Project Proposal: The COVID-19 Epidemic, Public Health Restrictions, and Mental Health

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Load Packages

```
library(tidyverse)
library(readxl)
```

Load Data

```
setwd('../')
restrictions_worldwide <- readr::read_csv("data/phsm-severity-data-short.csv")
search_canada <- read_excel("data/search_term_canada.xlsx")
search_iran <- read_excel("data/search_term_iran.xlsx")
search_italy <- read_excel("data/search_term_italy.xlsx")
search_japan <- read_excel("data/search_term_japan.xlsx")
search_sk <- read_excel("data/search_term_sk.xlsx")
search_uk <- read_excel("data/search_term_uk.xlsx")
search_us <- read_excel("data/search_term_us.xlsx")
search_worldwide <- read_excel("data/search_term_worldwide.xlsx")
```

Introduction and Data, including Research Questions

From the beginning of the COVID-19 pandemic until now, the global community has suffered social, economic, and medical burdens in unprecedented levels. Though the physical health of individuals has been of paramount concern due to the high infectivity of COVID-19, with 237.88 million cases and 4.85 million deaths in as of October 2021, another burden on individuals, governments, and health systems has manifested itself in the form of rapidly deteriorating mental health (Our World in Data, 2021). It has been widely accepted that as the COVID-19 pandemic has progressed, mental health has decreased (Centers for Disease Control and Prevention, 2021). However, there is a much less comprehensive body of data surrounding how certain mitigation efforts specifically have impacted mental health, and which mental health conditions each restriction affects the most. For example, the Centers for Disease Control and Prevention (2021) acknowledge that social distancing may increase loneliness, stress, and anxiety, but it is less understood if masking is more directly correlated to obsessive compulsive disorder than it is to depression. Therefore, there is a need to fully understand these intricate relationships in order to drive efforts towards creating more individualized mental health treatments, as well as being able to predict what kind of mental health treatment will be needed in response to an increase in any given public health restriction.

Our data analysis will answer the following research question: how do different COVID-19 mitigation efforts correlate to different types of mental illnesses? In doing so, our project will begin to uncover how certain restrictions may impact different mental illness depending on both the type of restriction and the type of mental illness. Our project will make use of two datasets and merge the datasets based on country in order to ensure there are sufficient relationships to explore in the data. The first dataset is of the frequency of different search terms related to mental health from June of 2019 through June of 2020 for a variety of countries. The data was collected from Google Trends and records the popularity of that search term for any given week in a given country. This dataset will be used to gauge how concern with certain mental health topics, including anxiety, depression, panic attacks, obsessive compulsive disorder, and insomnia, has changed over the course of the pandemic. The second dataset tracks implementation of various mitigation efforts in different countries. This dataset was derived from the World Health Organization's tracking of public health and social measures, and indices were calculated on the raw data in order to quantify the intensity of the restriction, whether the restriction is on masks, gatherings, businesses, schools, or travel.

Glimpse

```
## This is the PHSM severity index dataset.

glimpse(restrictions_worldwide)
```

```
## Rows: 142,506
## Columns: 11
## $ DATE_START   <chr> "8/20/2020", "9/4/2020", "3/13/2021", "10/18/2020", "4/18~
## $ COUNTRY      <chr> "Yemen", "Belarus", "Egypt", "Uzbekistan", "Finland", "Is~
## $ ISO3         <chr> "YEM", "BLR", "EGY", "UZB", "FIN", "IMN", "MLI", "MYS", "~
## $ WHO_REGION   <chr> "EMRO", "EURO", "EMRO", "EURO", "EURO", "EURO", "AFRO", "~
## $ MASKS        <dbl> 0, 67, 100, 100, 47, 0, 0, 67, 0, 0, 0, 67, 0, 100, 0, 10~
## $ TRAVEL       <dbl> 100, 0, 33, 100, 100, 0, 0, 67, 100, 100, 100, 33, 100, 1~
## $ GATHERINGS   <dbl> 30, 25, 50, 25, 5, 0, 0, 5, 0, 25, 0, 0, 0, 50, 0, 25, 25~
## $ SCHOOLS      <dbl> 25, 25, 25, 75, 25, 0, 50, 80, 25, 0, 25, 0, 25, 30, 25, ~
## $ BUSINESSES   <dbl> 13, 13, 67, 67, 67, 0, 0, 47, 0, 47, 33, 0, 0, 33, 0, 33,~
## $ MOVEMENTS    <dbl> 80, 40, 100, 40, 20, 0, 0, 20, 60, 60, 0, 0, 0, 40, 0, 80~
## $ GLOBAL_INDEX <dbl> 41, 28, 62, 68, 44, 0, 8, 48, 31, 39, 26, 17, 21, 59, 15,~
```

```
## This is an example of one of the Google Search trend data sets.
## This one is Canada, although ones exist for Canada, Iran, Italy, Japan,
## South Korea, the United Kingdom, the United States, and for worldwide results.
## All have been appropriately loaded and read into R.

glimpse(search_canada)
```

```
## Rows: 51
## Columns: 10
## $ Week                            <dttm> 2019-06-16, 2019-06-23, 2019-06-30, 2~
## $ depression                      <dbl> 81, 70, 67, 70, 76, 69, 67, 68, 70, 67~
## $ anxiety                         <dbl> 77, 73, 75, 73, 76, 88, 81, 76, 84, 78~
## $ `obsessive compulsive disorder` <dbl> 37, 96, 32, 57, 51, 60, 60, 30, 57, 57~
## $ ocd                             <dbl> 71, 61, 72, 71, 68, 66, 76, 66, 72, 75~
## $ insomnia                        <dbl> 77, 73, 66, 63, 71, 69, 82, 66, 73, 99~
## $ `panic attack`                  <dbl> 79, 76, 55, 80, 80, 94, 86, 75, 72, 66~
```

```
## $ ‘mental health‘                 <dbl> 56, 50, 44, 53, 49, 48, 44, 43, 48, 48~
## $ counseling                      <dbl> 62, 76, 62, 69, 69, 65, 70, 52, 67, 56~
## $ psychiatrist                    <dbl> 75, 61, 69, 75, 86, 69, 73, 48, 83, 68~
```

Data Analysis Plan

In order to conduct our analysis, we will examine various combinations of mental health search term popularity as explained by the index of public health measure severity. Mental health search term popularity will be used as an indicator for what mental illness is most prevalent during a given time frame, and will be analyzed alongside what restriction was most intense for the same time frame. This relationship will be explored across various countries in order to account for the differences in public health measures that each government enacted throughout the course of the pandemic, as well as determine global averages for mental health search term popularity for each public health measure.

In order to examine if there are some mental health issues that are impacted more strongly by certain public health measures, an analysis of variance (ANOVA) will be conducted on the data. This test will allow for the comparison across multiple means, where each mean is the global averages of mental health search term popularity for each public health measure. We hypothesize that there will be a statistically significant difference among mental illness prevalence as a result of certain public health measures. In order to reject the null hypothesis that there is no difference among certain public health measures disproportionately affecting certain mental illnesses, our p-value for this ANOVA would need to be less that 0.05 for a confidence level of 95%.

References

Centers for Disease Control and Prevention. (2021). Coping with stress. Centers for Disease Control and Prevention. Retrieved October 11, 2021, from (https://www.cdc.gov/mentalhealth/stress-coping/cope-with-stress/index.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fdaily-life-coping%2Fmanaging-stress-anxiety.html).

Our World in Data. Cumulative confirmed covid-19 cases and deaths. Our World in Data. (n.d.). Retrieved October 11, 2021, from (https://ourworldindata.org/grapher/cumulative-deaths-and-cases-covid-19).