Mental Health Plays Significant Role in Physical Wellness in 1972 to 2022 US General Social Surveys*

Mental Illness Being Overlooked in the Medical Field with Gender Disparities

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Mental health is a relatively newly introduced topic in the field, but would mental health issues influence physical health as well? Focusing on numerous variables correlated to mental and physical health, this study uses data from the U.S. General Social Survey (GSS) from 1972 to 2022 to investigate the impact of mental health unwellness on physical health unwellness, focusing specifically on "reported days of feeling unwell in a month." Our analysis reveals that mental unwellness leads to an increase in physical unwellness, and identifies disparities between demographic groups, with women disproportionately affected. These findings underscore the necessity for the importance of promoting mental health and supporting underrepresented groups in the medical field.

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*Code and data are available at: https://github.com/MjChen120/Mental_to_Physical_Health.git.

1 Introduction

Mental health is one essential aspect of the general health of an individual and yet it is often overlooked. Mental illnesses are not only "silent diseases" of one's mind, but could as well impact patients' physical well-being in general (Ohrnberger, Fichera, and Sutton 2017). This paper examines whether mental health-related and demographic factors impact the number of days an individual experiences physical unwellness in a month.

The estimand of the paper is the difference in whether an individual could experience more occasions of feeling physically unwell if they have mental health unwellness versus not. This is considered in terms of those who were diagnosed as having depression by a doctor. U.S. General Social Survey (GSS) data from 1972 to 2022 is therefore used for this paper to examine whether the demographic and mental health-related factors as indicators of physical health conditions.

The analysis of GSS data, including gender, age, and mental and physical health variables, seeks to provide detailed insights into how mental health issues impact physical unwellness, contributing to discussions on intersectionality (complex sociological analytical framework for studying social and political identities resulted from unique combinations of discrimination and privilege) and overlooked mental health in the medical field.

Findings in the paper highlight the significance of gender, sex, and counted days of feeling mentally unwell in terms of counted days of feeling physically unwell in a month. The effect of being diagnosed as having depression on physical health unwellness is not significant ($\beta_2 = -1.43$, p = .22), thus whether depression diagnosis affects physical unwellness is not evidence supported. On the other hand, counted days of feeling mentally unwell have a positive significance on counted days of feeling physically unwell ($\beta_1 = 0.27$, p = .01). This means that if an individual has 1 more day of feeling unwell mentally, they, in general, will report 0.27 more days when reporting the number of days they feel physically unwell.

This paper begins with Introduction framing the impact of mental health on one's well-being. The Data section details variables, methodology, and analysis cleaning processes. In the Model section, a model is proposed for determining how an individual's depression status and counted days of mental unwellness in the past 30 days impact their counted days of physical unwellness in the past 30 days. Results section analyzes how demographic and other mental health-related factors would affect physical health with model calculations, leading the Discussion section with gender intersectionality and mental health issues often being overlooked in the medical field. Limitations and Future Research sections are included for study limitations and future research directions. The Appendix provides further survey information.

2 Data

The paper uses data collected from the US General Social Survey (GSS) from NORIC at the University of Chicago ("General Social Survey" 2024). From the dataset, this paper focuses specifically on variables related to demographic backgrounds, mental health, and physical health, from 1992 to 2022. This longitudinal approach allows us to analyze whether an individual's demographic factors and mental health well-being could significantly contribute to their physical well-being.

2.1 Source Data

Physical and mental health variables such as "health", "depress" status, and reported days of feeling physical ("physhlth") and health ("mntlhlth") unwell in a month are selected from GSS ("General Social Survey" 2024) for the main analysis. Variable "year" is chosen for checking data consistency and non-response rate over the years. Demographic data, specifically age and gender, were used as well for further analyses. The data was downloaded and filtered for the selected variables from the selected data variables from GSS[1]. The data cleaning was performed based on value definitions as defined in the GSS codebooks (NORC 2018). The variable names are renamed to be more informative (Table 1).

[1]https://gss.norc.org/documents/stata/GSS_stata.zip

Table 1: Source data retrieved from GSS

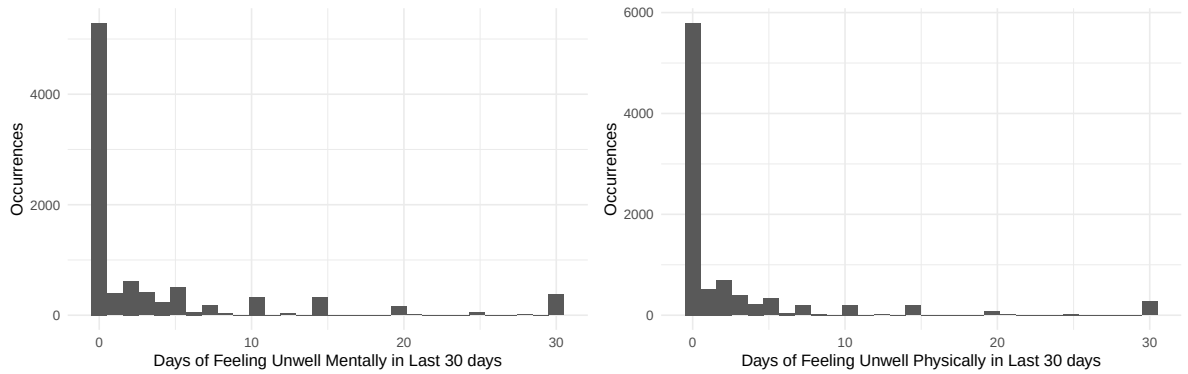
Variable	New Name	Description	Example
ID_	id	Response ID	1
YEAR	year	Year of the Data Recorded	1977
SEX	sex	Respondent's gender	Female/2
AGE	age	Respondent's age	25
HEALTH	health	Respondents' health condition	Good/2
PHYSHLTH	phys_days	Days of Respondents' physical health being not good	15
MNTLHLTH	ment_days	Days of Respondents' mental health being not good	20
DEPRESS	depress	Whether respondents have been told having depression	Yes/1

2.2 Data Cleaning

The data was cleaned by using the open source statistical programming language R (R Core Team 2024), with libraries `tidyverse` (Wickham et al. 2019), `ggplot2` (Wickham 2016), `ggpmisc` (Aphalo 2023), `dplyr` (Wickham et al. 2022), `readr` (Wickham, Hester, and Bryan 2022), `tibble` (Muller and Wickham 2022), `here` (Müller 2020), `kableExtra` (Zhu 2021), `janitor` (Firke 2023), `arrow` (Richardson et al. 2024), and `knitr` (Xie 2014). Below in Table 2 contains a snapshot of the main dataset being used for the purpose of analysis; two additional histograms (Figure 1) are included as well, illustrating number of responses for each question. In general, most respondents have only a few or zero days of feeling both physically and mentally unwell in the past 30 days.

Table 2: Counted days of Mental unwellness with General Health Status

ID	Physical Unwellness	Mental Unwellness
1	0	0
2	0	0
3	0	2
4	0	0
5	0	30
6	0	0



(a) Mental Unwellness

(b) Physical Unwellness

Figure 1: Histograms for Number of Responses for Each Question

2.3 Survey Methodology

From 1992 until 2018, the General Social Survey (GSS) relied on face-to-face interviews to gather data. This method offered a robust data collection environment, allowing interviewers to delve deeper into responses and clarify any uncertainties. It provided an optimal means of gathering comprehensive data. However, in response to the COVID-19 Pandemic, between 2020 and 2021, the GSS transitioned primarily to web surveys for data collection.

The GSS targeted English or Spanish-speaking adults aged 18 and above residing in US households ("General Social Survey" 2024). This inclusive criteria aimed to attract a diverse pool of participants. Nevertheless, individuals falling outside this target demographic were deemed ineligible for the survey. Those who didn't speak English or Spanish or had mental and/or physical impediments preventing survey participation were considered outside the scope of the GSS ("General Social Survey" 2024).

Changes in the GSS's respondent selection process, such as modifications to the Kish grid methodology, present additional hurdles, potentially skewing the demographic representation of respondents. The move towards web-based surveys may have inadvertently excluded older demographics, who are typically less inclined to engage with online platforms, thus impacting the survey's demographic balance. This demographic shift is significant, as older populations may offer distinct perspectives, particularly concerning mental health issues.

The survey queried participants with questions, such as "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" and "Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good?" and expecting a response of the number of days in a month. Significantly, between 1998 and 2022, the structure of the questions has consistently remained the same. This consistency in formatting ensures the data's stability, facilitating a

high level of consistency for thorough analysis. The data consists of a combination of in-person, telephone, and web surveys.

2.4 Demographic Variables

Demographic variables such as gender and age are used to compare and contrast differences between population groups. To further analyze age, as showcased in Table 3, the continuous variable is categorized into cohorts "0-19", "20-39", "40-59", "60-79", and "80+". Below is an overview of the sub-dataset used for demographic analysis. In total, as shown in Table 4, 9049 responses (with 51% from female respondents and 44% from age cohort 40 to 59) containing mentioned variables were collected.

Table 3: Counted days of Physical and Mental unwellness of Population by Age and Gender Groups

ID	Gender	Age	Physical Unwellness	Mental Unwellness	Age Cohort
1	Female	25	0	0	20-39
2	Male	43	0	0	40-59
3	Female	30	0	2	20-39
4	Female	55	0	0	40-59
5	Male	37	0	30	20-39
6	Male	47	0	0	40-59

Table 4: Number of Responses from Each Demographic Group

(a) Sex

Sex	Responses
Male	4649
Female	4400
Total	9049

(b) Age Cohorts

Age Cohort	Responses
0-19	81
20-39	3895
40-59	3953
60-79	1088
80+	32
Total	9049

2.5 Mental and Physical Unwellness and Depression Diagnosis

One of the key variables used for further analysis is whether the respondent has been diagnosed as having depression by a doctor in the past. The survey used the question "Now I would like to ask you some questions about general health conditions. Has a doctor, nurse, or other health professional EVER told you that you had: D. Depression?" to collect a categorical response of "Yes" or "No". The variable is an external indication of respondents' mental health status, accompanying the main counted days variable that is used for the analysis (Table 5).

Table 5: Counted days of Physical and Mental unwellness with Depression Diagnosis

ID	Physical Unwellness	Mental Unwellness	Depression Diagnosis
1	0	0	No
2	0	0	Yes
4	0	0	No
14	0	0	No
16	14	7	No
19	0	0	No

2.6 Mental Unwellness and General Health Status

A variable collecting general health status is furthermore included for additional analyses (Table 6). The variable is used as a supplementary tool indicating respondents' health in general to assist the analysis result. The question consists of four categorical responses asking the respondents: "Would you say your own health, in general, is excellent, good, fair, or poor?" The respondents are expected to choose one of the options to answer.

Table 6: Counted days of Mental unwellness with General Health Status

ID	Mental Unwellness	General Health
1	0	1
2	0	2
3	2	2
5	30	2
6	0	1
9	5	2

2.7 Non-response Rate and Limitations

To mitigate non-responses in the survey, the GSS implemented a technique known as subsampling for non-respondents. The core concept of subsampling entails selecting a subset of non-respondents and adjusting their weights to ensure an impartial design (NORC 2014). This chosen subsample is then expanded to effectively mirror all non-respondents up to a predetermined cutoff date. By focusing resources on a more manageable subset of difficult cases for further follow-up, subsampling offers the potential to reduce both response error and non-response bias (NORC 2014).

The GSS's approach to managing non-responses underwent changes, notably in its recent iterations – specifically during the COVID-19 Pandemic. As web surveys were used in the 2021 survey, modifications were made to balance non-responses. Historically, the survey employed subsampling techniques to mitigate the impact of non-responses, ensuring a representative dataset.

However, with the introduction of web-based surveys, new categories like "Skipped on Web" were introduced to categorize non-responses. This change raises questions about the comparability of data across years and the potential for increased non-response rates. Non-responses (Figure 2) can significantly affect the analysis of physical and mental health status trends, particularly in capturing the full extent of respondents' health status. Furthermore, mental health is a later introduced science compared to physical health and thus is not included in most of the previous surveys. Although survey data lack mental health-related questions filtered out for analyses, it is important to consider that fact.

As shown in Figure 2, some of the questions in the dataset are not included resulting in no responses collected in certain years due to the change in survey methodology. This fact requires extra attention when cleaning and handling since the number of available responses will decrease when additional variables are added. Hence, an additional sub-set of the data that only includes counted days of mental and physical un-wellness in the past 30 days (Table 2)

is also included for only speculating these two variables while keeping as many responses as possible.

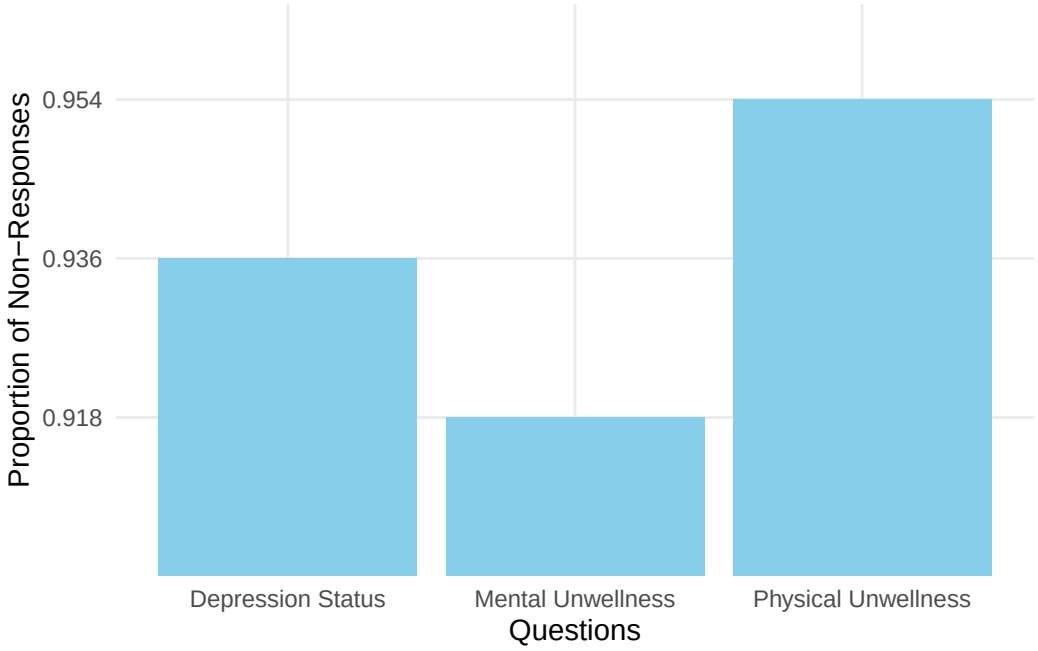


Figure 2: Nonresponse Rates - Responses for counted days of feeling physically unwell have the highest nonresponse rate

3 Model

Through the data analysis of the paper, a potential correlation between counted days of feeling mentally and physically unwell is detected. To further analyze and estimate counted days of feeling physically unwell based on an individual's counted days of feeling mentally unwell and whether they were diagnosed as depressive in the past, a linear regression analysis is conducted.

Background details and diagnostics are included in Appendix A.2.

3.1 Model set-up

Define y_i as the number of days that an individual felt physically unwell in the past 30 days. Then β_1 is the coefficient for the number of days that this individual felt mentally unwell and β_2 indicates the coefficient of whether the individual is diagnosed as depressive by a doctor. y_i and days are measured in days.

$$y_i|\mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{1}$$
$$\mu_i = \beta_0 + \beta_1 days + \beta_2 diagnosis \tag{2}$$
$$\beta_i \sim \text{Normal}(0, 2.5) \tag{3}$$
$$\sigma \sim \text{Exponential}(1) \tag{4}$$

We run the model in R (R Core Team 2024) using the `rstanarm` package of Goodrich et al. (2024). We use the default priors from `rstanarm`. Model justification and result will be explained later in this paper.

3.2 Model justification

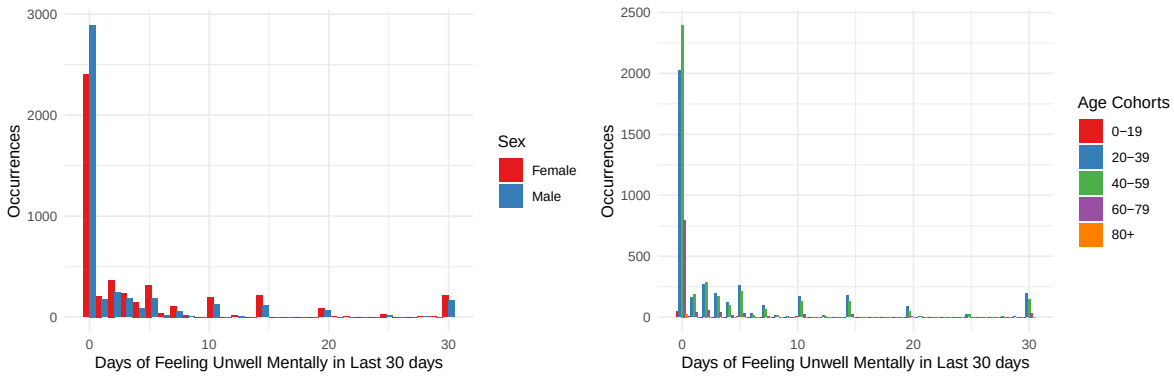
We anticipate that the counted days of feeling physically unwell would be closer to a normal distribution, as different types of health-related factors would contribute to number of days people feeling unwell in a month; however, the relationship between days feeling unwell physically (dependent variable), days feeling unwell mentally (independent variable), and whether being diagnosed as having depression before (independent variable) is hypothesized to be linear. This is because we think feeling mentally unwell and having depression would contribute to a higher possibility of feeling unwell physically, corresponding to our estimand. Since these three questions were not included in all past surveys, only data that contains all three questions will be used for testifying the model.

4 Results

4.1 Differences Detected between Demographic Populations

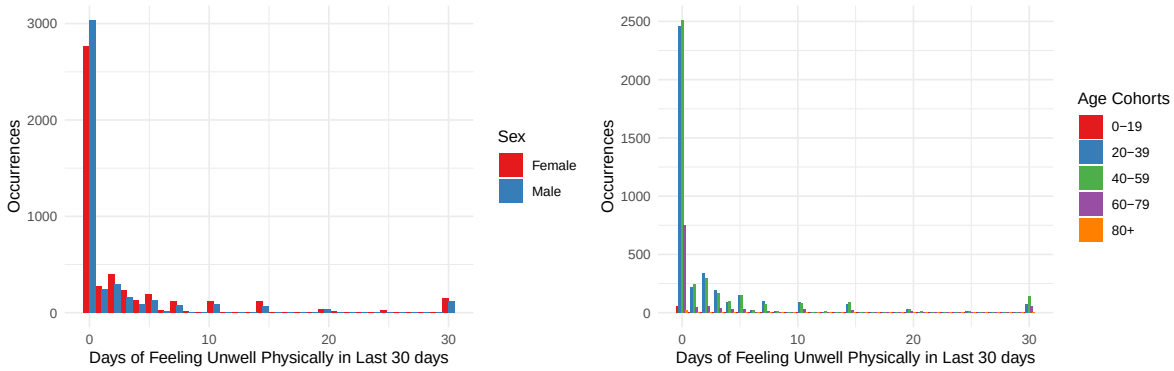
To speculate possible demographic factors influencing days of feeling mentally and physically unwell in a month, gender and sex are used. In general, females from 20 to 39 years old are more likely to report a higher number of days feeling mentally unwell (Figure 3). In terms of physical health, females from 40 to 59 years old report a higher number of days of feeling unwell (Figure 4).

As we can see, females in general report a higher number of counted days of feeling both physically and mentally unwellness in a month. The difference could be discrimination between gender groups, such as females usually being less represented in medical research. On the other hand, females are reported to be more sensitive to their mental health, which could be the reason why they tend to have a higher number of reports of being mentally unwell.



(a) Gender (b) Age cohorts

Figure 3: Female Participants from 20 to 39 Years Old are More likely to Experience Mental Unwellness



(a) Gender (b) Age cohorts

Figure 4: Female Participants from 40 to 59 Years Old are More likely to Experience Physical Unwellness

4.2 Mental Health and Health in General

In addition to model and demographic analyses, a variable indicating respondents' general health was as well included for supplementary support of the paper. The general health variable is categorical, consisting of four responses: "1" for Excellent, "2" for Good, "3" for Fair, and "4" for Poor. As shown in Figure 5, we can see that the number of days feeling mentally unwell has a positive correlation with the general health status, meaning that if an individual has more days feeling mentally unwell, they are more likely to have poor general health as well. This result connects back to our estimand, supporting mental health's influence on one's physical health status.

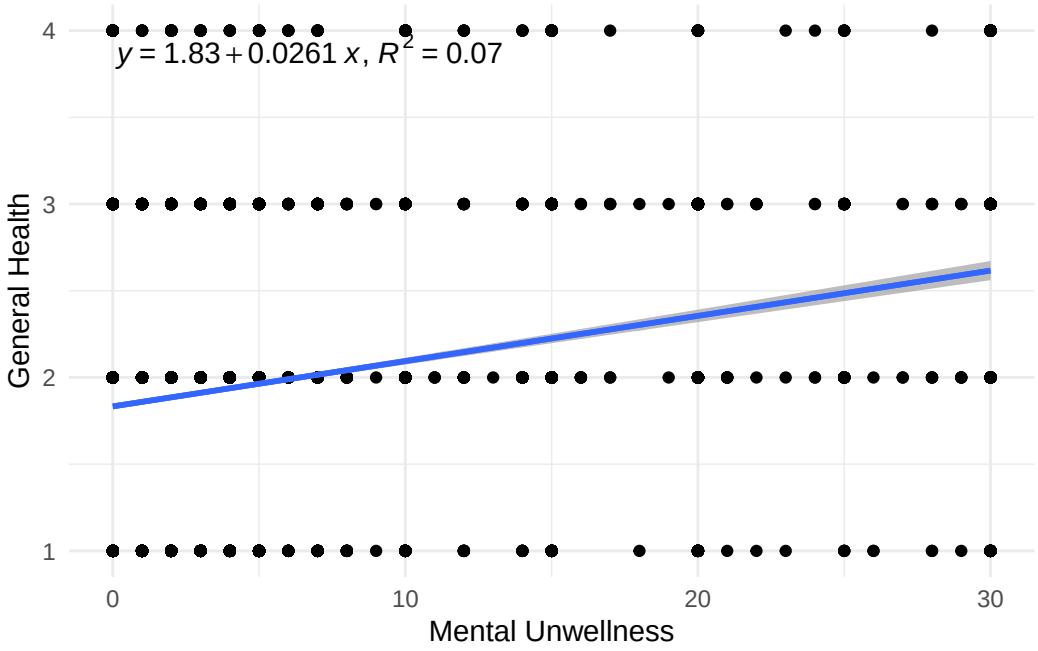


Figure 5: Counts of Days Feeling Unwell in Last 30 Days

4.3 Depression Playing a Role

With linear regression model analysis, the result in Figure 6 shows that counted days of feeling mentally unwell are positively correlated to counted days of feeling physically unwell. The diagnosis of depression has a further positive effect on counted days of feeling physically unwell, making the correlation stronger. This result means that individuals with 1) higher counted days of feeling mentally unwell and 2) being diagnosed as having depression tend to report a higher number of days feeling physically unwell.

Based on Table 7, however, although having influences on linear equation in Figure 6, depression diagnosis's influences on counted days of feeling physically unwell is not significant ($\beta_2 = -1.43$, p = .22). Counted days of feeling mentally unwell, on the other hand, do have a significant positive correlation with counted days of feeling physically unwell ($\beta_1 = 0.27$, p = .01). Even though one of the correlation is not significant, it is still important for us to consider the variable for possible future research.

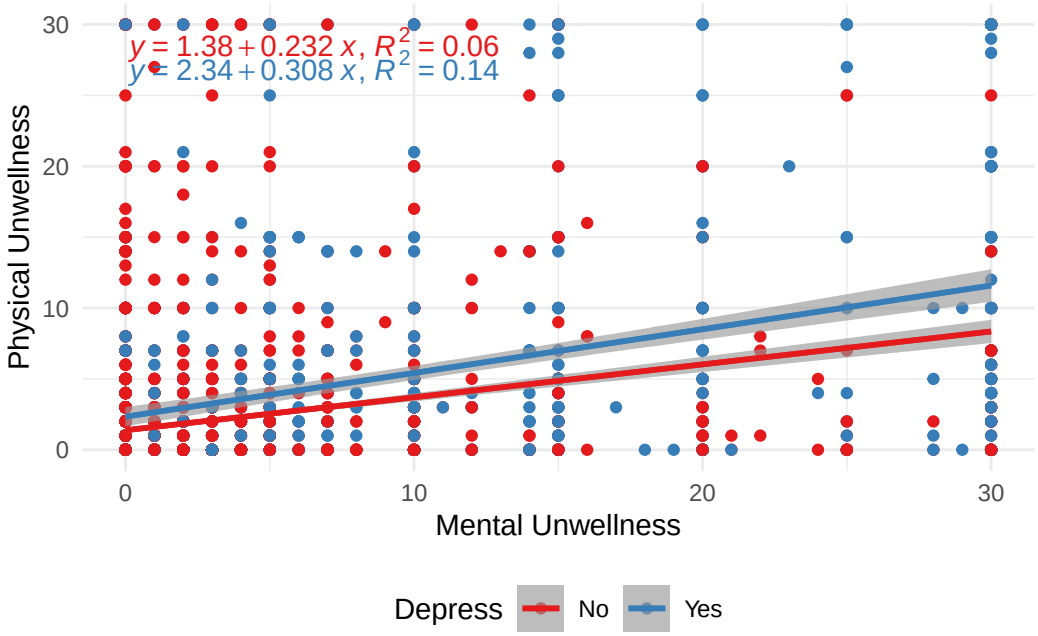


Figure 6: Counts of Days Feeling Unwell in Last 30 Days

Table 7: Explanatory models of counted days of physical unwellness based on counted days of mental unwellness and depression diagnosis

	First model
(Intercept)	1.30
	(0.10)
ment_days	0.27
	(0.01)
depressYes	1.44
	(0.22)
Num.Obs.	4527
R2	0.132
R2 Adj.	0.130
Log.Lik.	−14 351.369
ELPD	−14 358.2
ELPD s.e.	118.9
LOOIC	28 716.3
LOOIC s.e.	237.8
WAIC	28 716.3
RMSE	5.76

5 Discussion

We find a positive correlation between mental and physical health, where depression diagnosis strengthens the correlation; on the other hand, we detect a disparity between gender groups, hinting at an association with the fact that females are underrepresented in the medical field.

5.1 Mental Health Issues Impact Physical Health

Corresponding to the results in the journal by Ohrnberger, Fichera, and Sutton (2017), although not strong, the result of the paper supports the positive correlation between mental and physical health status ($\beta_1 = 0.27$, p = .01). The variables that are used for main analysis were only available in years 2002, 2006, 2010, 2014, 2018, and 2022 as mental health is a newly introduced concept in health science compared to physical health, hence the sample size (n = 9049) of our data may not accurately represent U.S. population in past decades. Moreover, mental health education may not be common, and even mistreated as a taboo, in the population at the time, causing individuals to dismiss mental discomfort. The correlation or impact thus could be strengthen by mental health promotions and educations in the future.

In addition, counted days of feeling physically and mentally unwell might not fully capture an individual's health status for analysis, more relevant factors should be included for future analysis. Due to that reason, a variable capturing respondents' general health status was included for supplementary evidence. A positive correlation between counted days of mental unwellness and general health (Figure 5) was detected to further support our estimand. To elaborate, since the categorical variable is coded reversely (i.e. Excellent - 1 and Poor - 4), we can conclude that as the number of counted mental unwellness increases, the health status of that individual correspondingly worsens.

5.2 Influence by Depression Diagnosis

To support our estimand, an additional variable was added to indicate the respondents' depression diagnosis. From the graph (Figure 6) and model (Table 7) results, depression diagnosis contributes to increase the influence of mental unwellness to physical unwellness. Depression diagnosis, therefore, could be a positive moderator, which strengthens the relation between mental health (independent variable) and physical health (dependent variable). Other than depression diagnosis, other mental health issues have not been specifically speculated for the purpose of this particular study.

5.3 Gender Disparity in Health

By comparing counted days of feeling mentally and physically unwell between different gender groups, we found that female respondents in general reported higher numbers of occasions

feeling unwell (Figure 3 and Figure 4). The trend could be a result of gender disparity in medical field, where women benefit less from medical research and advances because they are underrepresented as potential patients. The gender disparity in medical research, compounded by pervasive misogyny, translates into tangible disadvantages for female patients in real-world scenarios.

From the literature review conducted by Merone et al. (2022), women continue to be significantly underrepresented in medical literature, with inadequate reporting and analysis of sex and gender in research and misogynistic perceptions persistently shape the narrative surrounding these issues. The result in this paper again highlights the disparity, reminding us that We still have a long way to acknowledge and solve gender and minority disparity problems in the research field.

5.4 Weaknesses and Next Steps

There are many limitations and weakness in the analysis. For instance, counted days of feeling physically and mentally unwell in past 30 days might not fully capture an individual's mental and physical health status; although feeling unwell in a few days, the severity of the unwellness was not measured. An individual could feel seriously unwell physically or mentally, which could as well contribute to a factor for analyzing. On the other hand, no other mental health issues other than depression was being studied in the paper; different kinds of mental health issues could contributes to physical unwellness in different ways, further research could include those variables for a better narrative of the relationship.

Not enough education on mental health could also influence variables we collected, based on the fact that the variables are collected in a self-report manner. Participants might reported inaccurate information due to not having mental health related knowledge. On the other hand, the disparity in gender and other minority groups could influence the variable validity as those groups are more likely to be underrepresented in medical research. There is still much room of improvements.

Lastly, by posterior predictive check, the posterior distribution indicates that the model is not doing a good job of fitting the data. The check result could be due to limitations of data mentioned above; furthermore, adding more relevant variables to the linear regression equation could as well improve the strength of the model.

With existing study and limitations, future studies could be conducted to improve and capture the relationship between mental and physical health more efficiently in the future.

A Appendix

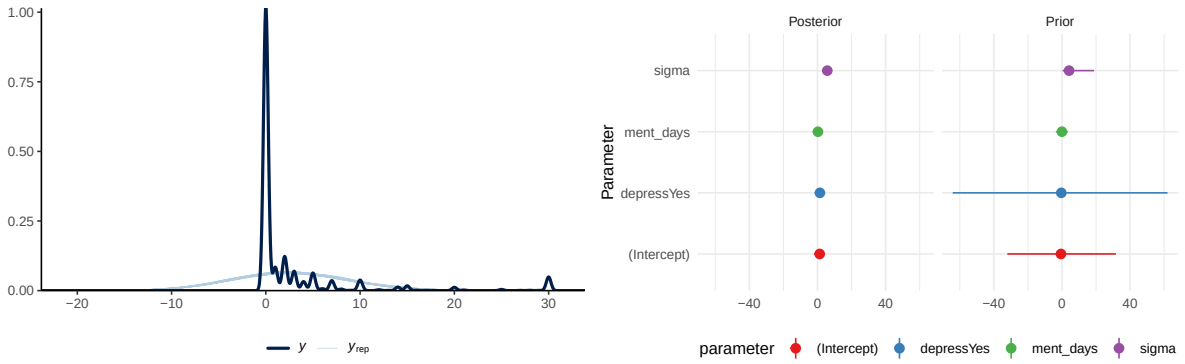
A.1 Survey Questions

1. What is your age group?
    - Type in a Number
    - Not Applicable
2. Please specify your gender:
    a) Male
    b) Female
    c) Prefer not to say
3. Would you say your own health, in general, is excellent, good, fair, or poor?
    a) Excellent
    b) Good
    c) Fair
    d) Poor
    e) Not Applicable
4. Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?
    - Type in a Number
    - Not Applicable
5. Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good?:
    - Type in a Number
    - Not Applicable
6. Now I would like to ask you some questions about general health conditions. Has a doctor, nurse, or other health professional EVER told you that you had Depression?
    a) Yes
    b) No
    c) Not Applicable

A.2 Model details

A.2.1 Posterior predictive check

In Figure 7, we implement a posterior predictive check and compared the posterior with the prior. By definition, the posterior should be able to be used to simulate data similar to the actual data; however, the posterior simulated data barely recollect the characteristic of the dataset from GSS. This means that the model lack of strength in terms of the relationship. The weakness could be a result of data limitations mentioned in Discussion.



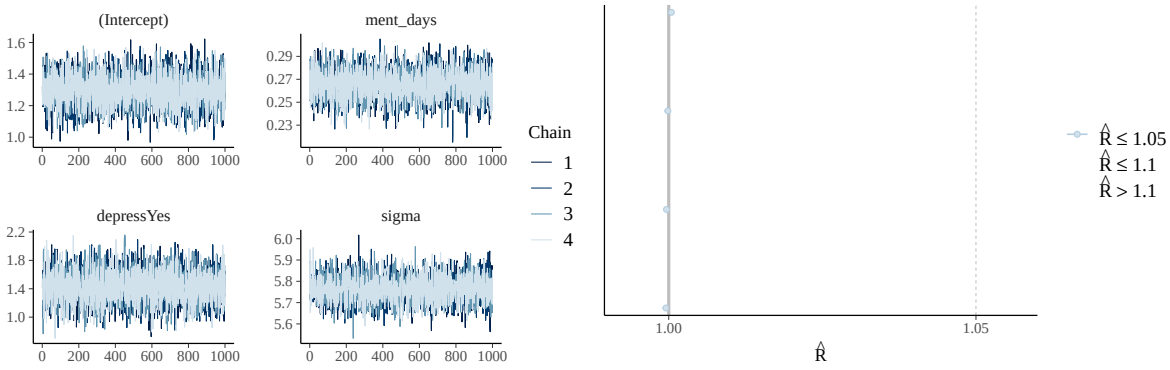
(a) Posterior prediction check

(b) Comparing the posterior with the prior

Figure 7: The Model Fits Barely to the Data, Hinting A Weak Model for Explaining the circumstances

A.2.2 Diagnostics

Figure 8a is a trace plot. It shows lines bouncing around horizontally and have a nice overlap between the chains. Figure 8b is a Rhat plot. From the plot, $\widehat{R} = 1.05$, which is very close to 1, and ideally no more than 1.1. These results suggest no problems in model we built for our paper.



(a) Trace plot (b) Rhat plot

Figure 8: Checking the convergence of the MCMC algorithm

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