Evaluation of Home Life Variables on Depression

---

Lauren Dulick

*University of Florida*

04.26.2024

Table of Contents

[I. Introduction 3](#_Toc165036731)

[A. Rational for the Study 3](#_Toc165036732)

[B. Explanation and Significance 3](#_Toc165036733)

[B. Comparison of Two Groups 3](#_Toc165036734)

[II. Experimental Design 4](#_Toc165036735)

[A. Methodology 4](#_Toc165036736)

[B. Execution of Study 4](#_Toc165036738)

[C. Justification for Chosen Experimental Design 4](#_Toc165036739)

[D. Inclusion Criteria and Participant Description 5](#_Toc165036740)

[III. Discussion of Results 5](#_Toc165036741)

[A. Analysis and Interpretation 5](#_Toc165036742)

[B. Results vs. Baseline 6](#_Toc165036743)

[C. Results on Training and Testing 8](#_Toc165036744)

[D. Feature Importance 9](#_Toc165036745)

[IV. Significance and Limitations 9](#_Toc165036746)

[A. Implications and Potential Limitations 9](#_Toc165036747)

[B. Future Applications 9](#_Toc165036748)

[C. Broader Implications and Societal Benefits 10](#_Toc165036749)

# Introduction

## A. Rational for the Study

The purpose of this study is to evaluate the relationship between one’s homelife and the mental health disorder, depression. By using a machine learning model, this study evaluates the weight of different homelife variables with respect to depression and days with poor mental health.

## B. Explanation and Significance

By noting which variables have the highest weight on the expected outcome of a depression diagnosis or large number of poor mental health days, greater clarity on the impact of homelife variables and the feasibility of real-world AI models might be gained. Additionally, the study hopes to identify which variables don’t hold much weight and understand which variables psychiatrists should stop evaluating.

## B. Comparison of Two Groups

Two groups will be evaluated in this study: men and women. By separating these two groups, psychiatrists might better understand the gender-specific differences related to the impact of homelife variables on the diagnosis of depression. Societal norms, cultural expectations, and other variables may impact the difference in the results of men and women.

# Experimental Design

## A. Methodology

### All data for homelife variables, depression diagnosis, and poor mental health days is sourced from the 2022 Behavioral Risk Factor Surveillance System (BRFSS). The homelife variables were limited after the Research Proposal in an effort to do a more in-depth research experiment, and these final variables include ‘Marital Status’ (MARITAL), ‘Own or Rent Home’ (RENTHOM1), ‘Income Level’ (INCOME3), ‘Living with Someone with a Mental Health Disorder’ (ACEDEPRS), ‘Living with a Problem Drinker/Alcoholic’ (ACEDRINK), ‘Living with Someone who Used Illegal Drugs or Abused Prescriptions’ (ACEDRUGS), ‘Living with Someone who Served Prison/Jail Time’ (ACEPRISN), ‘Divorced/Separated Parents’ (ACEDIVRC), and ‘Parents who Swear at You’ (ACESWEAR). The modeling technique is a machine learning model, which loads the BRFSS data, applies the specified inclusion criteria and covariate mappings, and splits the data into training and testing sets for evaluation.

## B. Execution of Study

This experiment will be centered around training a model on different homelife variables. By training the model to understand the relation between the outputted diagnosis of depression with how people responded to homelife-specific questions, it should efficiently demonstrate the weight that different homelife variables have on the output of depression and poor mental health days.

## C. Justification for Chosen Experimental Design

By placing the inclusion criteria and covariates in their respective location, the machine learning algorithm will output the weight of each homelife variable on the expected output of a previous diagnosis of depression and real response to poor mental health days. These results have the potential to yield valuable insights for mental health research and clinical practice.

## D. Inclusion Criteria and Participant Description

This study’s inclusion criteria are the mental health diagnosis of depression (ADDEPEV3) and the number of poor mental health days a respondent has had (MENTHLTH). The original number of samples is 200,000, but the filtered number of participants meeting this specific criterion is 40,061.

# III. Discussion of Results

## A. Analysis and Interpretation

The analysis revealed that the homelife variables "Living with Someone with a Mental Health Disorder" (ACEDEPRS), "Parents who Swear at You" (ACESWEAR), and “Own or Rent Home” (RENTHOM1) exert significant influence on depression diagnosis and poor mental health days. Minimal differences in these results exist between men and women. These insights provide valuable guidance for healthcare professionals in evaluating patients, tailoring interventions to address patients' specific homelife challenges, and improving mental health outcomes.

A graph with blue squares and black text

Description automatically generated

*Figure 1: ACE homelife variables with respect to women*

A graph with blue squares

Description automatically generated

*Figure 2: homelife variables with respect to men*

*A graph with blue squares

Description automatically generated*

*Figure 3: Married/Rent/Income homelife variables with respect to women*

*\*the ‘RENTHOM1’ variable refers to women who RENT a home rather than own one*

*A graph with blue squares

Description automatically generated*

*Figure 4: Married/Rent/Income homelife variables with respect to men*

*\*the ‘RENTHOM1’ variable refers to men who RENT a home rather than own one*

## B. Results vs. Baseline

To evaluate the impact of homelife variables on depression diagnosis and poor mental health days, the machine learning model must be compared to a baseline scenario. In the baseline scenario, no homelife variables are considered, therefore only the dataset is utilized to output a depression diagnosis and real response to poor mental health days with respect to different sexes.

## A blue rectangular graph with black text Description automatically generated

*Figure 3: depression/poor mental health days with respect to women*

*A blue rectangular graph with black text

Description automatically generated*

*Figure 4: depression/poor mental health days with respect to men*

## C. Results on Training and Testing

The Train MSE slowly rose as new variables were introduced and training took place, while the Train R2 Score decreased. The higher mean square error signals the model was becoming less accurate over time, and the lower R2 score signals the model’s difficulty with describing the variance in target variable over the training period. Overall, this means the model’s overall understanding from the training data decreased as training went on.

## D. Feature Importance

# The analysis of feature importance revealed that "Living with Someone with a Mental Health Disorder" (ACEDEPRS), "Parents who Swear at You" (ACESWEAR), and “Rent or Own Home” (RENTHOM1) are the most influential predictors of depression diagnosis and poor mental health days. These variables consistently displayed high weights across both demographics, men and women, indicating their strong association with adverse mental health outcomes and depression diagnoses. No gender-specific outputs were different, which suggests the impact that homelife variables have on the output of depression and poor mental health days does not vary greatly between men and women.

# IV. Significance and Limitations

## A. Implications and Potential Limitations

With these results, psychiatrists might be able to weigh a patient’s response of ‘Yes’ to if they live with someone with a mental health disorder, if their parents swear at them, and if they rent rather than own a home at a greater level when evaluating a patient at risk of depression. One potential limitation of this study is the absence of distinct categorization between respondents of different ages. Incorporating this criterion might help psychiatrists understand which age ranges are impacted greater by their homelife experiences and are at a higher risk of developing depression.

## B. Future Applications

This study allows psychiatrists to understand the impact of homelife variables on one’s depression diagnosis. By understanding which variables have a greater impact on one’s mental health, psychiatrists might understand which survey questions hold greater significance and are necessary to ask when evaluating a patient. Additionally, this machine learning algorithm could be implemented within an AI-conducted survey, which asks patients about their homelife before their psychiatric examination, giving the psychiatrist a greater understanding of their potential diagnosis before their interview.

## C. Broader Implications and Societal Benefits

This study may lead to improved diagnosis accuracy, leaving less room for psychiatrists to question their diagnosis. Additionally, by evaluating one’s homelife with respect to their mental health, earlier intervention and prevention might be possible. Because machine learning algorithms can analyze large datasets, individuals at higher risk of depression due to their homelife experiences may be identified and take action to mitigate the risk. Moreover, by understanding how homelife variables contribute to depression, psychiatrists can personalize their treatment plans to each patient in an effort to address special challenges or stresses present in the patient’s home.