Depression's Influence on Academic Performance

By Harley Clifton, Sara Bancale, and Matt McMahon

I. Background

Depression is a common mental health issue among students which may be influenced by many extraneous factors (e.g. comparison of academic achievements to peers, relationship issues, stressful life events, etc.). Many students who struggle with depression experience decreased energy, lack of motivation, and often struggle with school work and due dates (Mayo Clinic Health System, 2021).

The PHQ-9 form, where patients suspected of depression self-report their symptoms and severity of symptoms, consists of 9 questions, each scored 0 to 3, for a total severity score between 0 and 27. Scores for the PHQ-9 form of 5, 10, 15, and 20 represent the minimum scores that qualify as someone having mild, moderate, moderately severe, and severe symptoms of depression respectively (Eack, 2006) (Form 1). The PHQ-9 form is recommended by the DSM-V, the Diagnostic and Statistical Manual of Mental Disorders, and used as the standard tool for measuring and diagnosing depression by medical professionals across the country. When a patient has diagnosed depression, or their doctor suspects they have symptoms of depression, they will be given the PHQ-9 form to fill out routinely at their appointments. There is potential for response bias since patients may underreport the severity of symptoms in fear of the consequences of being completely transparent with their health care provider. However, since depression symptoms are not visual, self-reporting is the only way to detect them.

We suspect that higher levels of depression will result in a higher likelihood of students being placed on academic probation, and are curious if the data support this or if there are other confounding variables that contribute to a change in performance.

II. Data Set Description

This data set was sourced from *Kaggle*, a data-sharing platform open to the public, and shared by an individual named Kane Rudolph (2021). The data was collected via surveying students at varying education levels across the United States. A total of 352 students' responses to the questionnaire - completed with informed consent - were included in the study. Of the 352 students, 124 were high schoolers, 204 were undergraduates pursuing their Bachelor's degree, and the remaining 24 were graduate students enrolled in Master's programs.

The raw data set consists of 18 different variables of which 15 were of interest to us. Sex is an indicator variable with two levels: female and male. Age is a categorical indicator with three levels, "18 years or less", "19 to 24 years", and "25 years and above". Educational Level specifies the degree each subject is pursuing, with three levels, "High School", "Bachelors", and "Masters". Variables four through twelve are the individual questions on the PHQ-9 form (Form 1). In this dataset, subjects ranked each question on a scale of 1-4, 4 being the highest, as opposed to the normal 0-3 ranking scale. The Job status variable has three levels: "None", "Part-time", and "Full-time". Living Situation indicates where the student lived during the school term with three levels; "Home (with parents)", "Private rented accommodation", and "University hall or Residence". Study time measures the amount of time the student spends studying each day with three levels: "1-2 hours", "3-4 hours", and "More than 4 hours". Next is the students' GPA from the previous semester, measured quantitatively.

We created and modified additional variables for our research purposes. 'DepressionScore' was created by summing all responses for each individual on the PHQ-9 questionnaire. The 'DepressionScore' variable was adjusted to account for the difference between the total points possible on our questionnaire and the official scale by subtracting one point for every question in the PHQ-9 (total deduction of 9 points) from the overall score for each student. Subsequently, a categorical variable called 'DepressionLevel' was generated to provide a more descriptive assessment of the 'DepressionScore' variable. It was created according to the PHQ-9 guidelines of a Depression score of 0-4 as "Normal", 5-9 as "Mild", 10-14 as "Moderate", 15-19 as "Moderately

Severe", and 20+ as "Severe". Additionally, 'Standing' was created by mutating the GPA variable; a GPA < 2 indicates the student qualifies for academic probation, and a GPA ≥ 2 indicates a student is in good standing. Lastly, a Binary version of the Standing variable was created and called 'Stand.Bin', with a 0 representing good standing and a 1 representing probation - which will be considered a 'success' in our analysis. The 'Stand.Bin' variable will be our response since it allows us to measure the estimated probability of academic probation.

III. Scientific Goals and Primary Questions of Interest

We seek to explore the relationship between depression severity, measured via an individual's adjusted cumulative score on the PHQ-9 questionnaire, and academic performance. We aim to determine whether there is a measurable impact on overall passing grades. A GPA of 2.0 is the cutoff that most higher education institutions use to dictate whether a student is put on academic probation (Moody, 2019). If a student is placed on academic probation, typically a faculty member(s) will check in with the student and provide opportunities for additional support if needed. If a student fails to improve their performance over the academic probation period, they will face academic dismissal.

As students ourselves, we know that numerous factors may influence an individual's academic performance. Therefore, we want to determine if depression index (cumulative PHQ-9 score) is a good predictor of academic standing and explore potential confounding variables. Specifically, we are curious to discover how age, sex, job status, education level, living situation, and daily study time use relate to our two main variables of interest.

IV. Data Visualization

The relationships between variables of interest were visualized in R via a Scatterplot and Correlation matrix from the 'psych' package (Revelle, 2021) (Figure 1). Job Status and Age Group were correlated, although weakly (r = -0.22). A barplot was created using the 'ggplot2' package to visualize the counts of students with good standing and students on academic probation (Wickham,

2016) (Figure 2). Upon further examination, there are a total of 324 students that have good standing and 23 who qualify for academic probation in our sample. We suspect the disparity in the number of subjects in each category may be attributed to the time sensitivity of the academic dismissal decision process.

Additional plots were generated to inquire about other intriguing variables and relationships; these include a histogram showing the distribution of depression scores (Figure 3), a scatterplot displaying the relationship between depression scores and academic standing (Figure 4), and boxplots comparing the same variables indicating an outlier in the probation group (Figure 5) (R Core Team, 2021). To visualize the relationship between our two main variables of interest, an Enhanced Violin Plot was created with the ‘yarrr’ package in R (Phillips, 2017).

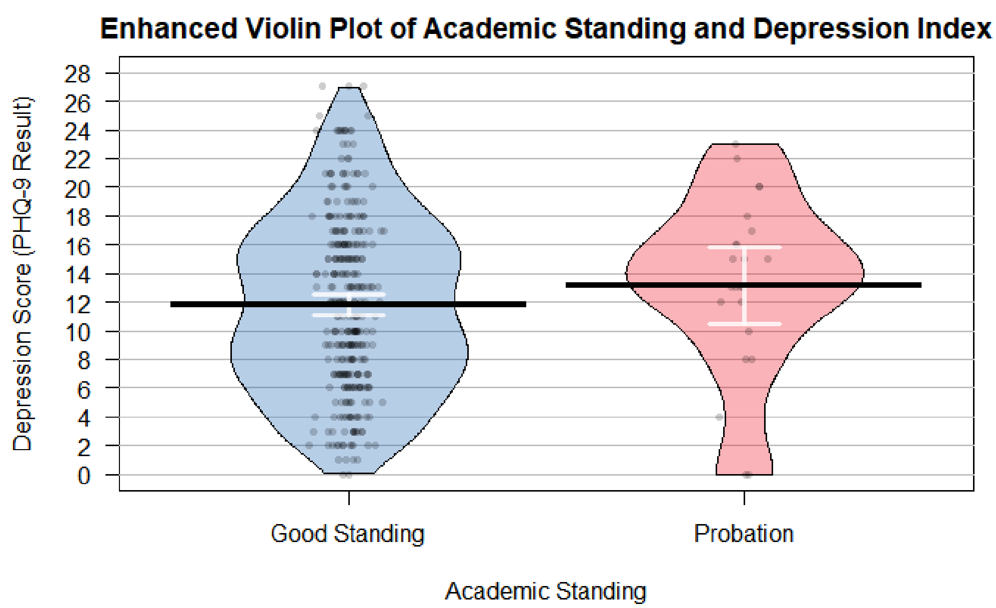


Figure 6: Enhanced Violin Plot of the Distribution of Depression Scores within each Academic Standing Category.

The plot above shows that, on average, depression scores for students with good standing are slightly lower compared to students on academic probation. Through further data exploration using the ‘mosaic’ package in R, the mean PHQ-9 score for those with good standing was 11.81 points compared to a mean of 13.17 points for those who qualify for academic probation (Pruim, 2017). It is also worth noting that the variability of depression scores in the probation group is much larger than for the good standing group; This is most likely due to the vast difference in the total number of students in each group.

Tables were generated to get a preliminary idea of the distribution of students on academic probation within the sex, age, and depression level subgroups (Tables 1, 2, & 3).

Table 1: Counts of Students within the combinations of Academic Standing and Sex.

		Sex	
		Female	**Male**
Academic Standing	**Good Standing**	286	38
	Probation	23	0

Table 1 indicated that there are notably more female participants than male participants. Surprisingly, none of the male participants in this sample qualified for academic probation. As a result, we cannot use 'Sex' as a predictor in our model since we would be unable to make valid predictions about the population of students. Table 2 explored the relationship between age groups and academic standing and found that there were no students 18 and younger in this sample who qualified for probation. Thus, we decided to remove the age group 18 or less altogether. Table 3 suggests that there are a larger number of students who have "Mild", "Moderate", or "Moderately Severe" depression compared to those with "Normal/Minimal" and "Severe" depression. Table 4 reveals that there are no Master's students who qualify for academic probation, meaning we cannot make realistic likelihood estimates - hence, why we excluded this level in our analysis. Interestingly, Table 5 displays an unexpected relationship between age groups and education levels in this data set. We expected the majority of students ages 18 or less to be high schoolers, but this was not the case.

V. Modeling

Since academic standing is a binary variable, modeling this data with logistic regression is appropriate. Initially, a full additive model was fit with academic standing as the response and included depression score, age, job status, education level, living situation, and daily study time as predictors. The summary of this model revealed large p-values for all of our predictors, indicating we have too many in our model (Table 6).

Since our main research question is to see how depression score influences a student's academic standing, we need to include that variable in the model. Model selection was conducted using the 'MuMIn' package in R on all models containing depression score as a predictor (Barton, 2022). The model with the lowest AIC score had depression score, job status, and their interaction as predictors. However, this model was only 1.64 AIC units better than the mean-only model, meaning there was equivocal support for both models. Hence, the interaction between job status and depression score called for further investigation.

Effects plots were generated with the 'effects' package (Fox and Weisberg, 2019) (Figures 7 & 8). The incongruity of the blue smoothing lines and the pink fitted lines in Figure 7, specifically for unemployed students, suggests missed curvature which indicates evidence of an interaction. Figure 8 illustrates that for both unemployed students and those who work full-time, higher depression scores are directly related to an increased likelihood of qualifying for academic probation. However, the opposite is true for students who work part-time; Higher depression indices are associated with a decrease in the likelihood that a student qualifies for academic probation. Since both effects plots provide evidence of an interaction between depression scores and job status, we chose to include the interaction term in the final model. Despite this model being within two AIC points of the mean-only model, we believe the mean-only model would result in insufficient information regarding the nuance in the relationship between these two variables.

The Final Estimated Model (Model 1), intended to predict the likelihood of academic probation based on a student's depression score and job status, is as follows:

$$log\left(\frac{\hat{\pi}}{1-\hat{\pi}}\right) = -3.30492 + 0.06797x_D + 2.53250 * I_{Job=PartTime} - 0.60706 * I_{Job=FullTime} - 0.23327(x_D * I_{Job=PartTime}) + 0.04044(x_D * I_{Job=FullTime})$$

Where $\hat{\pi}$ is the probability that an individual in our sample will be placed on academic probation, x_D is the cumulative result of the PHQ-9 questionnaire (recorded as an individual's Depression Score) in points, $I_{Job=PartTime}$ is an indicator variable that is 1 when the individual is working a part-time job and 0 otherwise, and $I_{Job=FullTime}$ is an indicator variable that is 1 when the individual is working a full-time job and 0 otherwise.

The standard suite of diagnostic plots was created in R, but since we are dealing with a binary response, most of our typical diagnostic tools are not applicable (R Core Team) (Figure 9). The only relevant diagnostic plot is the Residual vs. Leverage plot, which is used to assess whether the Pearson Residuals indicate a potential for influential points (R Core Team) (Figure 10). No points in our data set have a Cook's Distance greater than 0.5 in the Residual vs. Leverage plot, suggesting no evidence of influential points in our data set.

VI. Interpretations

Final Model: Model Coefficients and Confidence Intervals on the Response Scale.

	Estimate	**95% CI Lower Bound**	**95% CI Upper Bound**
(Intercept)	0.03670216	0.002905629	0.2530766
DepressionScore	1.07033487	0.931920639	1.2377777
Job = Part Time	12.58493415	0.963519540	231.1870373
Job = Full Time	0.54495135	0.035224234	10.4751672
DepressionScore:PartTimeJob	0.79193628	0.631427794	0.9702319
DepressionScore:FullTimeJob	1.04127021	0.872376878	1.2419959

The following interpretations are the exponentiated coefficients from our model, summarizing what the model communicates. The estimated odds of qualifying for academic probation for students with a depression score of 0 and no job are 0.03670216 to 1 (95% CI: 0.0029 to 0.2531). For unemployed students, a one point increase in depression score is associated with an estimated 7.03% increase in the odds of qualifying for academic probation (95% CI: 6.81% decrease to a 23.78% increase). Among individuals with the same cumulative PHQ-9 score, a part time job is associated with an estimated 1158% increase in the odds of qualifying for academic probation (95% CI: 3.648% decrease to 23018.7% increase). For students who score the same on the PHQ-9, a full time job is associated with an estimated 45.5% decrease in the odds of qualifying for academic probation (95% CI: 96.48% decrease to 947.52% increase). The estimated odds of qualifying for probation for students who work part time decrease by 20.81% for each additional point in the cumulative PHQ-9 score (95% CI: 36.86% decrease to 2.98% decrease). Interestingly, the estimated odds of qualifying for probation for students who have full time jobs increase by 4.13% for each additional point in the cumulative PHQ-9 score (95% CI: 12.76% decrease to 24.20% increase).

VII. Model Assessment

To evaluate how well our final model fits our data, we ran a Hosmer-Lemeshow Goodness of Fit Test using the 'ResourceSelection' package in R (Lele, 2019). This test is used to determine how well the observed number of students currently on academic probation matches the expected amount of students on academic probation. The results of the Hosmer-Lemeshow Test provide little to no evidence that the final model explains the data better than a mean-only model would (χ^2 = 5.135, df = 8, p-value = 0.7431). This result is expected since the final model was within two AIC points away from the mean-only model.

The primary purpose of this model is to predict how likely a student is to be placed on academic probation based on their depression score and job status. To assess the predictive ability of our model, we created a ROC curve using the 'ROCR' package in R (Sing, 2005) (Figure 11). In our context, the 'true positive rate' would translate to how often a student on academic probation was accurately predicted to be on academic probation; The 'false positive rate' would represent when a student is predicted to qualify for probation but actually has good standing. When visually gauging prediction accuracy, we noted our ROC curve is similar to what we would expect to see if the model were making predictions by random chance (Figure 11). After creating the plot, the area under the curve was calculated to quantify the model's prediction ability (Sing, 2005). The area under the ROC curve is about 0.6784, indicating that the model does not predict academic probation very well. Specifically, the probability that a randomly chosen student on academic probation has a higher estimated probability of probation than a randomly chosen student with good standing is 0.6784.

VIII. Discussion

Overall, we determined that a student's depression score is not a very useful tool to predict the likelihood of academic probation, given the results of our data. With proper funding and data collection methods, we believe a relationship between a student's depression score and academic standing may potentially be revealed. However, the data collection method and model provided insufficient evidence of such a relationship. It was intriguing to discover that both unemployed students and those who worked full time were more likely to qualify for probation with higher depression scores, but students who worked part time were less likely to qualify with higher PHQ-9 results.

This was an observational study and the data were obtained through a survey, so any statistical findings cannot be assumed to have a causal association. Since the data were not collected via a random sample, findings may be generalized only to individuals similar to those in the study (i.e. U.S students who consent to complete a PHQ-9 form when prompted).

In addition, using surveys for data collection introduces the potential for sampling biases. Not only is there potential for response bias, such as patients downplaying the severity of symptoms to avoid involuntary hospitalization, but individuals who fill out the PHQ-9 form may be fundamentally different than the overall population of students with depression. It is likely that students who are prompted to complete a PHQ-9 form are actively seeking out medical help. Whether it be for symptoms of depression or other reasons, students who actively seek medical aid may differ from students who avoid medical attention for the purposes of this study.

One observed oddity is that the source advertised the data set as exploring the relationship between academic performance and symptoms of depression and anxiety. This suggested that students who participated took the General Anxiety Disorder assessment (GAD-7) as well, but results from this form were not included in the data. Unfortunately, this could be an unaccounted for confounding variable as depression and anxiety are often comorbidities; Anxiety disorders are associated with a unique set of debilitating symptoms that may contribute to a student's performance in school.

Should further research be conducted, some form of random sampling would be preferable for the generalizability of findings and independence of observations. We recommend collecting data regarding each student's cumulative GAD-7 score in addition to the existing variables. Including anxiety as a predictor in our model may better explain academic performance. Once in the model, there is potential for an interaction between depression and anxiety score, meaning the relationship between depression score and academic performance may differ with different levels of anxiety. Thus, the interaction between symptoms of depression and anxiety on academic performance is important to explore.

Appendix

References

H. Wickham. The ggplot2 Package: Elegant Graphics for Data Analysis (2016). Springer-Verlag New York. https://ggplot2.tidyverse.org.

J. Fox and S. Weisberg. The effects Package: Visualizing Fit and Lack of Fit in Complex Regression Models with Predictor Effect Plots and Partial Residuals (2018). Journal of Statistical Software, 87(9):1-27. https://doi.org/10.18637/jss.v087.i09.

J. Moody. "What Academic Probation Is and How to Avoid It." (2019). U.S. News & World Report, U.S. News Education, 2 Apr. 2019, www.usnews.com/education/best-colleges/articles/2019-04-02/what-academic-probation-is-and-how-to-avoid-it.

K. Barton. The MuMIn Package: Multi-Model Inference (2022). R package version 1.46.0. https://CRAN.R-project.org/package=MuMIn

K. Rudolph. "Depression and Academice Performance of Students" (2021). *Kaggle*. https://www.kaggle.com/datasets/kanerudolph/depression-and-academic-performance-of-students.

Mayo Clinic Health System. College students and Depression (2021). Mayo Clinic Health System. Retrieved April 8, 2022. https://www.mayoclinichealthsystem.org/hometown-health/speaking-of-health/college-students-and-depression.

N. Phillips. The yarrr Package: A Companion to the e-Book "YaRrr!: The Pirate's Guide to R" (2017). R package version 0.1.5. https://CRAN.R-project.org/package=yarrr.

R Core Team. R: A language and environment for statistical computing (2021). R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

R. Pruim, D. Kaplan, and N. Horton. The mosaic Package: Helping Students to 'Think with Data' Using R (2017). The R Journal, 9(1):77-102. https://journal.r-project.org/archive/2017/RJ-2017-024/index.html

S. Eack, C. Greeno, and B. Lee. “Limitations of the patient health questionnaire in identifying anxiety and depression: Many cases are undetected” (2006). Research on social work practice. Retrieved April 8, 2022. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3899353/.

S. Lele, J. Kiem, and P. Solymos. The ResourceSelection Package: Resource Selection (Probability) Functions for Use-Availability Data (2019). R package version 0.3-5. https://CRAN.R-project.org/package=ResourceSelection

T. Sing, O. Sander, N. Beerenwinkel, and T. Lengauer. The ROCR Package: Visualizing Classifier Performance in R (2005). Bioinformatics, 21(20):3940-3941. http://rocr.bioinf.mpi-sb.mpg.de

W. Revelle. The psych Package: Procedures for Personality and Psychological Research (2021). Northwestern University, Evanston, Illinois, USA. https://CRAN.R-project.org/package=psych.

Figures

Figure 1: Scatterplot and Correlation Matrix for a Subset of Interesting Variables.

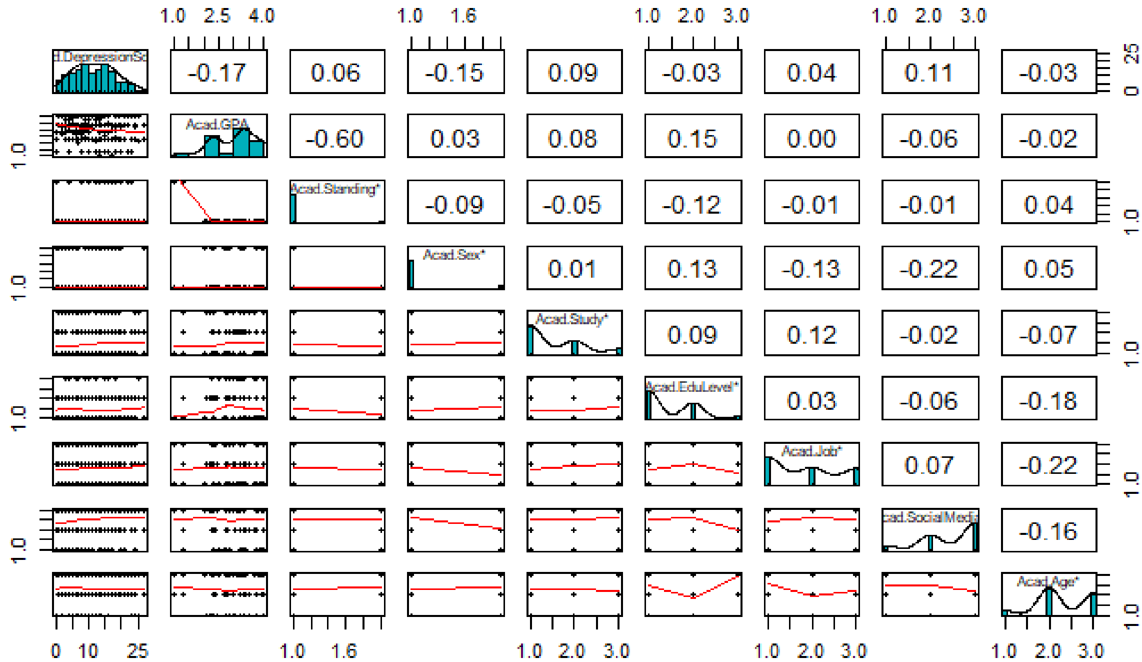


Figure 2: Bar Plot of Academic Standing.

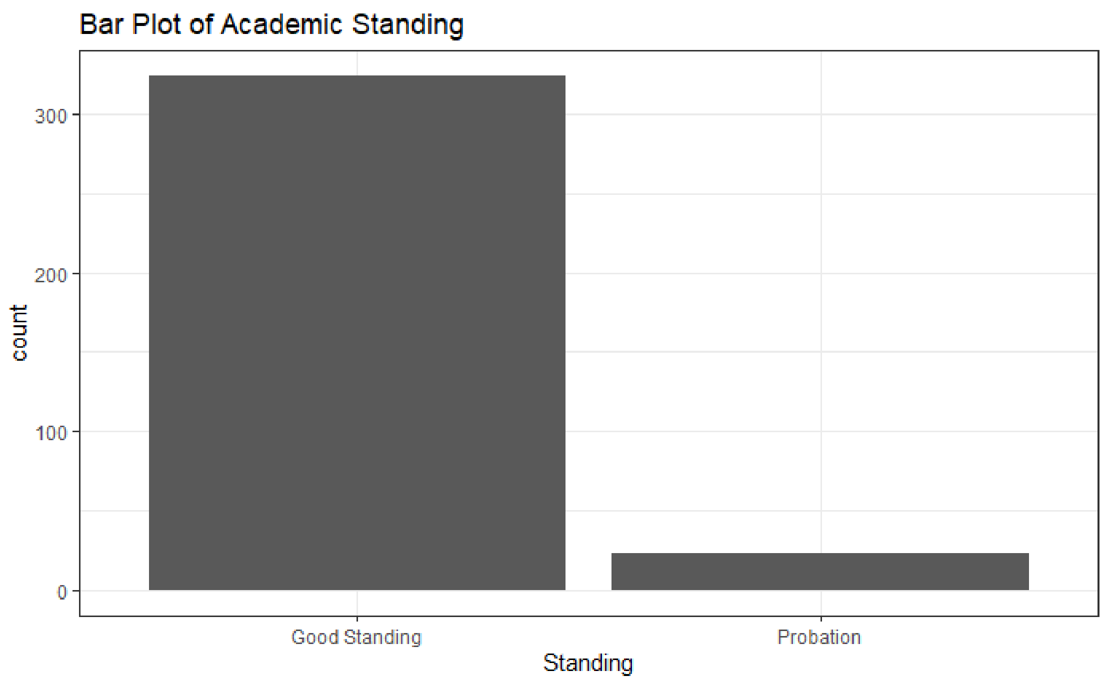


Figure 3: Histogram of Depression Score Index.

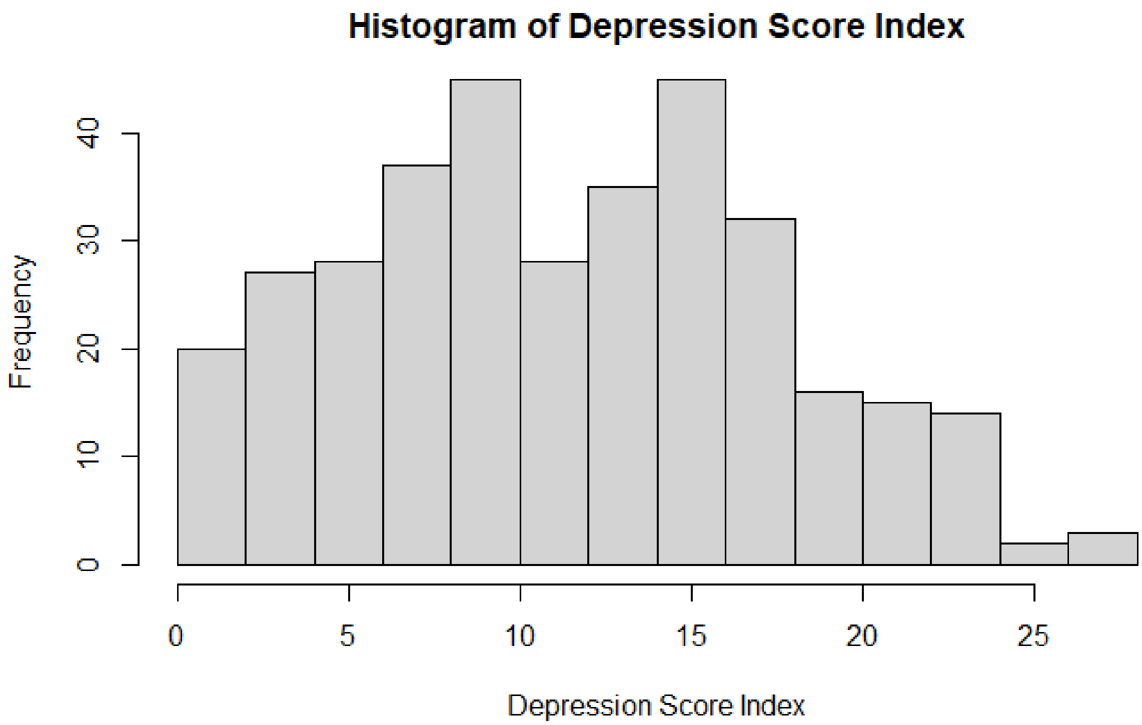


Figure 4: Scatterplot of Academic Standing and Depression Score.

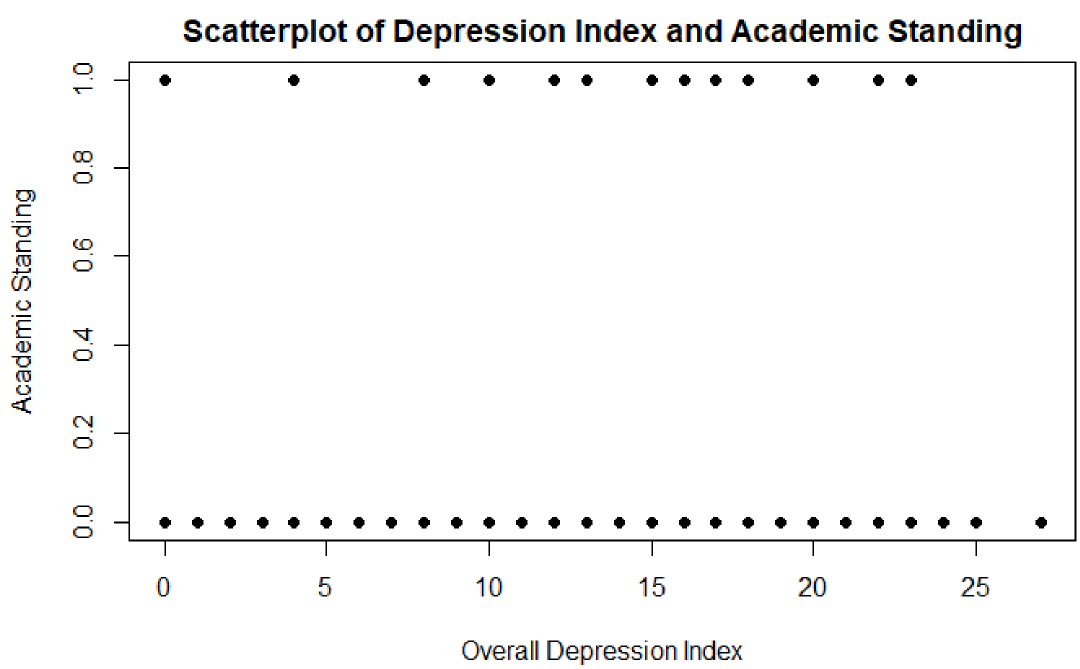


Figure 5: Boxplot of Depression Score and Academic Standing.

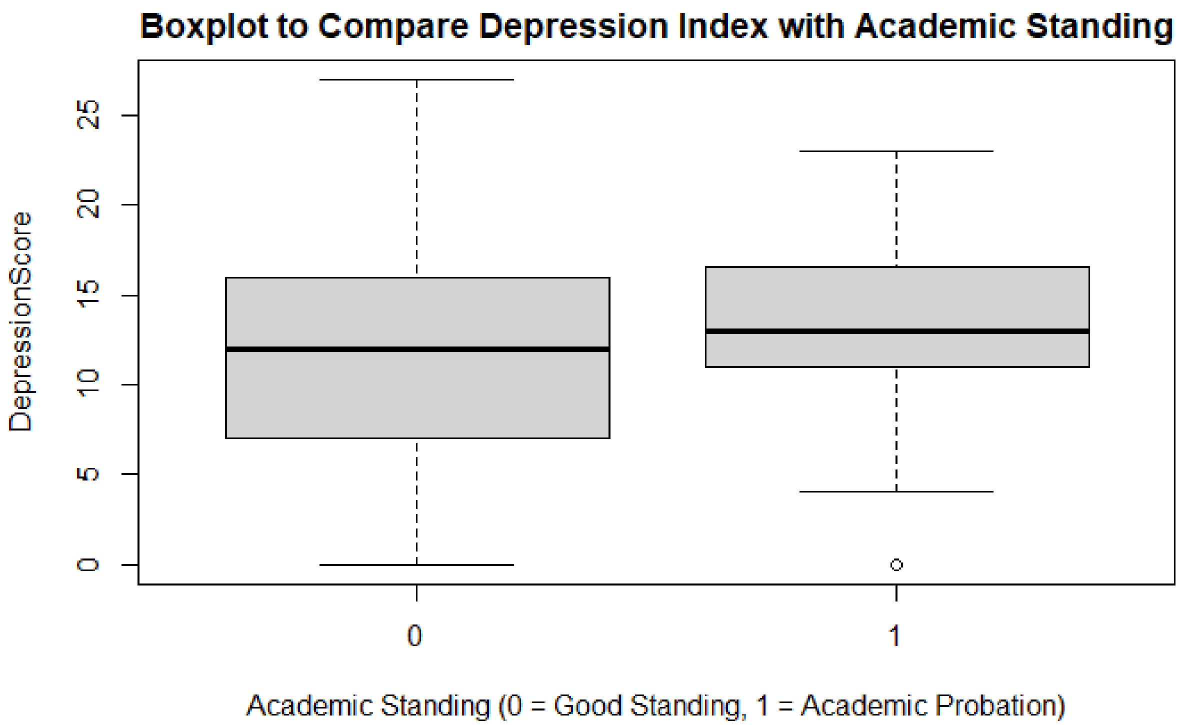


Figure 7: Effects Plot of Depression Score and Job on Academic Standing

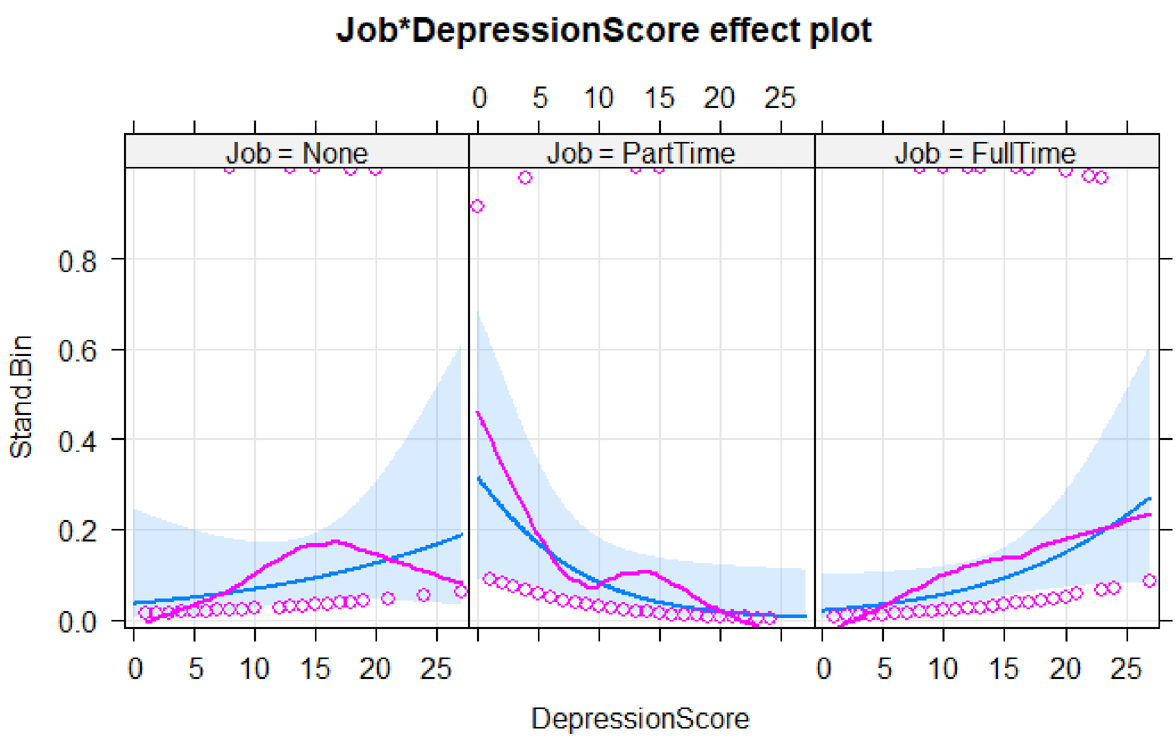


Figure 8: Superimposed Effects Plot of Depression Score and Job on Academic Standing.

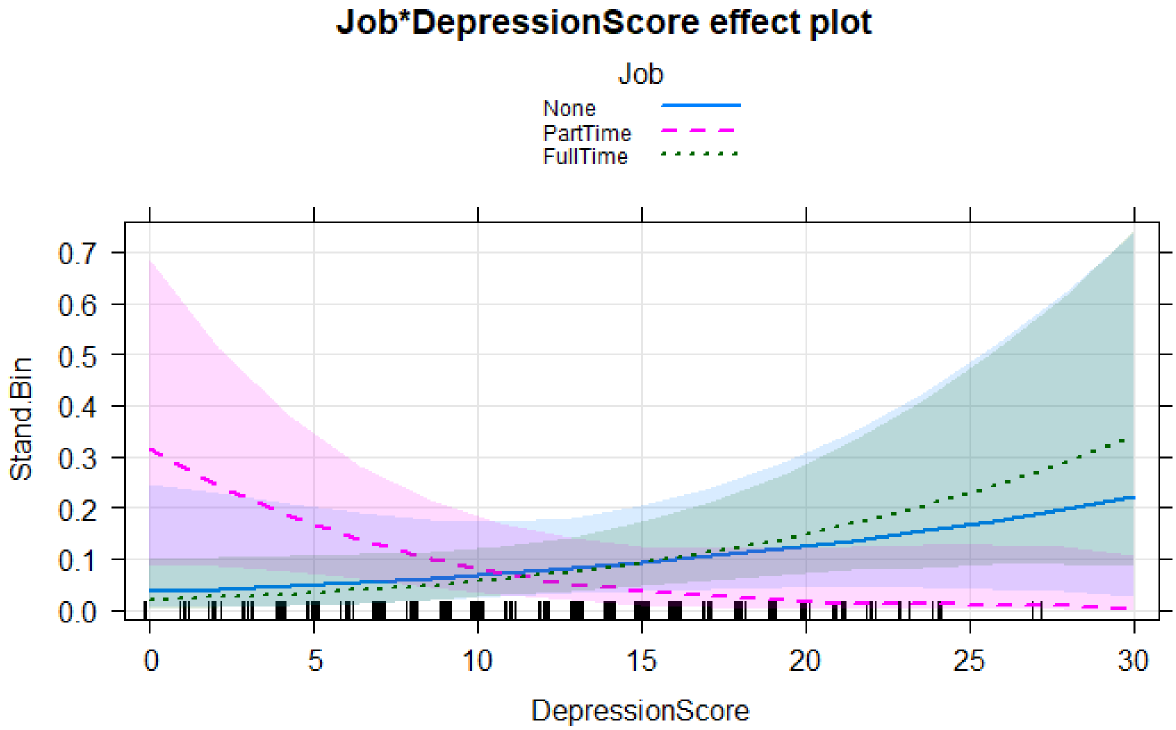


Figure 9: Standard Suite of Diagnostic Plots for the Final Model.

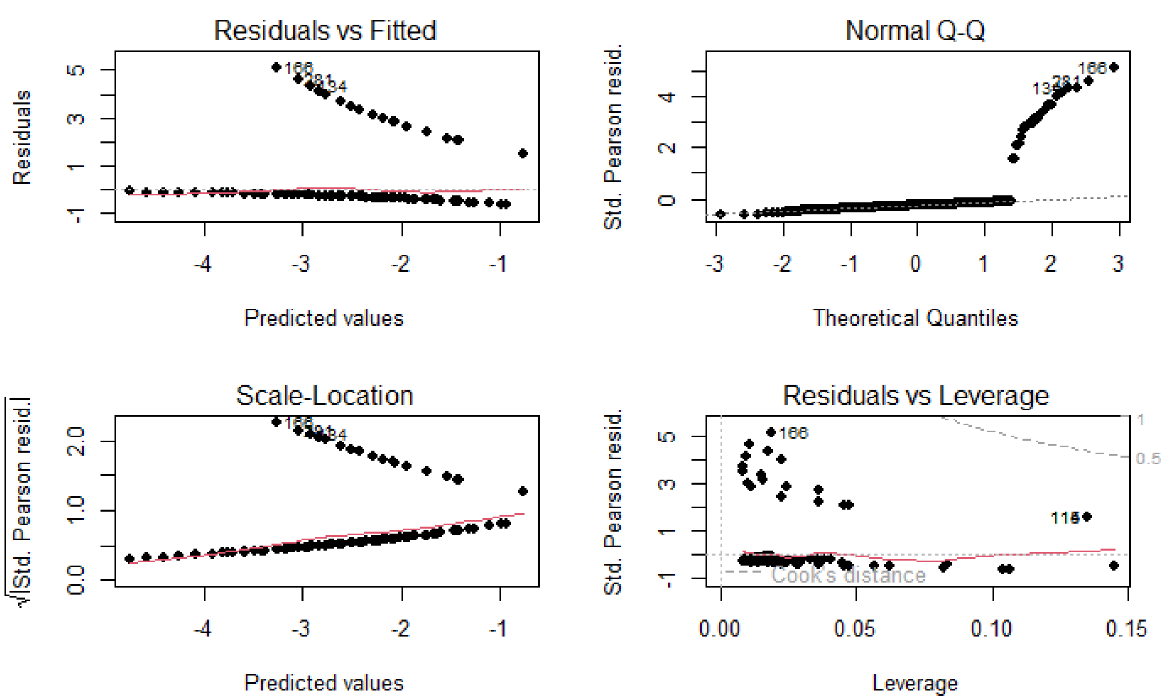


Figure 10: Residual vs. Leverage Diagnostic Plot for the Final Model.

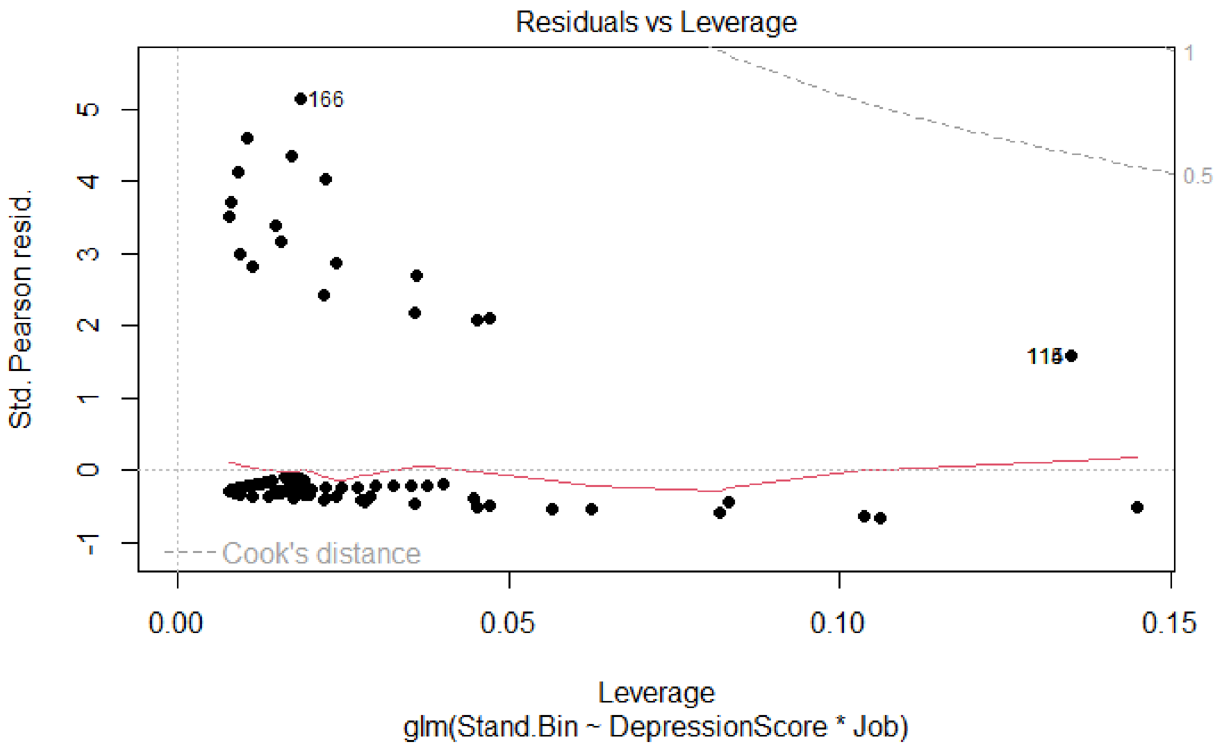
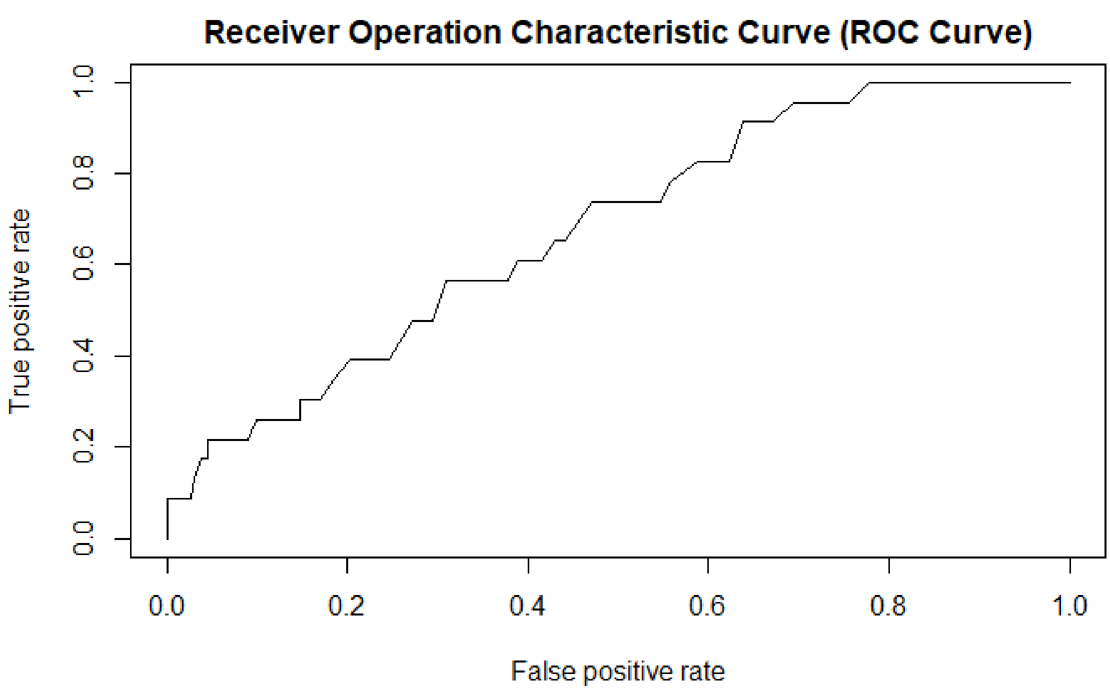


Figure 11: Receiver Operation Characteristic Curve (ROC)



Model Summaries

Model 1: Estimated Coefficients for the Model estimating the Probability of a student being placed on Academic Probation with Sex, Age, and Depression Score Index as predictors (on the log-scale).

	Estimate	**Standard Error**	**z value**	**p-value**
(Intercept)	-3.30492	1.11604	-2.961	0.00306
DepressionScore	0.06797	0.07059	0.963	0.33562
Job = Part Time	2.53250	1.36754	1.852	0.06405
Job = Full Time	-0.60706	1.41569	-0.429	0.66806
DepressionScore:PartTimeJob	-0.23327	0.10783	-2.163	0.03052
DepressionScore:FullTimeJob	0.04044	0.08890	0.455	0.64918

95% Confidence Intervals for the Estimated Model Coefficients on the Response Scale.

	95% CI Lower Bound	**95% CI Lower Bound**
(Intercept)	0.002905629	0.2530766
DepressionScore	0.931920639	1.2377777
Job = Part Time	0.963519540	231.1870373
Job = Full Time	0.035224234	10.4751672
DepressionScore:PartTimeJob	0.631427794	0.9702319
DepressionScore:FullTimeJob	0.872376878	1.2419959

Tables

Table 2: Counts of Students within the combinations of Academic Standing and Age Group.

		Age Group		
		18 and younger	**19 to 24 years old**	**25 and older**
Academic Standing	**Good Standing**	36	157	131
	Probation	0	14	9

Table 3: Counts of Students within the combinations of Academic Standing and Depression Level.

		Depression Level				
		Normal	**Mild**	**Moderate**	**Moderately Severe**	**Severe**
PHQ-9 Score Range		**0-4 points**	**5-9 points**	**10-14 points**	**15-19 points**	**20+ points**
Academic Standing	**Good Standing**	44	86	78	78	38
	Probation	3	2	7	7	4

Table 4: Counts of Students within the combinations of Academic Standing and Education Levels.

		Education Level		
		High School	**Bachelor's**	**Master's**
Academic Standing	**Good Standing**	116	185	23
	Probation	5	18	0

Table 5: Counts of Students within the combinations of Age Groups and Education Levels.

		Age Group		
		18 and younger	**19 to 24 years old**	**25 and older**
Education Level	**High School**	33	70	18
	Bachelor's	3	98	102
	Master's	0	3	20

Table 6: Summary of the Model that includes All Interesting Predictors Additively.

	Estimate	**Standard Error**	**z value**	**p-value**
(Intercept)	-15.60105	1455.39766	-0.011	.991
DepressionScore	0.03535	0.03608	0.980	.327
Age = 25+	-0.31396	0.50868	-0.617	0.537
Education Level = High School	-0.65422	0.57136	-1.145	0.252
Job = Part Time	-0.03571	0.61592	-0.058	0.954
Job = Full Time	-0.09215	0.55719	-0.165	0.869
Housing = Off Campus	13.19898	1455.39772	0.009	0.993
Housing = With Parents	13.06202	1455.39770	0.009	0.993
Study Time = 2-4 Hours Daily	0.01834	0.49584	0.037	0.970
Study Time = 4+ Hours Daily	-1.13848	1.07513	-1.059	0.290

Forms

Form 1: Medical PHQ-9 Depression Screening Questionnaire.

PATIENT HEALTH QUESTIONNAIRE (PHQ-9)

ID #: ______________________ **DATE:** ______________

Over the last *2 weeks*, how often have you been bothered by any of the following problems? *(use "✓" to indicate your answer)*	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself—or that you are a failure or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed. Or the opposite — being so figety or restless that you have been moving around a lot more than usual	0	1	2	3
9. Thoughts that you would be better off dead, or of hurting yourself	0	1	2	3
	add columns		+	+
(Healthcare professional: For interpretation of TOTAL, please refer to accompanying scoring card).	TOTAL:			

10. If you checked off *any problems*, how *difficult* have these problems made it for you to do your work, take care of things at home, or get along with other people?	
	Not difficult at all ______
	Somewhat difficult ______
	Very difficult ______
	Extremely difficult ______

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Relevant R Output

Output 1: Estimated Coefficients for the Model estimating the Probability of a student being placed on Academic Probation with Depression Score, Job Status, and their interaction as predictors.

```
Call:
glm(formula = Stand.Bin ~ DepressionScore * Job, family = binomial,
    data = Acad.final)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8129  -0.4568  -0.3510  -0.2586   2.5651

Coefficients:
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -3.30492    1.11604  -2.961  0.00306
DepressionScore              0.06797    0.07059   0.963  0.33562
JobPartTime                  2.53250    1.36754   1.852  0.06405
JobFullTime                 -0.60706    1.41569  -0.429  0.66806
DepressionScore:JobPartTime -0.23327    0.10783  -2.163  0.03052
DepressionScore:JobFullTime  0.04044    0.08890   0.455  0.64918

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 160.38  on 287  degrees of freedom
Residual deviance: 150.11  on 282  degrees of freedom
AIC: 162.11

Number of Fisher Scoring iterations: 6
```

Output 2: Summary of the Model that includes All Interesting Predictors Additively.

```
Call:
glm(formula = Stand.Bin ~ DepressionScore + Age + EduLevel +
    Job + LivingSituation + Study, family = binomial(link = "logit"),
    data = Acad.final)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5996  -0.4462  -0.3932  -0.3253   2.5256

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)              -15.60105 1455.39766  -0.011    0.991
DepressionScore            0.03535    0.03608   0.980    0.327
Age25above                -0.31396    0.50868  -0.617    0.537
EduLevelHS                -0.65422    0.57136  -1.145    0.252
JobPartTime               -0.03571    0.61592  -0.058    0.954
JobFullTime               -0.09215    0.55719  -0.165    0.869
LivingSituationoffCampus  13.19898 1455.39772   0.009    0.993
LivingSituationwParents   13.06202 1455.39770   0.009    0.993
Study2to4hrs               0.01834    0.49584   0.037    0.970
Study4above               -1.13848    1.07513  -1.059    0.290

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 160.38  on 287  degrees of freedom
Residual deviance: 156.47  on 278  degrees of freedom
AIC: 176.47

Number of Fisher Scoring iterations: 14
```

Output 3: Results of the Hosmer-Lemeshow Test for our Final Model.

```
### Assessing Model Fit

```{r}
# Goodness of Fit for binary data: Hosmer-Lemeshow Test

obs <- Acad.final$Stand.Bin
expected <- fitted(mod.final)
hoslem.test(obs, expected, g = 10) # g = # of groups
```
```

```
        Hosmer and Lemeshow goodness of fit (GOF) test

 data:  obs, expected
 X-squared = 5.135, df = 8, p-value = 0.7431
```