Analysis of Seven-Day Anxiety and Depression Symptoms Frequency

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Abstract- The Study utilizes the Household Pulse Survey data from the U.S. Census Bureau to explore the prevalence and patterns of anxiety and depression symptoms reported by American adults during the COVID-19 crisis. Developed through a collaboration among five federal agencies, the study aims to assess the pandemic's effects quickly and accurately across various sectors such as economic conditions, food security, and mental health. This study specifically examines the mental health data, analyzing the changes in reported anxiety and depression symptoms across a week. The results reveal significant trends and differences among demographics, enhancing our understanding of the psychological impact of the pandemic on the American population.

Keywords — Data Cleaning, Data Transformation, Statistics, Visualisation, Household Pulse Survey, Pandemic Mental Health,

I.INTRODUCTION

The COVID-19 pandemic has significantly disrupted global social and economic structures, triggering widespread mental health challenges. To understand these effects, the U.S. Census Bureau, together with five federal agencies, launched the Household Pulse Survey, which swiftly collects data on the pandemic's impacts, including mental health issues like anxiety and depression. The study focuses on analyzing self-reported mental health data, specifically tracking the frequency of anxiety and depression symptoms over a week. The study utilizes a multi-step methodological approach, employing tools such as Python, R, SQL, and Excel to analyze the data thoroughly. The study progresses to data transformation to facilitate comprehensive statistical analysis, starting with dataset loading and data cleaning to remove null values and inconsistencies. Through univariate, bivariate, and multivariate analysis, the study identifies patterns and correlations better to understand the pandemic's impact on mental health across Demographics. This structured approach helps provide critical insights for policymaking to mitigate the pandemic's mental health fallout.

II RELATED WORK

Extensive research has revealed the significant immediate and long-term mental health effects of pandemics on global populations. Researchers have identified numerous mental health challenges, which have informed the development of psychological support strategies and improved data collection methods. This knowledge is crucial for enhancing future pandemic preparedness and response efforts to reduce psychological impacts.

Smith et al. (2018), in their research published in the Journal of Public Health Policy, explores the effects of major public health emergencies, such as pandemics and natural disasters, on worldwide health systems. The study scrutinizes the difficulties these emergencies create for health infrastructures, focusing on areas like emergency preparedness, the allocation of resources, and healthcare delivery. The authors underline the essential need for strong health systems capable of adapting to the heightened demands of such crises, highlighting the significance of resilience and swift response mechanisms in health policy planning [2].

Johnson et al. (2020) explores the sustained impacts of pandemics on critical societal health metrics, including mortality rates, mental well-being, and chronic disease rates. Published in the International Journal of Health Sciences, their research comprehensively examines the effects of pandemics on public health, economic stability, and social structures. The researchers call for unified health and social policies to address these persistent impacts. They highlight the crucial connection between public health efforts and overall societal health, suggesting holistic approaches to enhance societal resilience [3].

Zhao and colleagues (2021) explore methods for quickly gathering data during pandemics using digital platforms and internet questionnaires. Their research, published in the Health Informatics Journal, evaluates these digital tools' effectiveness, scalability, and reliability in capturing essential real-time data for public health responses. The study confirms the utility of digital methods in crises, emphasizing their importance in enabling prompt healthcare actions [4].

Doe and his team study different policy responses to health crises and their effects on society and the economy, as detailed in the Policy Studies Journal. Their research assesses how these policies handle public health emergencies and lessen their impact on economic, educational, and social areas. The study offers insights into crafting policies that tackle immediate health issues and support long-term socio-economic recovery. This helps in designing strategies that effectively balance health priorities witheconomic sustainability [5].

III DATA SET

I Have used “Analysis of Seven-Day Anxiety and Depression Symptoms Frequency Dataset” which includes Indicator, Group, State, Subgroup, Phase, Time Period Start Date, Time Period End Date, Time Period, Time Period label, Low Ci, High Ci, Confidence Interval, Quartile Range. The above variables can be categorized to following ‘NOIR’ characteristics [1].

Nominal: Indicator, Group, Subgroup, State, Time Period label

Ordinal: Phase, Quartile Range

Ratio: Value, Low Ci, High Ci, Confidence Interval

Interval: Time Period Start Date, Time Period End Date

Figure 1

Indicator	Group	State	Subgroup	Phase	Time Period	Time Period Label	Time Period Start Date	Time Period End Date	Value	Low CI	High CI	Confidence Interval	Quartile Range
Symptoms of D	National Estimate	United States	United States	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	23.5	22.7	24.3	22.7 - 24.3	
Symptoms of D	By Age	United States	18 - 29 years	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	32.7	30.2	35.2	30.2 - 35.2	
Symptoms of D	By Age	United States	30 - 39 years	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	25.7	24.1	27.3	24.1 - 27.3	
Symptoms of D	By Age	United States	40 - 49 years	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	24.8	23.3	26.2	23.3 - 26.2	
Symptoms of D	By Age	United States	50 - 59 years	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	23.2	21.5	25	21.5 - 25.0	
Symptoms of D	By Age	United States	60 - 69 years	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	18.4	17	19.7	17.0 - 19.7	
Symptoms of D	By Age	United States	70 - 79 years	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	13.6	11.8	15.5	11.8 - 15.5	
Symptoms of D	By Age	United States	80 years and at	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	14.4	9	21.4	9.0 - 21.4	
Symptoms of D	By Sex	United States	Male	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	20.8	19.6	22	19.6 - 22.0	
Symptoms of D	By Sex	United States	Female	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	26.1	25.2	27.1	25.2 - 27.1	
Symptoms of D	By Race/Hispanic ethr	United States	Hispanic or Lat	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	29.4	26.8	32.1	26.8 - 32.1	
Symptoms of D	By Race/Hispanic ethr	United States	Non-Hispanic	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	21.4	20.6	22.1	20.6 - 22.1	
Symptoms of D	By Race/Hispanic ethr	United States	Non-Hispanic	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	23.6	23.7	27.5	23.7 - 27.5	
Symptoms of D	By Race/Hispanic ethr	United States	Non-Hispanic	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	23.6	20.3	27.1	20.3 - 27.1	
Symptoms of D	By Race/Hispanic ethr	United States	Non-Hispanic,	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	26.3	24.8	32	24.8 - 32.0	
Symptoms of D	By Education	United States	Less than a hig	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	32.7	27.8	38	27.8 - 38.0	
Symptoms of D	By Education	United States	High school dig	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	25.4	23.9	26.9	23.9 - 26.9	
Symptoms of D	By Education	United States	Some college/a	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	25.6	24.4	26.9	24.4 - 26.9	
Symptoms of D	By Education	United States	Bachelor's deg	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	17.6	16.8	18.4	16.8 - 18.4	
Symptoms of D	By State	Alabama	Alabama	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	18.6	14.6	23.1	14.6 - 23.1	16.5 - 20.7
Symptoms of D	By State	Alaska	Alaska	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	19.2	16.8	21.8	16.8 - 21.8	16.5 - 20.7
Symptoms of D	By State	Arizona	Arizona	1	1	1 Apr 23 - May 5, 2020	04/23/2020	05-05-2020	22.4	19.4	25.5	19.4 - 25.5	22.2 - 24.0

Utilizing this dataset enables us to perform an analysis that will answer the following research questions.

1. How has the detailed frequency of uneasiness and misery side effects changed over time amid the Covid-19 widespread among American families, and are there any recognizable patterns or patterns?

2. What static variables (such as age, sex, race/ethnicity, and instructive achievement) are related with a better predominance of anxiety and misery indications detailed within the final seven days?

3. Are there any critical territorial varieties within the detailed recurrence of uneasiness and discouragement indications among American family units, and on the off chance that so, what components might contribute to these contrasts?

IV. ANALYSIS AND INTERPRETATION

The initial phase of the analysis involves importing the pandas library, which is crucial for data handling and analysis. Next, load the data from a CSV file into a Data Frame named df. This file provides data on indicators of anxiety or depression, detailing the frequency of symptoms reported over the past week.

Figure 2

```
# Data exploration and ingest
import pandas as pd
df = pd.read_csv("C:/Users/mkatika/Downloads/Indicators_of_Anxiety_or_Depression_Based_on_Reported_Frequency_of_Symptoms_Duri
```

After importing the dataset and libraries our study included the following steps:

Step 1: Printing the basic information about the Data Frame using df.info() to understand the Data Frame structure such as number of entries, columns, non-null counts, and data types.

Figure 3

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15156 entries, 0 to 15155
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Indicator              15156 non-null  object
 1   Group                  15156 non-null  object
 2   State                  15156 non-null  object
 3   Subgroup               15156 non-null  object
 4   Phase                  15156 non-null  object
 5   Time Period            15156 non-null  int64
 6   Time Period Label      15156 non-null  object
 7   Time Period Start Date 15156 non-null  object
 8   Time Period End Date   15156 non-null  object
 9   Value                  14453 non-null  float64
 10  Low CI                 14453 non-null  float64
 11  High CI                14453 non-null  float64
 12  Confidence Interval    14453 non-null  object
 13  Quartile Range         9946 non-null   object
dtypes: float64(3), int64(1), object(10)
memory usage: 1.6+ MB
None
```

Step 2: Printing statistical summaries of numerical columns using df.describe() which includes count, mean, standard deviation, min, max, and percentile values. **Figure 4**

```
print(df.describe())
```

```
        Time Period         Value        Low CI       High CI
count  15156.000000  14453.000000  14453.000000  14453.000000
mean      32.347981     29.246025     25.669785     33.067834
std       19.549689      8.464886      8.193473      8.926661
min        1.000000      5.600000      4.400000      6.300000
25%       15.000000     23.600000     20.200000     27.200000
50%       33.000000     28.700000     25.100000     32.600000
75%       49.000000     34.000000     30.300000     38.000000
max       65.000000     85.200000     79.900000     89.500000
```

Step 3:

Removing the duplicate rows from the DataFrame to ensure data uniqueness.

Figure 5

```
#Removing Duplicate Rows
df.drop_duplicates()
```

	Indicator	Group	State	Subgroup	Phase	Time Period	Time Period Label	Time Period Start Date	Time Period End Date	Value	Low CI	High CI	Confidence Interval	Quartile Range
0	Symptoms of Depressive Disorder	National Estimate	United States	United States	1.0	1	Apr 23 - May 5, 2020	04/23/2020	05/05/2020	23.5	22.7	24.3	22.7 - 24.3	NaN
1	Symptoms of Depressive Disorder	By Age	United States	18 - 29 years	1.0	1	Apr 23 - May 5, 2020	04/23/2020	05/05/2020	32.7	30.2	35.2	30.2 - 35.2	NaN
2	Symptoms of Depressive Disorder	By Age	United States	30 - 39 years	1.0	1	Apr 23 - May 5, 2020	04/23/2020	05/05/2020	25.7	24.1	27.3	24.1 - 27.3	NaN
3	Symptoms of Depressive Disorder	By Age	United States	40 - 49 years	1.0	1	Apr 23 - May 5, 2020	04/23/2020	05/05/2020	24.8	23.3	26.2	23.3 - 26.2	NaN
4	Symptoms of Depressive Disorder	By Age	United States	50 - 59 years	1.0	1	Apr 23 - May 5, 2020	04/23/2020	05/05/2020	23.2	21.5	25.0	21.5 - 25.0	NaN

Step 4:

Handle missing values by dropping rows that contain any missing data.

Figure 6

```
original_count = len(df)  # Number of rows before removing rows with missing values

df = df.dropna()  # Remove rows with missing values

new_count = len(df)  # Number of rows after removal
deleted_rows = original_count - new_count  # Calculate the number of rows deleted

print(f"Number of rows deleted due to missing values: {deleted_rows}")
```

```
Number of rows deleted due to missing values: 5211
```

Step 5:

Converting date columns (Time Period Start Date and Time Period End Date) to datetime format, making it easier to perform Statistical analysis and Visualization.

Figure7

```

# Convert columns to datetime
df['Time Period Start Date'] = pd.to_datetime(df['Time Period Start Date'])
df['Time Period End Date'] = pd.to_datetime(df['Time Period End Date'])

# Print the head of the changed columns
print("First few entries of the date columns:")
print(df[['Time Period Start Date', 'Time Period End Date']].head())
```

```
First few entries of the date columns:
   Time Period Start Date Time Period End Date
19             2020-04-23           2020-05-05
20             2020-04-23           2020-05-05
21             2020-04-23           2020-05-05
22             2020-04-23           2020-05-05
23             2020-04-23           2020-05-05
```

Step 6:

Renaming the column names to make them more descriptive: the column 'Low CI' is renamed to 'Lower Confidence Interval', and 'High CI' is renamed to 'Upper Confidence Interval'.

Figure 8

```
df = df.rename(columns={'Low CI': 'Lower Confidence Interval', 'High CI': 'Upper Confidence Interval'})

# Print the head of the renamed columns
print("First few entries of the renamed columns:")
print(df[['Lower Confidence Interval', 'Upper Confidence Interval']].head())
```

```
First few entries of the renamed columns:
    Lower Confidence Interval  Upper Confidence Interval
19                       14.6                       23.1
20                       16.8                       21.8
21                       19.4                       25.5
22                       22.3                       31.3
23                       22.5                       28.6
```

Step 7:

Dropping the unnecessary columns that are not needed for further analysis. The columns dropped are 'Phase', 'Time Period', and 'Time Period Label'.

Figure 9

```
# Define columns to drop
columns_to_drop = ['Phase', 'Time Period', 'Time Period Label']

# Drop the columns
df = df.drop(columns=columns_to_drop)

# Print the names of the deleted columns
print("Deleted columns:")
print(columns_to_drop)
```

```
Deleted columns:
['Phase', 'Time Period', 'Time Period Label']
```

Step 8:

Dropping the 'Confidence Interval' column as it might be redundant after renaming and using individual confidence interval columns are lower and upper confidence intervals.

Figure 10

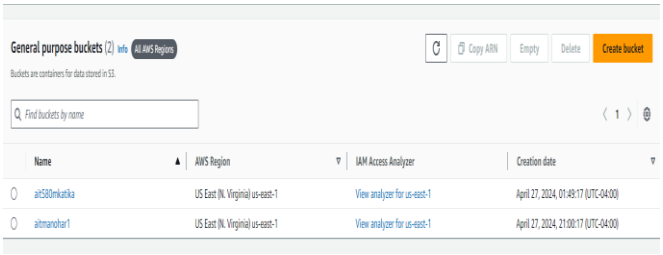
```
# Drop the 'Confidence Interval' column
df.drop(columns=['Confidence Interval'], inplace=True)
# Print the name of the dropped column
print("Dropped column: 'Confidence Interval'")
```

```
Dropped column: 'Confidence Interval'
```

The next stage involves preparing the dataset and creating S3 bucket and loading dataset into s3 bucket. Then setup AWS Gluedatabrew and explore data using the aws Gluedatabrew The subsequent stage involves access and analyze utilizing statistical methods like grouping and calculating minimum, maximum, and mode values using SQL language in the AWS SQL Query editor.

Figure 11

Creating the S3 bucket



An Amazon S3 bucket provides a robust platform for secure data storage, capable of accommodating various data types such as databases, website content, and backups. It offers scalable storage solutions, ensuring that data management and retrieval are easily manageable from any location.

Data analysis tool showing a sample dataset in grid format, focusing on 'Symptoms of Depressive Disorder' across various U.S. states. It features a summary section indicating counts of distinct, unique, and total entries in columns like 'Indicator', 'State', and 'Time_Period_Start_Date'. With 51 distinct states and 4 distinct start dates in April 2020.

Figure 11a

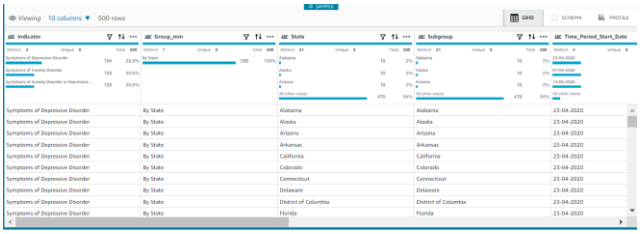
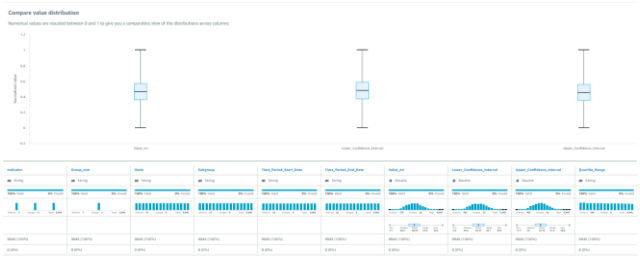


Figure 11b

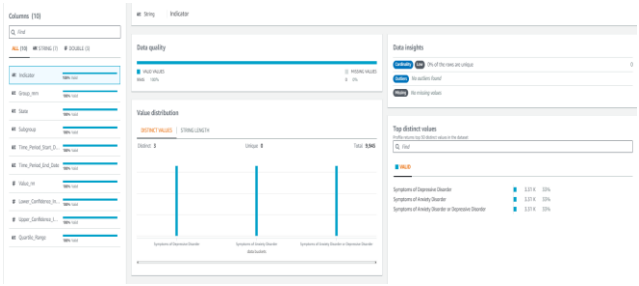
In the summary section on the left, the report provides a concise overview of the dataset's composition, indicating there are 9,945 total rows and 10 total columns. It classifies the data types present in the dataset, revealing that there are 3 double data type columns and 7 string data type columns. It's also showing the correlation matrix.

Figure 11c



comparative value distribution using box plots for three different numerical variables. These variables are displayed as 'Value_mm', 'Lower_Confidence_Interval', and 'Upper_Confidence_Interval'. The values are rescaled between 0 and 1 to allow for a comparative view of the distributions across the columns.

Figure 11d



Data analysis interface with a focus on data quality, value distribution, and insights for a dataset concerning health indicators. On the left side, there's a column summary indicating all fields are 100% valid across 10 columns, with data types listed as either strings or doubles.

Our study will proceed with the following steps:

Step 1:

Create a new table named Symptoms with various columns to store data about health indicators. These columns include textual descriptions, numerical values, and date ranges. Each column is tailored to specific data types, such as text for descriptions and real numbers for statistical values.

Figure 11e.

Query 1 | Query 2 | Query 3

```
CREATE EXTERNAL TABLE Symptoms (
    Indicator STRING,
    Group_mm STRING,
    State STRING,
    Subgroup STRING,
    Time_Period_Start_Date STRING,
    Time_Period_End_Date STRING,
    Value_nn DOUBLE,
    Lower_Confidence_Interval DOUBLE,
    Upper_Confidence_Interval DOUBLE,
    Quartile_Range STRING
)
ROW FORMAT DELIMITED
FIELDS TERMINATED BY ','
STORED AS TEXTFILE
```

Step 2:

Create the S3 bucket and load the CSV file into it. Using the data from the S3 bucket, perform SQL queries.

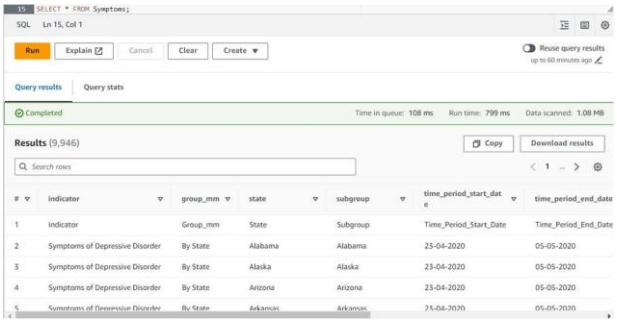
Figure 12

```
ROW FORMAT DELIMITED
FIELDS TERMINATED BY ','
STORED AS TEXTFILE
LOCATION 's3://aitmanohar1/data/';
```

Step 3:

Retrieve all records from the Symptoms table to view the entire dataset.

Figure 13



Step 3:

Calculate summary statistics for each state, calculating total entries, average, sum, minimum, and maximum of the Value_nn column, and similar statistics for the lower confidence interval and upper confidence interval Group these results by the State column to understand variations across different states.

Figure 14

```
SELECT
    "State",
    COUNT(*) AS "Total_Entries",
    AVG("Value_nn") AS "Average_Value",
    SUM("Value_nn") AS "Total_Value",
    MIN("Value_nn") AS "Minimum_Value",
    MAX("Value_nn") AS "Maximum_Value",
    AVG("Lower_Confidence_Interval") AS "Average_Lower_CI",
    MIN("Lower_Confidence_Interval") AS "Minimum_Lower_CI",
    MAX("Lower_Confidence_Interval") AS "Maximum_Lower_CI",
    AVG("Upper_Confidence_Interval") AS "Average_Upper_CI",
    MIN("Upper_Confidence_Interval") AS "Minimum_Upper_CI",
    MAX("Upper_Confidence_Interval") AS "Maximum_Upper_CI"
FROM "Symptoms"
GROUP BY "State";
```

#	State	Total_Entries	Average_Value	Total_Value	Minimum_Value	Maximum_Value	Average_Lo
1	Alaska	195	29.252820512820524	5704.300000000002	15.1	44.6	24.897948
2	Colorado	195	28.724615384615376	5601.299999999998	11.0	45.8	25.139487
3	Connecticut	195	27.249230769230756	5313.599999999998	12.7	41.8	23.281025
4	Indiana	195	29.050256410256388	5664.799999999996	14.9	43.7	25.230769
5	Michigan	195	27.92051282051282	5444.5	12.3	45.6	24.536410
6	Nevada	195	32.390256410256406	6316.099999999985	13.3	47.6	27.939999
7	New Hampshire	195	26.440512820512833	5155.900000000002	9.5	41.7	22.039487
8	Utah	195	29.138974358974334	5682.099999999997	17.5	44.3	25.655897
9	West Virginia	195	32.157948717948714	6270.799999999999	13.6	49.7	26.544615
10	Wyoming	195	27.296410256410254	5322.799999999999	14.4	44.8	22.045641

Step 4:

Display the first five rows of the Symptoms table to get a quick data view.

Figure 15

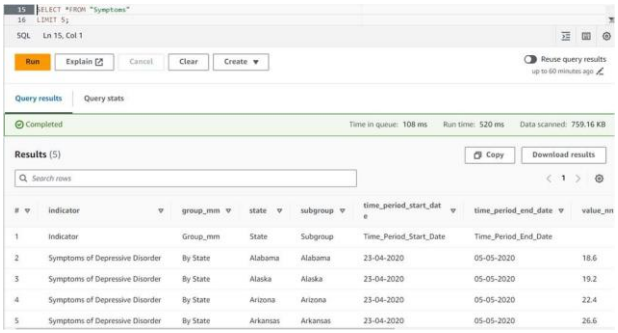


Figure 16

Count the total number of rows in the Symptoms table to understand the scale of the dataset.

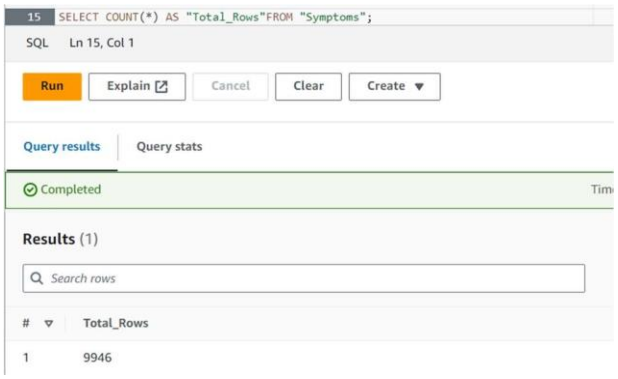
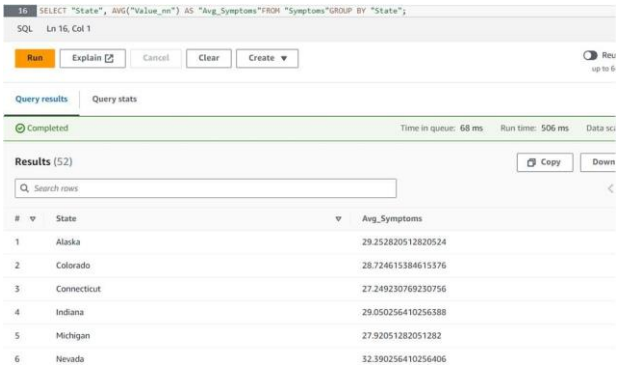


Figure 17

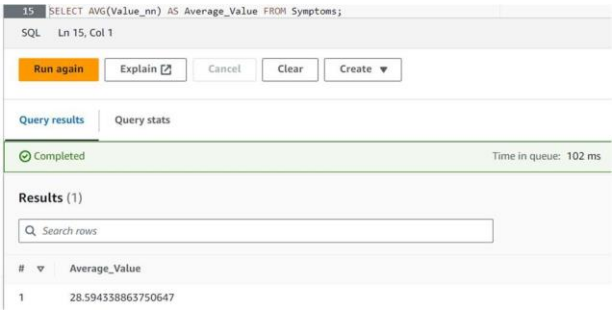
Calculate the average value of Value_nn grouped by State to see how symptoms vary by state.



Step 5:

Calculate Average Value Across All States

Figure 18

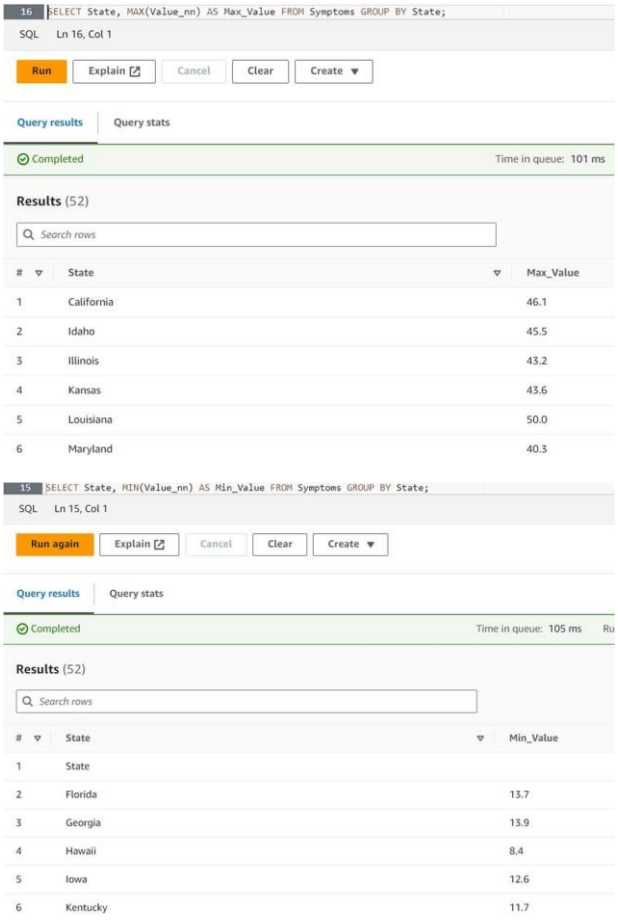


It calculates the average value of the Value_nn column for all entries in the Symptoms table. This provides a general sense of the average symptom severity across all states.

Step 6:

Calculate Maximum and Minimum Values by State

Figure 19

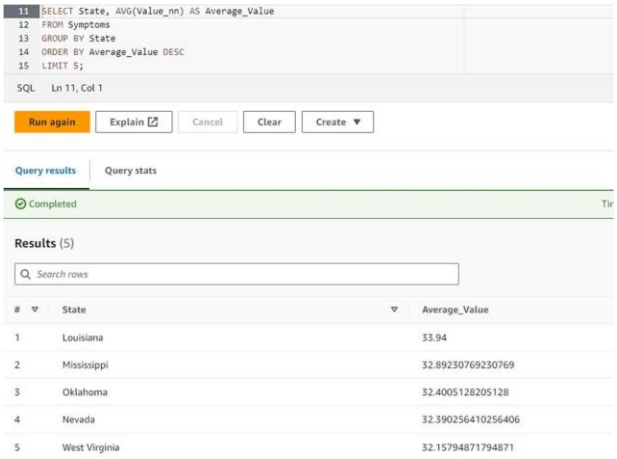


The first part finds the maximum value of Value_nn and the state it belongs to, grouped by each state. The second part finds the minimum value and its corresponding state. These queries help identify the states with the highest and lowest symptom severity values.

Step 7:

Top 5 States with the Highest Average Value

Figure 20



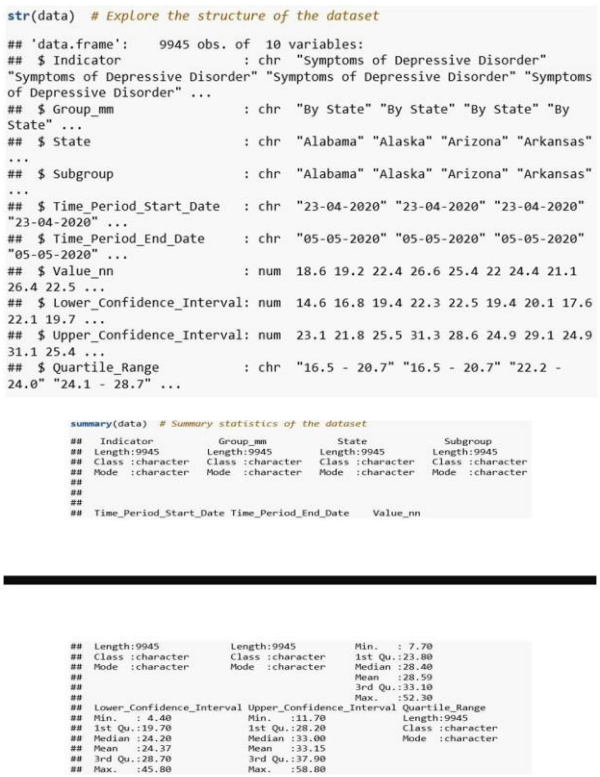
Which displays the Lists of top 5 states with the highest average Value_nn, limiting the result to the top five for focused analysis on the most impacted states.

The next step involves using visualization to analyze the data and interpret the findings, which aids in addressing the research questions.

The initial focus in visualization is on Univariate Analysis, which involves the following types of plots:

Step 1: First is to load the data and find the structure of the data then calculate the summary statistics of the cleaned data.

Figure 21



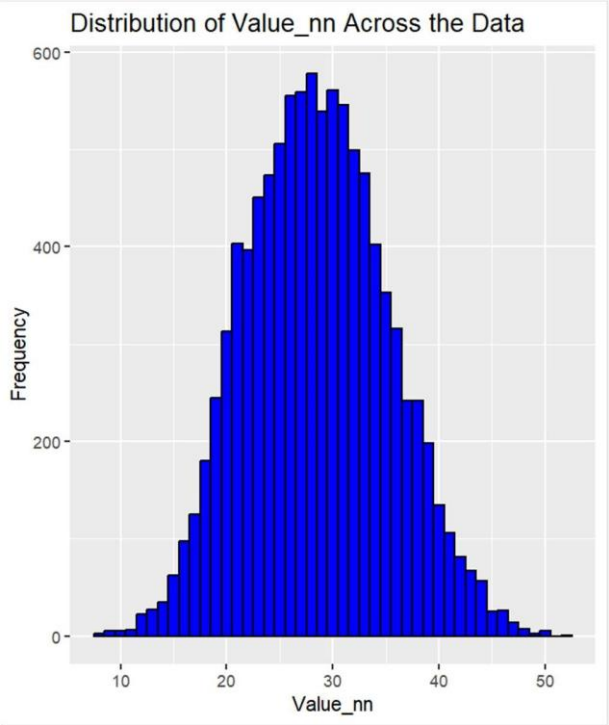
Plot 1:

Distribution of value across the data

Figure 22

```
ggplot(data, aes(x=Value_nn)) +
  geom_histogram(binwidth=1, fill="blue", color="black") +
  labs(title="Distribution of Value_nn Across the Data",
       x="Value_nn",  # Label for the x-axis
       y="Frequency")  # Label for the y-axis
```

Figure 23



The above script creates a histogram for the variable Value_nn from the data.

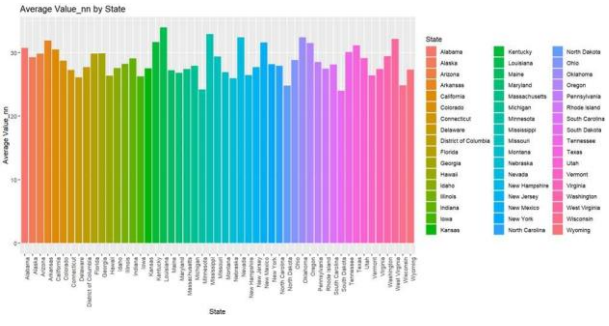
Plot 2:

This plot visualizes the average of Value_nn for each State in the data.

Figure 24

```
ggplot(data, aes(x=State, y=Value_nn, fill=State)) +
  geom_bar(stat="summary", fun="mean") +
  labs(title="Average Value_nn by State",
       x="State",  # Label for the x-axis
       y="Average Value_nn") + # Label for the y-axis
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```

Figure 25



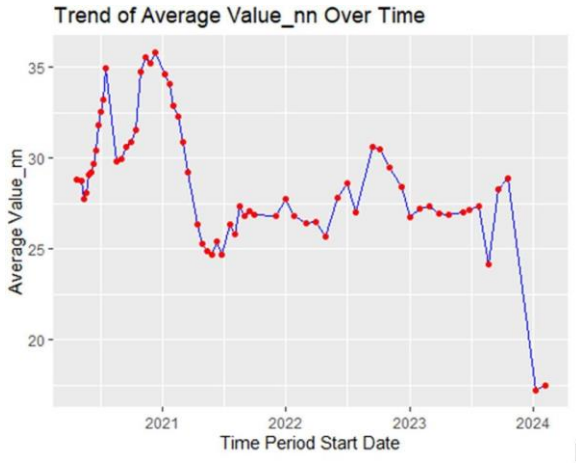
The above bar chart is particularly useful for comparing the average Value_nn across different states, identifying patterns.

Plot 3:

Figure 26

```
# Create a line plot to visualize the average Value_nn over Time
ggplot(avg_time_value, aes(x=Time_Period_Start_Date, y=Average_Value)) +
  geom_line(color="blue") +
  geom_point(color="red") +
  labs(title="Trend of Average Value_nn Over Time",
       x="Time Period Start Date",
       y="Average Value_nn")
```

Figure 27



The above plot focuses on analyzing the trend of the variable Value_nn over time through a line plot.

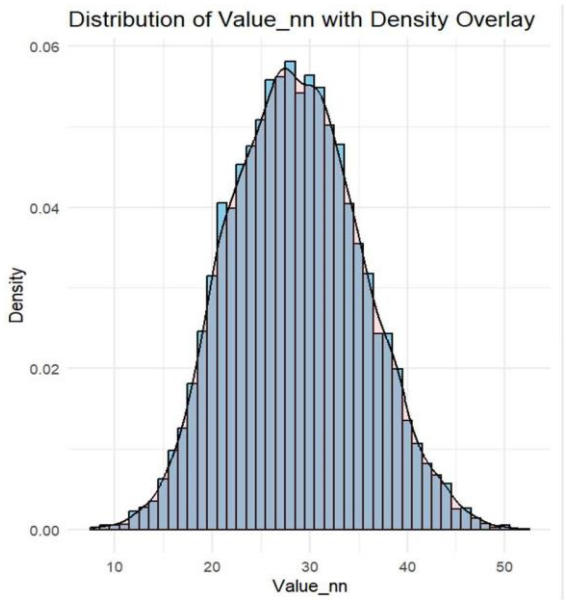
Plot 4:

Distribution of Value_nn with Density Overlay

Figure 28

```
ggplot(data, aes(x=Value_nn)) +
  geom_histogram(aes(y=..density..), binwidth=1, fill="skyblue", color="black") +
  geom_density(alpha=.2, fill="#FF6666") +
  labs(title="Distribution of Value_nn with Density Overlay",
       x="Value_nn",
       y="Density") +
  theme_minimal()
```

Figure 29



This above plot generates a histogram paired with a density plot for the variable Value_nn from the data.

The next phase is the bivariate analysis is used to find relationships between two variables

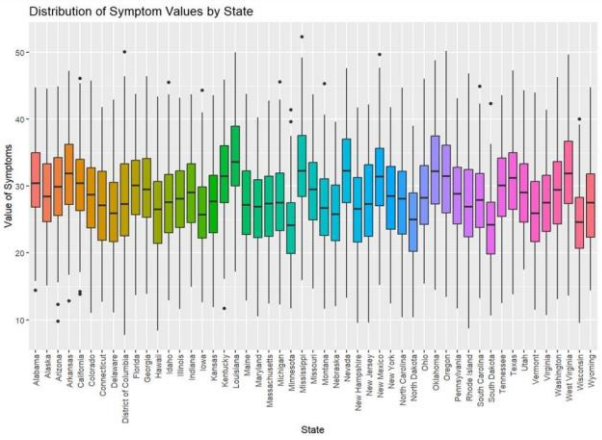
Plot 5:

The Relationship between Value_nn and the State

Figure 30

```
# Create a boxplot of Value_nn by State
ggplot(data, aes(x=State, y=Value_nn, fill=State)) +
  geom_boxplot() +  # Boxplot showing distribution of Value_nn by State
  theme(axis.text.x = element_text(angle=90, vjust=0.5, hjust=1)) +  #
  labs(x="State",  # Label for the x-axis
       y="Value of Symptoms",  # Label for the y-axis
       title="Distribution of Symptom Values by State")
```

Figure 31



The above boxplot displays the median, quartiles, within each state's data.

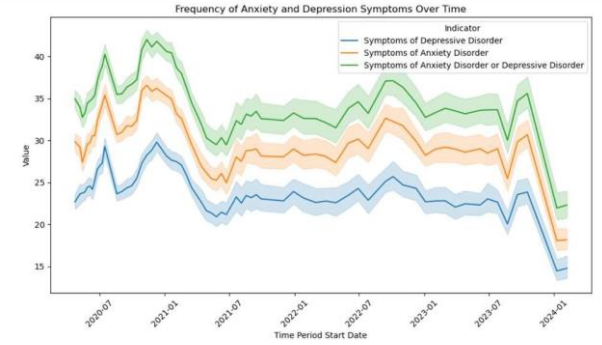
Plot 6:

Visualize frequency of anxiety and depression symptoms over time

Figure 32

```
#Trend Analysis Over Time
#Visualize frequency of anxiety and depression symptoms over time
import seaborn as sns
plt.figure(figsize=(10, 6))
sns.lineplot(data=df, x='Time_Period_Start_Date', y='Value_nn', hue='Indicator')
plt.title('Frequency of Anxiety and Depression Symptoms Over Time')
plt.xlabel('Time_Period_Start_Date')
plt.ylabel('Value_nn')
plt.xticks(rotation=45)
plt.show()
```

Figure 33



The last visualization stage involves conducting multivariate analysis to explore the relationships among three or more variables.

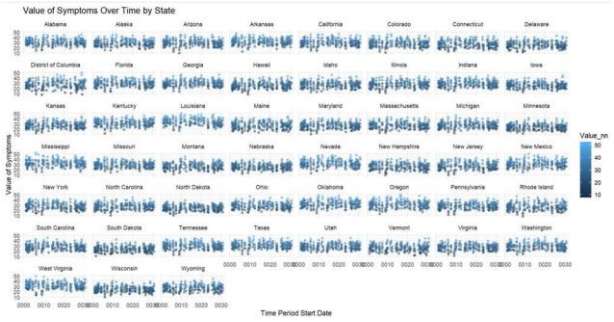
Plot 7:

Multivariate Analysis of Value of Symptoms Over Time by State

Figure 34

```
# Create a faceted scatter plot of Value_nn over Time_Period_Start_Date by State
ggplot(data, aes(x=Time_Period_Start_Date, y=Value_nn)) +
  geom_point(aes(color=Value_nn), alpha=0.5) +
  facet_wrap(~State) +
  labs(title="Value of Symptoms Over Time by State",
       x="Time Period Start Date",
       y="Value of Symptoms") +
  theme_minimal()
```

Figure 35



Plot 8:

Calculating the correlation matrix

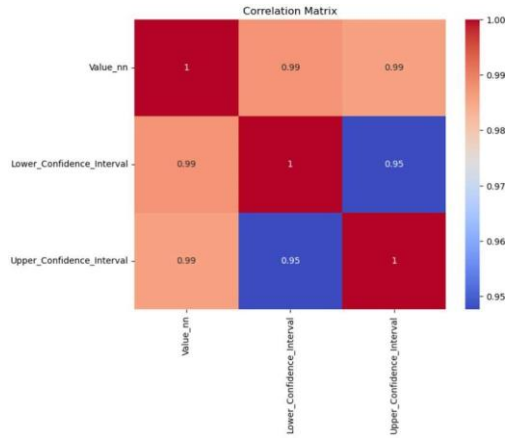
Figure 36

```
import seaborn as sns
import matplotlib.pyplot as plt

# Calculate the correlation matrix
correlation_matrix = df_subset.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')

# Create a heatmap to visualize the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

Figure 37



V. DISCUSSION

The Household Pulse Survey has been pivotal in tracking the effects of COVID-19 on mental health in the U.S., revealing trends aligned with pandemic events and policy changes. It shows significant mental health disparities across demographic lines, underscoring the need for targeted interventions. A comparison with pre-pandemic data highlights a worsening of mental health issues. Socioeconomic factors are also shown to significantly impact mental well-being, suggesting a need for comprehensive policy approaches. The survey's methodology, while extensive, has limitations due to its reliance on self-reporting, which could affect data interpretation.

VI. FUTURE WORK

Future research based on the Household Pulse Survey should include longitudinal studies to observe mental health changes over time and expand demographic coverage to include diverse populations. Evaluating the effectiveness of mental health interventions during the pandemic is also essential. Integrating AI and machine learning can enhance the precision of data analysis. Additionally, analyzing the effects of specific policy decisions on mental health can provide insights for effective policymaking. These strategies aim to understand better and address the mental health crisis exacerbated by the pandemic.

VII. SUMMARY

Below are the answers to the research questions:

1. How has the detailed frequency of uneasiness and misery side effects changed over time amid the Covid-19 widespread among American families, and are there any recognizable patterns or patterns?

The scatterplot has visualized the value_nn over time period start date grouped by State, is clearly answered view of how symptom frequency has evolved over the duration of the COVID-19 pandemic. Can identify patterns such as decreases in symptoms related to specific pandemic phases (e.g., initial outbreak, post-vaccination).

2. What statistic variables (such as age, sex, race/ethnicity, and instructive achievement) are related with a better predominance of anxiety and misery indications detailed within the final 7 days?

Upon examining the data, found certain factors that link closely with more reported anxiety and depression: gender differences in symptoms, the influence of one's race or ethnicity on their mental health, and a connection between education levels and the intensity of these feelings.

3. Are there any critical territorial varieties within the detailed recurrence of uneasiness and discouragement indications among American family units, and on the off chance that so, what components might contribute to these contrasts?

Yes, there are significant regional variations in the reported frequency of anxiety and depression symptoms among American households. Several factors contributed to regional variations in the reported frequency of anxiety and depression, such as pandemic impact, economic conditions, accessibility, and qualityof mental health services.

VIII. REFERENCES

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