	0.12***	-				
20. Trust: parties	3.73	0.96	-0.19***	-0.13***	0.01	-0.13***	-0.10*	0.04	-0.08	.00	.00	-0.08	-0.07	0.02	0.07	0.04	-0.08	-0.06	-0.02	-0.02	0.12***	-			
21. Trust: scientists	2.35	0.99	-0.05	0.06	0.24***	0.20***	0.08	0.07	-0.22***	0.20***	0.11***	-0.02	-0.17***	-0.14***	0.08	-0.04	0.16***	-0.11***	0.07	0.21***	0.28***	0.23***	-		
22. Analytical thinking	1.90	1.61	.00	-0.08	-0.19***	-0.10**	-0.19***	-0.07	0.08	-0.15***	-0.10**	-0.07	-0.05	0.01	-0.11***	0.01	-0.21***	0.09*	-0.07	-0.17***	0.06	0.11***	-0.15***	-	
23. Conspiracy belief (CMQ)	7.03	1.83	-0.05	.00	0.19***	-0.07	0.10**	0.11***	.00	0.24***	0.16***	0.03	-0.03	0.05	0.09*	0.05	0.10**	-0.06	0.15***	0.25***	0.21***	0.16***	0.09*	-0.13***	-

Note. N = 2019, correlation coefficients rounded to two decimal places. * $p < .05$ ** $p < .01$ *** $p < .001$ (Bonferroniadjusted alpha for 253 bivariate correlations).

7. Supporting Information

Further supporting information can be found in the document “supporting_information.docx”.

The corresponding OSF project can be found under the following link:

https://osf.io/ckjyp/?view_only=fcd99a9d7e634a7ebfd442ba8b4272e9