Effects of Socialization on Mental Health

STA130 Course Project

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STA130: An Introduction to Statistical Reasoning and Data Science
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Introduction

Social interactions play a pivotal role in shaping individual mental health outcomes. It is becoming increasingly easier, especially for teenagers, to connect with their friends virtually from the comfort of their homes. One may argue that this is harmful for their mental health; is this always the case?

Through this research, we aim to highlight the difference between physically interacting with community members as opposed to virtually connecting with them. We used the Canadian Social Connections Survey (CSCS) to investigate the relationship between various forms of social interactions (physical and non-physical) and how they affect the individuals' mental health states. This presentation outlines the variables we're using, our hypotheses, analyses, key findings, and the conclusions we've drawn from these findings.

Our research questions

Question 1

Is there an association between the frequency of days where an individual spends at least 5 minutes physically socializing and their level of depression?

Question 2

Is there an association between playing video games and feeling depressed, and can going on walks counteract that?

Question 3

How does the association between loneliness and video chatting compare to text messaging?

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Question 1: Variables

Independent variables:

`CONNECTION_social_days_family_p7d_grouped`:
days where individuals spent at least 5 minutes socializing with family.

`CONNECTION_social_days_friends_p7d_grouped`:
days where individuals spent at least 5 minutes socializing with friends.

`CONNECTION_social_days_coworkers_and_classmates_p7d_grouped`:
days where individuals spent at least 5 minutes socializing with co-workers or classmates.

`CONNECTION_social_days_neighbours_p7d_grouped`:
days where individuals spent at least 5 minutes socializing with neighbours.

Dependent variable:
`WELLNESS_phq_score`:
metric used to characterize an individual's level of depression on a scale of 0-6.

Preliminary analysis

After keeping only the columns we're interested in and cleaning the data, we were left with 575 rows and 6 columns.

```
import pandas as pd

# Load the data
file_name = 'Untitled spreadsheet - finalized_data (1).csv'
df = pd.read_csv(file_name)

# Replace empty strings with NaN for easier cleaning
df.replace('', pd.NA, inplace=True)

df =  df.dropna()
# Keep only the relevant columns
columns_to_keep = [
    'CONNECTION_social_days_family_p7d_grouped',
    'CONNECTION_social_days_friends_p7d_grouped',
    'CONNECTION_social_days_coworkers_and_classmates_p7d_grouped',
    'CONNECTION_social_days_neighbours_p7d_grouped',
    'WELLNESS_phq_score_y_n',  # Binary PHQ score
    'WELLNESS_phq_score'       # Continuous PHQ score
]
df_cleaned = df[columns_to_keep]

df_cleaned
df_cleaned.shape
```

```
(575, 6)
```

Figure: 6x575 cleaned dataframe

Preliminary analysis

The independent variables were categorical with 4 categories each:

```
df_cleaned['CONNECTION_social_days_family_p7d_grouped'].unique()
```

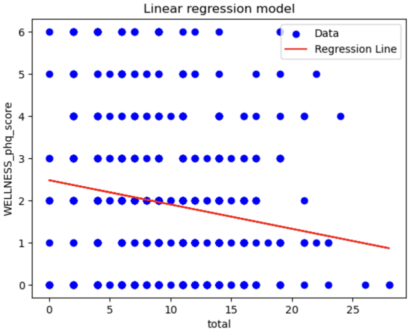
```
array(['None (0 Days)', 'Most days (4 - 6 days)',
       'Some days (1 - 3 days)', 'Every day (7 days)'], dtype=object)
```

Figure: Unique data entries in one of the columns

To better analyze the data, we gave each category a numeric value based on the midpoint of the interval. For example, the 'Most days (4-6)' category was assigned 5 (representing the midpoint of the number of days). Then, we added another column to represent the total number of days where each individual spent at least 5 minutes socializing with any one of the groups above using the numeric values we assigned to each category.

Analysis

First, we examined the relationship between the total column and the numeric PHQ score column. We did this by fitting a simple linear regression through the data.



OLS Regression Results

Dep. Variable:	WELLNESS_phq_score	**R-squared:**	0.026
Model:	OLS	**Adj. R-squared:**	0.025
Method:	Least Squares	**F-statistic:**	15.49
Date:	Sat, 23 Nov 2024	**Prob (F-statistic):**	9.30e-05
Time:	18:39:11	**Log-Likelihood:**	-1153.2
No. Observations:	575	**AIC:**	2310.
Df Residuals:	573	**BIC:**	2319.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.4779	0.158	15.675	0.000	2.167	2.788
total	-0.0576	0.015	-3.936	0.000	-0.086	-0.029

Omnibus:	47.542	**Durbin-Watson:**	1.575
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	53.879
Skew:	0.722	**Prob(JB):**	2.00e-12
Kurtosis:	2.595	**Cond. No.**	22.9

Limitations and assumptions

For this analysis, we only considered days where individuals spent at least 5 minutes socializing. However, this threshold is vague and is not specific enough. One could spend 5 minutes socializing and another could spend 5 hours socializing yet they would still be considered under the same category. I also made some assumptions to convert the categorical values into numeric values. However, given that the mapping of involved the midpoint of each interval, I believe this conversion was suitable.

Analysis

We then created a bootstrapped distribution of model slope coefficients by repeatedly resampling from our original sample and refitting OLS models through the samples. Then, we created a 95% confidence interval of our bootstrapped coefficients for inference.

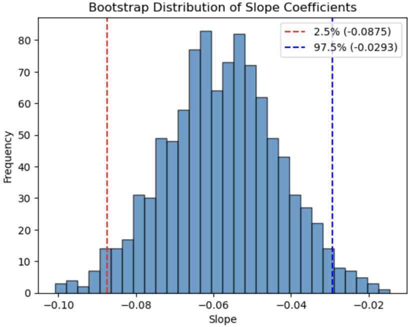


Figure: 95% confidence interval

Summary and conclusion

The confidence interval we constructed only contained negative slopes between -0.0875 and -0.0293 and so we can conclude with 95% confidence that the true value of the slope coefficient lies in that interval. This means that as the number of days where an individual spends at least 5 minutes socializing increases, the average depression score decreases. However, the values of the slopes are very small and so the effect of socializing on depression scores is minuscule.

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Question 2: Variables

Independent variables:

CONNECTION_activities_onlinegames_p3m:
how often an individual has played online games in the past 3 months

Ordinal categorical outcomes: Not in the past three months, Less than monthly, Monthly, A few times a month, Weekly, A few times a week, Daily or almost daily

CONNECTION_activities_walk_p3m:
how often an individual has gone on a walk with friends in the past 3 months

Ordinal categorical outcomes: Not in the past three months, Less than monthly, Monthly, A few times a month, Weekly, A few times a week, Daily or almost daily

Dependent variable:

WELLNESS_malach_pines_burnout_measure_depressed:
how often an individual feels depressed **Ordinal categorical outcomes:** Never, Almost never, Rarely, Sometimes, Very Often, Always

Limitations and assumptions

It is not possible to perfectly map the ordinal categories for how often an individual feels depressed Never, Almost never, Rarely, Sometimes, Very Often, Always numerically. It shouldn't be assumed that the "distance" between each category is "1", but I will map it to the numbers 0 through 5 for multiple linear regression.

It is not possible to measure level of depression in a binary variable, if I wanted to do something like a logistic regression.

I will keep the outcomes as a continuous variable (intended to be interpreted from a 0 through 5 scale), rather than converting it back to categorical.

Cleaning data

First, I want to assign numbers to the ordinal categories of how often an individual feels depressed.
I will just use the consecutive numbers 0 (never) through 5 (always).

```python
# Mapping the variables to numeric values
mapping_dict = {
    'WELLNESS_malach_pines_burnout_measure_depressed': {
        'Never': 0,
        'Almost never': 1,
        'Rarely': 2,
        'Sometimes': 3,
        'Very Often': 4,
        'Always': 5
    }
}
```

After renaming variables, removing empty values, etc., this is what my DataFrame looks like.

	OnlineGamesC	WalkWithSomeoneC	DepressionC	DepressionN
0	Not in the past three months	Daily or almost daily	Rarely	2.0
1	Not in the past three months	A few times a week	Almost never	1.0
2	Not in the past three months	A few times a month	Almost never	1.0
3	Weekly	Less than monthly	Rarely	2.0
4	Weekly	Monthly	Almost never	1.0
...	...	...	...	...

The table below retains only the significant (p-value ≤ 0.05) outcomes (rest are omitted) from a multiple linear regression. I will create a new column that will show the predicted $\hat{y}$ values, and plot this on a bar plot.

```python
# Fit the OLS model using categorical values (OnlineGamesC and SocialFriendsC)
ols_model_c = smf.ols("DepressionN ~ C(OnlineGamesC) * C(WalkWithSomeoneC)", data=df)

fitted_ols_model_c = ols_model_c.fit()
```

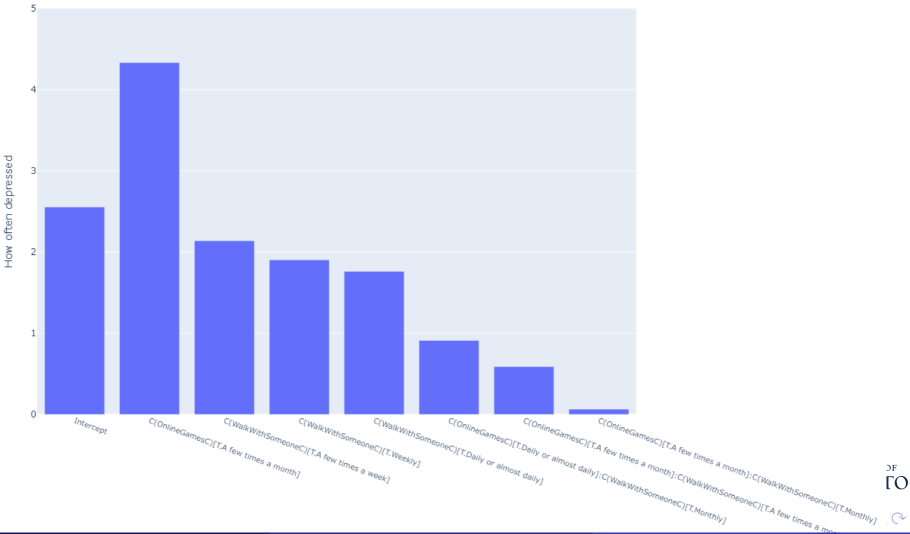
```python
summary = fitted_ols_model_c.summary()

# The summary is a text object, so we need to extract the coefficients and p-values from it
# We can use the summary.tables[1] for extracting the coefficient table
summary_lines = summary.tables[1].data

# Convert the summary table into a DataFrame
summary_df = pd.DataFrame(summary_lines[1:], columns=summary_lines[0])

# Convert the p-values to float type and filter
summary_df['P>|t|'] = summary_df['P>|t|'].astype(float)
filtered_summary = summary_df[summary_df['P>|t|'] <= 0.05]
```

```python
coefficients = filtered_summary['coef'].astype(float)
intercept = coefficients[0]

values = intercept + coefficients
values.loc[0] = intercept

values_rounded = values.astype(int)

depression_values = [list(mapping_dict["WELLNESS_malach_pines_burnout_measure_depressed"].keys())[value] for value in va

pd.set_option('display.max_colwidth', None)  # Show full content in each cell

filtered_summary = filtered_summary.assign(value=values, depression_value=depression_values)
filtered_summary
```

		coef	std err	t	P>|t|	[0.025	0.975]	yhat
0	Intercept	2.5546	0.122	21.001	0.000	2.316	2.793	2.5546
3	C(OnlineGamesC)[T.A few times a month]	1.7787	0.776	2.293	0.022	0.255	3.302	4.3333
10	C(WalkWithSomeoneC)[T.Weekly]	-0.6510	0.190	-3.430	0.001	-1.024	-0.278	1.9036
11	C(WalkWithSomeoneC)[T.A few times a week]	-0.4154	0.193	-2.157	0.031	-0.794	-0.037	2.1392
12	C(WalkWithSomeoneC)[T.Daily or almost daily]	-0.7927	0.238	-3.328	0.001	-1.260	-0.325	1.7619
21	C(OnlineGamesC)[T.A few times a month]:C(WalkWithSomeoneC)[T.Monthly]	-2.4898	0.997	-2.498	0.013	-4.447	-0.533	0.0648
24	C(OnlineGamesC)[T.Daily or almost daily]:C(WalkWithSomeoneC)[T.Monthly]	-1.6440	0.777	-2.115	0.035	-3.170	-0.118	0.9106
27	C(OnlineGamesC)[T.A few times a month]:C(WalkWithSomeoneC)[T.A few times a month]	-1.9651	0.987	-1.991	0.047	-3.903	-0.027	0.5895

Bar plot

Sorted in descending order, with intercept first.



Findings

Recall that the values on the bar chart is how level of depression changes as the variables in the x-axis changes.

We find that the intercept (no online games, no going on walks with friends) is 2.5 on this 0-5 scale. It is interesting that the intercept is at the halfway point.

We find that even just playing online games a few times a month can increase one's level of depression a lot.

As an individual's frequency on walks with friends increases, their level of depression decreases.

This change is apparant in playing and not playing online games.

In conclusion, we find that only playing online games will correlates positively with one's level of depression, while going on walks with friends will significantly lower that.

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Question 3 Variables

How does the association between loneliness and video chatting compare to text messaging?

Independent Variables:

Video chatted with friends/family in the past 3 months:
Texted or messaged someone in the past 3 months to check in:

7 Options:

"Not in the past three months" ... "Daily or almost daily",

Dependent Variables:

How many days felt lonely in the past week:

5 Options:

'None of the time (e.g., 0 days)': 0 ... 'All of the time (e.g. 5-7 days)': 6

```
CONNECTION_activities_text_or_messaged_p3m_combined
Few times a month or weekly      266
Few times a week or daily        226
Less than monthly or monthly     209
Not in the past three months     106
Name: count, dtype: int64
```

```
CONNECTION_activities_video_chat_p3m_combined
Not in the past three months     254
Few times a month or weekly      234
Less than monthly or monthly     202
Few times a week or daily        117
Name: count, dtype: int64
```

We combined the independent variables into categories of two options to reduce the number of options from 7 to 4

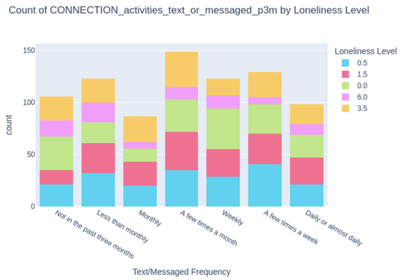
More narrowed down results

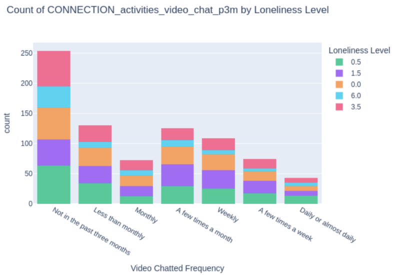
We selected "Few times a month or weekly" as the baseline (since it is a moderate level of frequency)

Assumptions

- Converting the categorical variable to numerical values makes it not completely accurate since it assumes an exact number of days that they feel lonely (it is not a continuous variable but it being treated as one)
- How many days people feel lonely in a week is not reflective of how lonely they feel on average
- Converting independent variables into 4 categories of options instead of 7 is not reflective of how the surveyors actually responded to the question and narrows down the frequency of their activities

Visualization of the Raw Data





Graph 1 - Text/Messaged

Graph 2 - Video Chatting

Simple Linear Regression & Data Wrangling

We first tried to analyze the two factors separately with simple linear regression.

Dep. Variable:	LONELY_direct_continuous	**R-squared:**	0.009
Model:	OLS	**Adj. R-squared:**	0.005
Method:	Least Squares	**F-statistic:**	2.406
Date:	Sun, 01 Dec 2024	**Prob (F-statistic):**	0.0660
Time:	16:53:34	**Log-Likelihood:**	-1621.2
No. Observations:	807	**AIC:**	3250.
Df Residuals:	803	**BIC:**	3269.
Df Model:	3		
Covariance Type:	nonrobust		

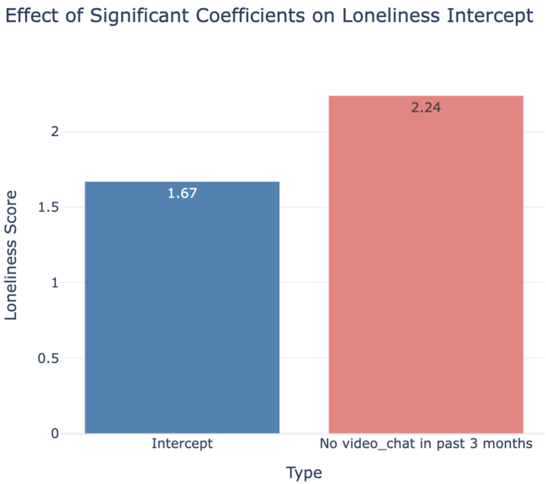
Loneliness vs. Video Chatting Frequency

Dep. Variable:	LONELY_direct_continuous	**R-squared:**	0.008
Model:	OLS	**Adj. R-squared:**	0.005
Method:	Least Squares	**F-statistic:**	2.230
Date:	Sun, 01 Dec 2024	**Prob (F-statistic):**	0.0834
Time:	16:53:33	**Log-Likelihood:**	-1621.5
No. Observations:	807	**AIC:**	3251.
Df Residuals:	803	**BIC:**	3270.
Df Model:	3		
Covariance Type:	nonrobust		

Loneliness vs. Text Messaging Frequency

The fitting of the model was poor, so we decided to analyze with a multilinear regression model with interactions.

Final Result & Analysis



R-squared value = 0.32

The condition number = 26.4

Residual analysis suggests minimal bias

Conclusions:

- Treating texting and video chatting a few times a month or weekly as the baseline
- Comparing that intercept to no video chat in the past 3 months
- Final Result - Not video chatting in the past 3 months increases the days one feels lonely from 1.67 (when texting and video chatting a few times a month or weekly) to 2.24 days
- So, video chatting could be beneficial to reducing loneliness

*Reminder that this is not completely accurate due to assumptions mentioned previously

*Reminder that correlation $\neq$ causation

Conclusion

Connections

- Aim to analyze how people's mental health is associated with different socializing forms

Findings

- Socializing and Depression:
  - The average depression score decreases when physical socialization ≥ 5 min/day
  - Depression levels also drop when taking a walk with others.
  - Playing video games, however, may have an opposing effect on depression levels.
- Socializing and Loneliness:
  - Not video chatting in the past 3 months increases the days one feels lonely

Acknowledgments

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