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Modeling anxiety and fear of COVID-19 using machine learning in a sample of Chinese adults: associations with psychopathology, sociodemographic, and exposure variables

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ABSTRACT

Objectives: Research during prior virus outbreaks has examined vulnerability factors associated with increased anxiety and fear.

Design: We explored numerous psychopathology, sociodemographic, and virus exposure-related variables associated with anxiety and perceived threat of death regarding COVID-19.

Method: We recruited 908 adults from Eastern China for a cross-sectional web survey, from 24 February to 15 March 2020, when social distancing was heavily enforced in China. We used several machine learning algorithms to train our statistical model of predictor variables in modeling COVID-19-related anxiety, and perceived threat of death, separately. We trained the model using many simulated replications on a random subset of participants, and subsequently externally tested on the remaining subset of participants.

Results: Shrinkage machine learning algorithms performed best, indicating that stress and rumination were the most important variables in modeling COVID-19-related anxiety severity. Health anxiety was the most potent predictor of perceived threat of death from COVID-19.

Conclusions: Results are discussed in the context of research on anxiety and fear from prior virus outbreaks, and from theory on outbreak-related emotional vulnerability. Implications regarding COVID-19-related anxiety are also discussed.

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Introduction

The COVID-19 pandemic (Li et al., 2020) introduced social distancing and home quarantine globally (Xiang et al., 2020). Because of COVID-19, anxiety and fear has increased (e.g., Cao et al., 2020; Taylor et al., 2020). Research from prior virus outbreaks has revealed psychopathology, sociodemographic, and virus exposure-related variables influencing emotional distress including anxiety and fear. However, the disease burden and ease of transmission renders COVID-19 substantially more severe than previous outbreaks (Li et al., 2020). We selected numerous vulnerability-related

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psychopathology, sociodemographic, and exposure variables from prior virus outbreak literature, using machine learning to model their influence on anxiety and fear within the context of COVID-19.

Research from prior virus outbreaks has examined psychopathology variables associated with increased anxiety and fear. Taylor (2019) reviewed these findings, with college students, first responders, and participants recruited online, involving SARS, Avian and Swine flu, Zika, and Ebola outbreaks. Increased anxiety and fear from an outbreak was positively associated with negative affectivity variables, including greater neuroticism (e.g., Lu et al., 2006; Smith et al., 2009), trait anxiety (Cheng & Cheung, 2005; Wheaton et al., 2011), stress (Wheaton et al., 2011), intolerance of uncertainty (Taha et al., 2014), contamination fears (Blakey & Abramowitz, 2017; Blakey et al., 2015; Wheaton et al., 2011), and disgust sensitivity (Blakey & Abramowitz, 2017; Blakey et al., 2015; Wheaton et al., 2011). Outbreak-related anxiety was also positively associated with somatic concern, including body vigilance, health anxiety, and anxiety sensitivity from physiological changes (Blakey & Abramowitz, 2017; Blakey et al., 2015; Wheaton et al., 2011).

In addition to psychopathology, other variables associated with outbreak-related anxiety and fear include receiving inadequate (Xie et al., 2011) or excessive (Hansen, 2009) virus news exposure. Furthermore, perceived adverse threat from a virus correlated with greater anxiety (Taha et al., 2014; Xie et al., 2011) and younger age and female sex were risk factors for negative emotion (Smith et al., 2009). Asmundson and Taylor (2020a, 2020b) recently discussed this research and its applicability to COVID-19. Unique to COVID-19 is that many people needed to reside away from their homes because of travel restrictions implemented to limit spread (Wilder-Smith et al., 2020), which can increase distress.

Several published studies have reported emotional reactions to COVID-19, mostly sampling Chinese participants. The virus started in China and the Chinese population was the earliest affected (Li et al., 2020). Chinese studies conducted in late-January to early February 2020 examined emotional distress based on general depression, anxiety, and stress scale symptoms, but not specifically anchored to COVID-19. These studies demonstrate increased depression, anxiety and stress related to female sex, age range in the 20s or 30s, increased social media exposure, lower social capital, knowing someone with COVID-19, and worse physical health (Cao et al., 2020; Gao et al., 2020; Wang et al., 2020, 2021; Xiao et al., 2020).

Other studies examined *COVID-19-specific* fear and anxiety, such as a Chinese study finding COVID-19 anxiety severity related to non-middle-age groups (Zhang & Ma, 2020) and an Iranian study showing COVID-19-specific anxiety related to depression, anxiety severity, and perceived vulnerability to disease (Ahorsu et al., in press). Additionally, American studies found COVID-19 anxiety levels related to mental health constructs including alcohol use, hopelessness, and suicidal ideation (Lee, 2020). And Taylor et al. (2020) have identified evidence of a COVID Stress Syndrome in large population-representative samples from Canada and the United States, encompassing anxiety and stress about COVID-19 regarding danger and contamination, socioeconomic consequences, xenophobia, traumatic stress, and compulsive checking. Other studies also found similar correlates with COVID-19 anxiety (e.g., Asmundson et al., 2020; Jungmann & Witthöft, 2020).

Theory

Taylor (2019) noted the absence of theoretical frameworks explaining emotional reactions to pandemics; as such, he summarized other related frameworks that may serve as pieces of the puzzle to explain outbreak-related emotional vulnerability, including personality traits, cognitive-behavioral models of health anxiety, the behavioral immune system, and social psychological factors involving attitudes, fear, and risk communication. Recently, Schimmenti and colleagues (2020) developed a theoretical framework to understand the nature of fear and anxiety from COVID-19. They proposed a model with four components, including (1) body-related fear, involving hypervigilance of changes in physiological symptoms, (2) fear related to significant others and interpersonal relationships, involving worry about transmitting disease and decreased contact from social distancing, (3) uncertainty, in balancing learning about the pandemic versus avoidant coping, and (4) fear regarding action and inaction, involving apprehension of both offering help to those affected and not offering assistance. Interestingly, fears discussed in this model involve the emotional aspect of anxiety and the cognitive and behavioral aspects (Schimmenti et al., 2020).

Aims

We explored vulnerability factors related to COVID-19-related anxiety using machine learning – an innovation over prior relevant work. We included two separate dependent variables: (a) anxiety symptoms rated specifically within the context of COVID-19, and (b) perceived threat of death from COVID-19. We incorporated numerous psychopathology, sociodemographic, and virus exposure predictor variables, drawn from literature on outbreak-related emotional vulnerability discussed above. Our aim was to empirically identify the subset of predictor variables most robustly associated with COVID-19-related anxiety.

We used supervised machine learning (Hastie et al., 2016; Kuhn & Johnson, 2013) to model vulnerability factors of outbreak-related anxiety and fear, for several reasons. First, this approach allowed sample separation into training and testing subsets, conducting analyses in the training subset to detect patterns and train our statistical model, which was subsequently applied to the testing subset. The distinction between training and testing has enabled machine learning to outperform traditional data analyses (Jordan & Mitchell, 2015). Second, we used specific machine learning algorithms (described below) that alleviate limitations from traditional statistical analyses, such as predictor collinearity, statistical overfitting, and linearity. Machine learning has been used to model mental health variables, including anxiety symptoms (reviewed in Shatte et al., 2019).

Our analytic approach was exploratory, given limited literature on vulnerability factors for COVID-19-specific anxiety. These vulnerability factors could be quite different than those from prior outbreaks given the substantially greater severity and transmission of COVID-19 (Li et al., 2020). Additionally, machine learning is an inherently exploratory analytic procedure (Jordan & Mitchell, 2015). Nonetheless, we infused theory into machine learning analyses by selecting predictor variables from prior theory and relevant empirical work (Elhai & Montag, 2020).

Method

We conducted a cross-sectional web survey of Chinese adults from 24 February to 15 March 2020, when social distancing was heavily enforced in China. Data collection was thus conducted quite early in course of the pandemic, with little information known about the transmission of COVID-19 or optimal protection methods. We invited participants through the Chinese social networking site app “WeChat” (Montag et al., 2018), which includes location-based online communities. We arranged for WeChat community moderators in Tianjin, China (a large city of 12 million people) to invite participants. We presented an online consent statement to interested participants, and for those enrolling we presented the survey in Chinese hosted on Survey Star, a web survey platform with features to minimize bot participation. We compensated participants for survey completion with digital payments, randomly ranging from 3 to 10 Chinese RMB (about 50 cents-$1.50 USD). The Tianjin Normal University Psychology Ethics Committee approved the project.

There were no missing data, as participants were prompted to complete skipped items. After removing participants with large numbers of consecutive identical responses, our effective sample included 908 participants. Age averaged 40.37 years ($SD = 9.27$), ranging from 17 to 64 years. Most participants were women ($n = 752$, 82.82%), and most were of Chinese Han ethnicity ($n = 875$, 96.37%). A slight majority reported fear of death from COVID-19 ($n = 582$, 64.10%). A minority reported having to stay in a different city because of virus-related travel restrictions ($n = 203$, 22.36%).

Instruments

We queried demographic characteristics, including age and sex, and administered the following self-report measures. Internal consistency for multi-item measures is displayed in Table 1.

The *Depression Anxiety Stress Scale-21* (DASS-21) has 7-item depression, anxiety, and stress subscales (Zanon et al., in press), validated in Chinese (Wang et al., 2016); we assessed symptoms using the instrument's standard past-week instructions, but without specific reference to the COVID-19 pandemic. The *Ruminative Responses Scale* has 22 items measuring ruminative thought using a total score (Treynor et al., 2003), validated in Chinese (Han & Yang, 2009). The *Anxiety Sensitivity Index-3* has 18 items representing fear of anxiety sensations using a total score (Taylor et al., 2007) supported in Chinese (Wang et al., 2014). The *Generalized Anxiety Disorder Scale-7* (GAD-7) is a 7-item measure of anxiety and worry (mapping onto DSM-5 GAD symptom criteria), forming a total score (Plummer et al., 2016), validated in Chinese (He et al., 2010). We modified the GAD-7 instructions to specifically rate symptoms within the context of COVID-19 (C-GAD-7), to minimize pre-existing symptoms assessed (e.g., "Based on your own feelings since the outbreak of the novel coronavirus, how often have you been bothered by … Not being able to stop or control worrying?").

We also administered instruments not previously validated in Chinese. We used a rigorous process of translation/back translation by bilingual Chinese/English speakers to adapt English measures in Chinese, resolving discrepancies before finalizing them.[1] The *Disgust Propensity and Sensitivity Scale-Revised* has 8-item disgust propensity and sensitivity subscale scores, validated previously (van Overveld et al., 2010). The *Penn State Worry Questionnaire* has 16 items summed for a

Table 1. Internal consistency alpha values; and means and standard deviations for primary continuous variables separated by perceived threat of death from COVID-19.

Variable	Coefficient alpha	Did not fear death ($n = 326$) *M* (SD)	Feared death ($n = 582$) *M* (SD)	$F(1, 906)$	p	η_p^2
Depression	.82	2.42 (2.91)	2.96 (3.29)	6.18	.01	.007
DASS-21 anxiety	.76	3.38 (2.85)	4.24 (3.36)	15.27	<.001	.017
Stress	.80	4.26 (3.41)	5.20 (3.79)	13.66	<.001	.015
COVID-19-related anxiety	.90	3.46 (3.48)	4.80 (4.00)	25.87	<.001	.028
Rumination	.94	34.02 (9.23)	36.31 (10.42)	10.88	.001	.012
Anxiety sensitivity	.95	11.56 (11.21)	15.79 (13.70)	22.55	<.001	.024
Disgust propensity	.84	15.54 (4.99)	17.03 (5.66)	15.68	<.001	.017
Disgust sensitivity	.88	12.53 (4.74)	14.19 (5.71)	19.93	<.001	.022
Worry	.89	39.80 (10.05)	43.13 (11.47)	19.26	<.001	.021
Social anxiety	.90	15.60 (11.22)	18.10 (12.25)	9.26	.002	.010
Health anxiety	.86	10.47 (4.76)	13.32 (5.64)	59.30	<.001	.061
Negative consequences of illness	.75	2.34 (1.79)	3.25 (2.36)	36.84	<.001	.039
Age	N/A	41.00 (9.48)	40.01 (9.13)	2.37	.12	.003
COVID-19 news exposure	N/A	2.69 (.68)	2.72 (.65)	.63	.43	.001

Note. DASS-21 = Depression Anxiety Stress Scale-21; Threat of death was coded "1" for "yes," and 0 for "no."

total score, validated by Kertz et al. (2014). The *Social Interaction Anxiety Scale* is a 20-item measure of social anxiety and we used the 17 non-reverse-coded items to form a total score (Rodebaugh et al., 2007). The *Short Health Anxiety Inventory* has validated 14-item health anxiety and 4-item negative consequences of illness subscales (Alberts et al., 2013). Thus, only the C-GAD-7 Scale included instructions for rating items specifically within the context of COVID-19; all other scales used standard instructions.

We queried extent of COVID-19-related news exposure, asking "How much have you heard or learned about coronavirus in the news? (By news we mean national, international, regional/local news and other topical events accessed via radio, TV, newspaper or online)?" We used the news definition by Newman and Levy (2014), with a Likert scale from "0 = Not at all" to "4 = Quite a lot." We also inquired "Have you had to stay in a different city, because of the coronavirus?" using a Yes/No response format. Finally, we asked "Have you feared that you may die from the coronavirus?" using a Yes/No response format, adapted Norris et al. (2006).

Analysis

We used R version 3.6.3 (R Core Team, 2020) for data pre-processing and preliminary analysis with R packages of *careless* (detecting careless responding), *fmsb* (coefficient alphas), *pastecs* (descriptives), *sjstats* (ANOVA effects) and *corrplot* (bivariate correlations). We used the R *caret* package for machine learning, with packages for specific algorithms of *glmnet* (lasso, ridge and elastic net regression), *rf* (random forest), *xgbTree* (extreme gradient boosted regression), and *svmRadial* (support vector machine with a radial basis function kernel).

Predictor variables included sex, age, COVID-19 news exposure, staying in a different city, and summed scores for depression, DASS-21 anxiety, stress, rumination, anxiety sensitivity, disgust propensity, disgust sensitivity, worry, social interaction anxiety, health anxiety, and negative consequences of illness. When modeling COVID-19-relevant anxiety (C-GAD-7) as the dependent variable (a summed total score), we added perceived threat of death as a predictor. When modeling perceived threat of death due to COVID-19 as the dependent variable (a binary "yes"/"no" item), we added COVID-19-relevant anxiety as a predictor. Variable distributions were normal; kurtosis was highest for DASS-21 anxiety (3.22), and skewness was highest for depression (1.66).

Statistical tests were two-tailed. Correlations among continuous variables are displayed in Table 2. Group differences on continuous variables between those endorsing versus not endorsing perceived threat of death from COVID-19 are displayed in Table 1. We tested relations between categorical variables using chi-square analyses.

We randomly shuffled the 908 data rows, using a fixed number seed for subsequent replication. We randomly allocated 70% (in detail: 70.04%) of the sample ($n = 636$) as the training subset, and 30% (in detail: 29.96%, $n = 272$) as the "hold-out" test subset. For analyses using threat of death in relation to COVID-19 as the binary dependent variable, we stratified training/test allocation by the dependent variable to ensure that we did not have too few participants in the (smaller) test subset who did not endorse COVID-19-related threat of death. After subset allocation, we preprocessed continuous predictor and dependent variables with z-score transformations (Kuhn & Johnson, 2013).

We used a variety of machine learning algorithms to test our COVID-19-specific anxiety model and perceived threat of COVID-19 death model. We included three "shrinkage" algorithms-elastic net, lasso, and ridge regression-assigning a size constraint penalty to regression coefficients from highly correlated predictor variables, alleviating collinearity problems. While ridge regression shrinks coefficients *toward zero*, elastic net and lasso regression can additionally shrink empirically unimportant predictors to *exactly zero*, conducting parsimonious model subset selection (Zou & Hastie, 2005). Because of the advantage of parsimony in model subset selection, especially with models containing many predictor variables, lasso and elastic net algorithms are often preferred to algorithms that do not offer subset selection (Hastie et al., 2016).

Table 2. Bivariate Pearson correlations among continuous variables.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Depression													
2. Anxiety	.68**												
3. Stress	.75**	.76**											
4. C-Anx	.59**	.64**	.70**										
5. Age	−.06	−.05	−.04	−.01									
6. C-News	−.01	−.01	.01	.02	.11**								
7. Rumination	.62**	.57**	.65**	.64**	−.06	.02							
8. AS	.46**	.58**	.52**	.55**	−.03	.03	.68**						
9. Disgust *P*	.48**	.49**	.52**	.52**	.02	−.02	.64**	.67**					
10. Disgust S	.39**	.49**	.47**	.52**	.06	.01	.60**	.74**	.78**				
11. Worry	.46**	.52**	.56**	.58**	−.08*	.02	.58**	.61**	.51**	.49**			
12. Soc Anx	.41**	.44**	.44**	.40**	−.15**	−.06	.53**	.57**	.50**	.46**	.58**		
13. Health Anx	.29**	.36**	.33**	.39**	−.04	.02	.39**	.43**	.39**	.37**	.43**	.29**	
14. Neg Conseq	.36**	.33**	.35**	.36**	−.05	.03	.36**	.39**	.33**	.31**	.45**	.35**	.52**

Note. Anxiety = Depression Anxiety Stress Scale-21 (DASS-21) Anxiety; Health Anx = Health Anxiety; Neg Conseq = Negative Consequences of Illness; C-Anx = COVID-19-related anxiety; Disgust *P* = Disgust Propensity; Disgust S = Disgust Sensitivity; AS = Anxiety Sensitivity; Soc Anx = Social Anxiety; C-News = COVID-19-related news exposure.
* indicates $p < .05$. ** indicates $p < .01$.

We also used a support vector machine algorithm that maps relationships in three dimensions to improve linear separability in a dependent variable. We implemented a radial basis function kernel for the support vector machine, allowing for non-linear relations, and producing flexible decision boundaries in the dependent variable. We also tested two ensemble algorithms – random forest and extreme gradient boosted regression – both conducting subset selection. In these ensemble algorithms, weaker learners (many subsets of participants and/or predictors) are iteratively tested to form a final model, reducing overfitting and variance through weaker learner results aggregation. Random forest conducts iterative aggregation independently, while boosted regression uses prior iterations to prospectively fix learner errors. For all algorithms, we used grid search to automatically hypertune optimal parameters (e.g., alpha and lambda for the shrinkage algorithms). We chose these algorithms because across research areas, they are among the best, most accurate machine learning algorithms, with their advantages (and little disadvantage) over traditional statistics extensively discussed (Hastie et al., 2016; Kuhn & Johnson, 2013). We compared the performance of these algorithms using our data, because different research areas can yield different optimal performing machine learning algorithms (Fernández-Delgado et al., 2015). In modeling COVID-19-related anxiety and threat of death, no available literature can help determine a priori which algorithm would perform best, but our results could inform future studies on virus outbreak-related emotional distress regarding which algorithms to ideally select.

For modeling COVID-19-related anxiety as a continuous dependent variable (regression-based machine learning), we compared algorithm performance using mean absolute error (MAE), root mean squared error (RMSE), R-squared values, and Bonferroni-adjusted pairwise statistical tests. For modeling COVID-19-related threat of death as a binary dependent variable (classification-based machine learning), we compared algorithms using area under the curve, accuracy, sensitivity, specificity, and Bonferroni-adjusted pairwise statistical tests. For each algorithm separately, we first used k-folds repeated cross-validation in the training subset to simulate test data, using a fixed number seed (Kuhn & Johnson, 2013). We split the training subset into 5 orthogonal subsamples/folds, using four folds as simulated training data and the fifth fold as simulated test data. We repeated this procedure so each fold served as the simulated test fold once, repeating the entire process nine more times, for a total of 50 replications. After simulation testing, we applied the aggregated, trained predictor model to the external hold-out test sample, for each algorithm separately to validate external performance. We computed variable importance metrics for the best performing algorithms.

Results

Preliminary analyses

Table 2 displays bivariate Pearson correlations among continuous variables. COVID-19-relevant anxiety significantly correlated with all variables (even with a Bonferroni-adjusted p value of .004), except age and COVID-19 news exposure. ANOVA demonstrated that COVID-19-specific anxiety was not associated with sex, $F(1, 906) = 2.40$, $p = .12$, $\eta^2 = .003$. Descriptive statistics for continuous variables are displayed in Table 1, in association with perceived threat of death from COVID-19. Table 1 demonstrates that perceived threat of death was associated with all continuous variables except age and COVID-19 news exposure. Perceived threat of death was positively associated with staying in a different city, $\chi^2(1, N = 908) = 5.31$, $p = .02$, phi = .08, but not with sex, $\chi^2(1, N = 908) = .54$, $p = .46$, phi = .02.

Modeling COVID-19-related anxiety

Table 3 presents machine learning results for modeling COVID-19-relevant anxiety as the dependent variable. The table shows comparisons for the training subset using repeated cross-validations, and performance results applied to the hold-out test sample. Lasso and elastic net algorithms performed

Table 3. Comparison of six machine learning-based algorithms, reported separately for the training sample using repeated cross-validation, and the external hold-out test sample.

Modeling COVID-19-related anxiety severity as the dependent variable						
	Mean (and Standard Deviation) Model fit findings over repeated cross-validations in the training sample			Model fit findings in the test sample		
	RMSE (SD)	MAE (SD)	R^2 (SD)	RMSE	MAE	R^2
Lasso	.6468 (.0505)	.4917 (.0330)	.5868 (.0775)	.6538	.4902	.5752
Ridge	.6489 (.0508)	.4930 (.0334)	.5831 (.0754)	.6531	.4912	.5756
Elastic Net	.6468 (.0504)	.4916 (.0330)	.5872 (.0775)	.6535	.4903	.5670
Support vector machine	.7004 (.0546)	.5185 (.0316)	.5216 (.0555)	.7503	.5442	.4547
Extreme gradient boosting	.6796 (.0542)	.5169 (.0366)	.5482 (.0747)	.6966	.5317	.5183
Random forest	.6622 (.0492)	.5047 (.0328)	.5719 (.0723)	.6835	.5103	.5430

Modeling perceived threat of death from COVID-19 (yes/no) as the dependent variable							
	Mean (and standard deviation) classification accuracy findings over repeated cross-validations in the training sample				Model fit findings in the test sample		
	Accuracy	AUC (SD)	Specificity (SD)	Sensitivity (SD)	Accuracy (95% CI)	Specificity	Sensitivity
Lasso	.6499	.6524 (.0413)	.0000 (.0000)	1.0000 (.0000)	.6531 (.5932–.7097)	.1031	.9598
Ridge	.6427	.6364 (.0403)	.0835 (.0376)	.9490 (.0312)	.6458 (.5856–.7027)	.0103	1.0000
Elastic Net	.6493	.6526 (.0416)	.0000 (.0000)	1.0000 (.0000)	.6568 (.5970–.7132)	.0928	.9713
Support vector machine	.6386	.5986 (.0357)	.0652 (.0715)	.9554 (.0443)	.6421 (.5818–.6992)	.0309	.9828
Extreme gradient boosting	.6322	.6084 (.0431)	.2175 (.0510)	.8598 (.0496)	.6421 (.5818–.6992)	.2784	.8448
Random forest	.6369	.6006 (.0446)	.2245 (.0573)	.8684 (.0426)	.6273 (.5668–.6850)	.1649	.8851

Note. Higher values for R^2, but lower values for RMSE and MAE, indicate better fit. RMSE = root mean squared error; MAE = mean absolute error; AUC = Area under the curve.

best in the training sample. Bonferroni-adjusted tests for pairwise comparisons demonstrated that the three shrinkage algorithms performed significantly better than other algorithms, but not better than each other. Training sample results generalized well to the hold-out test sample, especially observed for the shrinkage algorithms, without worsening of fit. In the hold-out test sample, shrinkage algorithms performed best, but did not outperform each other. Shrinkage algorithms individually explained between 58 and 59% of variance during training, and between approximately 57 and 58% variance during testing, in modeling COVID-19-relevant anxiety. Therefore, results suggest that (especially using shrinkage algorithms) the model of predictors was successfully trained and subsequently applied and validated in the hold-out test sample in modeling COVID-19-related anxiety severity.

We estimated relative variable importance for predictor variables in modeling COVID-19-related anxiety. These estimates are interpreted as standardized regression coefficients, as variables were ztransformed.[2] For example, using elastic net regression, Table 4 demonstrates stress (importance = .32) and rumination (importance = .21) as the most important predictors of COVID-19-relevant anxiety; these predictors were followed next by somewhat less important predictors of DASS-21 anxiety, health anxiety, and worry, with each importance value roughly only .10 or lower. As elastic net regression shrinks empirically unimportant regression coefficients to zero, the bottom eight predictors (see Table 4) were excluded from the final model as they were empirically unimportant in the model. Furthermore, stress and rumination (in that order) were the top performing predictors across all other algorithms, and in fact rankings of variable importance were quite similar across algorithms. Thus stress and rumination appeared most robust in association with COVID-19-relevant anxiety severity.

One issue with the machine learning analyses is that anxiety was used as a predictor variable (DASS-21 anxiety) and also as the dependent variable (C-GAD-7). As discussed above, a major difference between these two measures was that unlike DASS-21 anxiety, the C-GAD-7 assessment was specifically anchored within the context of COVID-19. Nonetheless, we re-computed the machine learning analyses by excluding DASS-21 anxiety as a predictor variable. We found extremely similar results for the machine learning algorithms to those reported in Table 3 which included DASS-21 anxiety as a predictor. And using elastic net regression as we presented in Table 4 that included DASS-21 anxiety, when now excluding DASS-21 anxiety we found the same ordered ranking of remaining predictors based on variable importance estimates, almost exactly the same magnitude of estimates, and the same set of variables excluded based on subset selection (for empirical unimportance). These revised results are available by contacting the second author.

Modeling perceived threat of death from COVID-19

Table 5 also presents machine learning results modeling perceived threat of death as the (binary) dependent variable. The table displays comparisons for the training subset using repeated cross-validations, and results applied to the hold-out test sample. Algorithms performed better in training (and testing) by ruling in individuals fearing death from COVID-19 (sensitivity) than ruling out individuals (specificity). Thus the model was best at correctly identifying participants reporting fear of death, but often identified participants without fear of death erroneously as fearing death. In training, area under the curve and accuracy values were best for lasso and elastic net regression, with Bonferroni-adjusted tests demonstrating superiority over other algorithms, but no superiority over one another. In testing, elastic net and lasso regression also yielded the best accuracy values.

Table 4. Relative variable importance for the predictor variables in modeling COVID-19-related anxiety severity, using elastic net regression.

Predictor variable	Importance estimate
Stress	.3247
Rumination	.2119
DASS-21 anxiety	.1051
Health anxiety	.0879
Worry	.0795
Disgust sensitivity	.0684
Depression	.0243
Threat of death from COVID-19	.0119
Age	0
Anxiety sensitivity	0
Disgust propensity	0
Negative consequences of illness	0
News exposure to coronavirus	0
Sex	0
Social anxiety	0
Stayed in a different city	0

Note. DASS-21 = Depression Anxiety Stress Scale.

Table 5. Relative variable importance for the predictor variables in modeling perceived threat of death from COVID-19, using extreme gradient boosted regression.

Predictor variable	Importance estimate
Health anxiety	.3732
Negative consequences of illness	.1273
Disgust sensitivity	.1010
Anxiety sensitivity	.0919
Stress	.0848
Rumination	.0499
COVID-19-related anxiety	.0481
Worry	.0429
News exposure to coronavirus	.0274
Disgust propensity	.0235
Social anxiety	.0188
Stayed in a different city	.0111
Age	0
DASS-21 anxiety	0
Depression	0
Sex	0

Note. DASS-21 = Depression Anxiety Stress Scales.

However, the best compromise between sensitivity and specificity was achieved by extreme gradient boosted regression.

We estimated relative variable importance for predictor variables in modeling perceived threat of death from COVID-19. For example, using elastic net regression, the only relative important predictor of perceived threat of death was health anxiety. All other predictors were excluded using subset selection because they were empirically unimportant to the model (contact the corresponding author for these full results). For comparison purposes using gradient boosted regression (with subset selection; Table 5), health anxiety was also the most important relative predictor; however, 11 additional variables were significant but only mildly important predictors, and the four bottom variables were excluded from the final model. Nonetheless, health anxiety was the most important relative predictor of perceived threat of death across all machine learning algorithms, and variable importance rankings across algorithms were quite similar.

Discussion

In the present paper, we examined numerous relevant psychopathology, sociodemographic, and virus exposure-related variables associated with anxiety regarding COVID-19. Bivariate analyses demonstrated that COVID-19-related anxiety levels and perceived threat of death individually correlated with nearly all variables tested. We subsequently used machine learning to empirically identify the most important predictor variables from among more than a dozen tested. We found most support for shrinkage machine learning algorithms, generalizing from model training to testing in an external sample. The shrinkage algorithms performed quite similarly to each other, with only mild performance differences between them. Generalization of performance from training to testing suggests that the predictor model was successfully trained and subsequently validated in modeling COVID-19-related anxiety levels. Results remained the same when excluding DASS-21 anxiety as a predictor of COVID-19-related anxiety, suggesting that DASS-21 anxiety was not a strong driver of the results.

Stress and rumination were the most potent relative contributors to COVID-19-related anxiety across machine learning algorithms; and these findings (and magnitude of effects) were replicated when we removed DASS-21 anxiety as a predictor variable. These findings are consistent with evidence that stress bivariately correlated with virus-related anxiety during the Swine flu pandemic, but not in adjusted multivariate models (Wheaton et al., 2011). Rumination has not been examined in relation to outbreak-related anxiety. However, rumination largely involves negative affectivity

(Samtani & Moulds, 2017), and other negative affectivity variables are supported in relation to outbreak-related emotional distress (Ahorsu et al., in press; Blakey & Abramowitz, 2017; Blakey et al., 2015; Cheng & Cheung, 2005; Lee, 2020; Wheaton et al., 2011). Stress and rumination can result from social distancing requirements, including stress from decreased contact with significant others, or rumination about virus-related information (Schimmenti et al., 2020). Additionally, we found other anxiety-related variables (e.g., general anxiety, health anxiety, and worry) as the next most important variables in predicting COVID-19-relevant anxiety, but their adjusted effects were mild in contrast to stress and rumination. These anxiety-related variables were previously related to outbreak-related anxiety (Ahorsu et al., in press; Blakey & Abramowitz, 2017; Blakey et al., 2015; Cheng & Cheung, 2005; Wheaton et al., 2011). Thus people reporting greater levels of anxiety-related psychopathology, including general and health anxiety, but especially stress and repetitive negative thinking such as rumination, also reported greater COVID-19-relevant anxiety. These anxiety-related negative affectivity variables may therefore be vulnerability factors to virus outbreak-related anxiety (Taylor, 2019).

Machine learning results identified health anxiety as the most important relative contributor to perceived threat of death from COVID-19. Health anxiety was bivariately associated with Swine flu and Zika outbreak anxiety previously (Blakey & Abramowitz, 2017; Wheaton et al., 2011), but not in multivariate models (Wheaton et al., 2011). Similarly, Ahorsu and colleagues (Ahorsu et al., in press) found that perceived vulnerability to disease was related to COVID-19 anxiety. Health anxiety fits within the Schimmenti et al. (2020) conceptual framework as a major COVID-19 fear; that is, body-related fears and hypersensitivity to physiological sensations, and is consistent with theoretical perspectives previously discussed (Asmundson & Taylor, 2020b; Taylor, 2019). The next most important predictors of perceived threat of death found in extreme gradient boosted regression also involved health anxiety, specifically regarding negative consequences from illness and disgust sensitivity, though with mild effects. Nonetheless, disgust sensitivity is supported in relation to outbreak-related anxiety (Blakey & Abramowitz, 2017; Blakey et al., 2015; Wheaton et al., 2011). Not everyone during a major virus outbreak will fear death from the virus. Anxiety about one's health may be an important vulnerability factor that explains why some people have heightened virus-related anxiety while others do not (Taylor, 2019).

Limitations

Our participants were limited to one country, China, in the early stages of the pandemic when little was known about the virus in terms of transmission mode or optimal protection methods. We cannot conclude how well results generalize to other countries, given differences in COVID-19 prevalence and local orders regarding social distancing and quarantine. COVID-19 anxiety in China may be less severe currently, as more information is now known about the virus and how to protect oneself from exposure to it. Additionally, we only included self-report measures of psychopathology. Because of required social distancing, we could not interview participants using structured interviews. Some of our measures share conceptual similarities, such as between the C-GAD-7 and DASS-21's Stress subscale, and perhaps between the health anxiety subscales and fear of death from COVID-19 item. Furthermore, the DASS-21 anxiety subscale and C-GAD-7 both inquire about anxiety from the time of the pandemic. Though as stated above, unlike the stress and health anxiety variables, we instructed participants to rate the C-GAD-7 specifically within the context of COVID-19 rather than reflecting pre-existing symptoms, and removing the DASS-21 anxiety subscale from analyses yielded essentially the same results. Furthermore, we were unable to measure all constructs that we reviewed from prior literature as vulnerability factors of virus outbreak-related anxiety. This study also used a cross-sectional design; therefore, causal conclusions between background psychopathology as predictor variables and COVID-19-related anxiety cannot be inferred; nonetheless, we attempted to minimize this limitation by anchoring dependent variable symptom ratings specifically within the context of COVID-19. Future work following participants over time using a longitudinal research design would allow more confidence in drawing causal conclusions.

Conclusion

Despite limitations, our results provide initial insight into the most robust emotional vulnerabilities to COVID-19-related anxiety and fear of death-stress, rumination, general anxiety, health anxiety, and worry for the former, and health anxiety alone for the latter. As earlier studies outlined the importance of studying personality traits in highly uncertain situations, such as the anxiety versus fear debate (Reuter et al., 2015), future work should examine stable individual differences like the Big Five personality traits or measures linked to Reinforcement Sensitivity Theory (Corr & McNaughton, 2012). Such individual differences could also be emotional vulnerability factors to COVID-19-related distress. Future work might also apply machine learning to examine the most robust predictors of broader conceptualizations of COVID-19-related anxiety and fear, such as the Taylor et al. (2020) COVID Stress Syndrome.

Notes

1. The second author can be contacted to obtain the Chinese translations: yanghaibo@tjnu.edu.cn.
2. In linear and logistic regression, standard errors are computed for regression coefficients, from which to calculate statistical tests and resulting *p* values. However, standard errors are not computed for variable importance estimates, using the algorithms we tested. This is because these algorithms purposefully introduce substantial bias in order to reduce statistical overfitting and variance, and such bias is used to estimate the model's mean square error. Yet it is not possible to precisely or reliably measure such bias in a way that would translate to standard error computation (Kuhn & Johnson, 2013).

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Outside the scope of the present paper, Dr. Elhai notes that he receives royalties for several books published on post-traumatic stress disorder (PTSD); is a paid, full-time faculty member at University of Toledo; is a paid, visiting scientist at Tianjin Normal University; occasionally serves as a paid, expert witness on PTSD legal cases; and receives grant research funding from the U.S. National Institutes of Health. Also Dr. McKay notes that he receives royalties for several books written on anxiety disorders in adults and children, obsessive-compulsive disorder, and research methodology; is a paid full-time faculty member at Fordham University; holds a research fellow position in a joint relationship between Fordham University and Columbia University; and has private grant funding from a venture capital research corporation to investigate methods of reducing public speaking fears. Dr. Asmundson is the Editor-in-Chief of the Journal of Anxiety Disorders and Development Editor of Clinical Psychology Review. He receives financial support through payments for his editorial work on the aforementioned journals and royalties from various book publishers. He also currently hold research grants awarded by the Canadian Institutes of Health Research.

Data availability statement

The de-identified data from this paper may be requested from the second author, upon reasonable request.

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