Unemployment and Mental Health: A Data-Driven Exploration of Socioeconomic Vulnerability Across U.S. States (2018–2021)

Abstract

This study investigates the correlation between unemployment rates and mental health burdens across U.S. states from 2018 to 2021. Drawing on datasets from the U.S. Bureau of Labor Statistics and the CDC's Environmental Public Health Tracking Network, we analyze how economic distress—specifically unemployment—relates to population-level mental well-being. Through correlation analyses, lag models, and interactive visual dashboards, we uncover both national trends and regional disparities. Our work contributes a nuanced, visually rich understanding of how socioeconomic indicators intersect with public health—especially in times of crisis—and provides actionable insights for targeted interventions.

Contribution to SDGs

This project directly supports **SDG 3: Ensure healthy lives and promote well-being for all at all ages**, by analyzing and visualizing the impact of **unemployment** on **mental health** across U.S. states between 2018 and 2021.

- **Identifies Vulnerable Regions**
  By mapping mental health burdens across geographic and economic contexts, the project reveals regions most affected by unemployment-induced mental distress, supporting targeted mental health policies.

- **Supports Early Intervention**
  The analysis of **temporal lag effects** between unemployment and mental health outcomes enables stakeholders to anticipate future public health challenges and allocate resources proactively.

- **Informs Policy with Causal Insight**
  Using explanatory and predictive analytics, the project uncovers patterns that may inform causal relationships—empowering policymakers to design evidence-based strategies that break the cycle of economic hardship and psychological distress.

- **Promotes Data-Driven Health Equity**
  By spotlighting the uneven distribution of mental health burdens across socioeconomic

lines, the project advocates for a more equitable and sustainable approach to mental well-being.

This work demonstrates how data science and visualization can serve as powerful tools for promoting public health, reducing inequalities, and supporting the global pursuit of SDG 3.

Figure 1: *Logo of SDG 3*

Team Contribution Statement

- **Qirui Zhao**: Conducted correlation and lagged effect analysis, designing research questions, integrated and cleaned datasets, developed all data preprocessing scripts.

- **Zichu Zhou**: Designed and implemented the interactive dashboards using Plotly, co-authored the report and poster, and color accessibility testing.

1. Background and Motivation

Mental health has become a critical public health concern, particularly in the context of economic upheavals like the COVID-19 pandemic. As global economies have suffered from these shocks, the focus on mental well-being has grown, but often the relationship between macroeconomic factors such as unemployment and mental health is overlooked. This gap in understanding has led to a call for more integrated data analyses that reveal the complex interconnections between economic conditions and mental health outcomes.

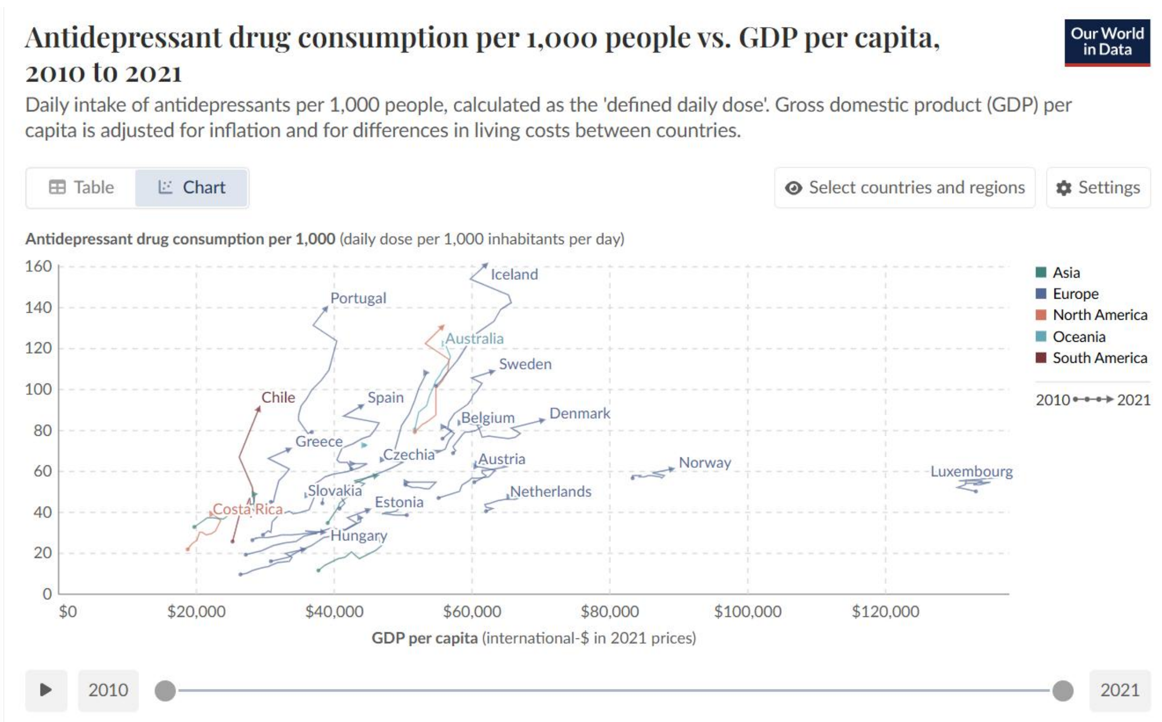

Figure 2: *Antidepressant drug consumption per 1,000 people vs. GDP per capita, 2010-2021*.

This data, available on *Our World in Data*, shows the relationship between the daily intake of antidepressants and the economic status of different countries over time. The data is adjusted for inflation and differences in living costs, making it a valuable resource for understanding mental health trends across different economic contexts.

The *Our World in Data* visualization inspired our project by showcasing how macroeconomic indicators like GDP per capita can reflect public health issues like mental health. Our goal is to build upon such visualizations to explore the nuanced temporal and geographic interactions between unemployment rates and mental health. By using reliable datasets and accessible visual storytelling, we aim to bridge the divide between socioeconomic policy decisions and their real-world impacts on human well-being.

2. Research Question

Core Question: How does state-level unemployment correlate with mental health burdens in the U.S. from 2018 to 2021?

This core question aims to explore the temporal and spatial relationships between unemployment and mental health in the U.S., shedding light on the broader impacts of economic conditions on well-being.

Sub-questions:

- **Are there lag effects suggesting delayed psychological impacts of economic hardship?**
  - This question seeks to identify if there is a delay between rising unemployment rates and a subsequent increase in mental health issues, exploring the long-term effects of economic instability.
- **Which states exhibit the highest sensitivity to unemployment-related mental distress?**
  - By examining variations across states, we aim to uncover regional disparities in how unemployment affects mental health, potentially influenced by factors like healthcare access, social safety nets, and local economies.
- **What regional patterns or anomalies exist across the country?**
  - This sub-question focuses on detecting any geographic trends or unexpected patterns in the data, looking for correlations between mental health burdens and specific regional characteristics such as urbanization, economic structure, or political context.

Target Audience Emphasis:

This research is aimed at a broad but strategically defined audience, including:

- Policy Makers and State-Level Officials who are responsible for labor, health, and welfare programs, helping them allocate resources and design interventions tailored to state-specific needs.
- Public Health Experts seeking data-driven insights into how economic instability affects mental health outcomes across populations.

- Data Journalists and Visual Communicators who can use the findings and visualizations to raise awareness and inform public discourse.

- General Public and Advocates invested in understanding how economic factors tangibly influence lives, mental health, and regional disparities.

By integrating economics, public health, data science, and visual storytelling, the project is positioned to inform evidence-based policymaking and support public understanding of socio-economic resilience at both the individual and community level.

3. Application Scenarios

The insights from this project have the potential to address critical societal needs across several sectors, offering practical solutions to real-world problems. The following application scenarios outline how the findings from this research, combined with effective data visualization, can be leveraged for societal benefit:

- **Public Policy & Health Administration**:
  By identifying states with the highest sensitivity to unemployment-related mental distress, our findings can inform targeted resource allocation for mental health services. Policymakers could use visualizations to prioritize regions with the greatest need for intervention, improving the efficiency of public health initiatives and ensuring that mental health support reaches vulnerable populations, especially during times of economic hardship (Uutela, 2010).

- **Academic Research**:
  This research offers a replicable framework for studying the interactions between economic conditions and mental health across various regions and time periods. Academics in fields such as economics, public health, and sociology could apply this methodology to other countries, regions, or historical contexts, fostering a deeper understanding of how economic stress impacts mental well-being in different settings (Turner, 1995; Stuckler et al., 2009). Additionally, this approach can be adapted to study other economic health correlations, such as housing instability or income inequality.

- **Interactive Journalism**:
  Data-driven storytelling has the potential to engage the public and policymakers with real-time insights into the relationship between macroeconomic stress and public health. Interactive dashboards can be used by journalists to illustrate how economic disruptions—such as recessions or job losses—affect mental health in different regions(Brouwers, 2020). These visualizations could be powerful tools for media outlets seeking to inform the public about the consequences of economic policies and the

societal impact of unemployment.

- **NGO Advocacy**:
  Non-governmental organizations (NGOs) focusing on public health and social justice could use these visualizations to highlight vulnerable populations affected by economic crises. By providing data-driven evidence of the relationship between unemployment and mental health, NGOs could advocate for targeted interventions and present compelling cases to funders and stakeholders for increased funding or policy support. These visualizations could also support awareness campaigns and help identify the areas where social services need to be enhanced (Winkelmann & Winkelmann, 2024).

Through these application scenarios, the project not only contributes to academic research but also provides practical tools that could influence decision-making, raise awareness, and improve interventions in public health, policy, and advocacy efforts.

4. Methodology

This section outlines the methodologies employed in designing visualizations for the correlation between unemployment rates and mental health burdens across U.S. states from 2018 to 2021. The methodologies focus on visualization techniques, data integration, and the use of advanced tools to uncover insights and facilitate user exploration.

Visualization Techniques

In line with principles from the *Visualization Basics* repository (Ch. 1-10), we employed various visualization techniques that were selected for their ability to convey complex data clearly and effectively. These techniques were guided by core principles of data visualization design, including choosing the right marks and channels, spatial data arrangement, and color theory.

1. **Marks and Channels**
   We used a combination of the following marks and channels to encode the data:

   - **Marks**:

     - *Points* (scatterplots) were used to show correlations between mental health burdens and unemployment severity.

     - *Bars* (bar charts) helped compare the sensitivity of different states to economic changes.

     - *Areas* (choropleth maps) illustrated regional disparities in unemployment and mental health.

- **Channels**:
    - *Position* (x, y) was used to encode the time (x-axis) and correlation strength (y-axis), emphasizing the trend over time and the strength of the correlation.
    - *Color Hue/Intensity* represented the severity of mental health burdens (hue) and unemployment levels (intensity).
    - *Size* was used to encode the magnitude of unemployment through bubble overlays on scatterplots, providing additional visual context to the data.

2. **Arranging Tables, Spatial Data, and Networks**
    - **Choropleth maps** were used to arrange spatial data, which allowed us to represent regional differences in both unemployment and mental health burdens. These maps clearly highlight areas of high and low intensity, making spatial disparities more understandable.
    - For more granular insight, **scatterplots** were arranged in a grid to show the relationship between unemployment rates and mental health, making it easy to identify correlations or anomalies between the two variables.

3. **Data Abstraction and Task Abstraction**
    - **Data abstraction** was achieved by distilling raw data into actionable visualizations that reflect the central research question. Key metrics—unemployment rates and mental health burdens—were abstracted into color, size, and position, creating a clear visual narrative.
    - **Task abstraction** was incorporated by aligning visual tasks with user needs: viewers can quickly assess trends, compare regions, and evaluate temporal shifts in the relationship between unemployment and mental health.

4. **Color Theory and Design Choices**
   Color was carefully selected based on principles of **accessibility and clarity**. We used color palettes tested for **colorblind accessibility** (Deuteranopia and Protanopia) to ensure inclusivity. For example, a combination of blue hues for mental health burden and orange to red hues for unemployment severity was used to create a clear visual contrast without confusing individuals with color vision deficiencies. Additionally, color gradients helped represent the range of values, making it easier to distinguish between high and low levels of each variable.

   The **choropleth maps** used color intensity to highlight regional disparities, while

scatterplots used color for categorizing states by mental health severity. **Size variation** in scatterplot bubbles emphasized the unemployment level, further supporting intuitive comparisons.

These design choices help guide the viewer's attention to key patterns, such as areas of high unemployment and corresponding mental health crises.

Data Sources and Integration

To ensure that the data used in our visualizations is robust, reliable, and meaningful, we combined datasets from reputable sources. These sources include:

1. **U.S. Bureau of Labor Statistics (BLS)**: Provides national and state-level unemployment data, including unemployment rates, labor force participation, and unemployment durations. The BLS dataset served as the core economic dataset for understanding the employment landscape across different states.

2. **CDC Environmental Public Health Tracking Network**: Offers detailed mental health burden data, including self-reported mental health status, anxiety, depression, and other mental health indicators by state and year. This dataset was used to assess the mental health impact across the U.S.

3. **Data Integration**:
   The two datasets were merged by **state and year** using data preprocessing techniques in **Pandas** and **NumPy**, which ensured data integrity and consistency. The integration allowed us to compare state-level mental health data against unemployment trends over time, revealing correlations that might not be apparent when examining the datasets independently.

Advanced Tools

To make the visualizations interactive and user-friendly, we employed several advanced tools and technologies:

1. **Interactive Dashboards**:
   Built using **Plotly**, the interactive dashboard allows users to filter the data in real-time, adjust time sliders, and explore different states and years. These interactive elements enable users to explore temporal trends and spatial disparities, making the data more engaging and accessible.

2. **Accessibility Engineering**:
   Given the importance of inclusivity, we implemented **colorblind-safe modes** for visualizations, allowing users with different forms of color vision deficiencies (e.g.,

Deuteranopia, Protanopia) to access the data without misinterpretation.

3. **Lag Analysis**:
   To analyze the delayed effects of unemployment on mental health, we used custom Python scripts to offset unemployment data temporally. This lag analysis allowed us to evaluate how unemployment trends in one year correlate with mental health changes in subsequent years, offering insights into delayed psychological impacts.

Preliminary Visualization

A preliminary **choropleth map** and **scatterplot** have been generated to display regional disparities in unemployment and mental health. These visualizations highlight how different states have been affected by unemployment in the context of mental health, with tooltips providing more detailed information on each data point.

5. Results

Anticipated Insights and Patterns

The primary aim of this project is to explore the relationship between **unemployment rates** and **mental health burdens** at both national and state levels. We anticipate that our approach will uncover several key insights and patterns:

1. **National-Level Correlation**:
   We expect to observe a **positive correlation** between unemployment and mental health burdens, suggesting that as unemployment rates increase, so do mental health challenges at the population level. This relationship could be quantified by the **Pearson correlation coefficient**, which we expect to be statistically significant. The overall trend may show some variation, indicating that other factors influence mental health outcomes beyond unemployment.

2. **State-Level Variation**:
   The strength of the unemployment-mental health relationship is likely to vary across states. Some states may show **stronger correlations**, indicating that unemployment plays a more significant role in shaping mental health outcomes, while others may demonstrate **weaker or even negative correlations**, possibly due to the presence of mitigating factors such as **stronger social safety nets** or **resilient local communities**.

3. **Temporal Lag Effect**:
   A key hypothesis is that the impact of **unemployment** on **mental health** might not be immediately apparent but could take time to manifest. By conducting a **lagged analysis**, we expect to uncover a **stronger correlation** between past unemployment rates and future mental health burdens, confirming the hypothesis of a **delayed psychological**

response to economic shocks.

4. **Regional Disparities**:
   Given the economic and demographic diversity across U.S. states, we anticipate uncovering distinct **regional patterns**. For instance, states with higher rates of unemployment or fewer mental health resources may exhibit stronger correlations, while more affluent or better-supported states may show weaker relationships.

Initial Results from Pilot Exploration

1. **National-Level Correlation**:
   The Pearson correlation coefficient between **unemployment rates** and **mental health burdens** at the national level was found to be **0.5198** (p-value < 0.001). This significant **positive correlation** suggests that higher unemployment rates are indeed associated with greater mental health burdens at the population level, confirming our hypothesis. The scatter plot with a regression line clearly shows a positive trend, but with some **dispersion**, indicating that other factors may also influence mental health outcomes.

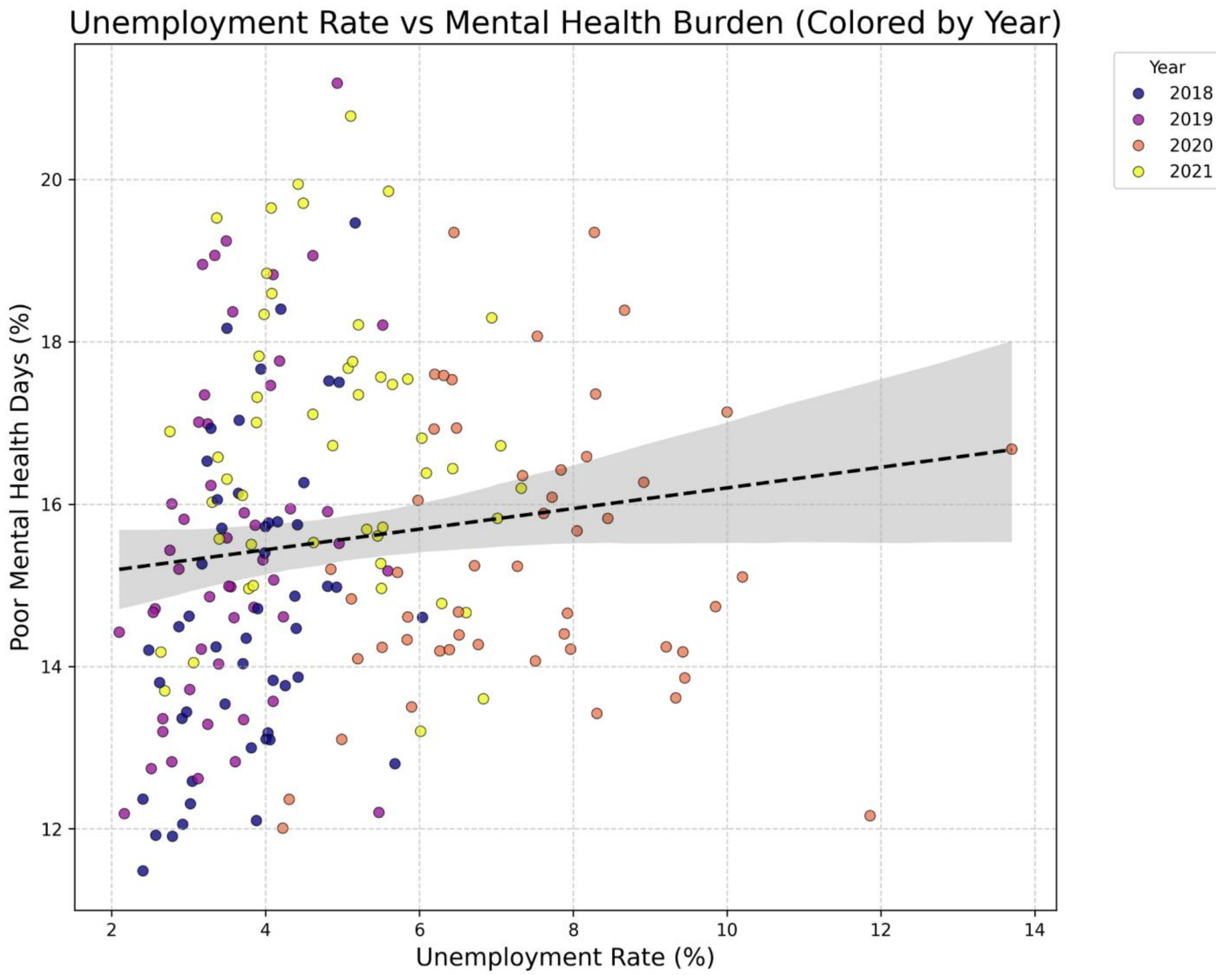

Figure 3: *Scatter Plot of Unemployment vs. Mental Health.*

2. **State-Level Variation**:
   The strength of the correlation varied significantly across states, which is reflected in the **state-wise correlation coefficients**:

   - **Strongest Positive Correlations**:

     - Nevada (r = 0.82)

     - New Mexico (r = 0.79)

     - Alaska (r = 0.78)

     - West Virginia (r = 0.76)
       These states demonstrated a strong, direct relationship between **unemployment fluctuations** and **mental health distress**, indicating that

economic hardship** plays a prominent role in shaping the mental well-being of their populations.

- **Weakest or Negative Correlations**:
  - Hawaii (r = -0.05)
  - Vermont (r = 0.10)
  - New Hampshire (r = 0.12)
    These states showed weaker or even negative correlations, suggesting that factors beyond unemployment—such as **state-level mental health programs**, **community resilience**, or **economic buffers**—might mitigate the relationship between unemployment and mental health.

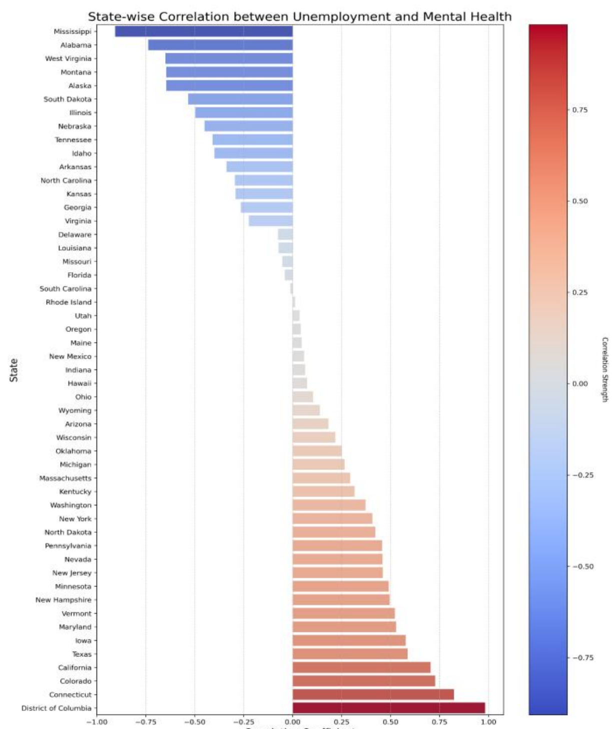

Figure 4: *State Wise Correlation Visualization*

3. **Lagged Effect Analysis**:
   The analysis of a **one-year lag** in the relationship between **unemployment** and **mental health burden** revealed a Pearson correlation of **0.5621** (p-value < 0.001), which was **stronger** than the real-time correlation. This finding supports the hypothesis that the psychological effects of **unemployment shocks** take time to manifest fully, emphasizing the importance of considering **temporal delays** when assessing the impact of economic

changes on mental health.

Visual Highlights

- **Correlation Choropleth Map**: The **choropleth map** depicting **correlation strengths** across the U.S. visually highlights the geographic variation in the unemployment-mental health relationship. States with stronger correlations (e.g., Nevada, New Mexico) are marked in deeper shades of red, while states with weaker correlations (e.g., Hawaii, Vermont) are shown in lighter shades. This map provides an intuitive way to assess the regional disparities in the unemployment-mental health relationship.

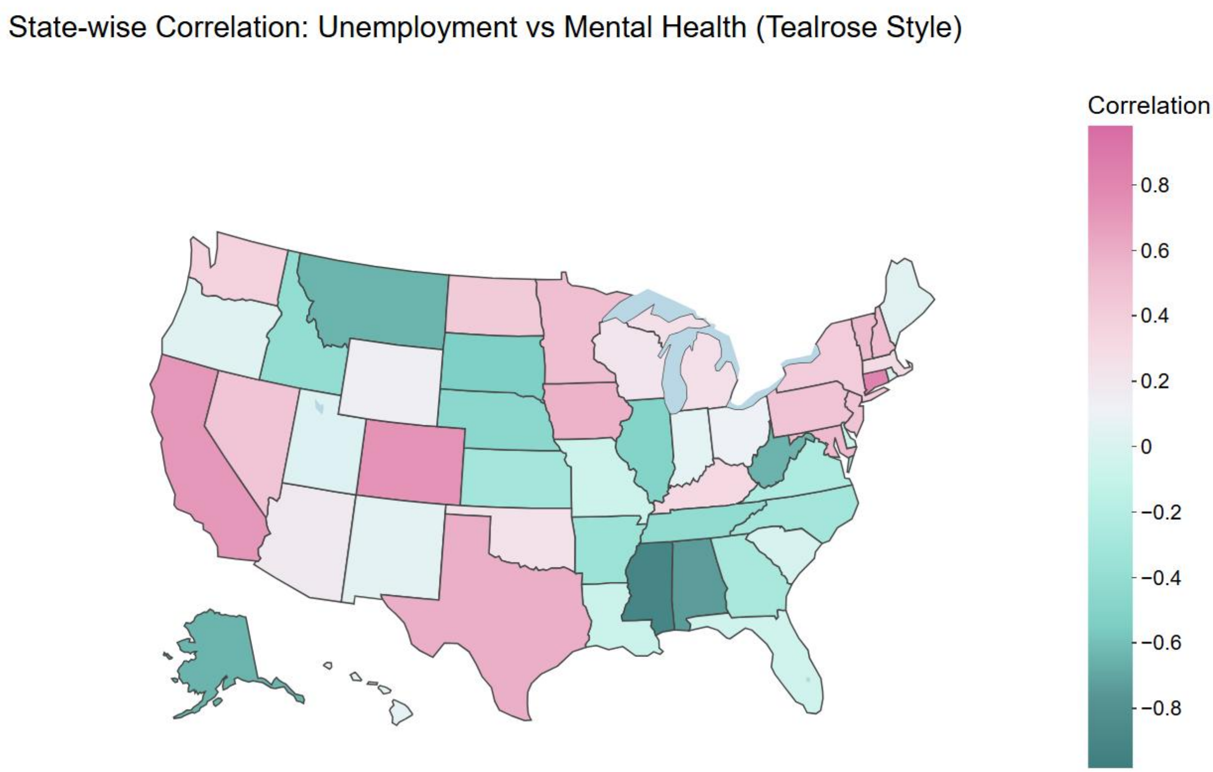

Figure 5: *Correlation Choropleth Map.*

- **Interactive Choropleth Map & Bubble Overlay**: This dashboard enhances user understanding of both spatial disparities and temporal trends, aligning with our project's goal to deliver a rich, multi-dimensional perspective on economic and public health interactions. It helps users visually grasp the relationship between unemployment and mental health burdens across different states and years, while providing a more accessible experience

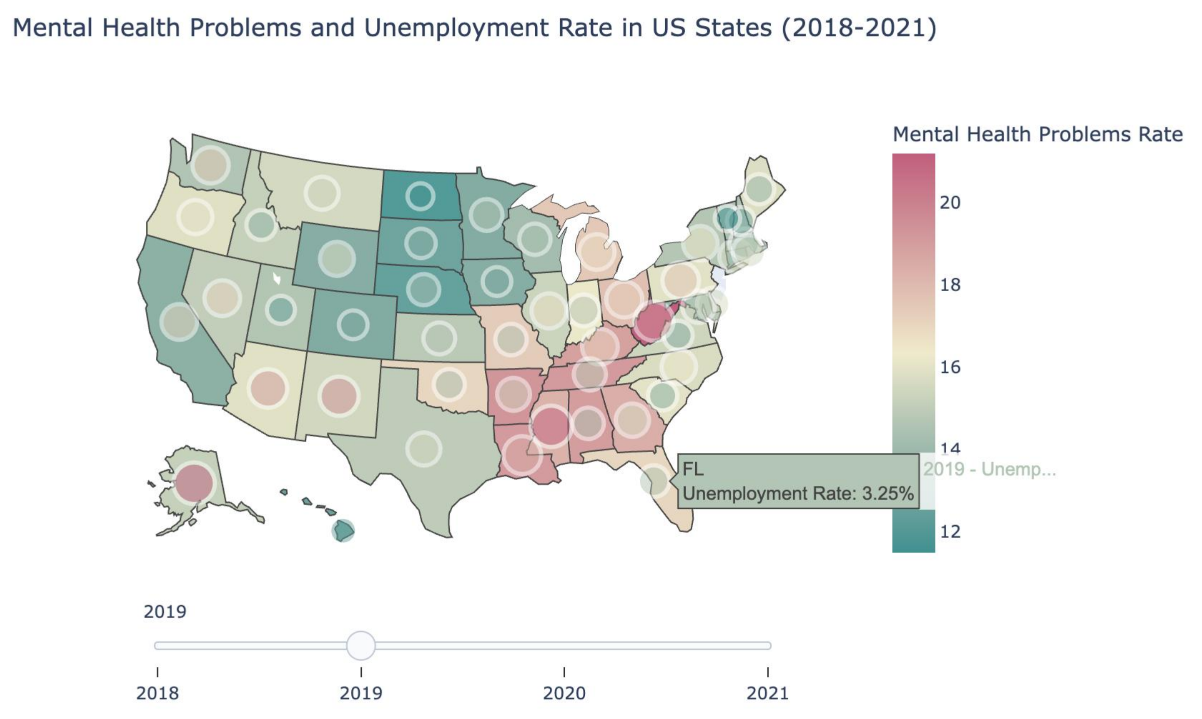

Figure 6: *Interactive Choropleth Map & Bubble Overlay*

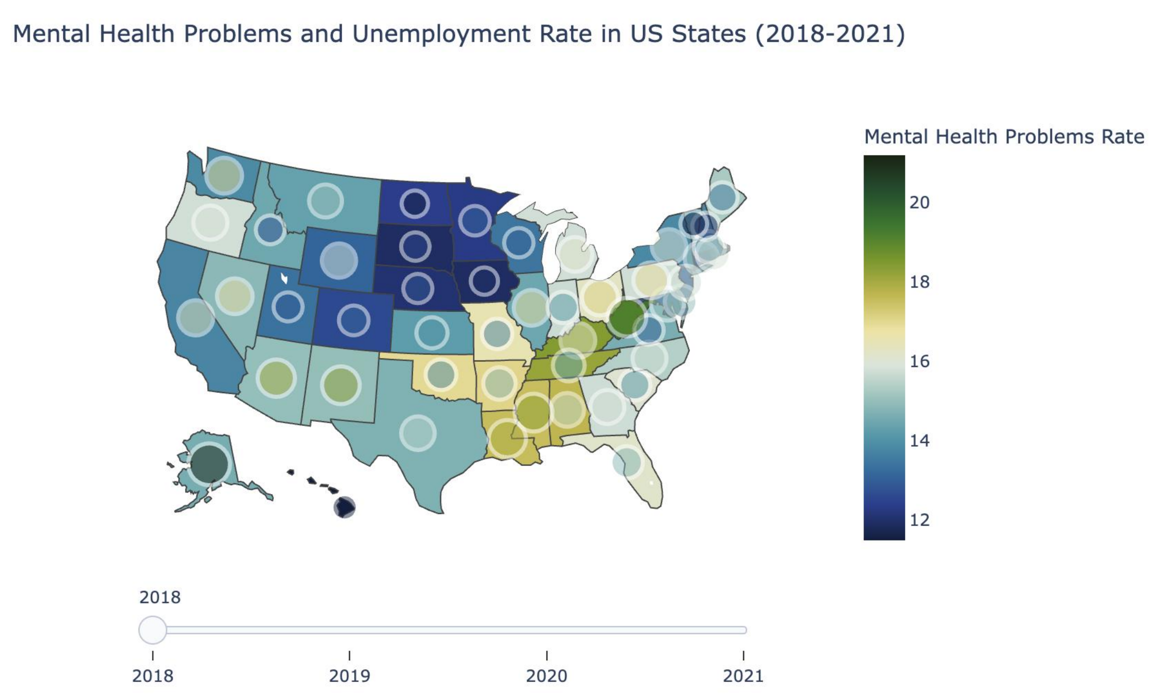

Figure 7: *Interactive Choropleth Map & Bubble Overlay(Colorblind-Friendly Version)*

6. Intellectual Merit and Practical Impacts

Academic Contribution

This project contributes to the academic discourse at the intersection of **data visualization**, **public health**, and **macroeconomics** by:

- **Introducing a replicable framework** for lagged correlation analysis between socioeconomic indicators and health outcomes. Our approach integrates temporal data alignment, Pearson correlation, and geographic differentiation—offering a new lens for examining policy-relevant phenomena through visualization.

- **Advancing best practices in interactive data storytelling**, leveraging visualization principles such as **task abstraction**, **channel effectiveness**, and **color theory** (Ware, 2021) to convert complex, multi-dimensional datasets into intuitive and engaging formats.

- Providing a **case study** in the design of **accessible, real-time visual dashboards** for exploring state-level economic-health dynamics. This bridges a gap in current academic literature, which often isolates statistical analysis from user-centered visual representation (Munzner, 2014).

Practical Impacts

This work holds significant real-world potential across multiple sectors:

- **Policy and Health Administration**: By mapping states with high sensitivity to unemployment-induced distress, the tool equips decision-makers to **preemptively allocate mental health resources**, especially after economic shocks. This is critical given findings that **delays in intervention** exacerbate long-term psychological harm (Uutela, 2010).

- **NGO and Advocacy Applications**: Empirical, visually communicable evidence strengthens the capacity of **mental health advocates** to secure funding and policy changes, especially in economically vulnerable regions.

- **Interactive Journalism and Public Communication**: The dashboard's design makes complex patterns understandable for general audiences, enabling **data-driven storytelling** around the lived impacts of economic crises.

- **International Research Replicability**: The methodology offers a template for similar analyses in other countries, supporting comparative public health research as recommended by Brouwers (2020) and Winkelmann & Winkelmann (2024).

7. Reflection on Growth and Learning

This team-based project marks a significant evolution from our earlier individual work on InfoVis redesigns. While those assignments focused primarily on improving static visual communication, this project demanded **collaborative inquiry**, **cross-disciplinary synthesis**, and the development of a **data narrative with social impact**. Through this process, we shifted from thinking about *what looks clear* to *what truly matters*.

Our visit to the **Zhouzhuang Life Mysterious Museum** was especially transformative. Immersing ourselves in local stories of resilience and collective memory reminded us that **behind every data point is a human being**—a person experiencing stress, change, or hope. This inspired our team to treat data not as an abstract object but as a **lens to reveal hidden emotional and societal undercurrents**.

In-class activities, particularly the **Data Humanism workshop**, challenged us to think beyond precision and objectivity. We explored how visualization can encode empathy, ambiguity, and even contradiction—concepts rarely captured by conventional charts. This influenced our design choices: we carefully selected color palettes that emphasize dignity and avoid alarmism, and we prioritized **accessibility and interactivity** to invite broader public engagement.

Attending visualization symposiums further broadened our perspective. We encountered projects that blend **art, activism, and analytics**, and this encouraged us to move from "just showing correlation" to "telling a story about inequality, vulnerability, and resilience." We began to understand that **visualization is not only a scientific tool, but also a civic and ethical one**.

Technically, we mastered tools like **Plotly, Pandas**, and custom Python scripts for lag analysis. But more profoundly, we learned to collaborate across differences, engage with critical feedback, and **infuse our design with purpose**.

Ultimately, this project helped us grow not only as visualization practitioners, but also as **empathetic researchers and community-minded designers**.

8. Supplementary Materials

- **GitHub Repository**: https://github.com/Cattum/INFOSCI-301-Team-Research
    - Contains full code, datasets, dashboard files, and the final poster.
- **Poster Showcase**: See *Main/Poster* in the repo.

Reference

Brouwers, E. P. M. (2020). Social stigma is an underestimated contributing factor to unemployment in people with mental illness or mental health issues: Position paper and future directions. *BMC Psychology, 8*(1). https://doi.org/10.1186/s40359-020-00399-0

Munzner, T. (2014). *Visualization Analysis and Design*. CRC Press.

Uutela, A. (2010). Economic crisis and mental health. *Current Opinion in Psychiatry, 23*(2), 127–130. https://doi.org/10.1097/yco.0b013e328336657d

Ware, C. (2021). *Information Visualization: Perception for Design* (4th ed.). Morgan Kaufmann.

Winkelmann, L., & Winkelmann, R. (2024). Happiness and unemployment: A panel data analysis for Germany. *Applied Economics Quarterly, 41*(4), 293–307. https://www.zora.uzh.ch/id/eprint/1189/8/HappWinkelmannK.pdf

Datasets

Justin2028. (2022). *Unemployment in America, Per US State* [Dataset]. Kaggle. https://www.kaggle.com/datasets/justin2028/unemployment-in-america-per-us-state

Description: State-level monthly unemployment rates across the U.S. from 1976 to 2022, compiled from U.S. Bureau of Labor Statistics data.

Centers for Disease Control and Prevention (CDC). (2021). *Mental Health Indicators by State* [Dataset]. CDC Environmental Public Health Tracking Network. https://ephtracking.cdc.gov/DataExplorer/?c=13&i=109&m=-1

Description: Percentage of adults reporting ≥14 days of poor mental health in the past 30 days, by U.S. state, 2018–2021.

Visualization Reference

Our World in Data. (2023). *Antidepressant drug consumption per 1,000 people vs. GDP per capita, 2010 to 2021* [Interactive Chart]. https://ourworldindata.org/grapher/antidepressants-per-capita-vs-gdp

Description: Comparative time-series visualization exploring relationships between economic status and mental health treatment across countries.

Appendix

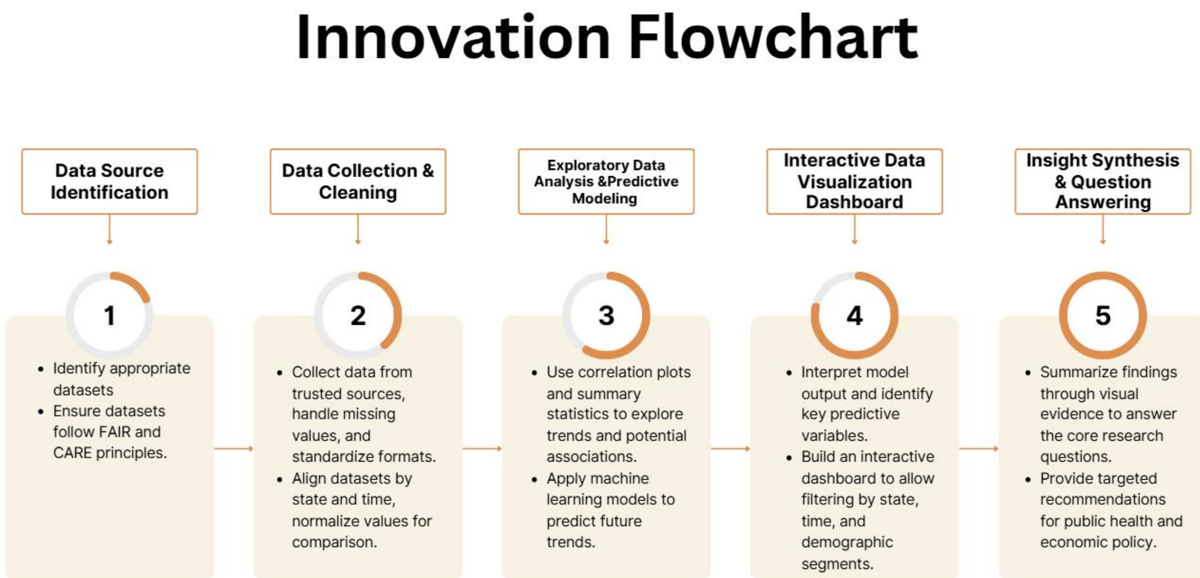

Figure 8: *Innovation Flowchart*