What is the determinant factor amongst overall well-being in determining self-reported happiness?

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1. Introduction

Historically, countries have assessed macroeconomic performance indicators that quantify a country's economic development over time through financial metrics such as the gross domestic product, inflation reports, and consumption. However, in 1972, King Jimgme Singye Wanchuck became the catalyst for expanding the scope of what a country's economic development truly means. By introducing the term "gross national happiness", he created a focus on the effect of individual satisfaction on a country's overall development, and raised the importance of not focusing solely on quantitative financial indicators ("Gross National Happiness"). Since this point, the recollection of data regarding happiness, satisfaction, well-being, and overall living conditions has been increasingly conducted, despite most of the data being self-reported.

This project aims to assess the relationship between key indicators of self-reported quality of life, in four domains (mental well-being as measured by the WHO-5 index, social-life satisfaction, overall life satisfaction, and perceived social exclusion) and self-reported happiness among UK adults. Using multiple linear regression, each association with happiness will be compared while controlling for different control variables that may influence the mentioned variables. These domains represent different influences on a person's happiness, and evaluating the domain with the strongest association can reveal insights into the influence that each of them has on self-reported happiness.

For the sample, 2,252 UK individuals' answers are considered as the dataset for the model, with the data sourced from a 2011 European Quality of Life Survey (EQLS) conducted every four years.

2. Data Exploration

A. Exploratory Data Analysis

The four selected variables described as domain variables will be complemented with seven different control variables, where their inclusion in the exploration stems from literature suggesting that they are predictors of happiness in their own right, and have the potential to confound the associations produced.

Figure 1: Table of Descriptive Statistics for QoL for Domain

Descriptive Statistics: QoL Predictors

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
mw_index	1	2,241	58.46	22.19	64	59.86	23.72	0	100	100	-0.51	-0.35	0.47
social_sat	2	2,237	7.06	2.39	8	7.31	2.97	1	10	9	-0.75	-0.09	0.05
life_sat	3	2,246	7.35	2.23	8	7.62	1.48	1	10	9	-0.94	0.49	0.05
soc_excl	4	2,160	2.32	0.81	2.25	2.28	0.74	1	5	4	0.52	-0.03	0.02

Figure 2: Table of Descriptive Statistics for Control Variables

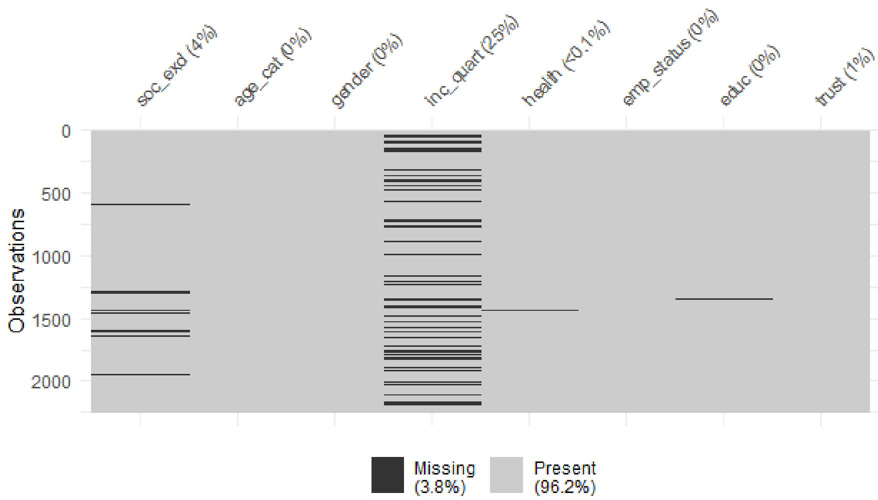
Descriptive Statistics: Control Predictors

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
age_cat	1	2,252	3.57	1.22	4	3.67	1.48	1	5	4	-0.44	-0.78	0.03
gender	2	2,252	1.57	0.50	2	1.59	0	1	2	1	-0.28	-1.92	0.01
inc_quart	3	1,695	2.50	1.12	2	2.50	1.48	1	4	3	0.002	-1.36	0.03
health	4	2,251	2.30	1.03	2	2.21	1.48	1	5	4	0.55	-0.17	0.02
emp_status	5	2,252	2.58	1.62	2	2.43	1.48	1	7	6	0.37	-1.23	0.03
educ	6	2,243	4.00	1.49	3	3.92	0	1	8	7	0.57	-0.87	0.03
trust	7	2,232	5.50	2.51	6	5.58	2.97	1	10	9	-0.34	-0.70	0.05

B. Missing-Data

Through an exploratory analysis of the entire UK dataset, we identified that over 10 predictors had around 75% missing data. Because of the nature of the questions, some questions are not applicable for certain participants, for example, questions on "hours worked on a second job". This is an important consideration moving forward, as some questions may not apply to our entire selected sample, leading to missing rows. Through our 11 predictors, 96% of the data includes responses. However, most of the missing data is concentrated in a single predictor, *inc_quart*, which describes income. With 25% of its data missing, a listwise deletion would eliminate a large proportion of our dataset, reducing statistical power, not being considered a "missing completely at random" case (MCAR), leading to potential biases (Kang 402)

Figure 3: Graph of Missing Values

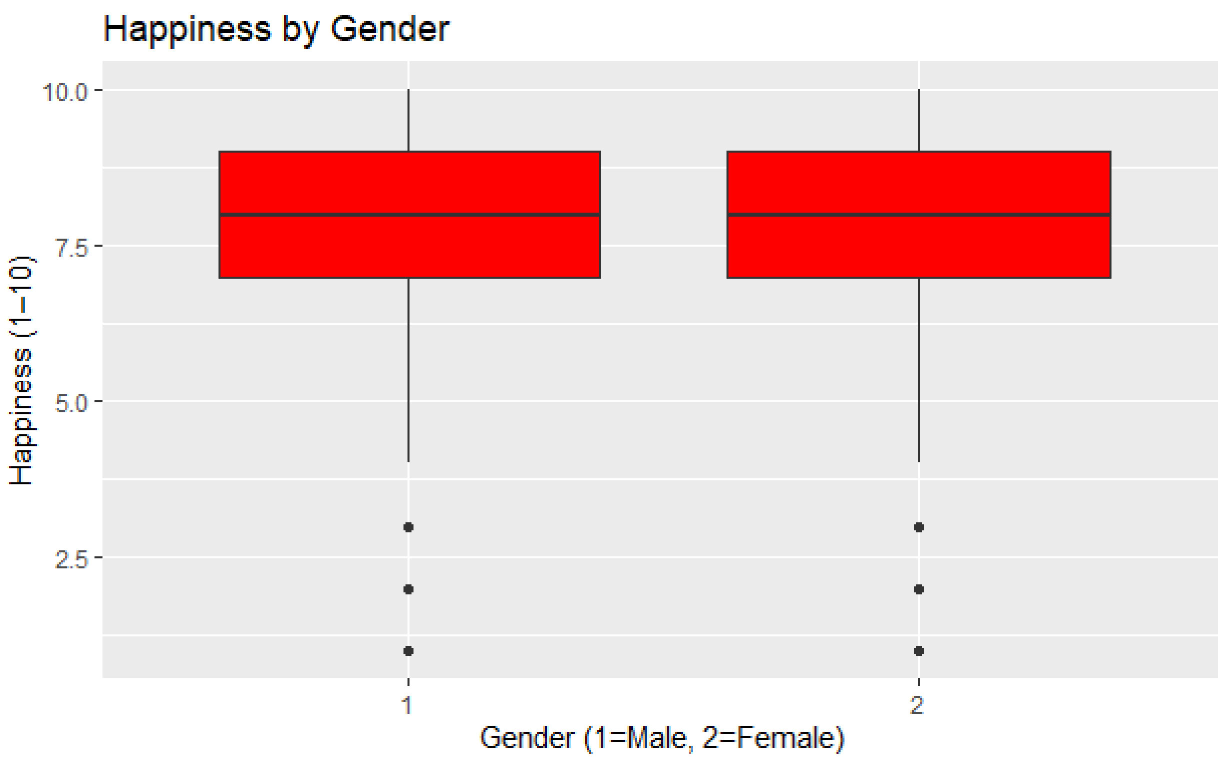


Two strategies can be considered for determining whether this absence of data can be classified as randomized were conducted. Firstly, the average happiness on rows where income was missing and present was conducted. This shows that the difference in average is minimal, indicating a counterintuitive result, considering this would mean that on average, people without an income are happier. However, further analysis cleared up this intuition. By grouping the percentage of missing income by age group, we can see how the youngest age group and oldest age group had a significantly higher proportion of missing data (see Appendix).

C. Boxplots & Bivariate Testing

Although each control variable was selected for its well-documented association with happiness in previous literature, our UK sample size can lead to the differences being minimized. Visually exploring this through boxplots, we can compare the distribution of self-reported happiness across the levels of each categorical control (see Appendix). With gender having only two response options, in contrast with how all other variables have at least five, the disparity among responses depends solely on these two options. In the boxplot below, the disparity clearly presents marginal research, inviting more exploration to evaluate the necessity of gender as a control variable.

Figure 4. Gender Box Plot

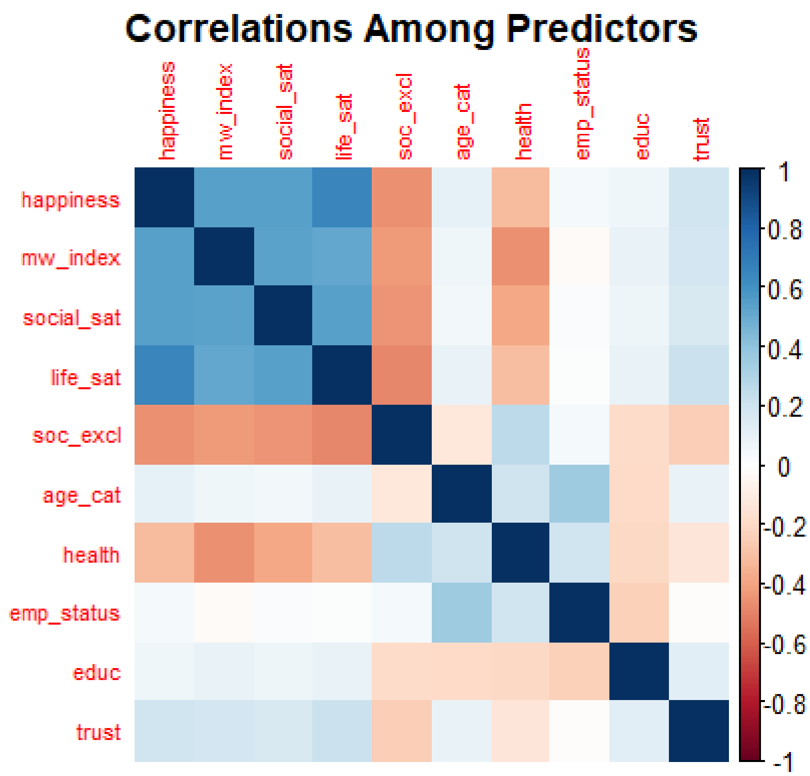


A t-test is conducted to evaluate if the minimal difference is not appreciated properly visually; however, with a p-value significantly above any threshold (0.59), and the differences in means between genders regarding their influence on happiness being less than 0.05, the recommended approach is to remove the variable. However, this stays consistent with present literature, which suggests that gender presents a difference in long-term measurements on quality of life, such as mental wellbeing, but a marginal difference in short-term measurements such as happiness (Batz and Tay).

D. Correlation Matrix

Through a correlation matrix, we can see the influence that the predictors can have on each other, indicating the potential prescense of multicollinearity. In this case, no values seem to critically indicate it.

Figure 5. Correlation Matrix



3. Regression

For both our domain and control variables, we evaluate the correlation visually to have an idea of what to expect when creating the regression model. For the domain variables (see Appendix), all correlations seem to fall under the moderate threshold. However, for our control variables, the correlation for our five retained control variables is significantly lower (see Appendix). However, despite this being the case, a low correlation coefficient on the response variable does not eliminate the chance of a correlation with another variable being present. As happiness is a short-term metric, it would intuitively make more sense that these variables were correlated with other long-term metrics (such as our domains).

A. Model Specification

A linear model is conducted with the four domain variables and the five retained control variables, having removed *gender* and *income* in the process. The following table shows the influence on happiness for each variable, for each increase per variable.

Figure 6. First Linear Regression Model

Full Linear Model Results

	Dependent variable:
	happiness
Life Satisfaction	0.371***
	(0.018)
Mental Well-Being Index	0.015***
	(0.002)
Social Satisfaction	0.155***
	(0.016)
Social Exclusion	-0.201***
	(0.045)
Trust	0.024
	(0.012)
Constant	3.179***
	(0.365)
Age Categories	Yes
Employment Status	Yes
Education	Yes
Health	Yes
Control Factors	Age, Employment, Education, Health
Observations	2,115
R2	0.537
Adjusted R2	0.531
Note:	*p<0.05; **p<0.01; ***p<0.001

B. Specification Results

All four domains were considered statistically significant, with the p-value being significantly low (all below 0.001). For every increase in life-satisfaction, an increase of 0.371 is gained in happiness, indicating a consistence with the literature that presents life-satisfaction as one of the most dynamic and predictive components of well-being .The variables of social exclusion, social-life satisfaction and mental wellbeing, have an estimate of -.201, 0.155, and 0.015 respectively. To compare the variables amongst each other, their scale needs to be considered and therefore standardized.

C. Standardizing the Model

Implementing a *z-score* on both the domain and control variables allows us to create a common scale for comparison. In this case, the standardization of values affected mental well-being index the most distinctively and scaled down social exclusion the most drastically. This is because their present scale presented an incomparable metric to other domain variables. We can now see how in case of an increase in one standard deviation, life satisfaction correlates to higher happiness with a change twice as large as other domain variables individually. In our first model, we can conclude that life-satisfaction is the most influential domain in happiness, however we can also evaluate how the scale was causing mental wellness index's estimate to be underrepresented, while social exclusion's metric was being overrepresented.

Figure 7. Comparison of Unstandarized and Standarized Model

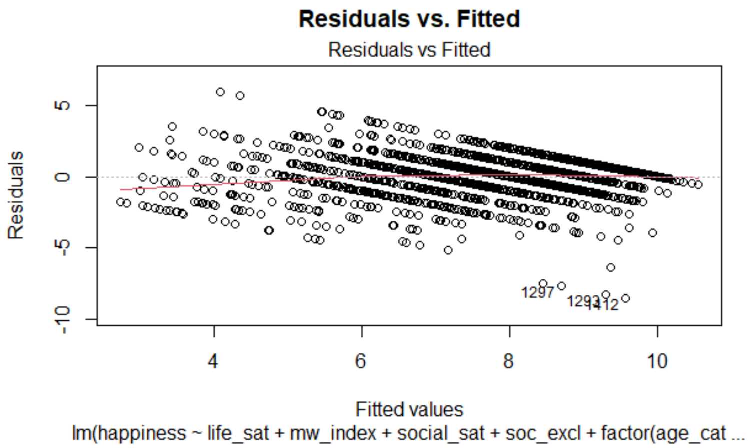
Comparison of Original and Standardized Linear Models

	Dependent variable:	
	Happiness	Happiness (z-scored)
	(1)	(2)
Life Satisfaction	0.371***	
	(0.018)	
Mental Well-Being Index	0.015***	
	(0.002)	
Social Satisfaction	0.155***	
	(0.016)	
Social Exclusion	-0.201***	
	(0.045)	
Age (factor)		0.415***
		(0.020)
Employment Status (factor)		0.172***
		(0.020)
Education (factor)		0.187***
		(0.020)
Health (factor)		-0.082***
		(0.018)
Observations	2,115	2,115
R2	0.537	0.537
Adjusted R2	0.531	0.531
F Statistic (df = 26; 2088)	93.141***	93.141***
Note:		*p<0.1; **p<0.05; ***p<0.01

D. Heteroscedasticity

Most results cluster near the 8, 9 and 10 area in happiness scale, which some extreme scores being identified to be further explored in other diagnostics. Despite this however, the residuals seem to be equally distributed along the axis, indicating that heteroscedasticity is most likely not present. Additionally, the LOESS line is mostly horizontal, showing no significant pattern for a non-linear relationship to be identified.

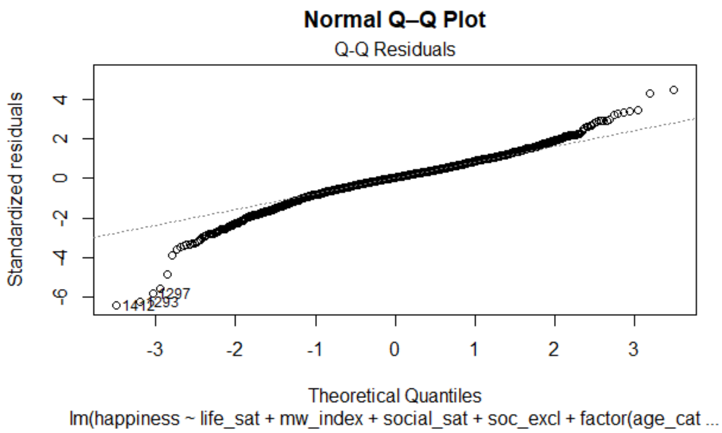
Figure 8. Residuals vs Fitted Graph



E. Normality of Residuals

In a large sample of 2,226 observations, small departures from the normal curve are expected to occur, more likely at random. Despite this, because of the nature of the data being capped usually on scales from 1-10, the far left and far right tails presenting standardized residuals below –3.5 and above 3.5 can be expected. Since the cluster of data points is formed tightly around the reference line, we can assume that the normality assumption holds well enough to not cause significant interference with linear regression.

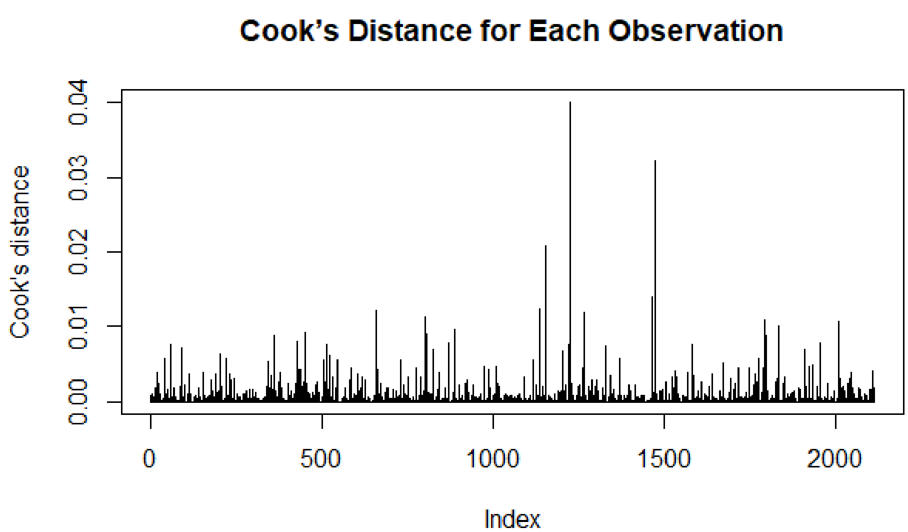
Figure 9. Normal Q-Q Plot



F. Outliers

When computing the visualization of Cook's distance for all cases, some extreme peaks immediately stand out. As mentioned previously, because of the size of the dataset, it is normal to expect outliers, however, it is important to indicate how most of the data falls well below the cutoff. Analyzing these outliers more closely (see Appendix), we realize how individuals with a really high mental wellbeing described their happiness very poorly, or inversely, individuals with really low mental wellbeing described themselves as being extremely happy. A similar pattern occurred with social satisfaction. While this is further discussed in limitations, the case stems from the natural variability of happiness as a short-term variable, differing from mental wellbeing as a long-term one.

Figure 10: Cook's Distance Plot



In order to mitigate the effect of the outliers highlighted in Cook's distance, we applied two standard transformations to our model. By implementing a log transformation on the mental wellbeing index variable, we attempt to compress the scores closer together, to ensure that they follow a pattern similar to life-satisfaction. When standardized, mental wellbeing performed better than expected. Additionally, the square root transformation on extreme social exclusion is accounted for in both ends by diminishing the differences to overall reduce the leverage of extreme cases. When tested (see Appendix), the model performed slightly better with an Aikaike Information Criterion of 17 points lower than the original model.

G. Multivariance

After conducting another test in variance (see Appendix), all the models successfully marked a scaled generalized VIF as lower than 1.5, however, without scaling the GVIF, both the age and employment variables exceeded the desired 5 threshold. To evaluate if the presence of residual inflation can affect the model, a ridge regression was conducted by a 10-fold cross validation on the transformed model. The new model was applied to the transformed model, performing slightly better than the original, with a CV-MSE of 1.80, compared to the original CV_MSE of 1.83.

H. Cross Validation

We have presented the original model, a transformed model with the square root of social exclusion and the log of mental wellbeing index, and a penalty ridge regression on the transformed model. The results of the model can be seen in the table below.

Figure 11. Final Three Models

Model Performance Comparison

Model	AIC	RMSE	MSE	Lambda
Original linear	7,263.010	1.349	1.834	
Transformed linear	7,246.583	1.336	1.809	
Ridge (on transformed)		1.342	1.802	0.130

The transformations for the model provided an important decrease in AIC, which cannot be accounted for in ridge models. Additionally, the difference between the ridge and the transformed in RMSE and MSE is minimal, which indicate a less that 1% improvement, meaning that the issue regarding variance-inflation was not critical enough to justify changing the model to a ridge regression. For that reason, we conclude on utilizing the transformed model, which performed the best across several metrics.

I. Final Model Presentation

Through this, we evaluate that the chosen model is the transformed model, which again presents that life-satisfaction stands as the domain variable with the biggest association to happiness.

Figure 12. Final Model

Transformed Linear Model (Best Fit)

	Dependent variable:
	happiness
Life Satisfaction	0.371***
	(0.017)
Log(Mental Well-Being +1)	0.618***
	(0.063)
Social Satisfaction	0.152***
	(0.016)
Sqrt(Social Exclusion)	-0.585***
	(0.134)
Observations	2,115
R2	0.541
Adjusted R2	0.535
Note:	*p<0.05; **p<0.01; ***p<0.001

4. Discussions and Limitations

A. Listwise Deletion

Despite a listwise deletion being included to remove 4% of cases because of missing social-exclusion data, our analysis still follows the assumption that those omissions are unrelated to the unobserved values. An accepted assumption for missing data is that data is missing at random (MAR), meaning that the chance that a given respondent skips the social-exclusion question depends on other observations, but not on their unreported social-exclusion score (Kang 408).

B. Outliers

As mentioned, the level of uncertainty regarding the origin of outliers remains, as two distinct assumptions can be made. Firstly, we can assume that some respondents misunderstood the scale and responded to happiness opposite to what they truly felt, for that reason, this would explain the high mental wellbeing with a low happiness and vice versa. The other assumption is that respondents did not get anything wrong, but rather because of the variability of happiness, that they could have opted for an extreme response opposite to what they have been feeling in recent times.

C. Happiness as a Response Variable

Despite happiness being a categorical value, we are treating it as a continuous value. This can influence the accuracy strength of our model and provide uncertainty on the effect that this decision could have on our model. Additionally, happiness as a response value can be misleading, as the set definition for happiness is not standardized, leading to the meaning of happiness to be the catalyst of bias getting introduced. One example is the framing of the question itself. For example, happiness could produce a different conclusion for researchers on two different surveys, and this could not only be explained by the difference in the data but by the methodology itself. One example is in the World Happiness Report, and in how their inclusion of the "Cantil Ladder", or ranking happiness based on a ladder can make people assume the question implies that they should rank their happiness in relation to how happy they are relative to other people in the ladder, making the overall happiness in the survey reduce (World Happiness Report).

5. Interpretation and Conclusions

This project explored the different aspects of quality of life and their relation to the self-reported happiness of adult individuals from the UK. The well-being of an individual is an important metric to consider, as it goes beyond just the aggregation of financial metrics, and it measures the overall satisfaction of an individual. Overall, we can conclude in our findings that overall life satisfaction is the stronger predictor of happiness. People who felt more satisfied with their life as a whole reported significantly higher happiness levels. However, the other domains mentioned were important too, with good mental well-being and a fulfilling social life being linked with greater happiness, while feeling isolated or excluded created an opposite effect, being at par with lower happiness, despite this, these factors were not close to an impact on happiness as large as life satisfaction. This suggests that when people have a positive outlook on their life in general, it can have a more significant effect than more specific aspects of life on its own, despite people often thinking the contrary.

This creates an emphasis on the alignment presented on how life satisfaction can align with higher subjective well-being, leading to a better outcome in health and longevity to economic performance (Ruggeri et al). In other terms, the benefits of improving how you feel about your life extend from just personal happiness but can also be parallel with broader societal gains. Research in some areas indicates that a higher life satisfaction amongst adults can be associated with fewer chronic health conditions and overall health-related quality of life (Megari).

The conclusion was reached with an exploratory analysis, inspecting the survey data to identify patterns amongst individuals who answered similarly on certain questions, and even evaluating if the individuals who were not answering a specific question shared similarity between them. We then built a statistical regression model to test which factors contribute the most to happiness, refining the model for accuracy as certain problems arise. As the data was self-reported, we had to evaluate decision-making on the inclusion of certain answers that could affect our results because of their unpredictability, to ensure a fair comparison between factors. Furthermore, we remained mindful of the nature of the data, as people may interpret questions or use rating scales in personal ways, so we tested our findings under different assumptions to ensure that the model was not randomly producing an output based on chance. By integrating our initial analysis with thoughtful model adjustments, we ensure that our conclusions on the effect of self-reported happiness and its drivers are reliable.

Despite life-satisfaction being the most important determinant in our analysis, the importance of the findings overall is the emphasis on the strong association that these four variables have with happiness. individuals who answered positively (meaning less for social exclusion, and higher for mental well-being, social satisfaction, and life satisfaction), it was predicted that their happiness score was also going to be positive, and this association stayed true for all the four domains explored. This means that if a person is only able to work on one of these factors at a time, an improvement in these metrics can be a predictor of a person's self-reporting as happier.

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Appendix

Figure 13. The aggrupation of Missing Income by Age Group

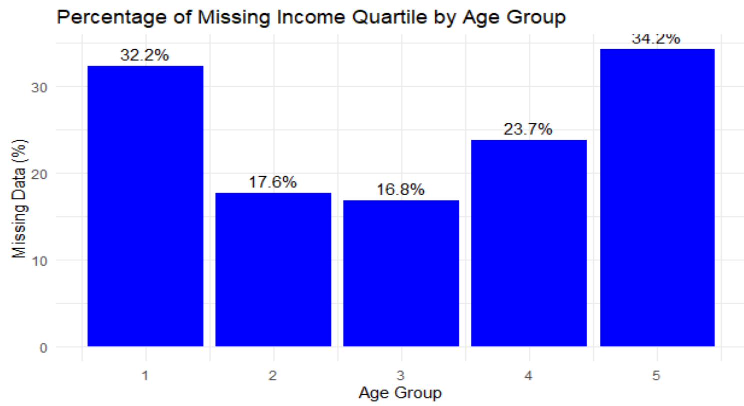


Figure 14-19. Visual Box Plot Representation of Control Variables

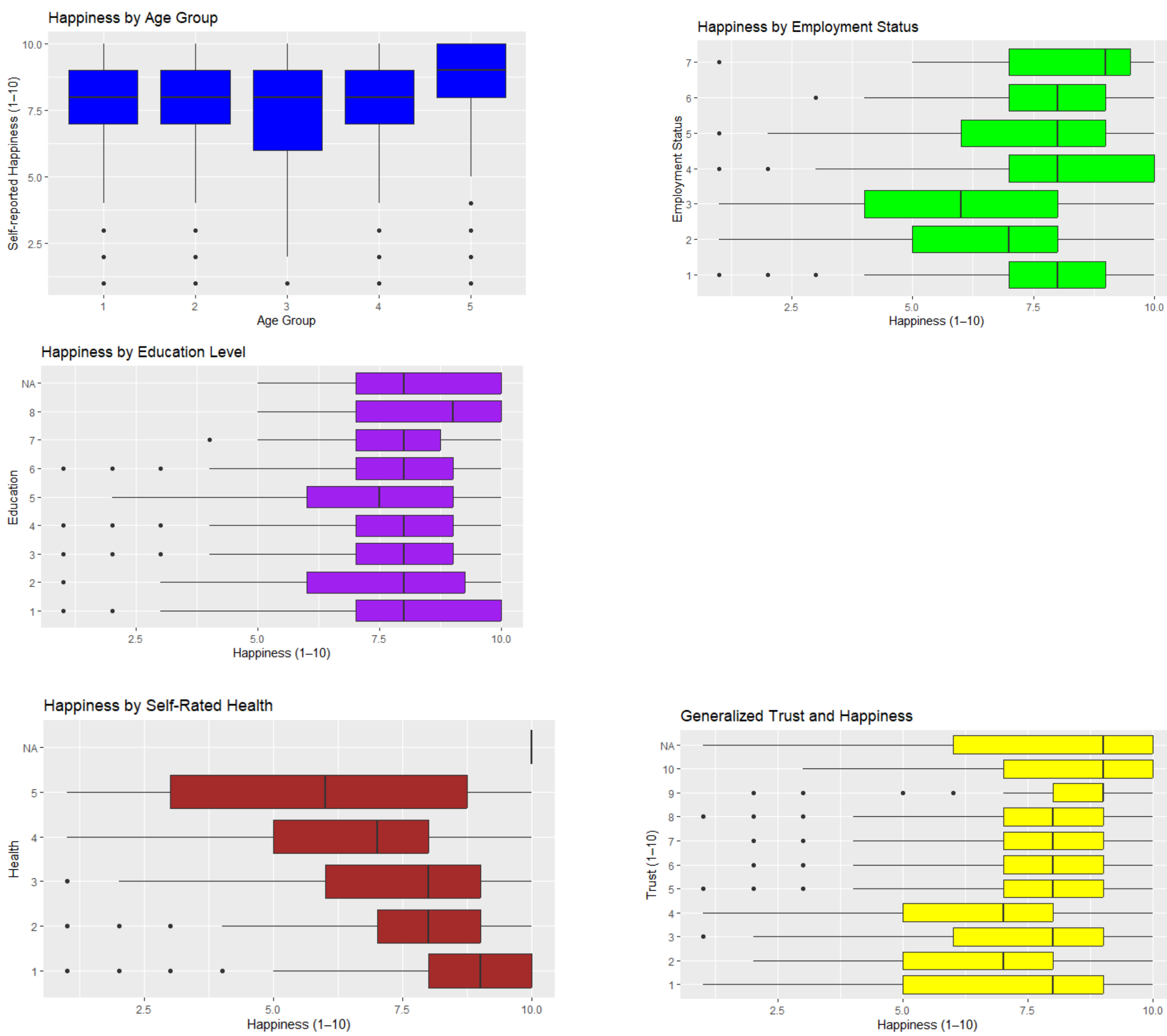
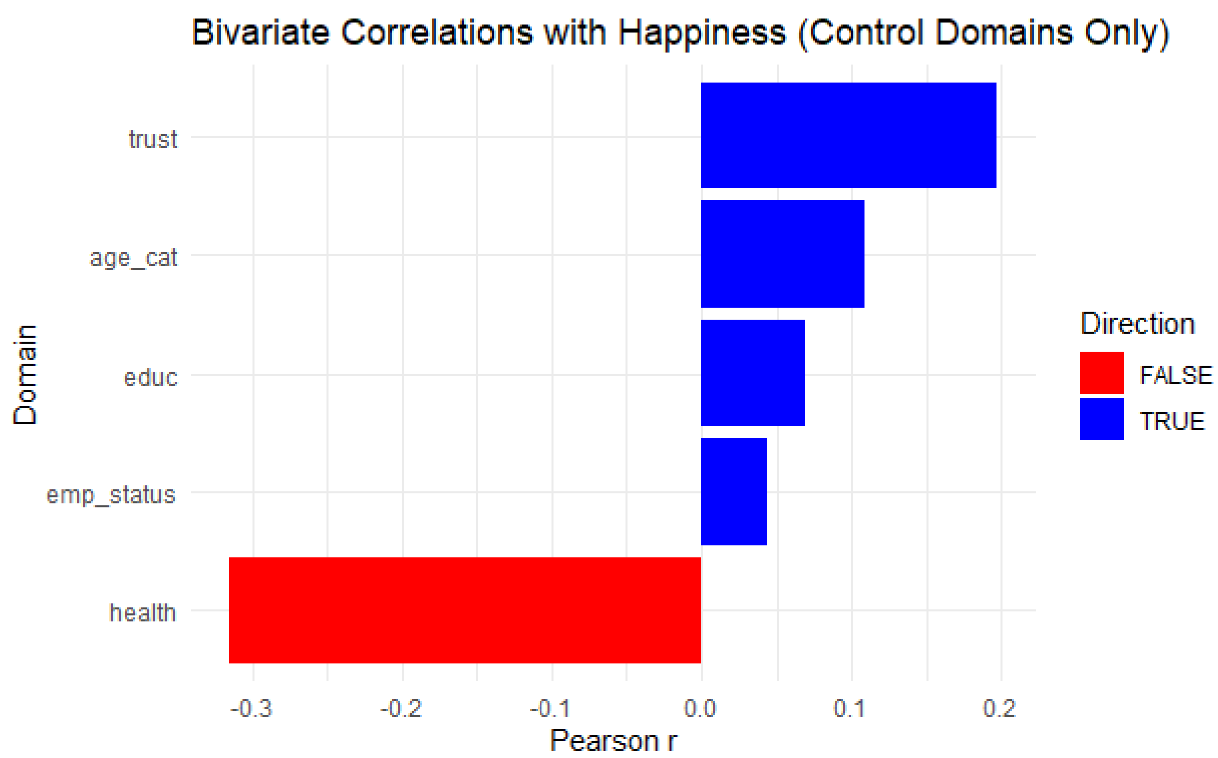
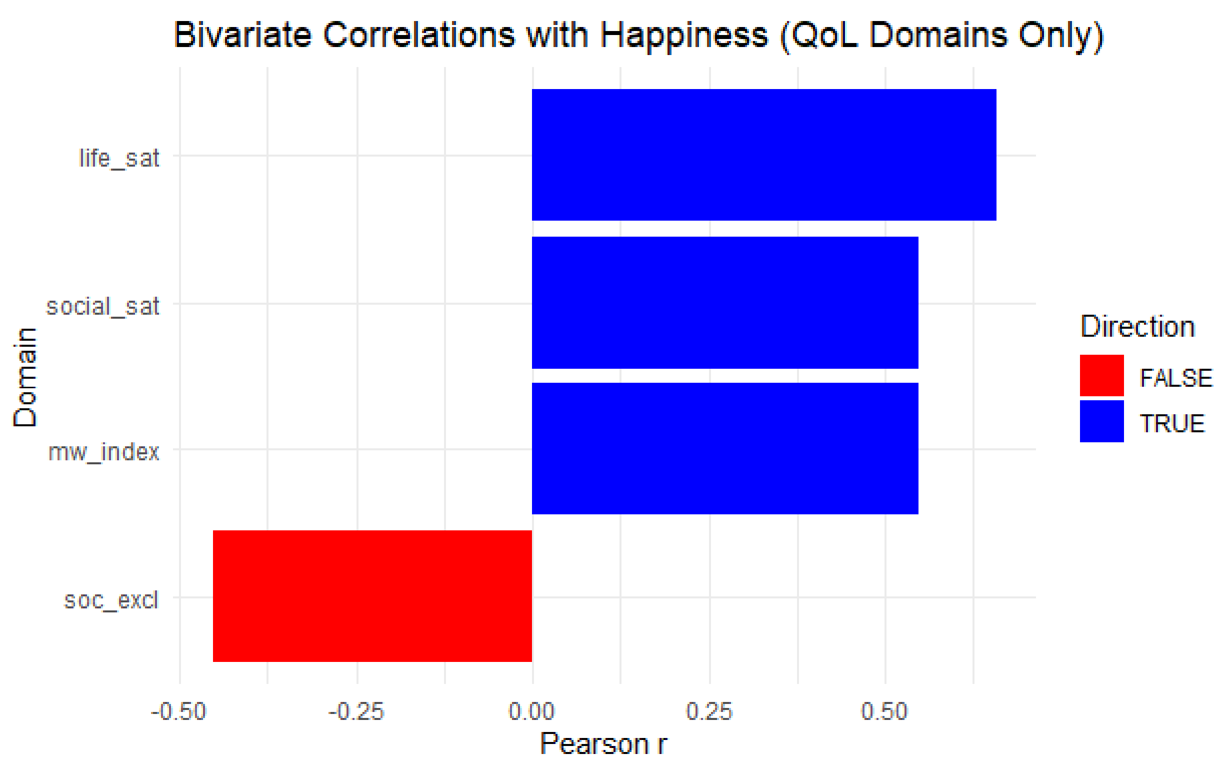


Figure 20. Visual Box Plot Representation of Control Variables



<u>Figure 21. Visual Box Plot Representation of Domain Variables</u>



<u>Figure 22. Cook's Distance's Highest Values</u>

```
Top 10 Influential Obs. by Cook's D
===========================================================================
Obs   MW Index Social Sat Life Sat Soc Excl             Cook's D
---------------------------------------------------------------------------
1297   100        1         10      2.25   c(`1375` = 1.28080992135755e-05)
1563    68        10        10       3     c(`1668` = 2.23258989433443e-06)
1223    36        1         1        2     c(`1295` = 5.27327549702373e-05)
1556    16        5         5       2.75   c(`1658` = 6.94234314166655e-06)
1203    88        9         4       1.75   c(`1272` = 0.000225511006431147)
692     8         1         3        3     c(`725` = 2.15746671962022e-05)
1342    68        4         1        2     c(`1424` = 2.3810919092194e-07)
846     52        5         5        3     c(`894` = 0.000157945565599031)
1917    20        3         6        1     c(`2044` = 0.000103650629555535)
2144    80        6         10      4.5              c(`NA` = NA)
---------------------------------------------------------------------------
```

Figure 23. Scaled VIF/GIF Check

```
Scaled VIFs for Predictors
========================
Variable             VIF
------------------------
life_sat             1.33
mw_index             1.34
social_sat           1.34
soc_excl             1.25
factor(age_cat)      1.23
factor(emp_status)   1.17
factor(educ)         1.02
factor(health)       1.07
trust                1.06
------------------------
```

Figure 24. Unscaled GVIF Check

```
Unscaled GVIF for Predictors
=========================
Variable             GIF
-------------------------
life_sat             1.76
mw_index             1.79
social_sat           1.80
soc_excl             1.57
factor(age_cat)      5.12
factor(emp_status) 6.67
factor(educ)         1.40
factor(health)       1.69
trust                1.11
-------------------------
```