Physical Activity is a Strong Predictor of Good Mental Health

Alen Mitrovski

22 December 2020

Abstract

Mental Health research is a rapidly growing field of study as rates of mental health problems in Canada have been increasing. In my report, I use a logistic regression model to examine the relationship between an individual's mental health and other health related variables. From my results, I find that poor mental health is likely associated with drug use, less physical activity, high stress, young, underweight and male individuals. These results are significant as they will aid us to understand the issue, focus on mitigating certain predictive variables and raise awareness in the scientific community.

Keywords: Mental Health, Physical Activity, Canadian Health, Logistic Regression, Propensity Score Modelling;

Introduction

Mental Health is a term that describes an individual's emotional and psychological condition. Over the years, the prevalence of mental health problems has grown exponentially and as a result, led to greater focus on it's research. According to Smetanin et al., 1 in 5 Canadians experience either a mental health or addiction issue in a given year (Smetanin et al. (2011)). Furthermore, by the age of forty, 50% of individuals in Canada have had a mental health illness (Smetanin et al. (2011)). With this upward trend, it will be important to conduct further research, improve current resources and educate individuals on the mental health risks.

Despite greater awareness, acceptance and access to services, there remains a stigma amongst the Canadian population. In a 2015 survey, researchers found that 39% of Ontarians would not tell their employers if they had a mental health issue (CMA (2008)). In addition, a 2016 survey found that 40% of respondents never sought medical help for depressive and anxiety pervaded feelings (Boak et al. (2016)). The underreporting of mental health problems is a concern as the fear of being socially stigmatized leads to an under-utilization of medical resources and further perpetuation of the present stigma.

In this study, I am interested in exploring the relationship between an individual's mental health and other key variables. In order to conduct this research, survey data has been obtained from the Canadian Community Health Survey for the years 2017-2018 (CCHS (2018)). This survey is accessed through the Computing in the Humanities and Social Sciences domain (Technology (n.d.)). The supporting README file will describe the steps to obtain the CCHS.

In addition to perceived mental health, I have also selected the following variables of interest from the Canadian Community Health Survey (CCHS): Age, Sex, Perceived Mental Health, Perceived Weight, Stress Levels, Drug Use and Weekly Physical Activity. The CCHS used in this study was conducted for the time period of 2017-2018. The objective of the survey was to gather health related information from all provinces and territories in Canada. The survey was conducted by 113, 291 respondents over the age of 12 and includes 399 variables. In order to conduct this analysis, I utilized a logistic regression model with perceived mental health as the binary dependent variable.

This report includes 4 sections, excluding the introduction. First, in the data section, I provide an overview of the CCHS 2017-2018 survey and dataset. Plots of key variables are included in this section to gain a better understanding of the respondent population. Second, in the model section, I discuss the logistic regression model and propensity score modelling used in this study and it's methodology. Thirdly, in the results section, I provide the statistical values determined through the analysis. Finally, in the discussion section, I further explore the results of my research and present weaknesses of this report. This report is conducted using R (R Core Team [2019]). Wickham et al. (2019) was the most utilized library in this study. The report was compiled using Allaire et al. (2020). Other packages used include Xie (2020), Zhu (2020), Robinson, Hayes, and Couch (2020), Wickham et al. (2020), Ho et al. (2011), Sjoberg et al. (2020).

Data

The Canadian Community Health Survey (CCHS) is a cross-sectional survey that collected responses from individuals aged 12 and over in 100 different regions across every province and territory in Canada (CCHS (2019)). A cross-sectional survey is an observational study design where the researchers measure the outcome and exposures in the study respondents simultaneously (Setia (2016)). Compared to cohort studies, it is a faster and cheaper method of study that is commonly used public health research (Setia (2016)).

For this survey, researchers divided each province into health regions (HR), while each territory was considered a single health region (Beland (2002)). The boundaries of these health regions were determined by Statistics Canada, using prior census data (Beland (2002)). In total, the CCHS compiled data from 133 HRs in the provinces and 3 HRs in the territories for a total of 136 HRs for Canada (Beland (2002)). In order to give equal importance to each of the HRs, a sample allocation strategy was incorporated (Beland (2002)). First, the sample is allocated to the territories and provinces according to their number of HRs and population size (Beland (2002)). Second, the sample of each province is allocated to the HRs within said province (Beland (2002)). This is done proportionally to the square root of each HRs estimated population (Beland (2002)). The approach is effective as it ensures each HR has a sufficient sample.

The CCHS data used in this study did not include individuals from Indian reserves, Crown Lands, remote regions, prisons, religious institutions and residents aged 12 to 17 living in foster homes within the survey sampling frame (CCHS (2019)). However, approximately 98% of Canadians aged 12 and over were covered by the CCHS (CCHS (2019)). Data was collected using computer-assisted interviewing through a combination of telephone interviews and personal interview (CCHS (2019)). The target population in this study is the general Canadian population. The sampling frame is Canadians over the age of 12 from each of the provinces and territories. The sample population is the 113, 291 individuals that completed the survey.

Figures 1 to 6 depict the distribution of respondent answers to key questions in the CCHS. This includes respondent age, sex, stress, weight, drug use and weekly physical activity. By examining the figures, it is evident that there are weakness in the dataset. For instance, the distribution of age groups is uneven (Figure 1). For example, far fewer individuals between the ages of 12-19 responded to the survey compared to individuals aged 50-69. This could be a result of a selection bias. Thus, the results of this analysis may not accurately represent that portion of the population. In addition, another weakness evident in these figures is the discrepancy between respondents and non-respondents to the drug use in the last 12 months question (Figure 5). As seen in this graph, there are more individuals who did not answer the question, than there were individuals who answered "Had used drugs" and "Had not used drugs" combined. This is likely due to fear of answering question regarding a stigmatized and sensitive topic (See Weaknesses section in Discussion for more). In addition, Figure 6 is slightly concerning as a vast majority of individuals reponded "Seven" days of physcial activity in a week compared to other options (Figure 6). However, this is likely due to the lack of a "physical activity" definition provided from the survey researchers. A strength of this survey is the relatively equal ratio of male to female respodents (Figure 2). This is close to the representation of the country. Likewise, stress and weight variables were represented as expected with distributions that are understandable given the topic of the question (Figure 3, 4).

Age was selected as a variable of interest due to the effect of age on brain processes, physical and mental condition. In addition, the experiences that individuals go through as they age can lead to more depressing mindsets. The concept of nearing death and the feeling of loneliness can begin to take shape as individuals age. The maturity gained through age can also change the way a person handles situations and processes emotions. All these factors can affect the mental well-being of an individual. Sex was selected as a variable in this study because men and women have different life experiences and use contrasting techniques when it comes to channeling their emotions. Men are particularly stubborn when it comes to reporting their mental illness or seeking medical help (Hamilton (2016)). Social norms, physiological differences and personality characteristics represent other possible ways in which men and women can vary in their predisposition to mental illnesses.

Sex was selected as a variable in this study because men and women have different life experiences and use contrasting techniques when it comes to channeling their emotions. Men are particularly stubborn when it comes to reporting their mental illness or seeking medical help (Hamilton (2016)). Social norms, physiological differences and personality characteristics represent other possible ways in which men and women can vary in their predisposition to mental illnesses.

I selected the Drug Use variable in this analysis because it has been reported that a great deal of individuals with substance use disorder (SUD) are also diagnosed with mental disorders (Drug Abuse (2020)). A critical period of life is when the brain undergoes a high degree of development during adolescence. Some of the most important executive functions of the brain, impulse control and decision making, are developed during this period and can influence the vulnerability to drug use (Drug Abuse (2020)). This can lead to SUD in the future and other mental illnesses (Drug Abuse (2020)). It should be noted that the drug use variable in this study determines whether an individual has used an illicit drug in the past 12 months.

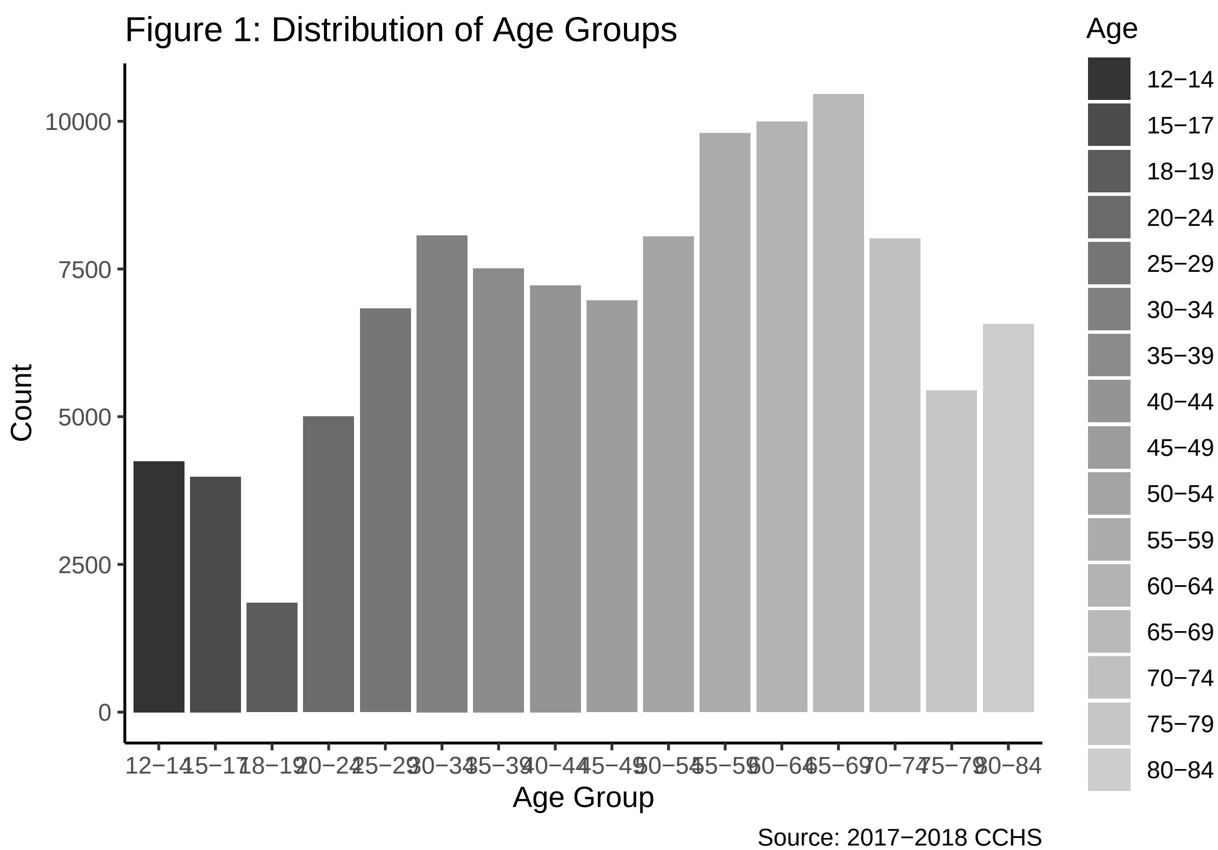


Figure 1: Distribution of Age Groups

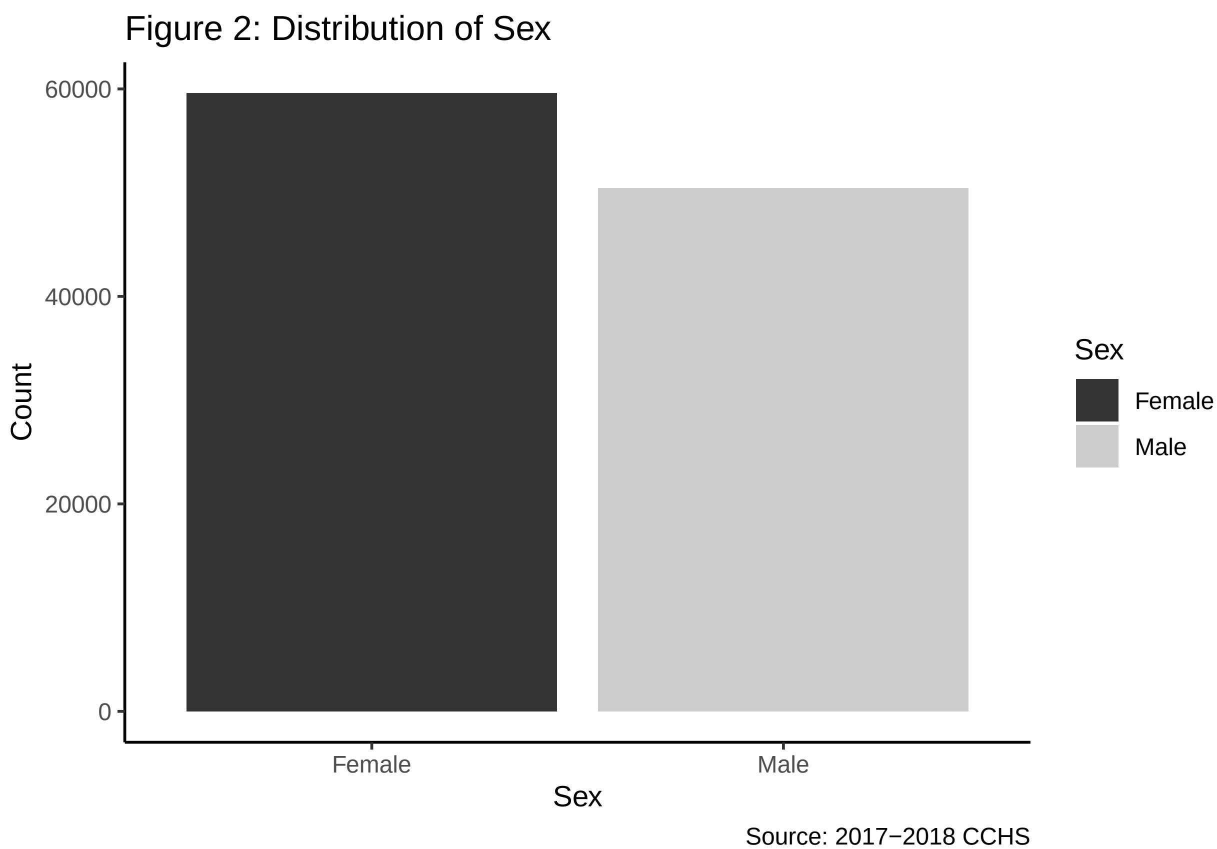
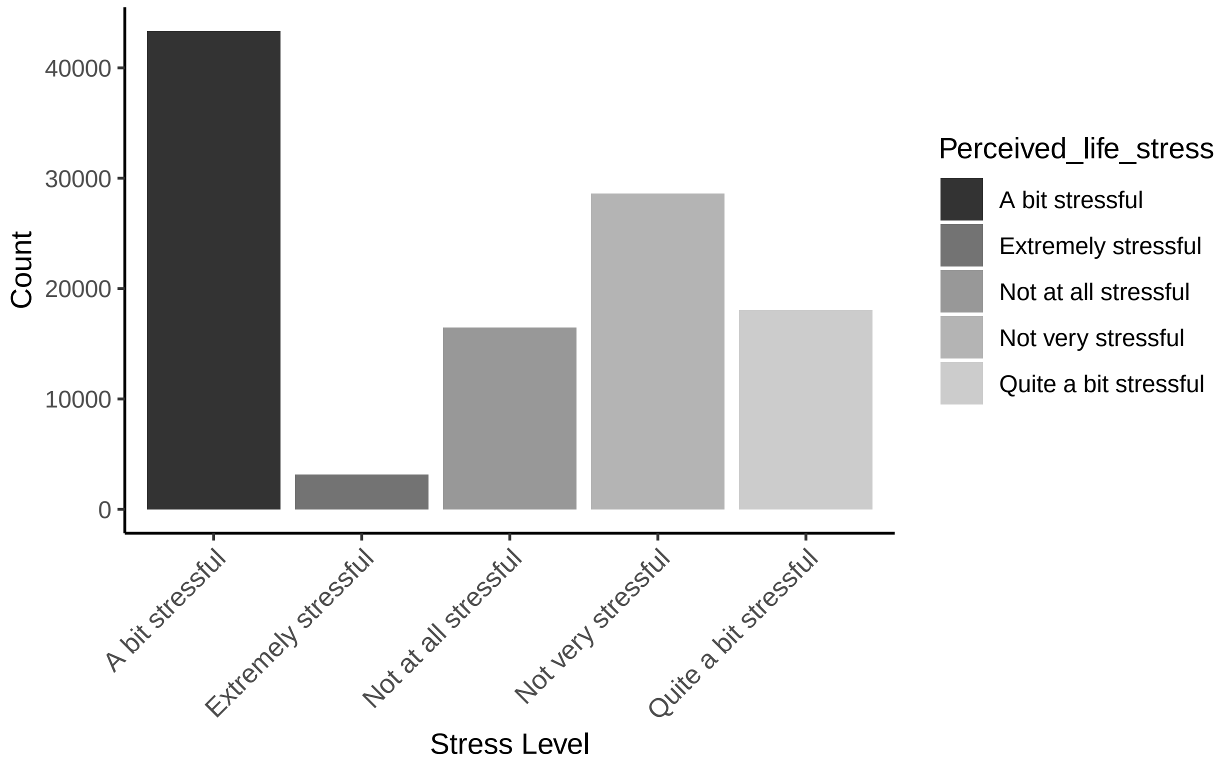


Figure 2: Distribution of Sex
60000
40000
20000
0
Count
Female
Male
Sex
Sex
Female
Male
Source: 2017−2018 CCHS

Figure 3: Perceived Life Stress



Source: 2017−2018 CCHS

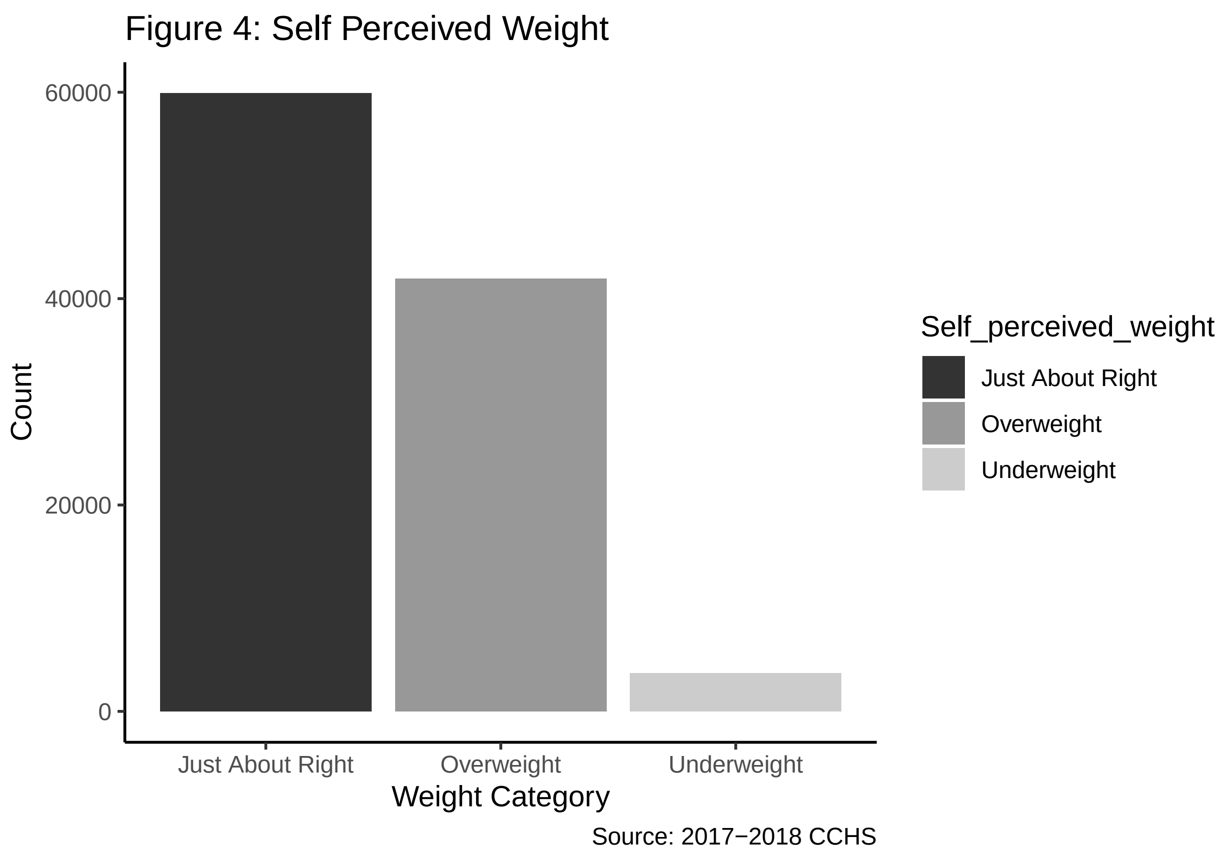


Figure 4: Self Perceived Weight
60000
40000
20000
0
Count
Just About Right
Overweight
Underweight
Weight Category
Source: 2017−2018 CCHS
Self_perceived_weight
Just About Right
Overweight
Underweight

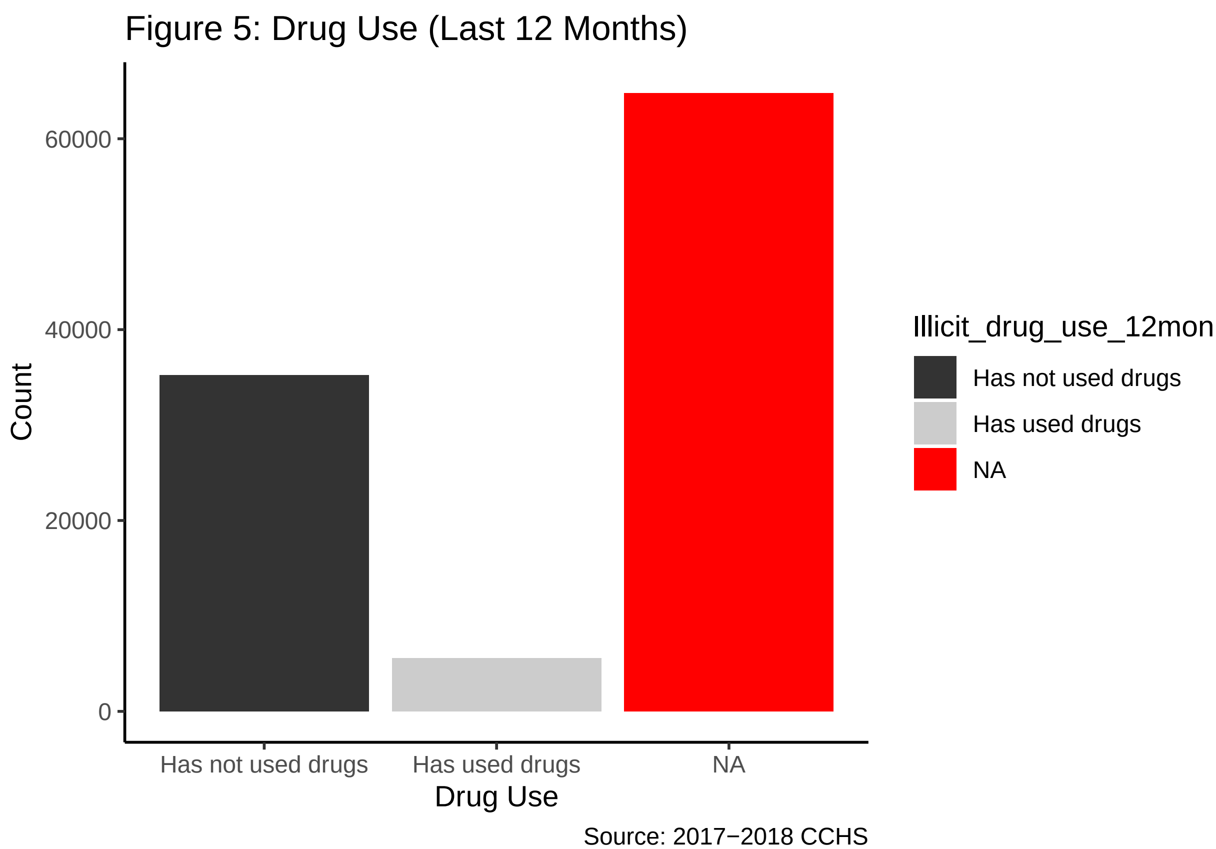
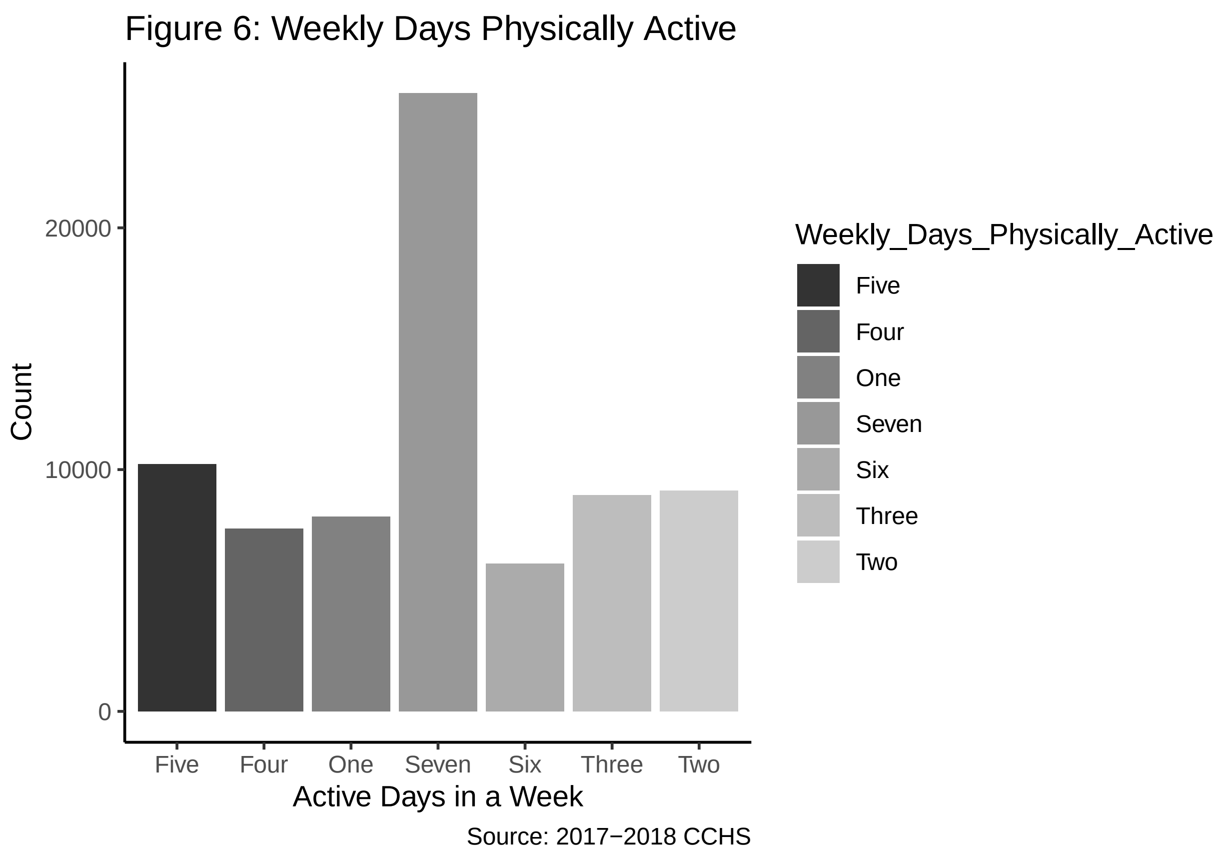


Figure 5: Drug Use (Last 12 Months)
Count
60000
40000
20000
0
Has not used drugs
Has used drugs
NA
Drug Use
Source: 2017−2018 CCHS
Illicit_drug_use_12mon
Has not used drugs
Has used drugs
NA



Model

Logistic Regression

This study uses a logistic regression model of the form:

$$log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_1 + \beta_2 * x_{PhysicalActivity} + \beta_3 * x_{Sex} + \beta_4 * x_{Weight} + \beta_5 * x_{Stress} + \beta_6 * x_{DrugUse} + \beta_7 * x_{AgeGroup}$$

Each B value represents a coefficient determined by the estimate values in our model. These coefficients are multiplied by the independent variables that were chosen for examining their relationship to mental health. In my case, these variables are: Age, Sex, Perceived Mental Health, Perceived Weight, Stress Levels, Drug Use and Weekly Physical Activity.

A logistic regression model is similar to linear regression; however, the response variable is binomial (Sperandei (2014)). In order to use the logistic regression model, the perceived_mental_health variable from the CCHS survey was mutated to represent positive responses as “Good” metal health (Variable of 1) and negative responses as “Poor” mental health (Variable of 0). All variables in this particular research equation are categorical in nature.

Propensity Score Modelling

Propensity score matching is a technique that can be used to make causal inferences in an observational study (Thavaneswaran (2008)). Normally, randomized design studies, where there is random selection of subjects and random separation into treatment groups are required to be able to make causal inferences (Thavaneswaran (2008)).

Propensity scores can be calculated either through logistic regression or classification and regression tree analysis (Thavaneswaran (2008)). As mentioned, logistic regression model is used in my analysis. In this logistic regression model, the dependant variable, self-perceived mental health is binary. 1 is the value that corresponds to the treatment group and 0 is the value for the control group.

In order to conduct propensity score matching, the MatchIt package was used in R.

Results

The following figure (Figure 7) displays the estimates of the coefficients in the logistic regression model. It also displays the standard error, p-value and confidence interval. Coefficients with positive values are more likely to be associated with good mental health. P-values are also included to determine the statistical signifigance.

Figure 7: Coefficients of the Logistic Regression Model

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	2.6300351	0.1521829	17.2820628	0.0000000	2.3377417	2.9348413
Age20-24	-0.1196123	0.1546757	-0.7733099	0.4393390	-0.4280001	0.1790261
Age25-29	0.2605065	0.1545454	1.6856312	0.0918669	-0.0475730	0.5589572
Age30-34	0.6068530	0.1560942	3.8877355	0.0001012	0.2959656	0.9085804
Age35-39	0.5389647	0.1562137	3.4501744	0.0005602	0.2278036	0.8408723
Age40-44	0.5836165	0.1578334	3.6976733	0.0002176	0.2694753	0.8889035
Age45-49	0.5287059	0.1589275	3.3267116	0.0008788	0.2125272	0.8362463
Age50-54	0.4522299	0.1549836	2.9179200	0.0035237	0.1432553	0.7514848
Age55-59	0.4877257	0.1546146	3.1544612	0.0016079	0.1794267	0.7862107
Age60-64	0.3116404	0.1556071	2.0027391	0.0452053	0.0014577	0.6121305
Age65-69	0.5078095	0.1629688	3.1159918	0.0018333	0.1841838	0.8237767
Age70-74	0.6548086	0.1824150	3.5896644	0.0003311	0.2960885	1.0122306
Age75-79	0.7391859	0.2162908	3.4175557	0.0006319	0.3204926	1.1704639
Age80-84	0.0755587	0.1920079	0.3935184	0.6939366	-0.3007158	0.4531589
SexMale	0.2882268	0.0484614	5.9475606	0.0000000	0.1934438	0.3834328
Perceived_life_stressExtremely stressful	-2.0937272	0.0818088	-25.5929482	0.0000000	-2.2537286	-1.9329627
Perceived_life_stressNot at all stressful	1.2435677	0.1355478	9.1743831	0.0000000	0.9864405	1.5187574
Perceived_life_stressNot very stressful	0.7505473	0.0792035	9.4761870	0.0000000	0.5971722	0.9077929
Perceived_life_stressQuite a bit stressful	-1.0879255	0.0545064	-19.9595872	0.0000000	-1.1948620	-0.9811690
Self_perceived_weightOverweight	-0.4105442	0.0499308	-8.2222619	0.0000000	-0.5085766	-0.3128264
Self_perceived_weightUnderweight	-0.7671187	0.1045743	-7.3356346	0.0000000	-0.9696427	-0.5595194
Illicit_drug_use_12monHas used drugs	-0.8878977	0.0551986	-16.0855041	0.0000000	-0.9958252	-0.7794225
Weekly_Days_Physically_ActiveFour	0.0511695	0.1009126	0.5070680	0.6121071	-0.1459217	0.2498482

term	estimate	std.error	statistic	p.value	conf.low	conf.high
Weekly_Days_Physically_ActiveOne	-0.2441758	0.0970917	-2.5148983	0.0119067	-0.4342421	-0.0534822
Weekly_Days_Physically_ActiveSeven	-0.1321350	0.0756904	-1.7457291	0.0808580	-0.2817784	0.0150205
Weekly_Days_Physically_ActiveSix	0.1361618	0.1111093	1.2254761	0.2203959	-0.0798510	0.3559830
Weekly_Days_Physically_ActiveThree	-0.0686550	0.0958346	-0.7163907	0.4737502	-0.2562675	0.1195666
Weekly_Days_Physically_ActiveTwo	-0.1668447	0.0939701	-1.7755088	0.0758139	-0.3510019	0.0175090

Using the glm() function, the logit function for this study is:

$$log\left(\frac{\hat{p}}{1-\hat{p}}\right) = -2.6 + -0.42 * x_{PhysicalActivity} + 0.29 * x_{Sex} + -1.18 * x_{Weight} + -1.25 * x_{Stress} + -0.89 * x_{DrugUse} + 5.63 * x_{AgeGroup}$$

This is the output of the logistic regression model used in this study. For simplicity, the terms for each variable were added up (ie. the Age variable in the above equation represents of all age groups in the survey with the exception of the default variable). Unlike other regression models, terms in this equation will be multiplied by 1 or 0 depending on whether the variable represents the respondant.

Figure 8: Distribution of Estimation of Coefficients

Bars represent estimated error

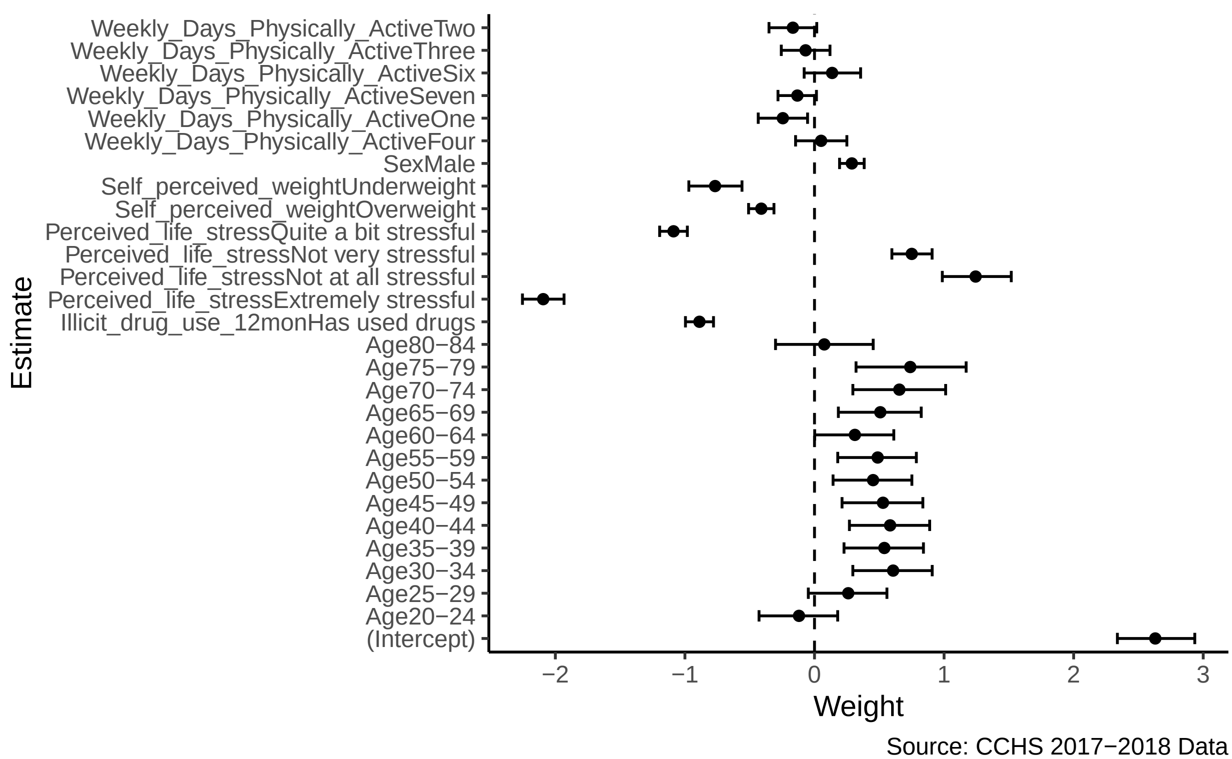


Figure 8 depicts the coefficients to the logistic regression model. This figure includes error bars that show the upper and lower estimates of the coefficients. Coefficients with positive values indicate that individuals who possess that characteristic are more likely to have a good self-perception of their mental health. In contrast, coefficients with negative values indicate that individuals who possess that characteristic are more likely to have a poor self-perception of their mental health.

Figure 9: Propensity Score Matching Statistics

```
##
## Call:
## matchit(formula = Perceived_Mental_Health ~ Sex + Weekly_Days_Physically_Active,
##     data = cchs_diff, method = "nearest")
##
## Summary of Balance for All Data:
##                               Means Treated Means Control Std. Mean Diff.
## distance                             0.9236        0.9230          0.0976
## SexFemale                            0.5302        0.5787         -0.0970
## SexMale                              0.4698        0.4213          0.0970
## Weekly_Days_Physically_Active        4.6340        4.6017          0.0150
##                               Var. Ratio eCDF Mean eCDF Max
## distance                          1.0199    0.0265   0.0513
## SexFemale                              .    0.0484   0.0484
## SexMale                                .    0.0484   0.0484
## Weekly_Days_Physically_Active     0.9341    0.0121   0.0223
##
##
## Summary of Balance for Matched Data:
##                               Means Treated Means Control Std. Mean Diff.
## distance                             0.9316        0.9230          1.2522
## SexFemale                            0.0000        0.5787         -1.1595
## SexMale                              1.0000        0.4213          1.1595
## Weekly_Days_Physically_Active        7.0000        4.6017          1.1135
##                               Var. Ratio eCDF Mean eCDF Max Std. Pair Dist.
## distance                               0    0.4606   0.8392          1.2522
## SexFemale                              .    0.5787   0.5787          1.1595
## SexMale                                .    0.5787   0.5787          1.1595
## Weekly_Days_Physically_Active          0    0.3426   0.6431          1.1135
##
## Percent Balance Improvement:
##                               Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max
## distance                              -1182.9  -322211.7   -1636.8  -1536.5
## SexFemale                             -1094.8          .   -1094.8  -1094.8
## SexMale                               -1094.8          .   -1094.8  -1094.8
## Weekly_Days_Physically_Active         -7324.3  -103849.2   -2727.2  -2778.8
##
## Sample Sizes:
##           Control Treated
## All          5777   69836
## Matched      5777    5777
## Unmatched       0   64059
## Discarded       0       0
```

Figure 9 displays the summary statistics created through the MatchIt package in R (Ho et al. (2011)). This was performed using the propensity score matching model. Perceived mental health was used as the binary outcome variable while sex and weekly physcial activity were used as dependent variables of interest.

Discussion

Analysis

As seen in Figure 7, men are more likely to have better mental health than women. A possible explanation for this result is that the two sexes handle their emotions differently. According to the American Psychological Association, men tend to externalize their emotions, leading to impulsive and aggressive behavior (Hamilton (2016)). In contrast, women generally internalize their emotions, which can cause withdrawal and depression (Hamilton (2016)). In turn, this emotional stress can lead to physical complications and mental illnesses (Hilary Jacobs Hendel, 2018). In addition, another possible reason for the gender differences is that men are less likely to report a mental illness. According to Dr. Powell, masculinity standards established throughout male upbringing can govern the way in which they pursue help (Audrey Hamilton). Some men feel ashamed of their emotions and avoid discussing their mental health issues with others. As a result, it's possible that men are reporting "Good" mental health status because they do not want to admit their condition or lack the knowledge to understand their mental health due to prior avoidance of the topic.

The results in Figure 7 indicate that young adults are more predisposed to having poor mental health. This is validated by the research from Twenge et al., where investigators have found that rates of major depressive episodes have increased substantially among individuals aged 12 to 25 between the years 2005 and 2017 (Twenge et al. (2019)). Twenge suggests that this is due to the rise of social media and it's affects on various aspects of life for young adolescents and adults (Twenge et al. (2019)). In particular, researchers believe a consequence of digital media use is mood disorders and potential suicidal ideation (Twenge et al. (2019)). Furthermore, older individuals are less likely to use digital media As such, older people are less likely sacrifice their sleep by staying up late at night using their digital media (Twenge et al. (2019)). Interestingly, Figure 7 also indicates that respondents over the age of 80 report "Poor" mental health. This seems reasonable since these individuals are nearing the end of their life and undergo physical and phycological changes that can deeply impact their mental well-being. The Canadian Mental Health Association discusses how loneliness, bereavement and weaker physical condition contribute to the deterioration of mental health in older individuals (Association (n.d.)).

Figure 7 also indicates overweight and underweight individuals are more likely suffer mental health issues than respondents that perceived their weight as "just about right". This could be explained by the relationship between the gut microbiome and neurological processes. An article by Bremner et al. cites that a bad diet can alter neurotransmitters and neuropeptides in the brain; Thus, influencing mood and behavior of the affected individual (Bremner et al. (2020)). Through the betterment of their diet, respondents who were over and under their desired weight can improve their mental well-being.

As seen in the results of this study, the more stress experienced by the respondent, the more likely they are to report "poor" mental health (Figure 7). As referenced in the 2020 article by Azza et al., stress can cause endocrine reactions that lead to increased HR (Azza et al. (2019)). Increased heart rate has been found to affect both an individual's ability to sleep and their susceptibility to develop mental health complications such as anxiety (Azza et al. (2019)). In addition, long term stress has been found to disrupt the body's digestive, cardiovascular, immune and reproductive system (NIMH (n.d.)). Considering the widespread affect of stress on the human body, it is realistic to expect that mental health would also be compromised, both directly and indirectly. Stress has the potential to lead to mental health precursors such as lack of motivation, social withdrawal, restlessness and depression (DiSalvo (2012)).

The results in this study also indicate that increased weekly exercise is likely to coincide with better mental health perception (Figure 7). This could be a result of phycological and/or physiological improvements caused by the increase in physical activity. Research has demonstrated that aerobic exercise such as swimming, cycling and jogging reduce mental health illnesses; in particular, anxiety and depression (Sharma, Madaan, and Petty (2006)). The proposed reasoning for this benefit is that improved blood circulation in the brain improves neurological processes and reduces reactivity to stress (Sharma, Madaan, and Petty (2006)). In terms of physiology, health benefits from physical activity include better endurance, stamina, weight reduction and improved cardiovascular fitness (Sharma, Madaan, and Petty (2006)). Some businesses are even now adding gyms and recreational areas within their company to increase productivity through exercise. Self esteem and social interaction can also be improved as a result of frequent physical activity, leading to better mental well-being (Sharma, Madaan, and Petty (2006)).

Weaknesses

This report was conducted using exclusively categorical variables. In retrospect, this is a weakness of the study as it limited the options of techniques that could be used to discuss causality. For example, instrumental variables and regression discontinuation were not possible without the inclusion of continuous variables.

The survey conducted by the CHHS had numerous questions where respondents either refused to answer the questions or input a non-applicable response. Individuals may be unwilling to disclose personal information regarding controversial topics. There is a stigma against mental health that is still persistent in society, particularly among men (Leah Campbell, 2019). In addition, the utilization of most drugs is illegal in Canada and as a result, may be a question that individuals do not want to answer or are ashamed of their response. Furthermore, respondents may be wary of the consequences should their answers be revealed. As a result, it is possible that answers for the illicit drug use (past 12 months) question may be unrepresentative of the actual situation.

For future studies, researchers can look to include other socio-economic variables to examine whether there is a correlation with mental health. This can include income, employment status and education. As mentioned by the Canadian Mental Health Association, poverty can lead to mental health issues (Canadian Mental Health Association). Money is an important resource today and as such, can influence an individual's happiness, confidence, self-esteem and overall mental well-being. Higher levels of education can lead to better paying job opportunities. However, poor individuals are not privy to the same resources as people who are in a financially stable environment. Therefore, poor individuals might be at an economic disadvantage when it comes to the level of education they are able to complete and what jobs are available for their education level. This can possibly lead to development of a mental illness.

A limitation of the survey dataset is that it is from the years 2017-2018. A more recent CCHS would include opinions after the COVID pandemic. The pandemic has led to city-wide lockdowns, store closures and social distancing. These factors may all contribute to a deterioration of mental health. Future research can look to incorporate COVID related variables. They can also use difference in differences to observe the difference between mental health prior to the COVID outbreak and afterwards. This can be done using the time group variable in the difference in differences model.

Code

Supporting code for this analysis can be found at: https://github.com/Alen-Mitrovski/Mental_Health

References

Allaire, JJ, Yihui Xie, Jonathan McPherson, Javier Luraschi, Kevin Ushey, Aron Atkins, Hadley Wickham, Joe Cheng, Winston Chang, and Richard Iannone. 2020. *Rmarkdown: Dynamic Documents for R*. https://github.com/rstudio/rmarkdown.

Association, Canadian Mental Health. n.d. "Aging and Mental Health." *CMHA Toronto*. https://toronto.cmha.ca/documents/aging-and-mental-health/.

Azza, Yasmine, Marcus Grueschow, Walter Karlen, Erich Seifritz, and Birgit Kleim. 2019. "How Stress Affects Sleep and Mental Health: Nocturnal Heart Rate Increases During Prolonged Stress and Interacts with Childhood Trauma Exposure to Predict Anxiety." *Sleep* 43 (6). https://doi.org/10.1093/sleep/zsz310.

Beland, Yves. 2002. "Canadian Community Health Survey–Methodological Overview." *Health Reports* 13 (3): 9–14. https://pubmed.ncbi.nlm.nih.gov/12743956/.

Boak, A., H. A. Hamilton, E. M. Adlaf, J. L. Henderson, and R. E. Mann. 2016. "The Mental Health and Well-Being of Ontario Students." *Centre for Addiction and Mental Health.* Centre for Addiction; Mental Health. https://youthrex.com/wp-content/uploads/2019/02/2015OSDUHS_Detailed-MentalHealthReport.pdf.

Bremner, J. Douglas, Kasra Moazzami, Matthew T. Wittbrodt, Jonathon A. Nye, Bruno B. Lima, Charles F. Gillespie, Mark H. Rapaport, et al. 2020. "Diet, Stress and Mental Health." *Nutrients* 12 (8): 2428. https://doi.org/10.3390/nu12082428.

CCHS. 2018. "Canadian Community Health Survey (Cchs) Annual Component 2017-2018." *Canadian Community Health Survey.* Statistics Canada. https://sda-artsci-utoronto-ca.myaccess.library.utoronto.ca/sdaweb/dli2/cchs/cchs2017/more_doc/index.htm.

———. 2019. "Canadian Community Health Survey (Cchs) Annual Component (User Guide)." *Canadian Community Health Survey.* Canadian Community Health Survey. https://sda-artsci-utoronto-ca.myaccess.library.utoronto.ca/sdaweb/dli2/cchs/cchs2017/more_doc/CCHS%202017-2018%20User%20Guide.pdf.

CMA. 2008. "8th Annual National Report Card on Health Care." *Canadian Medical Association.* Canadian Medical Association. http://www.bc-psychologist.com/downloads/other/National_Report_Card_EN.pdf.

DiSalvo, David. 2012. "How Stress Affects Your Mental Health." *Forbes.* Forbes Magazine. https://www.forbes.com/sites/daviddisalvo/2012/10/15/how-stress-affects-your-mental-health/?sh=26bf23f62714.

Drug Abuse, National Institute on. 2020. "Part 1: The Connection Between Substance Use Disorders and Mental Illness." *National Institute on Drug Abuse.* National Institute on Drug Abuse. https://www.drugabuse.gov/publications/research-reports/common-comorbidities-substance-use-disorders/part-1-connection-between-substance-use-disorders-mental-illness.

Hamilton, Audrey. 2016. "Speaking of Psychology: How Masculinity Can Hurt Mental Health." *American Psychological Association.* American Psychological Association. https://www.apa.org/research/action/speaking-of-psychology/men-boys-health-disparities.

Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart. 2011. "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." *Journal of Statistical Software* 42 (8): 1–28. https://www.jstatsoft.org/v42/i08/.

NIMH. n.d. "5 Things You Should Know About Stress." *National Institute of Mental Health.* U.S. Department of Health; Human Services. https://www.nimh.nih.gov/health/publications/stress/index.shtml.

Robinson, David, Alex Hayes, and Simon Couch. 2020. *Broom: Convert Statistical Objects into Tidy Tibbles.* https://CRAN.R-project.org/package=broom.

Setia, Manindersingh. 2016. "Methodology Series Module 3: Cross-Sectional Studies." *Indian Journal of Dermatology* 61 (3): 261–64. https://doi.org/10.4103/0019-5154.182410.

Sharma, Ashish, Vishal Madaan, and Frederick D. Petty. 2006. "Exercise for Mental Health." *The Primary Care Companion to the Journal of Clinical Psychiatry* 08 (02): 106. https://doi.org/10.4088/pcc.v08n0208a.

Sjoberg, Daniel D., Michael Curry, Margie Hannum, Karissa Whiting, and Emily C. Zabor. 2020. *Gtsummary: Presentation-Ready Data Summary and Analytic Result Tables.* https://CRAN.R-project.org/package=gtsummary.

Smetanin, P., D. Stiff, C. Briante, C. E. Adair, S. Ahmad, and M. Kahn. 2011. "The Life and Economic Impact of Major Mental Illnesses in Canada." *Mental Health Commission Canada.* Risk Analytica. https://www.mentalhealthcommission.ca/sites/default/files/MHCC_Report_Base_Case_FINAL_ENG_0_0.pdf.

Sperandei, Sandro. 2014. "Understanding Logistic Regression Analysis." *Biochemia Medica* 24 (1): 12–18. https://doi.org/10.11613/bm.2014.003.

Technology, Advancing Knowledge through. n.d. "Computing in the Humanities and Social Sciences." http://www.chass.utoronto.ca/.

Thavaneswaran, Arane. 2008. "Propensity Score Matching in Observational Studies." *UManitoba*. https://www.umanitoba.ca/faculties/health_sciences/medicine/units/chs/departmental_units/mchp/protocol/media/propensity_score_matching.pdf.

Twenge, Jean M., A. Bell Cooper, Thomas E. Joiner, Mary E. Duffy, and Sarah G. Binau. 2019. "Age, Period, and Cohort Trends in Mood Disorder Indicators and Suicide-Related Outcomes in a Nationally Representative Dataset, 2005–2017." *Journal of Abnormal Psychology* 128 (3): 185–99. https://doi.org/10.1037/abn0000410.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, Romain François, Lionel Henry, and Kirill Müller. 2020. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Xie, Yihui. 2020. *Knitr: A General-Purpose Package for Dynamic Report Generation in R*. https://yihui.org/knitr/.

Zhu, Hao. 2020. *KableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.