Predicting Psychological Distress under Coronavirus Disease Pandemic

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# Introduction

Since December 2019, the Coronavirus disease (COVID-19) has spread around the world which has caused 262,295,087 infections and 5,210,524 deaths up to November 30 2021 (Johns Hopkins Coronavirus Resource Center, 2021). Besides the negative physical impacts, COVID-19 has brought a serious global mental crisis. As compared with 2017, several meta-analyses revealed a significant rise of mental disturbance rate since the outbreak of COVID-19, the global pooled prevalence for depression and anxiety has elevated from 3.44% to 25%, and 7.3% to 25% respectively (Bueno-Notivol et al., 2021; Santabárbara et al., 2021). Among various emotional burden indicators, the general population suffer most from psychological distress during COVID-19, with a global pooled prevalence rate of 37% (Krishnamoorthy et al., 2020). Psychological distress is defined as the combined affective domains of major depressive disorder and general anxiety disorder (Kessler et al., 2002). Meanwhile, psychological distress is reported to predict ample amounts of maladaptive emotional and behavioral outcomes, such as major depressive disorder, general anxiety disorder, substance abuse, occupational and interpersonal relationship dysfunctioning, and myoptic decision-making process brought by maladaptive cognitive functioning (Hardy et al., 2003; Kessler et al., 2002; Lechner et al., 2020; Lee et al., 2001; Wells et al., 1999). In light of the high prevalence and serious potential consequences of psychological distress, this research paper will first review the factors that predict psychological distress, as well as numerous predictive models, then propose the most suitable model in predicting psychological distress under the outbreak of COVID-19.

## Theoretical Framework: Factors Predicting Distress Under COVID-19 Pandemic

### COVID-19 Situation

Undoubtedly, people are afraid of COVID-19 infection because of the basic human instinct of thanatophobia. Zheng et al. (2021) found that concern about the threat from COVID-19 towards self and significant others is the COVID-related primary stressor. In this case, the rising new infection cases and deaths will create a perception about likelihood of getting infected and death from COVID-19, which will introduce intense perceived life threats towards self and significant others (Holingue et al., 2020). Under threat perception, people with high trait anxiety tend to devote heightened attention towards threat, while people with low trait anxiety tend to avoid threat attentionally (MacLeod & Mathews, 1988). However, even attentional threat avoidance may reduce the acute impact of imminent threat, it comes at the price of an elevated risk for psychopathology (Bar-Haim et al., 2010). Hence, COVID-19 as a life threatening danger, has increased the public vigilance, stress, and psychological distress, whereas the general public has manifested attentional biases toward COVID-related cues, and this may be a warning sign that predict later onsets of COVID-related health anxiety (Cannito et al., 2020).

In addition, mass media plays a crucial role in delivering COVID-related information, whereas the way the mass media portrays the information has a major impact on psychological distress. Yao (2020) discovered the positive association between exposure to media information and psychological distress. To understand the underlying reasons, a content analysis study from Ogbodo et al. (2020) pointed out that the way the mass media framed the information has an effect on adoption of preventive measures against COVID-19, but also induces gloom, frustration and fear. Meanwhile, Rubin and Wessely (2020) suggested that ambiguous mass media messages will spread fear because of perceived uncertainty, and it will push people to seek information from less reliable sources. Therefore, because of ambiguity, fear, and attentional bias towards COVID-19, mass media is a factor that warrants public attention as it may predict psychological distress and various maladaptive emotional reactions.

### Governmental Policies and Trust in Government

Governments adopted various policies to prevent imported cases and local spread of COVID-19. Under containment and closing policies, people’s access to emotional, physical, and material social support are restricted, which significantly harm their wellbeing (Kalok et al., 2020). Moreover, the boredom and changes in working environment caused by movement restrictions, are related to basic need fulfilment frustration, questioning the meaning of life, distress, and excessive media use (Anand et al., 2021; Chao et al., 2020). In terms of health policies, policies such as tracing policy may imfridge people’s privacy that may induce stress and distress (Burke et al., 2020). Meanwhile, the stringent health policies may amplify the public awareness of the severity of COVID-19 and increased perceived health threat from COVID-19 (Koch & Park, 2022). Under heightened perceived threat posed by COVID-19, it increases psychological distress and various behaviors that predict the onset of COVID-related health anxiety (Özdin & Özdin, 2020). In terms of economic policies, it is useful in relieving the financial insecurity posed by COVID-19, which in turn relieved one of the COVID-related secondary stressors (Zheng et al., 2021), and negatively predict psychological distress (Duarte & Jiménez-Molina, 2021).

The negative influences from closing and health policies on psychological distress is found to be moderated by trust in government (O’Hara et al., 2020). Harris and Sandal (2020) suggested that people who have low trust in government health policies are prone to worrying, depression, anxiety, and psychological distress, especially for the medically vulnerable groups, possibly because of higher perceived risk and lower perceived medical security. Furthermore, stringent policies will trigger cognitive dissonance among people with low trust in government and anti-government political identity, resulting in psychological distress when complying with the restrictions and policies (Paolini et al., 2020). Because of cognitive dissonance, people with low trust in government also tend not to comply with the policies to avoid attacking their core beliefs that accompany with psychological distress (Newton, 2021). Lastly, people who distrust the government tend to seek more sources of information from mass media to validate the government information, which in turn predict psychological distress because of rumors, ambiguous, and less reliable messages (Porumbescu, 2017; Rubin & Wessely, 2020).

### Personal Traits and Coping Resources

Ample amounts of research explored the relationship between personal traits and coping capacity to confront stressful events. Nikčević et al. (2021) found that neuroticism in the big five personality is a significant predictor of psychological distress under the outbreak of COVID-19, while psychological distress further predicts health anxiety, general anxiety disorder, and major depressive disorder. The vulnerability of neurotic people may be due to their lower perceptual threshold and stronger brain reactivity toward stimuli (Passamonti et al., 2019), contributing to their lower stress tolerance and inability to adapt to lifestyle changes during the outbreak of COVID-19 (Balling et al., 2021; Haward, 1969). Meanwhile, Nikčević et al. (2021) identified consciousness serves as a strong protective factor, while agreeableness also produces a small but significant protective effect against psychological distress.

A meta-analysis conducted by ​​Harandi et al. (2017) concluded the secure effect of social support on mental health, however, the interpersonal trust at community level is collapsing because of the fear of potential infection (Gonzalez-Medina & V. Le, 2011; Goodwin et al., 2020), which may stop people from seeking social support. Numerous research have pointed out that social avoidance stemming from interpersonal distrust significantly predicts distress (Holingue et al., 2020; Varma et al., 2021; Yang et al., 2009), and interpersonal distrust will stop people from seeking social support (Grace & Schill, 1969; Saltzman et al., 2020).. Then, such social avoidance will increase perceived isolation and loneliness, that are intrinsically harmful to human beings (Beutel et al., 2017), and elevated the risk of adopting maladaptive coping strategies and prone to psychological distress and mental disorders (Henssler et al., 2021; Park et al., 2021). Taken together, the claim that interpersonal distrust and restricted social support predict distress is supported by the climbing psychological distress rate during COVID-19 outbreak (Krishnamoorthy et al., 2020), at the time when people are afraid of being infected and perform social distancing.

The COVID-19 has influenced people’s life to various degrees and the changes accompany stress (Birditt et al., 2021; Stewart & Salt, 1981), then how people cope with stress is crucial to sustain mental wellbeing. Active coping, avoidance coping strategies, seeking social support negatively predict distress during COVID-19 pandemic (El‑Zoghby et al., 2020; Nielsen & Knardahl, 2014; Park et al., 2021; SzKody et al., 2021), while coping with different kinds of substances, such as alcohol and drugs, positively predict psychological distress (Taylor et al., 2021). Although there is a general assumption that active coping is always helpful and disengagement coping is maladaptive coping (Ebata & Moos, 1991), the pandemic is an stressor that largely uncontrollable by individuals, then avoidance coping becomes helpful in relieving negative emotions caused by the unchangeable part of situations (Waugh et al., 2020).

### Demographics

The COVID-19 have influenced people in various demographic backgrounds, and people’s demographics have posed a risk for psychological distress under COVID-19 pandemic. Firstly, younger people are more prone to psychological distress in this critical period (Liu et al., 2021; Varma et al., 2021), possibly because youngsters have larger social needs to formulate their self-identity (Valkenburg et al., 2006). Moreover, there is contradicting evidence in the relationship between age and distress in older adults, García-Portilla et al. (2020) reported that elderly are at high risk of psychological distress because of their medical vulnerability and high perceived threat posed by COVID-19, while Horesh et al. (2020) found that older age is a protective factor, possibly because of their richer life experiences allow them to better adjust with the changes and stress.

Secondly, females are consistently reported as a risk factor of psychological distress under the COVID-19 pandemic (Olaseni et al., 2020). Females are reported to be more distressed than males under containment policies (Elvira et al., 2021). Xue and McMunn (2021) pointed out the possibility of gender inequality in the labor market which increased women’s financial instability, as well as unequal division of labor on housework and childcare, altogether making female’s stress spillover to other settings and having less time for rest.

Thirdly, it is well documented that adverse socio-economic conditions worsen the outcomes from COVID-19 (Rose et al., 2020). Regarding the employment status, people under employment uncertainty, such as unemployed, self-employed, and unpaid leave with absence, are at great risk of psychological distress (Achdut & Refaeli, 2020; Mimoun et al., 2020). When people have a larger number of dependents, the increased financial needs have further intensified the financial strain that predicts greater psychological distress (Kowal et al., 2020). On the other hand, self and parental educational level is known as a protective factor from psychological distress, because it links with better psychological adjustment and knowledge to seek external resources (Chen et al., 2020; Romeo et al., 2021; Thompson Jr et al., 1993). However, Anand et al. (2021) also pointed out highly educated people experience larger need fulfilment frustration under COVID-19, as the pandemic may stop highly educated people from maintaining their highly productive lifestyle.

## Knowledge gaps

Although numerous psychological distress predictors are being identified in various context, including under COVID-19 pandemic ​​(e.g., Heffner et al., 2020; Kimhi et al., 2020; Prout et al., 2020), those predictors’ relative contributions towards psychological distress remain unexplored. Besides, although psychological distress is a multifaceted variable, the majority of research only included limited numbers of predictors, which pose a difficulty in comparing the predictors’ importance and predictive power across studies. Moreover, most studies were conducted in small sample size, probably because of limited budget, which may increase the possibility of obtaining unrepresentative, biased, and contradicting results. For example, Sibley et al. (2020) conducted a 1003 sample size study and reported institutional trust is positively related to distress, which is contradictory to others studies (e.g., Harris & Sandal, 2021). Furthermore, there are limited predictive models to predict psychological distress under COVID-19 pandemic. Even though there are some, such as Choi et al. (2020) developed an artificial neural network to predict psychological distress, it is based on small sample size with small number of variables, which limited the model’s external validity. Because of limited available models, there is absence of study comparing the predictive performance of different predictive models for psychological distress under COVID-19. Taken together, a predictive model that includes larger amounts of predictors with a more representative sample size that can generalize the results to various cultures is needed. Lastly, comparing the predictive models will be beneficial to identify the more accurate model to predict psychological distress under the COVID-19 pandemic.

## Current Study

The present study developed five predictive models of psychological distress under COVID-19 that are based on more representative sample size from global datasets, with larger numbers of variables. This study endeavours to (1) examine the predictive power of the distress predictors, (2) compare the relative importance of the distress predictors, (3) test the predictive performance of linear regression, classification and regression trees, random forest, support vector machine, and XGBoost in predicting distress, and (4) identify the optimal predictive model of psychological distress that can be applied globally.

### Theoretical Significances

Under the current research design, this study can identify the ideal model for predicting psychological distress under COVID-19 pandemic. It also unveiled the relative contributions of numerous predictors toward psychological distress and the results can be generalized to a wide range of countries and cultures. Then, this study can reflect how mental health is influenced by various factors, specifically, how various environmental factors, cognitive appraisals, personality traits, and self-identities, altogether shape the maladaptive cognitive and emotional outcomes. Within the COVID-19 pandemic context, this study also provides insights into the psychological impacts of collective trauma, and the results can generalize to other contexts, such as natural and man-made disasters.

### Practical Significances

Furthermore, given the developed models took large amounts of variables into account, the results can obtain a detailed profile of what vulnerable groups will be like. Then, the findings may provide information for early identification of vulnerable groups that are at high risk of psychological distress and other affective disorders. Furthermore, current research also identified variables that are central to psychological distress, which may provide insights to various psychological interventions, such as psychotherapy and self-help programs, and develop more cost-effective interventions by targeting the most important predictors. Besides, current study findings can inform policy makers about the potential hidden threats of implementing different COVID-19-related policies, which help the society reduce potential additional costs in mental healthcare.

# Methods

## Data Source

The dataset used in this research was merged from projects: (1) COVIDiSTRESS Global Survey dataset can be downloaded at https://osf.io/cjxua/download; (2) Oxford COVID-19 Government Response Tracker (OxCGRT) dataset can be downloaded at https://raw.githubusercontent.com/OxCGRT/covid-policy-tracker/master/data/OxCGRT\_latest\_combined.csv. The data in COVIDiSTRESS was collected in a volunteer sample based on online and media appeals, including trust in government and others, personal traits and coping resources and demographics. The information related to government policies in OxCGRT was collected systematically from the JHU CSSE data repository. Variables ‘Country’ and ‘Date’ are considered for combining the COVIDiSTRESS dataset with the cross-cultural OxCGRT dataset (Yamada et al., 2021). The data was filtered based on a list of common countries in both datasets and a period of 62 days (30th March to 30th May, 2020).

## Variables of Interest

Dependent (target) variable: Distress

Independent (predictor) variables: Age, Gender, Education, Edu\_mother, Employment, Marital, Dependents, Risk\_group, Isolation, Stress, Loneliness, Trust\_people, Trust\_gov, Concern, Trust\_policies, Compliance, Neuroticism, Extraversion, Openness, Agreeableness, Conscientiousness, Provisions, Coping\_problem, Coping\_social, Coping\_avoidance, Coping\_religion, Media, C1\_School, C2\_Workplace, C3\_Events, C4\_Gatherings, C5\_Transport, C6\_Home, C7\_Internal, C8\_Travel, E1\_Income, E2\_Relief, H1\_Information, H2\_Testing, H3\_Tracing, H6\_Coverings, H8\_Protection, Stringency, Gov\_response, Econ\_support, New\_cases, New\_deaths

## Analytical Procedure

Several statistical learning techniques – Linear Regression, Classification and Regression Trees, Random Forest, Support Vector Machine and XGBoost are employed. The data is divided into the training set and the testing set with a ratio of 4:1. The training set is then splitted into 10 folds for cross validation to obtain the optimal parameters.

### Linear Regression

Linear regression analysis is used to predict the dependent variable based on one or more independent variables. The multiple linear regression can be defined by the formula (Tranmer & Elliot, 2008),

where *Y* represents the predicted value of the dependent variable, *β0* represents the constant and *β* represents the regression coefficient of each independent variable *x*.

Linear regression is one of the most common techniques for predicting the value of one dependent variable. Linear regression analysis is a relatively simple model which is easy to understand how it works and to interpret its results. In addition, linear regression provides enormous flexibility, which can be applied to various circumstances.

### Classification and Regression Trees

Classification and Regression Trees (CART) is a predictive algorithm used for classification or regression problems (Breiman et al., 1984). CART is a binary tree model constructed by splitting each node based on a predictor variable. Each node at the end is more homogeneous in terms of the target variable. Therefore, training data with a large sample size is critical to obtain an accurate prediction (McLachlan, 2005). The measure of the node impurity can be defined by the function (Bittencourt, 2003),

where *p(wj|t)* is the proportion of features *xi* being assigned to classes *wj* at node *t*. Each given node is divided into two subnodes, *tL* and *tR*, while *pL* and *pR* are the proportions of samples passed to the new subnodes *tL* and *tR* until stopping criteria is reached. The best partitioning is decided as the calculation of difference (Bittencourt, 2003),

The tree model of CART is a series of if-else conditions which is similar to the thinking process on a human level. Therefore, it is interpretable and easy to manipulate. In addition, the performance of tree models is not affected by the non linear relationship between features.

### Random Forests

Random forests is a supervised learning technique with a combination of tree predictors (Breiman, 2001). The random forest for regression is constructed by growing trees based on the values of a random vector *Θ*, being independent of the previous vectors but with the same distribution. Thus, the tree predictor *h(x, Θ)* takes continuous values instead of class labels. The mean squared generalization error for any numerical predictor *h(x)* is defined as (Breiman, 2001),

Random forest constructs a more generalized model by randomized selection of features. As a result, it has a higher level of accuracy in predicting target variables compared to decision trees. In addition, random forest is relatively robust to outliers and noise compared to other techniques such as linear regression.

### Support Vector Machines

Support vector machines (SVM) are proposed by Vapnik and coworkers (Boser et al., 1992). The objective of SVM is to find a hyperplane *(w,b)* with maximized quantity (Furey et al., 2000),

where *(w,ϕ(xi))* indicates an inner product, *ɣ* represents margin and the quantity *(w,ϕ(xi))-b* correlates with the distance between the data point *xi* and the decision boundary. When the margin *ɣ* gives a positive value, the data can be separated linearly.

SVM provides significant accuracy as the prediction error is minimized by finding a hyperplane with maximized quantity. Moreover, complex relationships between data points can be obtained without performing difficult transformations due to the kernel trick used in the SVM model.

### XGBoost

XGBoost is a scalable machine learning technique for gradient tree boosting. The objective of XGBoost at iteration *t* is defined by the function (Chen & Guestrin, 2016),

where *ŷi(t-1)* indicates the prediction of the *i*-th instance at the *t*-th iteration and *l* represents the differentiable convex loss function which computes the difference between the prediction and the target variable *yi*.

XGBoost provides superior speed and accuracy as it was developed for the model performance and computational speed. XGBoost is applied to various challenges such as The Netflix Price in the KDD Cup 2007 (Bennett & Lanning, 2007). In a machine learning competition held by Kaggle in 2015 (GitHub, n.d.), 17 out of 29 winning solutions employed XGBoost. In KDD Cup 2015, XGBoost was used by the top 10 winning teams (Bekkerman, 2015).

### Expected Outcome Statistics

From the models constructed, it is expected to obtain the most important features in predicting distress and the model with best performance among 5 statistical learning techniques selected in this research.

### Evaluation Criteria

In order to statistically evaluate the performance of statistical learning techniques, machine learning algorithms are assessed by mean squared error (MSE), root mean squared error and R squared (R2).

MSE represents the differences between actual and predicted values by computing the square of average differences of data defined by the formula,

The lower the MSE, the closer is predicted to the actual values. R2 is the percentage of the predicted dependent variable variation in a linear model defined by the formula,

where *yi* represents the data points and *ŷi* represents the estimated regression line. The higher the R2, the higher accuracy of the model.

# Results

## Descriptive Statistics

The final dataset used in the analysis consisted of 31,307 participants over 128 countries. None of the variables in the dataset shows missing values. 68.1% participants are female with a mean age of 40.337 (SD = 12.137). The demographic characteristics are summarized in Table 1, and the descriptive statistics for all variables of interest (except demographic variables) are summarized in Table 2.

**Table 1**

*Demographic Characteristics (N = 31,307)*

| Numerical variables | Min | Max | Mean | SD |
| --- | --- | --- | --- | --- |
| Age | 18 | 110 | 40.337 | 12.137 |
| Dependents | 0 | 77 | 1.273 | 1.392 |
| Categorical variables | *N* |  |  | % |
| Gender |  |  |  |  |
| Female | 21307 |  |  | 68.1 |
| Male | 10000 |  |  | 31.9 |
| Education |  |  |  |  |
| None | 477 |  |  | 1.5 |
| Up to 6 years of school | 464 |  |  | 1.5 |
| Up to 9 years of school | 444 |  |  | 1.4 |
| Up to 12 years of school | 3301 |  |  | 10.5 |
| Some College, short continuing education or equivalent | 5786 |  |  | 18.5 |
| College degree, bachelor, master | 17510 |  |  | 55.9 |
| PhD/Doctorate | 3325 |  |  | 10.6 |
| Employment |  |  |  |  |
| Not employed | 2786 |  |  | 8.9 |
| Student | 3788 |  |  | 12.1 |
| Part time employed | 3506 |  |  | 11.2 |
| Full time employed | 15841 |  |  | 50.6 |
| Self-employed | 3913 |  |  | 12.5 |
| Retired | 1473 |  |  | 4.7 |

### 

**Table 2**

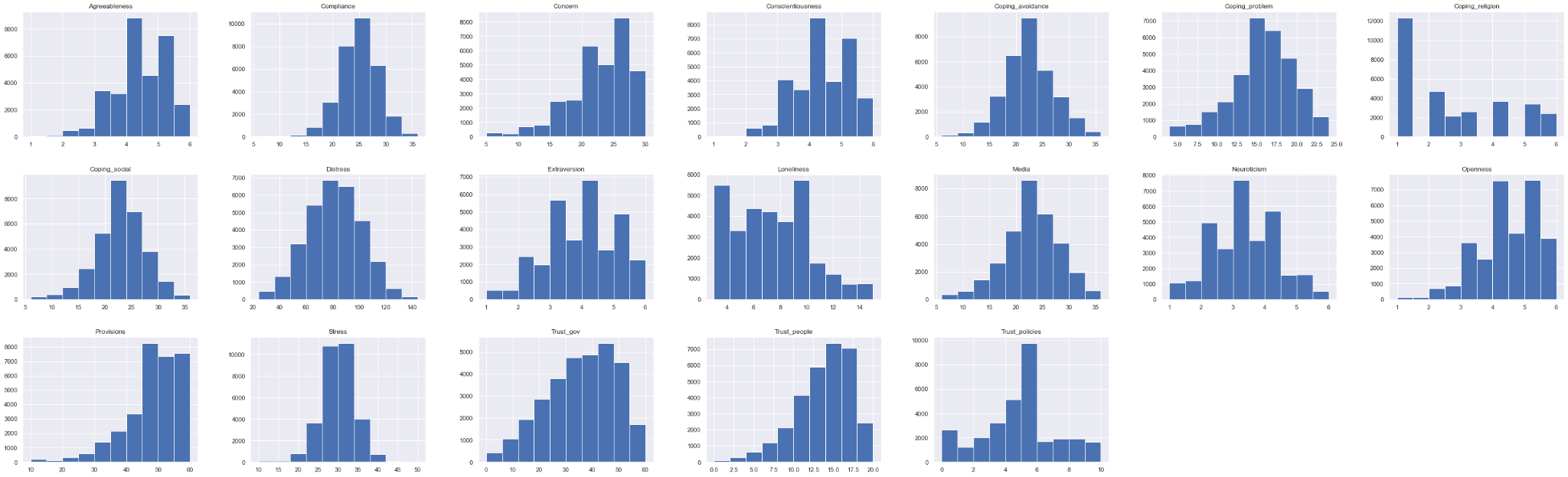
*Descriptive Statistics for All Variables of Interest except Demographic Characteristics*

| Numerical variables | Min | Max | Mean | SD |
| --- | --- | --- | --- | --- |
| Perceived stress for the past week | 10 | 50 | 29.489 | 4.221 |
| Perceived loneliness | 3 | 15 | 7.322 | 2.832 |
| Trust in people | 0 | 20 | 13.259 | 3.524 |
| Trust in country’s government and health system | 0 | 60 | 35.252 | 12.992 |
| Concern over coronavirus | 5 | 30 | 22.637 | 4.907 |
| Trust in own country’s preventative measures | 0 | 10 | 4.453 | 2.353 |
| Overall compliance with local prevention guidelines | 6 | 36 | 24.325 | 3.694 |
| Neuroticism | 1 | 6 | 3.290 | 1.014 |
| Extraversion | 1 | 6 | 3.903 | 1.101 |
| Openness | 1 | 6 | 4.413 | 0.952 |
| Agreeableness | 1 | 6 | 4.366 | 0.839 |
| Conscientiousness | 1 | 6 | 4.323 | 0.885 |
| Available social provisions in critical/ distressing situations | 10 | 60 | 47.948 | 8.826 |
| Coping/ decreasing discomfort on problem | 4 | 24 | 15.235 | 3.945 |
| Coping/ decreasing discomfort on social | 6 | 36 | 22.466 | 4.607 |
| Coping/ decreasing discomfort on avoidance | 6 | 36 | 21.944 | 4.661 |
| Coping/ decreasing discomfort on religion | 1 | 6 | 2.598 | 1.680 |
| Information sources and media behaviour | 6 | 36 | 22.402 | 5.227 |
| C1 Closings of schools and universities | 0 | 3 | 2.649 | 0.495 |
| C2 Closings of workplaces | 0 | 3 | 2.184 | 0.829 |
| C3 Cancelling public events | 0 | 2 | 1.806 | 0.382 |
| C4 Limits on gatherings | 0 | 4 | 3.156 | 1.470 |
| C5 Closing of public transport | 0 | 2 | 0.614 | 0.645 |
| C6 Orders to “shelter-in-place” and otherwise confine to the home | 0 | 3 | 1.304 | 0.768 |
| C7 Restrictions on internal movement between cities/ regions | 0 | 2 | 1.447 | 0.540 |
| C8 Restrictions on international travel | 0 | 4 | 3.50 | 0.625 |
| E1 Direct cash payments by government to people who lose jobs or cannot work | 0 | 2 | 0.988 | 0.859 |
| E2 Financial obligations freezed for households | 0 | 2 | 0.100 | 0.871 |
| H1 Presence of public info campaigns | 0 | 2 | 1.999 | 0.032 |
| H2 Government policy on who has access to testing | 0 | 3 | 1.203 | 0.588 |
| H3 Government policy on contact tracing after a positive diagnosis | 0 | 2 | 0.982 | 0.580 |
| H6 Policies on the use of facial coverings outside the home | 0 | 4 | 0.557 | 0.892 |
| H8 Policies for protecting elderly in Long Term Care Facilities and home setting | 0 | 3 | 2.069 | 1.024 |
| Stringency index | 12.04 | 100 | 73.824 | 15.765 |
| Government response index | 10.42 | 89.84 | 58.494 | 11.827 |
| Economic support index | 0 | 100 | 49.681 | 28.425 |
| New cases | 0 | 50740 | 1186.596 | 3753.010 |
| New deaths | 0 | 2587 | 121.666 | 312.357 |
| Stressors and sources of distress | 24 | 144 | 80.464 | 20.555 |

The histograms of all continuous variables of stress are collected in Figure 1. The target variable – Distress illustrates a normal distribution with a mean at 80.464. The distribution of the numerical data is summarized in Figure 2.

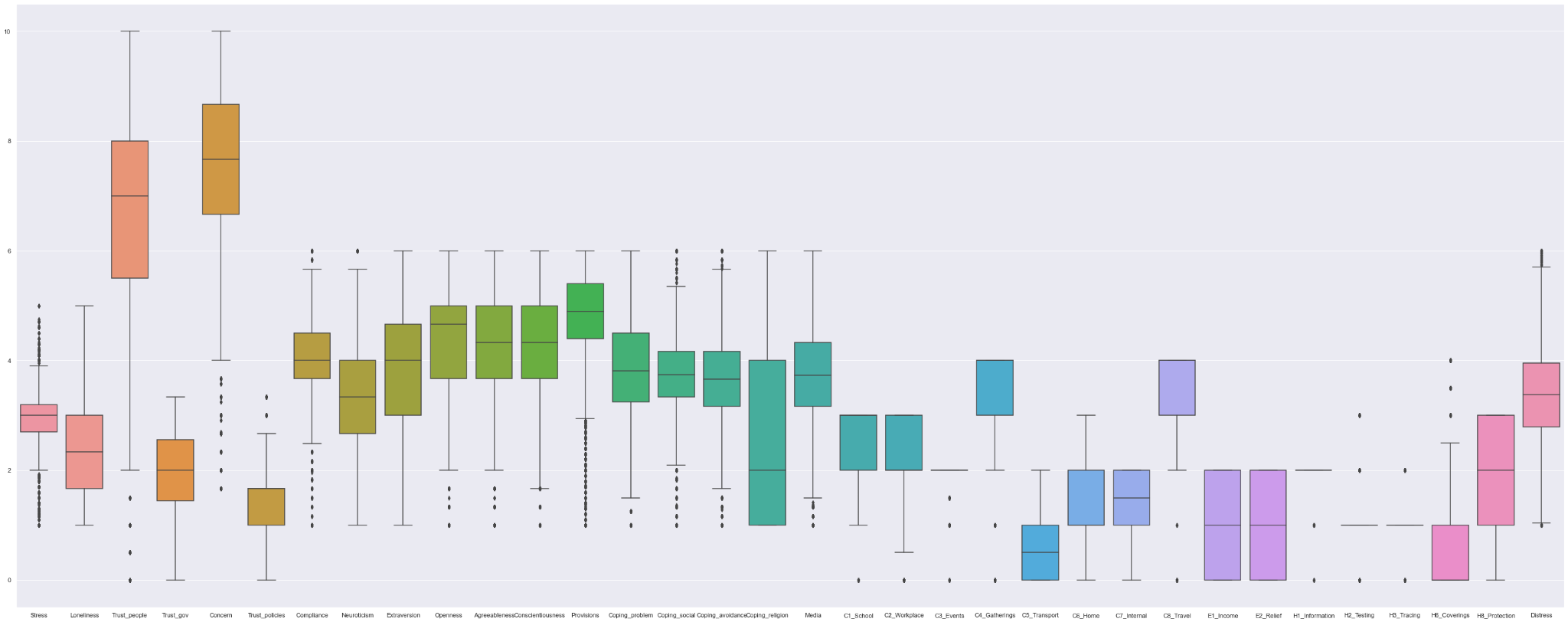
**Figure 1**

*Histograms of all Numerical Variables of Stress*

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**Figure 2**

*Boxplot of all Numerical Variables of Policy and Stress except New Cases & New Deaths*



## Outcome from the Modeling Procedure

Table 3 displays the accuracy generated based on the selected statistical techniques. Predicted distress is plotted against the actual distress for each model shown in Figures 2 to 6 respectively. The importance of features is generated from the XGBoost model in Figure 7.

**Table 3**

*Models metrics (Training MSE, Test MSE, RMSE & R2)*

|  | Linear Regression | CART | Random Forest | SVM | XGBoost |
| --- | --- | --- | --- | --- | --- |
| training MSE | 223.736 | 0 | 37.135 | 433.077 | 197.486 |
| test MSE | 223.202 | 470.897 | 230.390 | 403.822 | 211.032 |
| RMSE | 14.940 | 21.700 | 15.179 | 20.095 | 14.527 |
| R2 | 0.467 | -0.125 | 0.449 | -0.007 | 0.496 |

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| **Figure 2**  *Predicted vs Actual of Linear Regression* | **Figure 3**  *Predicted vs Actual of CART* |
| --- | --- |
| **Figure 4**  *Predicted vs Actual in Random Forest* | **Figure 5**  *Predicted vs Actual in SVM* |
| **Figure 6**  *Predicted vs Actual of XGBoost* | **Figure 7**  *Importance of Features (XGBoost)* |

# Discussion

Among five predictive models, the XGBoost model outperformed other models with higher accuracy, therefore, the results of XGBoost will be adopted for interpretations. Based on our results, neuroticism personality trait is the strongest predictor, followed by media exposure, and concern over COVID-19. Meanwhile, social coping, compliance to restrictions, loneliness, stress, females, transport closure, and number of dependents, are also strong positive predictors of psychological distress. On the other hand, perceived social support, income support policies, and trust in government are strong negative predictors of psychological distress. Interestingly, new cases and number of deaths are not strong predictors of distress, which may indicate that objective threat is not a major predictor of psychological distress, while subjective appraisal and people’s own behaviors contribute to their adverse emotional experiences.

## COVID-19-related Health Anxiety

The strongest predictors, neuroticism personality trait, media exposure, and concern over COVID-19, may suggest the maladaptive cognitive state and behavioral pattern of people with COVID-19-related health anxiety. Under the outbreak of COVID-19, a relatively new mental disturbance namely corona phobia emerged, it is characterized by individuals who are fearful and anxious about COVID-19, accompany with coherent set of unpleasant, physiological symptoms that are triggered by thoughts or information associated with COVID-19 (Asmundson & Taylor, 2020). Lee et al. (2020) pointed out neurotic people are highly prone to corona phobia because of their strong tendency towards death anxiety. Since neurotic people has strong tendency of selectively attend (attentional bias) to threat and stressful stimuli (Mogg & Bradley, 2016; Osorio et al., 2003), their heightened fear toward death then increased their concern over COVID-19 situation, and it can be reflected by their elevated media exposures. Given that phobic disorders are related to attentional avoidance (Armstrong et al., 2013), while health anxiety is related to attentional bias towards illness threat (Owens et al., 2004), the observed results may suggest the COVID-related health anxiety cognitive states and behavioral pattern. As aforementioned in our theoretical framework, since neurotic people have lower perceptual threshold (Passamonti et al., 2019) and lower stress tolerance (Balling et al., 2021), their media exposures created more than average amounts of psychological distress, possibly because of the rumors and ambiguous messages.

## Negative Impacts of Movement Restrictions

Since compliance to COVID-related guidelines and restrictions, and transport closures are strong predictors of psychological distress, this may suggest the strong negative impacts of movement restrictions. As Anand et al. (2021) mentioned, movement restrictions may induce boredom, existence crisis, and need fulfilment frustration which significantly predict psychological distress. Furthermore, under movement restrictions, people may have limited exposure to natural environments, where nature exposure is confirmed as an effective coping strategy that helps relieve people stress, distress and other negative emotions (Jimenez et al., 2021). Another possible explanation is as Kalok et al. (2020) suggested, containment and closure policies will restrict people to seek external support, while the inability to seek emotional support from others, or simply absence of interpersonal connection will induce perceived loneliness (Cacoppo et al., 2013), thereby predicting psychological distress (Beutel et al., 2017). Taken together, under movement restrictions and people really comply with the guidelines and restrictions, it predicts psychological distress through many possible pathways.

## Help Seeking Pattern Under COVID-19 Pandemic

It is surprising that social coping is a strong positive predictor of psychological distress, as it contradicts the long-standing findings that social coping is an adaptive coping strategy that negatively predicts psychological distress (Hobfoll et al., 2007). Meanwhile, our results also indicated perceived social support is a strong negative predictor of psychological distress. These results may suggest the people’s general tendency of adopting social coping only when they are highly distressed and at the edge of mental burnout, while the help seeking behaviors turn out well that help relieve people’s psychological distress. Another possible reason is that people tend to help seeking indirectly (Bornstein, 1998), and it is more difficult to detect indirect help seeking signals under the pandemic when face-to-face interactions are not available (Lai et al., 2020). In this case, people perceived they seeked help, but failed to receive actual support which predicted helplessness and psychological distress (Naidoo & Mwaba, 2010). Regardless of the forms of help seeking, perceived social support, in either emotionally or materially, negatively predicts psychological distress that is helpful for people to get through the challenges posed by the COVID-19 pandemic.

## Financial Uncertainties Posed by COVID-19 Pandemic

The strong negative predictor of income support policies has reflected the intense financial stress among people all over the world, which confirmed our theoretical framework that measures that relieve this COVID-related secondary stressor will negatively predict psychological distress under the pandemic. Under the COVID-19 pandmeic when containment and closing policies are in force, economic recession along with unemployment crisis appeared (Petrosky-Nadeau & Valletta, 2020). With more dependents, it further increases the financial stress and the perceived responsibilities to maintain stable support to the family which predict greater psychological distress (Kowa et al., 2020; McCarthy, 2011). Furthermore, Lee and Schachter (2018) found that trust in government is positively correlated to household income, which may reflect that people who distrust the government tend to have tighter financial strain, and are prone to psychological distress under the pandemic. In this case, the income support policies can relieve these at-risk groups’ financial stress, at least partially and temporally, thereby negatively predicting psychological distress.

## Implications

### Research Implications

The present findings have important implications on community-based psychological interventions. Given that our findings stress the importance of subjective interpretations of the COVID-19 situation, society needs to break down the cognitive bias towards COVID-19, in order to reduce people’s excessive vigilance on COVID-19 related information, and avoid compulsive news checking behaviors. Although such vigilance might be helpful to control the pandemic as it can increase people’s compliance on restrictions, a balance between alertness and calmness is needed to prevent further labor loss and burdening the healthcare units because of deteriorating mental healthiness. On the other hand, mental health stakeholders and the general public need to be aware of the counterproductive help seeking behavioral pattern. Accordingly, psychoeducational interventions are needed to educate people when, where, and how to seek help from others, and encourage the public not to hide their difficulties and emotions. One role model program is the “Shall we talk” initiative by the Hong Kong Advisory Committee on Mental Health (2021), and more similar campaigns are needed to transform the widespread maladaptive help seeking behavioral patterns.

The present findings also have implications on COVID-19 related policies. To prevent psychological distress induced by excessive media exposure, there is a need to break down the negative loop of news checking behaviors. One way is to control rumors or inaccurate information on the internet, and to ensure the media’s information is clear. Therefore, no matter how many information sources people reach, they receive accurate and consistent messages. Although this measure may threaten freedom of speech, it is necessary to avoid a global mental health crisis. Furthermore, the government may need to address financial difficulties faced by the citizens, thus, more income support policies are highly suggested to relieve the severe household financial stress.

### Model Implications

If one does not understand how a model works, the failure of the model cannot be noticed (Krishnan, 2020). Interpretability and transparency have become important factors when considering the application of machine learning techniques. This study proposed that XGBoost can be applied in real world challenges due to its prediction performance. Apart from the performance, XGBoost is relatively flexible as it consists of various parameters which can be tuned based on different situations. In addition, it has a built-in capability to handle missing values which is convenient to deal with real world data.

The model constructed in this study can estimate the level of distress by psychological and behavioural attributes and governmental policies in response to COVID-19. The general atmosphere under COVID-19 can be studied in this model.

## Strengths and Limitations

There are several strengths in the present study. The volume of data used to train the model is essential in order to obtain adequate performance, which means using a large dataset, the opportunity of overfitting is reduced drastically. The final dataset in this study is composed of 31,307 participants over 128 countries, which is large enough to train a machine learning model. In addition, in the COVIDiSTRESS Global Survey dataset, not all variables associated with distress are studied. Integrating multiple datasets is believed to increase the statistical predictive performance in general (Goel, A. 2018). The combination of the COVIDiSTRESS Global Survey dataset and the OxCGRT dataset can provide an integrative view on features correlated with distress. Besides, with the aim of finding the most suitable prediction model, optimal hyperparameters were tuned by grid search cross validation techniques. The optimization of hyperparameters in this study can minimize the loss function on independent data (Yang & Shami, 2020).

Despite the strengths and implications of our study, there are some limitations that may undermine the accuracy of the findings. For the COVIDiSTRESS dataset, the data are obtained through voluntary self-administered online questionnaires, where self-selection bias is likely to arise. In this case, the volunteers may process certain characteristics that are different from non-volunteers, which may hinder the generalizability of our findings. Furthermore, the purposes of the online questionnaire might be too explicit for the participants, which runs the risk of demand characteristics response bias where the participants altered their responses to fit the research purposes and hypotheses, resulting in threatening our study’s internal and external validity. Additionally, some important variables of the COVID-STRESS dataset are not measured by validated measurement tools, especially distress, which is measured by an original scale that tries to fit in the COVID-19 context. In this case, our predictive models may not accurately predict distress, and it posed a threat towards the study’s content validity. Although the COVIDiDISTRESS dataset possesses some shortcomings, it captured many important variables from a huge sample size that contained valuable information and ease the later research data collection process.

Although our models are developed based on multinational data, our research only captured the general trend across countries and cultures, in which our findings may not be applicable to certain countries. Meanwhile, both COVIDiSTRESS and OxCGRT did not collect data at a subnational level, which posed a difficulty in applying our findings into specific regions. Furthermore, OxCGRT adopted the data provided by the countries, and this runs the risk that certain countries may provide self-serving data, which undermines the validity and reliability of the conclusions drawn from the dataset. Regardless of the potential data quality issue, the datasets adopted in current study are highly valuable that allow us to picture the general patterns of how COVID-19 pandemic influences the public mental healthiness.

# Conclusion and Future Directions

The potential influence between COVID-19, governmental policies and distress among the public has been studied in this research. The research revealed that neuroticism personality trait, media exposure and concerns over COVID-19 are major distress in individuals within this research scope. We also believe that XGBoost is the best prediction model amongst all five models (i.e. linear regression, CART, Random Forest, SVM, XGBoost) in this research and might be in other similar analyses. This model can also be contributed to the public health system and the policymaking of the government.

As to future directions, we hope to enlighten the development of analytical methods on affection caused by the pandemic, governmental disease control policies and distress and arouse the research on developing large-scale methods for public mental health tracking systems. We are interested in a more flexible model to predict distress by the reason of the imperfect linear model between variables analysed by us. In addition, more relevant variables regarding family relationships, such as family support and cohesion are needed to be taken into account in future models (Fritz et al., 2020). Meanwhile, future studies may consider adopting more objective measures, or different types of data in the predictive model to avoid response biases. Lastly, We also hope to call attention to the mediators on the causal path between predictors and distress and create a predictive causal pathway in future research.

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