

Exploring the Impact of Pet Ownership, Age, and BMI Status on Depression*

An Analysis of Depression Status in Bangladesh in 2020

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The paper examines the factors influencing depression in Bangladesh in 2020. Using dataset from US National Library of Medicine, we employ logistic regression analysis to explore the influence of individual's pet ownership, age, and BMI status on the depression status. We find that pet owners are less likely to experience depression. Younger and middle-aged individuals are more susceptible to depression compared to elderly. Underweight individuals have a higher risk of depression compared to overweight and obese individuals. These findings can provide additional methods and approaches for addressing and alleviating depression, as well as new insights and ideas for research and treatment of depression.

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*Code and data are available at: https://github.com/YimiaoYuan09/Depression_Analysis

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1 Introduction

According to estimates, 3.8% of the global population suffers from depression, with approximately 700,000 people dying from depression each year (Staff 2023). It can affect a person's ability to work, their relationships, and undermines their quality of life. Therefore, it is important to find the causes of depression and how various demographic, economic, and social factors may influence individuals' depression status. While there is a lot of research exploring the factors influencing depression, studies specific to Bangladesh are scarce. We analyzed the depression status data from Bangladesh in 2020, obtained from a cross-sectional comparative study provided by the US National Library of Medicine (Chakma et al. 2021). We use the dataset from the study to establish a predictive model for individual depression status. This enabled us to discover how demographic and social factors influenced the depression status in 2020.

In this paper, we use a logistic regression model to predict depression status, as it is the optimal choice for predicting binary outcomes, such as depression status (depression or non-depression). The analysis focuses on estimating the likelihood of people being depressed or non-depressed, based on various factors captured in the dataset. We selected pet ownership, age, BMI status, and depression status from the dataset for analysis.

The estimand in this paper is the number of individuals who are depressed or non-depressed in reality. However, due to various reasons and difficulties, not all Bangladeshis will be assessed, making it challenging to measure the exact number of individuals who are depressed or non-depressed. Therefore, in this paper, we attempt to estimate the estimand using a logistic regression model trained with the 2020 depression status dataset from the US National Library of Medicine.

The logistic regression model indicates that in Bangladesh in 2020, pet owners are more likely to be non-depressed. As age increases, people are more likely to experience depression. However, for those over 56 years old, they are less likely to be depressed. Additionally, individuals who are underweight have a higher risk of depression compared to those who are overweight or obese.

The remainder of this paper is structured as follows. Section 2 displays the data used in the report, including tables and graphs to illustrate the statistical summaries and relationships between variables. Section 3 builds the model and discusses its justification and interpretation. Section 4 highlights the prediction results using tables and graphs. Section 5 contains discussions that conducted based on the findings, which addresses the depression status based on pet ownership, age, and BMI status.

Statistical programming language R (R Core Team 2023) is used in this report, with packages `tidyverse` (Wickham et al. 2019), `here` (Müller 2020), `rstanarm` (Goodrich et al. 2022), `modelsummary` (Arel-Bundock 2022), `ggplot2` (Wickham 2016), `haven` (Wickham, Miller, and Smith 2023), `knitr` (Xie 2014), `marginaleffects` (Arel-Bundock 2024), `tibble` (Müller and

Wickham 2023), `margins` (Leeper 2021), `testthat` (Wickham 2011) and `kableExtra` (Zhu 2021).

2 Data

2.1 Data Source

In this report, I use data from the 2020 Cross-Sectional Comparative Study of Depression in Bangladesh provided by the US National Library of Medicine as the primary dataset (Chakma et al. 2021). The dataset uses both online and offline methods to collect data. The questionnaire was divided into two main sections including socio-demographic questions and depression assessment. The first section asked participants about their place of residence, age, gender, height, weight, lifestyle habits, pet ownership and other questions. The second part used the Patient Health Questionnaire 9 (PHQ-9) depression scale to measure depression. The PHQ-9 is scored according to the Primary Care Evaluation of Mental Disorders Patient Health Questionnaire (PRIME-MD PHQ), and is a reliable and accurate measure of the severity and significance of depression. A total of 280 responses were recorded in the dataset, including 140 pet owners and 140 non-pet owners.

2.2 Features

The original dataset, which shows in Table 1, contains 280 responses and 19 variables. We choose to use these 6 variables: “Group”, “Agegroup”, “Gender”, “BMIStatus”, “Depressionstatus” and “Typeofpet” in our analysis. Information about other variables is shown in the Appendix Section A.

1. Group: the group of the respondent; numeric numbers starting from 0 correspond to options “Pet Owners” and “Non-Pet Owners” respectively.
2. Agegroup: the age group of the respondent; numeric numbers starting from 0 correspond to options “Less than 15 Years”, “15-25 Years”, “26-35 Years”, “36-45 Years”, “46-55 Years”, and “Greater than 56 Years”, respectively.
3. BMIStatus: the nutritional status of the respondent based on Body Mass Index (BMI); numeric numbers starting from 0 correspond to options “Under Weight”, “Normal Weight”, “Over Weight”, and “Obese”, respectively.
4. Depressionstatus: the depression status of the respondent; numeric numbers starting from 0 correspond to options “Depressed” and “Non-depressed” respectively.

Table 1: Preview of the raw depression status dataset

(a)

id	Group	Agegroup	Gender	Marital	BMIStatus	IncomeGroup	Occupation
141	1	2	1	1	1	0	3
142	1	1	0	1	2	0	0
143	1	4	0	1	1	0	3
144	1	2	1	0	3	0	2
145	1	1	0	1	2	0	0

(b)

Religion	Education	Tobacco	Alcohol	Disability	phqtotal	Depressionstatus
0	0	1	1	1	1	1
0	0	1	1	1	2	1
0	0	0	1	0	13	0
0	0	1	1	1	9	1
0	0	1	1	1	0	1

(c)

DifficultyofWorking	Typeofpet	MonthGroupofhavingPets	Purposeofpets
0		NA	
0		NA	
1		NA	
1		NA	
1		NA	

5. Typeofpet: the type of pets owned by respondent; numeric numbers starting from 0 correspond to options “Dog”, “Cat”, “Bird”, “Rabbit”, “Dog and Cat”, “Dog and Bird”, “Dog, Cat, Bird and Rabbit”, “Cat and Bird”, “Cat, Bird and Rabbit”, “Bird and Rabbit”, and “Others”, respectively.

2.3 Data Measurement

Since the data was collected through self-reported questionnaires, the measurement accuracy of variables may be influenced by various external factors. Among the six variables we selected, “age group”, “BMI status”, and “depression status” are susceptible to external factors that could result in inaccurate data.

The survey was conducted through both online and offline methods. During face-to-face interviews, individuals, especially women, may wish to hide their true age. Similarly, when filling out online surveys, some people may choose to fill out the wrong weight because they are not happy with their real weight. In addition, some individuals may be reluctant to disclose their

Table 2: Preview of the cleaned depression status dataset

pet_group	age_group	gender	bmi_status	depression_status	pet_type
non-pet owners	26-35 years	female	normal weight	non-depressed	NA
non-pet owners	15-25 years	male	over weight	non-depressed	NA
non-pet owners	46-55 years	male	normal weight	depressed	NA
non-pet owners	26-35 years	female	obese	non-depressed	NA
non-pet owners	15-25 years	male	over weight	non-depressed	NA

Table 3: Statistics summary of the cleaned depression status dataset

pet_group	age_group	gender	bmi_status	depression_status	pet_type
non-pet owners:140	less than 15 years : 0	male :117	under weight : 28	depressed : 89	cat : 93
pet owners :140	15-25 years :126	female:163	normal weight:149	non-depressed:191	dog : 13
NA	26-35 years :142	NA	over weight : 75	NA	dog, cat : 12
NA	36-45 years : 7	NA	obese : 28	NA	cat, bird: 9
NA	46-55 years : 3	NA	NA	NA	bird : 5
NA	greater than 56 years: 2	NA	NA	NA	(Other) : 8
NA	NA	NA	NA	NA	NA's :140

depression status and may intentionally select opposite choices when filling out the questionnaire. As a result, these inconsistencies may introduce bias and errors into our data, impacting the accuracy of our analysis.

2.4 Methodology

Since it is difficult to observe through many variables, this report will only explore and analyze through specific aspects. The original dataset contains demographic information about the respondents as well as health level and depression status. This report will only model and discuss the relationship between depression status and pet ownership, respondent's age, and respondent's BMI status. Other columns such as gender and pet type will also be kept in this report to explore some interesting relationships between the variables.

The dataset is cleaned by renaming the column names, selecting target columns, specifying the class of the columns, and changing the numbers in the table to corresponding description in the codebook to improve the readability. After the cleaning process, 280 rows and 6 variables remain. Table 2 shows a preview of the cleaned dataset.

Table 3 is a summary of the cleaned data, showing detailed statistics about the dataset. According to this table, we can see that the majority of the respondents are young adults, aged between 15 to 35 years. In this dataset, a higher percentage of these respondents are female. Furthermore, within the subset of respondents who reported pet ownership, a significant majority expressed a preference for owning cats.

2.5 Data Analysis

Figure 1 illustrates the distribution of different types of pets among respondents who identify as pet owners. From this graph, we can see that most of the respondents preferred to keep cats, with nearly 100 people, and only a small amount of people had more than two pets in their homes. In addition to cats, most people would choose to keep dogs or keep dogs and cats together to add some energy or enthusiasm to their homes.

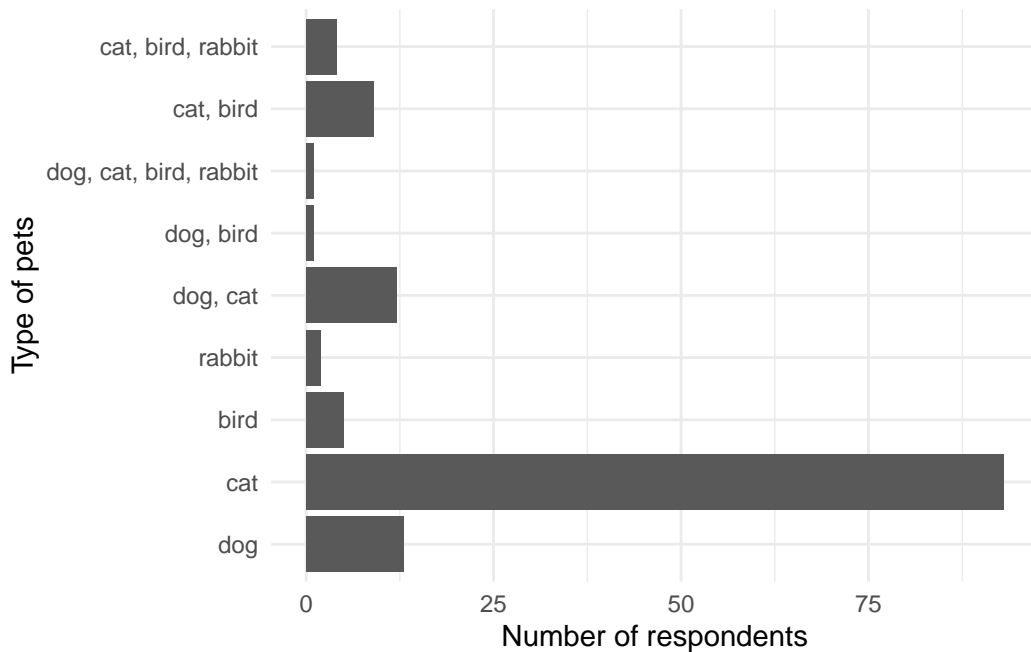


Figure 1: The distribution of pet species

Figure 2 shows the relationship between BMI status, pet ownership, and gender among respondents. As we can see from the graph, most respondents have normal weight, some are overweight, and only a small amount of people are falling into extreme categories, either underweight or obese. It is interesting to see that for women, there are more pet owners with normal weight than non-pet owners. However, the situation is different for men, as there are more normal weight non-pet owners than pet owners. Overall, pet owners tend to have a healthier weight compared to non-pet owners.

Figure 3 shows the relationship between depression status, pet ownership and age. As can be seen from the graph, the majority of respondents are between the ages of 15 and 35. Among respondents over the age of 36, the presence or absence of a pet have no significant effect on depression. However, for young people, pets seem to have a greater impact, especially in the 15 to 25 age group. The presence and companionship of pets reduces the number of depressed people.

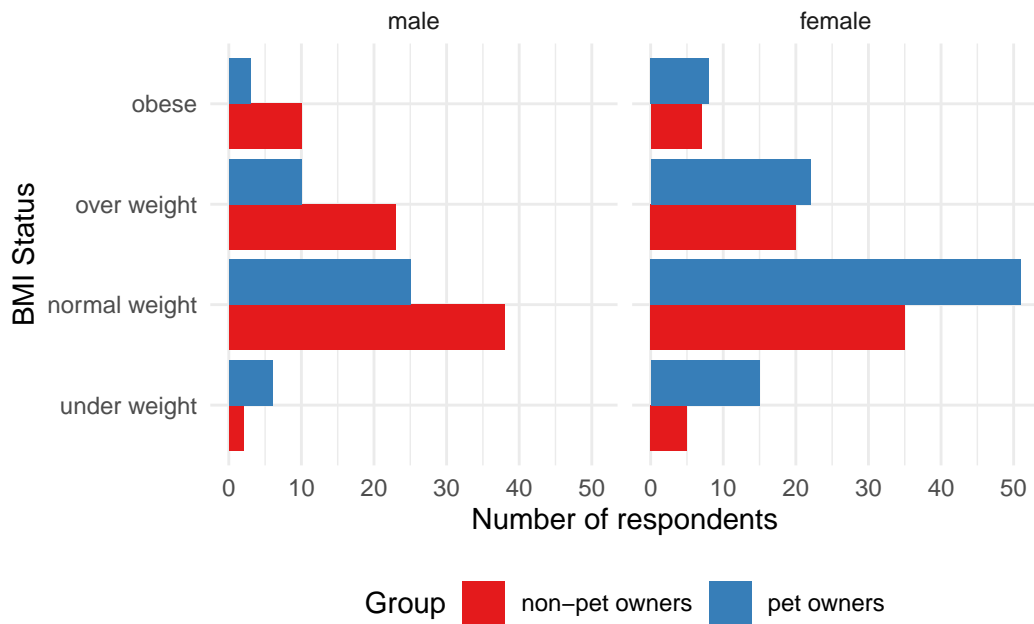


Figure 2: The relationship between BMI status and pet ownership by gender

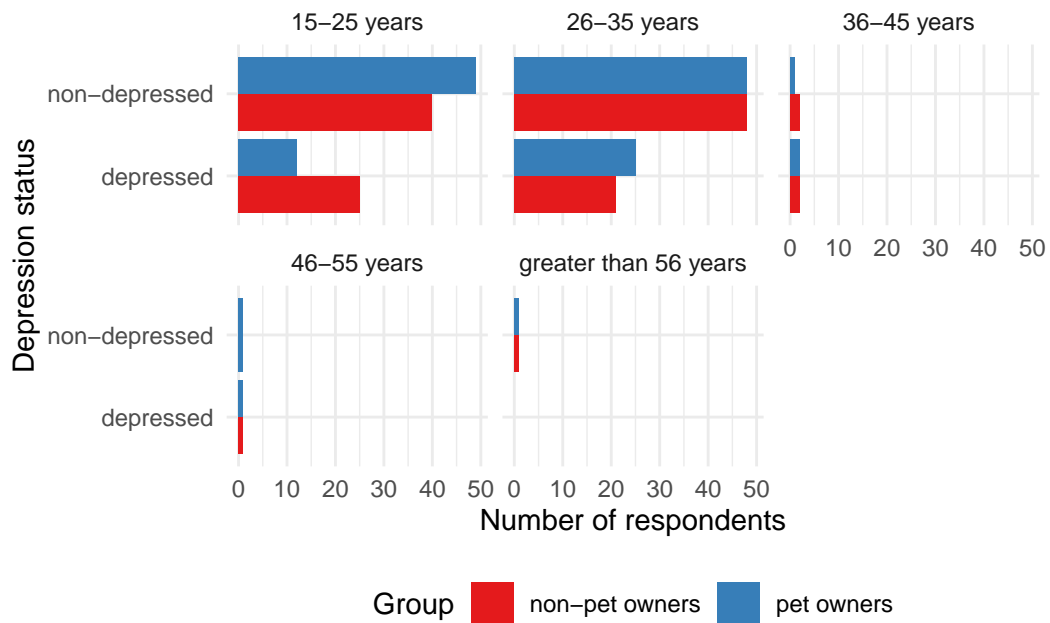


Figure 3: The relationship between depression status and pet ownership by age group

3 Model

3.1 Model Set-up

In this report, we use the Bayesian logistic regression model to analysis and examine the relationship between depression status and pet ownership, along with various demographic factors. The model is formulated as follows:

$$y_i | \pi_i \sim \text{Bern}(\pi_i) \quad (1)$$

$$\text{logit}(\pi_i) = \alpha + \beta_1 \times \text{pet ownership}_i + \beta_2 \times \text{age}_i + \beta_3 \times \text{BMI status}_i \quad (2)$$

$$\alpha \sim \text{Normal}(0, 2.5) \quad (3)$$

$$\beta_1 \sim \text{Normal}(0, 2.5) \quad (4)$$

$$\beta_2 \sim \text{Normal}(0, 2.5) \quad (5)$$

In this model, y_i represents the binary outcome variable indicating whether an individual is experiencing depression. The likelihood of depression (π_i) is captured through a logistic link function ($\text{logit}(\pi_i)$), which comprises a linear combination of the intercept (α) and the coefficients ($\beta_1, \beta_2, \beta_3$) corresponding to the predictor variables such as pet ownership, age, and BMI status. These predictor variables are denoted as `pet ownership_i`, `age_i`, and `BMI status_i`, where i indexes the individuals in the dataset.

Informative prior distributions are assigned to the intercept (α) and coefficients ($\beta_1, \beta_2, \beta_3$) to regularize the model. More specifically, we use a normal distribution with a mean of 0 and a standard deviation of 2.5 for each parameter. Additionally, enabling parameter autoscaling is employed to enhance the model's performance.

There are several reasons for choosing this model. Firstly, logistic regression is suited for binary outcome variables, hence it can be used to analyze depression status. Additionally, the utilization of Bayesian methods allows us to integrate prior knowledge and uncertainty into our analysis, resulting in more resilient estimations of the model parameters. Furthermore, by assigning prior distributions, Bayesian models can subtly tune the estimation procedure to reduce the risk of overfitting and improve the performance.

We also considered other modeling methods, such as linear regression model. However, we chose the Bayesian logistic regression model since the depression status is a binary variable.

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`. Rstanarm uses Markov chain Monte Carlo (MCMC) methods to estimate the posterior distribution of the parameters. Supplementary materials, such as convergence assessments and posterior summaries, can be found in Appendix Section B.

3.2 Model Justification

We expect a positive relationship between pet ownership and depression status, which means that pet owners are more likely to be non-depressed than non-pet owners. Pet owners spend a lot of time with and caring for their pets every day, including going out for walks, eating, drinking and taking medication. These trivial things can fill the gaps in life and prevent people from ruminating in their free time. At the same time, the soft touch and companionship of a pet can relieve stress and reduce negative emotions. Pets will also provide some daily exercise to help pet owners maintain a healthy body. People without pets may choose to play games, catch up on TV shows and other activities in their free time, but pet owners are more likely to choose some relatively healthy activities. The presence of pets gives people something to hold on to and rely on in their lives, and will make them more energized and motivated.

Conversely, we anticipate that there is a negative correlation between age and depression. We predict that compared to teenagers and the elderly, middle-aged people are more likely to experience depression. As age increases, people are under more pressure and have more things to consider, along with more responsibilities. Unlike childhood, where children freely shares their thoughts, middle-aged people tend to remain silent. Complex interpersonal relationships and pressure from different aspects increase the incidence of depression.

In terms of BMI status, we expect a negative relationship between underweight, overweight, and obesity and non-depressed status. This expectation arises from different lifestyles at different weights. People at extreme weights usually suffer from some physical or mental illness compared to normal people. These illnesses lead to lifestyle changes, such as reduced outdoor activities and lack of exercise. These factors negatively impact one's emotions, increasing the risk of depression. Overweight people may focus on managing their body weight. Due to large weight base, they may choose more unhealthy dieting methods to achieve weight loss goals, which can trigger eating disorders and further increase the risk of depression.

4 Results

4.1 Model Results

Our results are summarized in Table 4. Our results generally matches our expectation. Our model excluded one variable from each category as the reference level: `pet_group` Non-pet Owners, `age_group` 15-25 years, and `bmi_status` Normal Weight. The intercept represents the estimated log-odds of being non-depressed when all other predictor variables are held constant at their reference levels. In this scenario, for people who are non-pet owners, aged between 15 and 25 years, and have a normal BMI, the estimated log-odds of being non-depressed is 0.70.

People aged over 56 years are more likely to be non-depressed compared to other age groups. The estimated coefficient of 18.80 indicates that, holding all other variables constant, people

Table 4: Explanatory models of flight time based on wing width and wing length

	Non Depressed
(Intercept)	0.70 (0.27)
pet_group	pet owners 0.42 (0.27)
age_group	26-35 years -0.16 (0.27)
	36-45 years -1.30 (0.83)
	46-55 years -1.65 (1.34)
	greater than 56 years 18.80 (16.50)
bmi_status	obese 0.45 (0.49)
	over weight 0.08 (0.31)
	under weight -0.72 (0.45)
Num.Obs.	280
R ²	0.059
Log.Lik.	-169.659
ELPD	-179.8
ELPD s.e.	7.3
LOOIC	359.7
LOOIC s.e.	14.6
WAIC	358.0
RMSE	0.46

who aged over 56 years are estimated to have a 18.80 unit increase in the log-odds of being non-depressed compared to the reference group. However, people in other age groups are more likely to experience depression, with coefficients ranging from -0.16 to -1.65.

Having pets also affects the probability of non-depression. From the results, we can see that the coefficient for pet owners is 0.42, indicating that pets can help to reducing the likelihood of depression. However, this coefficient is not large, suggesting that the effect is moderate and not significant.

The coefficients for BMI status are slightly different from our expectations. Using individuals with a normal weight as the reference level, the coefficients for overweight and obese individuals are 0.08 and 0.45, respectively, which is a little bit surprising. Positive coefficients indicate that the overweight or obese people are more likely to be non-depressed, contrary to our expectations. However, these values are small, indicating that the correlation is not very strong.

Figure 9 (see Section B.3) displays the range of coefficient estimates of our model within a 90% probability range. Since the credibility interval for age_group “Greater than 56 years” is particularly large, we are unable to observe trends in the 90% confidence intervals of other variables. Therefore, we created Figure 10 and restricted the x-axis to -5 to 5 to obtain clear results.

Combining Figure 9 and Figure 10, we observe statistical significance for the coefficient estimates for individuals aged over 56 years and the intercept, non-pet owners between the ages of 15 and 25 who are of normal weight. Since the confidence interval does not cross 0, its estimate is significant. The estimates are in log-odds form, indicating that if the coefficient is positive, it means the person is not depressed, and if it is negative, the person is depressed.

4.2 Model Implication

For the posterior predictive checks in Figure 4, the great fit between the posterior distribution of our logistic regression model and the actual depression status data indicates that we accurately captured the depressive patterns. This suggests that our model’s predictions of whether individuals are likely to be depressed are accurate.

Figure 5 compares the posterior with the prior, which shows that besides the parameter “age_groupGreater than 56 years”, the changes in other parameters are minimal. Due to the low representation of “age_groupGreater than 56 years” in the dataset, the difference in the “age_group Greater than 56 years” parameter is not significant.

In the trace plot (Figure 6 and Figure 7), there are no indications of any anomalies. From the Rhat plot (Figure 8), we can see that all data points are close to 1 and do not exceed 1.05, indicating good convergence of the Markov chain Monte Carlo for our model.

More detailed explanation can be found in Appendix Section B.

5 Discussion

5.1 Influence of Pet Ownership on Mental Health

In Bangladesh, the levels of depression, anxiety, and stress has been reported to be as high as 54.3%, 64.8%, and 59.0%, respectively (Arusha and Biswas 2020). Depression is not an unfamiliar word in today's society. On the contrary, more and more people are suffering from depression, while the age of the sufferers is starting to get progressively younger. According to statistics, in Bangladesh, 14% of young people aged 15 to 24 often feel depressed or have little interest in doing things (Hossain 2021).

As people gain a deeper understanding of depression, more and more individuals are starting to pay attention to mental health, and extensive research is also beginning to explore methods for treating and preventing depression. In our analysis, the model supports that people who own pets are less likely to suffer from depression than those who do not own pets. There are also studies that show an association between pet ownership and lower levels of depression.

Pets can reduce stress, anxiety and depression, ease loneliness, encourage exercise and play, and even improve cardiovascular health. For example, birds can encourage social interaction and help keep your mind sharp. Even watching fish in an aquarium can help people reduce muscle tension and lower pulse rate (Robinson and Segal 2024).

In a U.S. research study, approximately 86% of pet owners reported that their pets had a positive impact on their mental health (Connors 2023). For pet-owning families, pets are not just animals. They are more like family members, an integral part of the household. Their presence can bring joy to your life and provide companionship during times of sadness and despair. While pets may only be a small part of your life, for them, you are their entire world. They are your concern and worry when you contemplate ending your life, and they also give you the courage to keep going.

5.2 Relationship between Physical Health and Depression

Our analysis highlights that underweight people are more likely to be depressed compared to normal weight people, while overweight and obese people are more likely to be un-depressed.

Some studies indicate that the greater the extreme values of the body mass index (BMI), whether very high or very low, the higher the risk of experiencing depressive symptoms (Badillo et al. 2022). Obesity affects parts of the brain that influence emotions. When individuals are feeling down, lack of energy and motivation may lead to a decrease in daily activities and exercise, which could contribute to weight gain, creating a vicious cycle. People with low body weight may be experiencing a certain illness or have anorexia nervosa, leading to insufficient food intake. Food can provide emotional comfort and enjoyment, and insufficient food intake or the mental burden caused by anorexia nervosa can affect mood, making people irritable, prone to anger, and anxious, thus increasing the risk of depression.

However, some studies suggest that obesity only becomes a risk factor for depression in cases of severe depressive relapse, and there is no association between these two factors in adolescent samples (Blasco et al. 2020). This may also be due to the reason that obese individuals tend to enjoy food more. They can derive pleasure from eating, leading to increased dopamine release and feeling happier, reducing the likelihood of depression onset.

Both extreme values of BMI are not ideal and can impact people's daily lives. Depression may result from a combination of genetic and/or biological factors, but environmental factors can also trigger depressive episodes (Badillo et al. 2022). Maintaining a healthy lifestyle, appropriate weight, and regular and balanced diet are essential to reduce the probability of depression.

5.3 Age Depression Connection

There is evidence that some natural body changes associated with aging may increase a person's risk of experiencing depression. Recent studies suggest that lower concentrations of folate in the blood and nervous system may contribute to depression, mental impairment, and dementia (Silk 2022). Our model shows that the risk of depression increases with age. However, individuals over the age of 56 are more likely to be non-depressed.

In a study conducted among adolescents in Bangladesh, it was found that among the 563 students aged 13-18, the prevalence of moderate to severe depression was 26.5% (Islam et al. 2021). Adolescence is a transitional period from childhood to adulthood, and a variety of physical, mental, and environmental changes can have an impact on their mental health. Adolescents face pressures from various aspects, including academic stress, conflicts with family or friends, being bullied in school or online, significant events or changes in their surroundings, all of which may cause depression. In addition, some parents may excessively prioritize their children's academic performance without caring about their mental health, arranging all kinds of tutoring classes and after-school homework, thus depriving these teenagers of time to relax and sleep, while also lacking an outlet for emotional release.

As these factors persistently impact an individual, the likelihood of developing depression significantly increases. Furthermore, when some teenagers communicate with their families about their depression, parents not only do not pay attention to it, but also think that it is an excuse to avoid studying. The lack of understanding and treatment can exacerbate the depression and ultimately lead to irreversible consequences.

As people age, middle-aged people enter a busy and depressing stage. They need to struggle for their jobs while also taking care of their parents and maintaining family's living expenses. Activities such as chauffeuring children, doing laundry, and cooking become routine for many people. Financial stress, feelings of confusion and anxiety, and a gradually declining physical condition can all contribute to depression.

Compared to middle-aged people, the life of elderly people are relatively relax but can also be monotonous. Lack of companionship and physical ailments are the main causes of depression among the elderly. They are often anxious in their free time and feel they may be a burden to their children.

5.4 Weaknesses and Future Steps

One weakness is that the primary dataset has limitations. The sample size is small, and participants may have recall biases when reporting information. The study population was drawn from a township in Dhaka Metropolitan area, so the results may not be generalizable to other urban or rural areas. In addition, during data collection, some participants may try to hide their depression status, leading to potential biases in the data compared to the actual situation.

Furthermore, our study establish correlation rather than causation. Since we only controlled for a few variables related to depression status, our results may lack essential variables, leading to omitted variable bias. For example, factors such as medication treatment and control, family understanding and companionship, and mood during questionnaire completion were not considered in the model but could potentially influence the final PHQ-9 score and depression status determination.

For future studies, we can incorporate more social factors, such as family perceptions, medication usage, and geographical regions, which are associated with depression status. Also, we can refine the grouping of each factor for more in-depth and detailed exploration and research. In addition, we should increase the sample size and collect data from people who from various areas and different environments to avoid sample bias. In order to infer causality, future research should adopt advanced methods and models to address selection bias and heterogeneity treatment bias.

Appendix

A Additional data details

Other variables in the primary dataset:

1. id: the sequential serial number.
2. Marital: the marital status of the respondent; numeric numbers starting from 0 correspond to options “Married”, “Unmarried”, “Divorced”, and “Widowed”, respectively.
3. IncomeGroup: the respondent’s average monthly family income in Bangladeshi Taka (BDT); numeric numbers starting from 0 correspond to options “Less than 60000 BDT” and “Greater than 60000 BDT” respectively.
4. Occupation: the respondent’s occupation; numeric numbers starting from 0 correspond to options “Job Holder”, “Business”, “Homemaker”, and “Others”, respectively.
5. Religion: the respondent’s religion; numeric numbers starting from 0 correspond to options “Islam” and “Others” respectively.
6. Education: the education level of the respondent; numeric numbers starting from 0 correspond to options “Greater than 12 Years Schooling” and “Less than 12 Years Schooling” respectively.
7. Tobacco: whether the respondent is a smoker; numeric numbers starting from 0 correspond to options “Yes” and “No” respectively.
8. Alcohol: whether the respondent drinks alcohol; numeric numbers starting from 0 correspond to options “Yes” and “No” respectively.
9. Disability: the physical disability status of the respondent; numeric numbers starting from 0 correspond to options “Yes” and “No” respectively.
10. phqtotal: the total PHQ-9 Score of the respondent.
11. DifficultyofWorking: the respondent’s difficulty in working, taking care of things or getting along with people with respect to PHQ-9 responses; numeric numbers starting from 0 correspond to options “Difficult” and “Not Difficult” respectively.
12. MonthGroupofhavingPets: the amount of time pet owners spend living with their pets; numeric numbers starting from 0 correspond to options “Less than 75 Months” and “Greater than 75 Months” respectively.
13. Purposeofpets: the purpose of pet owners living with their pets; numeric numbers starting from 0 correspond to options “Companion/Friend” and “Others” respectively.

B Model details

B.1 Posterior Predictive Check

In Figure 4, we implement a posterior predictive check. This compares the actual depression status of individuals with simulations from the posterior distribution through our logistic regression model. In this graph, we can see that the differences between the posterior distribution and actual data are minimal, indicating that the model is doing a good job of fitting the data and accurately captures the observed data patterns. Therefore, the posterior is able to generate simulated data that closely resembles the actual data (Gelman et al. 2020), which indicates that our logistic regression model effectively represents people’s actual depression status.

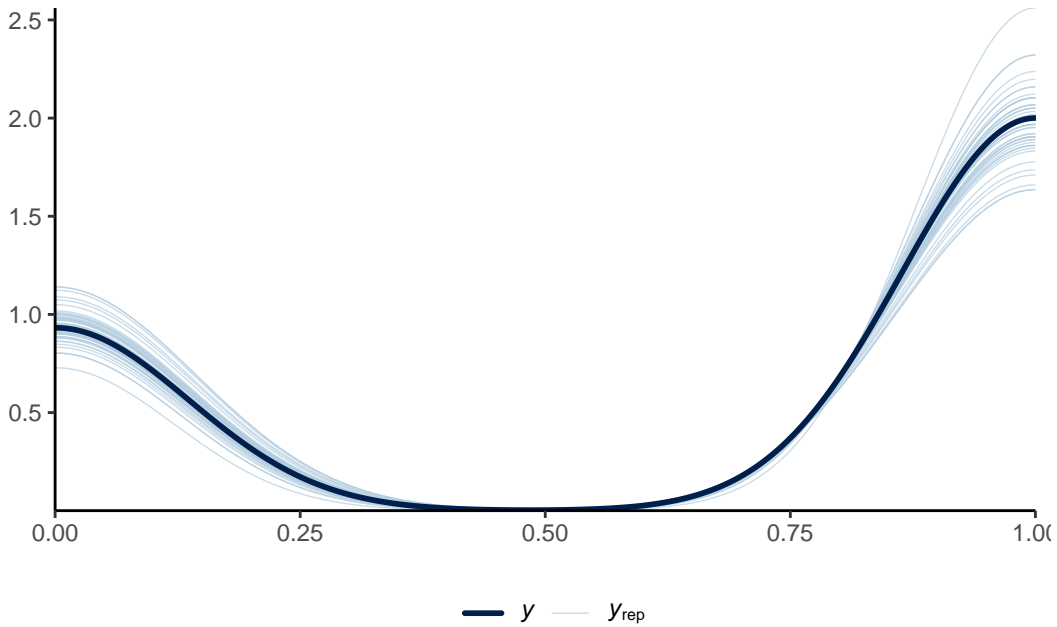


Figure 4: Posterior distribution for logistic regression model

In Figure 5, we compare the posterior with the prior. We can see that majority of the model parameters do not change once data are taken into account. This suggests that the observed data aligns with our initial beliefs and expectations regarding people’s depression status. However, for the “age_group Greater than 56 years” parameter, there is a shift in the posterior distribution compared to the prior distribution after we input the observed data. This may suggest that the observed data for the “age_group Greater than 56 years” contradicts our initial assumptions. Since the percentage of the “greater than 56 years” age group in our dataset is only 0.71% (as shown in Table 3, 2 out of 280), this isn’t a major concern.

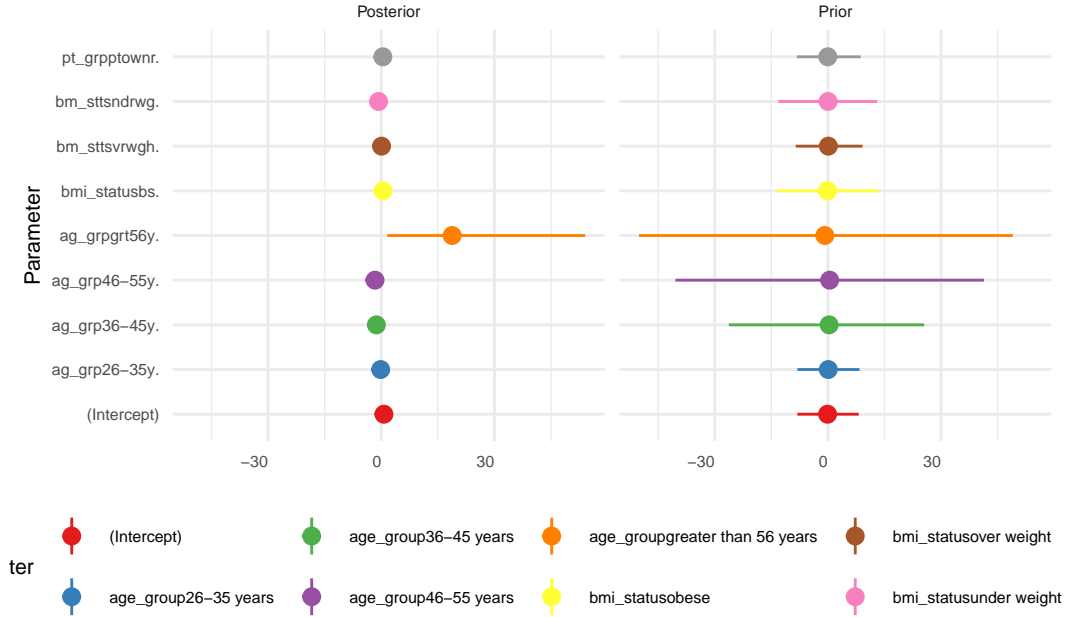


Figure 5: Comparing the posterior with the prior

B.2 Markov Chain Monte Carlo Convergence Check

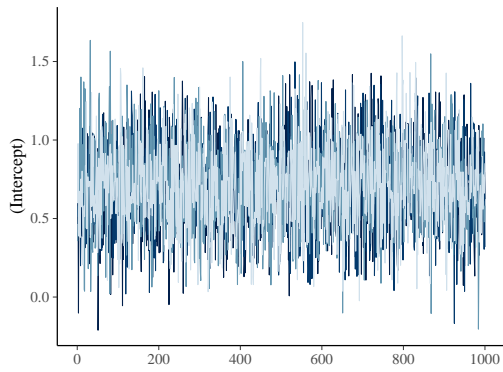
Trace plot and Rhat plot are used to check the convergence of the MCMC algorithm.

Figure 6 and Figure 7 are the trace plot of the model. It indicates whether there are signs of operational issues with our model. We observe that the lines are horizontal, oscillating, and have a nice overlap between the chains. The trace plot does not suggest anything out of the ordinary.

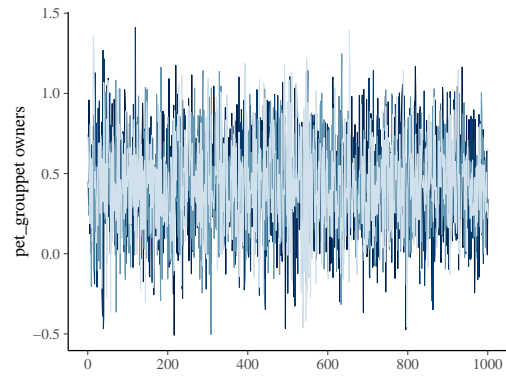
Figure 8 is the Rhat plot of the model. We can observe that everything is close to 1, and no more than 1.05, indicating that it does not suggest any problems.

B.3 Credibility Interval

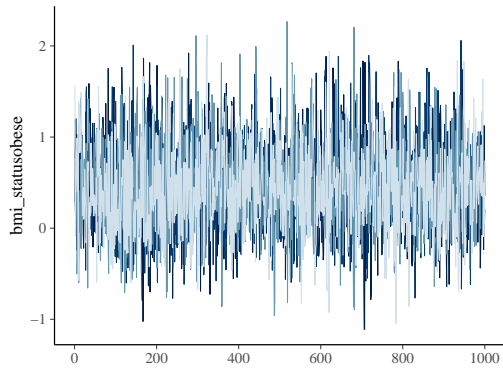
Figure 9 and Figure 10 shows the 90% credibility interval of the model.



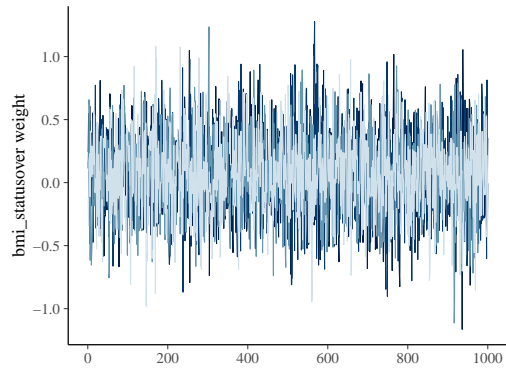
(a) Trace plot of Intercept



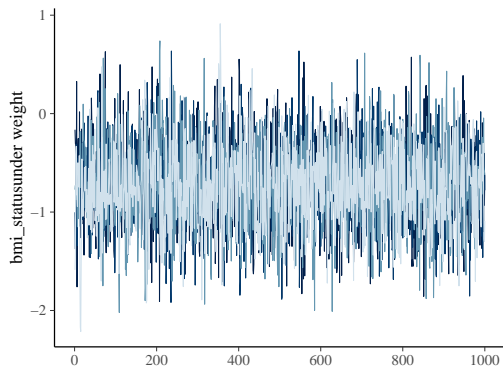
(b) Trace plot of pet_group Pet Owners



(c) Trace plot of bmi_status Obese

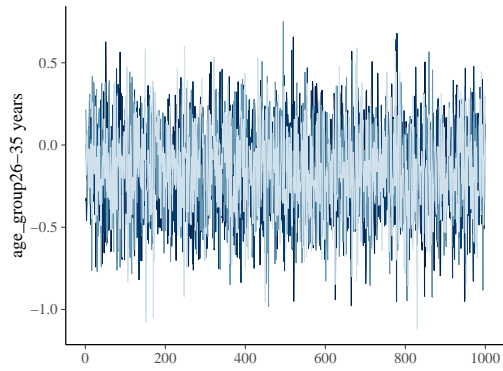


(d) Trace plot of bmi_status Over Weight

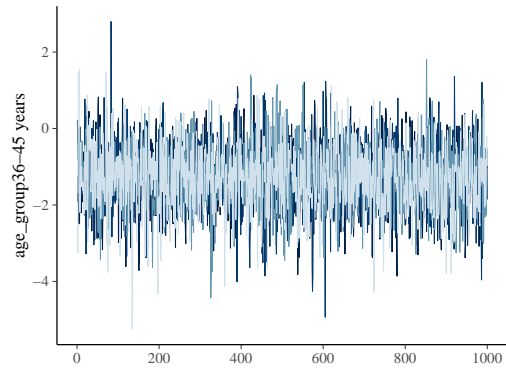


(e) Trace plot of bmi_status Under Weight

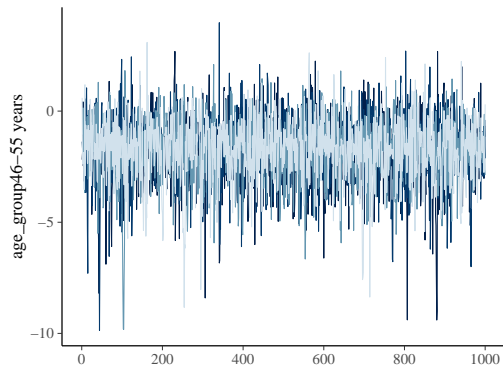
Figure 6: Trace plot of intercept, pet group and bmi status



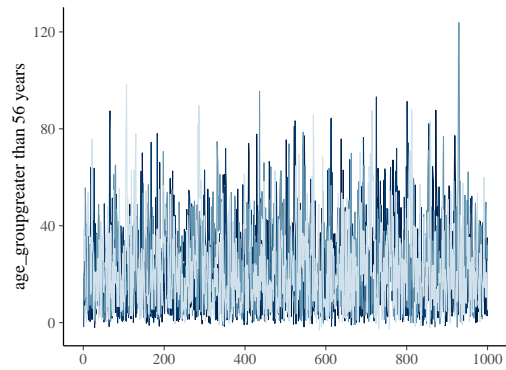
(a) Trace plot of age_group 26-35 years



(b) Trace plot of age_group 36-45 years



(c) Trace plot of age_group 46-55 years



(d) Trace plot of age_group Greater than 56 years

Figure 7: Trace plot of age group

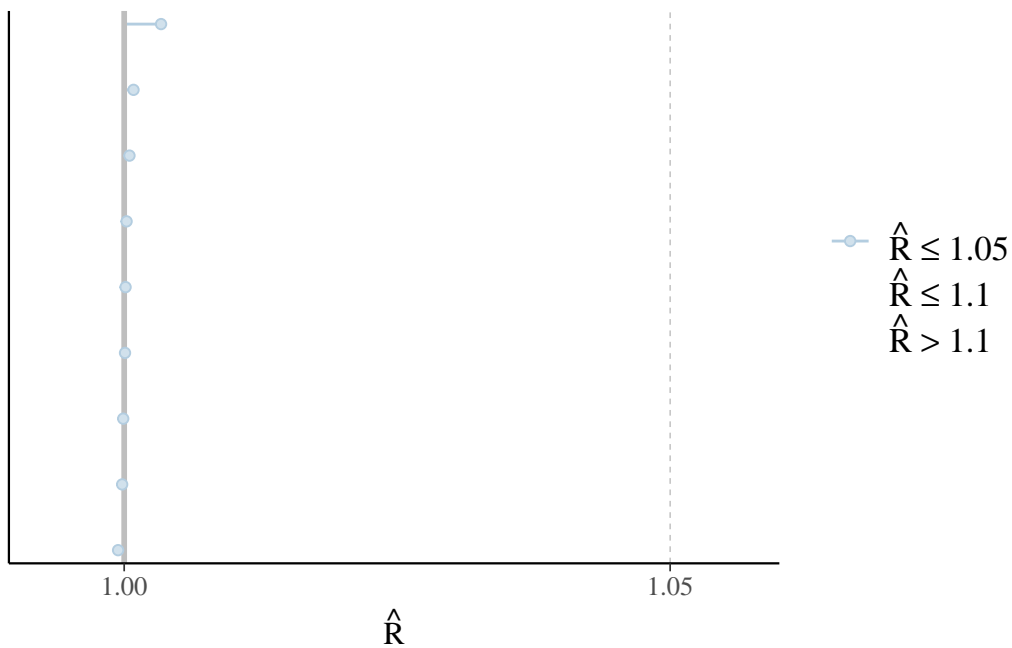


Figure 8: Rhat plot

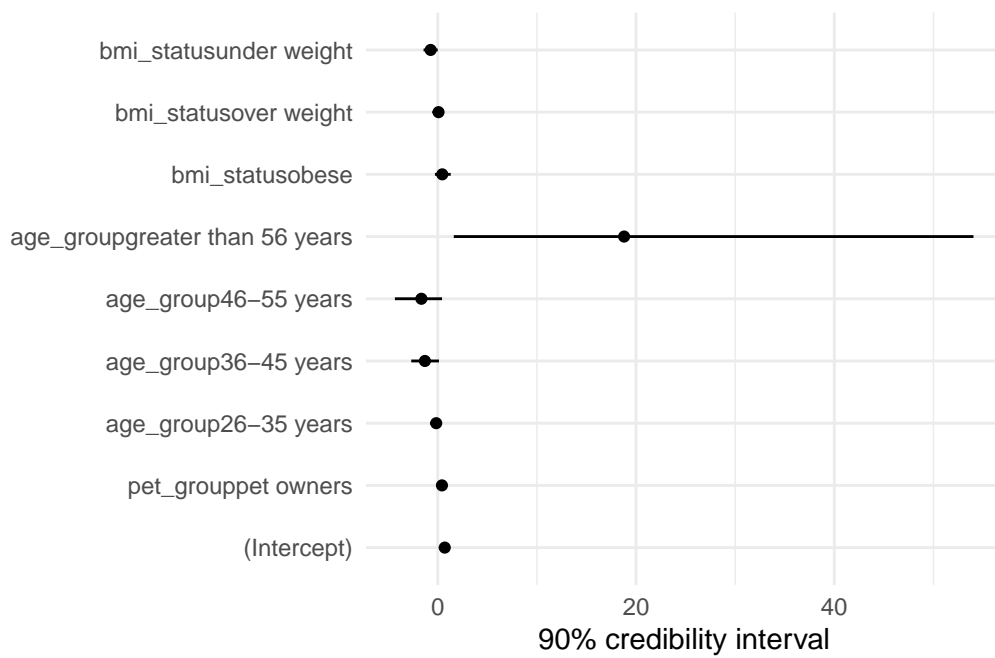


Figure 9: Credible intervals for predictors of non-depression

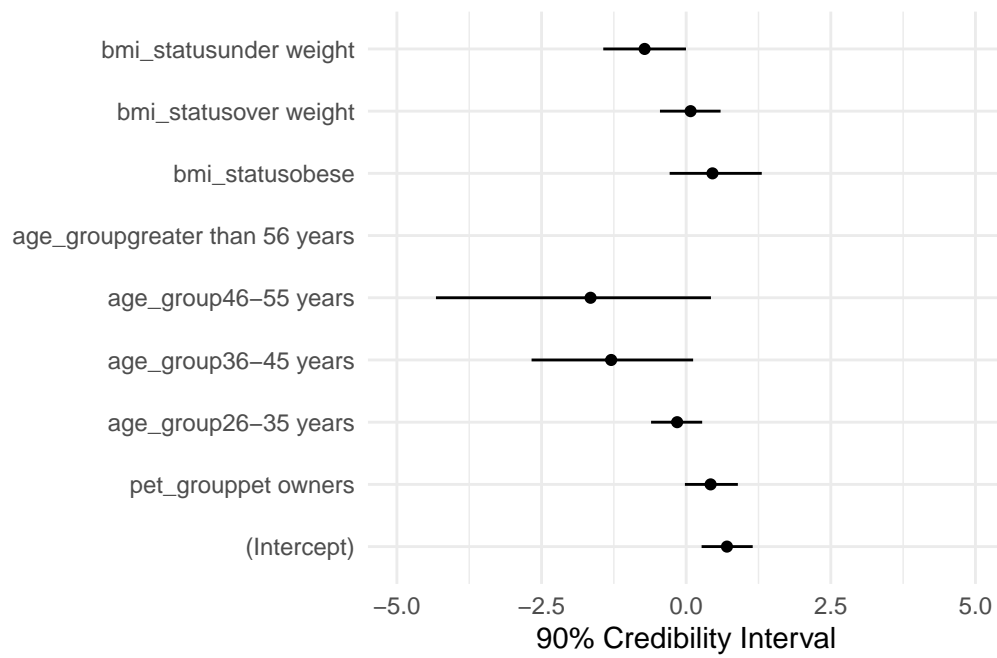


Figure 10: Credible intervals for predictors of non-depression with x_axis limits

References

- Arel-Bundock, Vincent. 2022. “modelssummary: Data and Model Summaries in R.” *Journal of Statistical Software* 103 (1): 1–23. <https://doi.org/10.18637/jss.v103.i01>.
- . 2024. *MarginalEffects: Predictions, Comparisons, Slopes, Marginal Means, and Hypothesis Tests*. <https://CRAN.R-project.org/package=marginalEffects>.
- Arusha, Anowara Rayhan, and Raaj Kishore Biswas. 2020. “Prevalence of Stress, Anxiety and Depression Due to Examination in Bangladeshi Youths: A Pilot Study.” *Children and Youth Services Review*. U.S. National Library of Medicine. [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7367775/#:~:text=In%20Bangladesh%2C%20the%20levels%20of,et%20al.%2C%202019\)](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7367775/#:~:text=In%20Bangladesh%2C%20the%20levels%20of,et%20al.%2C%202019)).
- Badillo, Nathan, Mohammed Khatib, Payal Kahar, and Deepesh Khanna. 2022. “Correlation Between Body Mass Index and Depression/Depression-Like Symptoms Among Different Genders and Races.” *Cureus*. U.S. National Library of Medicine. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8896404/#:~:text=The%20greater%20the%20extreme%20of,compared%20to%20men%20%5B14%5D>.
- Blasco, Beatriz Villagrasa, Jesús García-Jiménez, Isabel Bodoano, and Luis Gutiérrez-Rojas. 2020. “Obesity and Depression: Its Prevalence and Influence as a Prognostic Factor: A Systematic Review.” *Psychiatry Investigation*. U.S. National Library of Medicine. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7449839/>.
- Chakma, Samar Kishor, Taswib Tajwar Islam, Md. Shahjalal, and Dipak Kumar Mitra. 2021. “Depression Among Pet Owners and Non-Pet Owners: A Comparative Cross-Sectional Study in Dhaka, Bangladesh.” *F1000Research*. U.S. National Library of Medicine. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8383123/>.
- Connors, Erin. 2023. “Americans Note Overwhelming Positive Mental Health Impact of Their Pets in New Poll; Dogs and Cats.” *Psychiatry.org - Americans Note Overwhelming Positive Mental Health Impact of Their Pets in New Poll; Dogs and Cats*. <https://www.psychiatry.org/news-room/news-releases/positive-mental-health-impact-of-pets>.
- Gelman, Andrew, Aki Vehtari, Daniel Simpson, Charles C. Margossian, Bob Carpenter, Yuling Yao, Lauren Kennedy, Jonah Gabry, Paul-Christian Bürkner, and Martin Modrák. 2020. “Bayesian Workflow.” <https://arxiv.org/abs/2011.01808>.
- Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. “Rstanarm: Bayesian Applied Regression Modeling via Stan.” <https://mc-stan.org/rstanarm/>.
- Hossain, Imran. 2021. “UNICEF: 14.” *Dhaka Tribune*. <https://archive.dhakatribune.com/bangladesh/2021/10/05/unicef-battered-by-pandemic-kids-need-mental-health-help>.
- Islam, Md. Saiful, Md. Estiar Rahman, Mst. Sabrina Moonajilin, and Jim van Os. 2021. “Prevalence of Depression, Anxiety and Associated Factors Among School Going Adolescents in Bangladesh: Findings from a Cross-Sectional Study.” *PloS One*. U.S. National Library of Medicine. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8016317/>.
- Leeper, Thomas J. 2021. *Margins: Marginal Effects for Model Objects*.
- Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files*. <https://CRAN.R-project.org/package=here>.
- Müller, Kirill, and Hadley Wickham. 2023. *Tibble: Simple Data Frames*. <https://CRAN.R->

- [project.org/package=tibble](https://www.R-project.org/package=tibble).
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Robinson, Lawrence, and Jeanne Segal. 2024. “The Health and Mood-Boosting Benefits of Pets.” *HelpGuide.org*. <https://www.helpguide.org/articles/mental-health/mood-boosting-power-of-dogs.htm#:~:text=Pets%2C%20especially%20dogs%20and%20cats,valuable%20companionship%20for%20older%20adults>.
- Silk, Susan. 2022. “Aging and Depression.” *American Psychological Association*. American Psychological Association. <https://www.apa.org/topics/aging-older-adults/depression#:~:text=There%20is%20evidence%20that%20some,%2C%20mental%20impairment%2C%20and%20dementia>.
- Staff, World Health Organization. 2023. “Depressive Disorder (Depression).” *World Health Organization*. World Health Organization. <https://www.who.int/news-room/fact-sheets/detail/depression>.
- Wickham, Hadley. 2011. “Testthat: Get Started with Testing.” *The R Journal* 3: 5–10. https://journal.r-project.org/archive/2011-1/RJournal_2011-1_Wickham.pdf.
- . 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. <https://ggplot2.tidyverse.org>.
- Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Grolmund, et al. 2019. “Welcome to the tidyverse.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.
- Wickham, Hadley, Evan Miller, and Danny Smith. 2023. *Haven: Import and Export ‘SPSS’, ‘Stata’ and ‘SAS’ Files*. <https://CRAN.R-project.org/package=haven>.
- Xie, Yihui. 2014. “Knitr: A Comprehensive Tool for Reproducible Research in R.” In *Implementing Reproducible Computational Research*, edited by Victoria Stodden, Friedrich Leisch, and Roger D. Peng. Chapman; Hall/CRC.
- Zhu, Hao. 2021. *kableExtra: Construct Complex Table with ‘Kable’ and Pipe Syntax*. <https://CRAN.R-project.org/package=kableExtra>.