

Introduction

This report will present the main findings from an analysis of the predictors of prosocial COVID-19 behaviours, with a focus on Argentina versus other countries and a cluster of countries similar to Argentina. This research was conducted as part of a larger study aimed at identifying the most important factors that influence people's willingness to engage in actions that would reduce the spread of the COVID-19 virus. Generative AI was used in this assignment.

I. DESCRIPTIVE ANALYSIS AND PRE-PROCESSING

A. DATA DESCRIPTION

In the initial exploration of the data frame, using `dim(cvbase)`, it is found that the dataset consists of a total of 52 attributes and the total number of observations is 40,000.

Most of the attributes seem to be categorical with numeric representation, including Employment Status, Isolation offline, Isolation online, Loneliness, Life Satisfaction, Boredom, Conspiracy Beliefs, Corona Personal behaviour, Corona Radical Action, Corona Proximity, Gender, Age, Education and Corona ProSocial behaviour. The text attributes in the data encompass Rank Order Life as well as Country Of Residence.

a. NUMERICAL ATTRIBUTES

Employment Status

The employment status variables ('employstatus_1' to 'employstatus_10') are all coded as numeric, with a value of 1 indicating the respondent belongs to that particular employment category and NA values indicating the respondent does not belong to that category. To gain a clearer picture of the employment distribution across types of employment, we calculated the sum of these columns. Based on the histogram provided, it is evident that the highest form of employment is people who work more than 40 hours and students, and the lowest are volunteers and disabled people who cannot work, this can be shown in [Graph 1.a.1](#) in the Appendix.

Social Isolation

The data shows that, on average, the respondents had more in-person social contact with friends (`isoFriends_inPerson`) than with other people (`isoOthPpl_inPerson`) outside their household in the past 7 days. The mean value for in-person social contact with friends is slightly higher at 2.066 days compared to 1.959 days for other people. The median values for both are the same at 1 day, indicating that half of the respondents had one day of in-person contact or less.

The online interactions with friends, on the other hand, range between 0 to 7 days a week with an average of 4.4 days, indicating a high level of online social interaction. The median value of 5 suggests that half of the respondents have online interactions with friends for 5 days or more in a week. Online interactions with other people (excluding friends) range from 0 to 7 days a week, with an average of 2.854 days. The median value of 2 indicates that half of the respondents have online interactions with other people for 2 days or more in a week. Therefore, the data suggests that, on average, people have higher online interactions compared to offline interactions, this can be shown in [Graph 1.a.2](#) in the Appendix.

Boredom

The average scores for boredom are relatively low, ranging from 0.0378 to 0.3171, suggesting that respondents generally experience extreme levels of boredom, this can be shown in [Graph 1.a.3](#) in the Appendix.

Conspiracy Theories

consp01, consp02 and consp03 have a range from 0 to 10, with higher values indicating a stronger belief in conspiracy theories. The average scores for belief in conspiracy theories are relatively high, ranging from 5.58 to 7.148, suggesting that respondents tend to believe in conspiracy theories to some extent, this can be shown in [Graph 1.a.4](#) in the Appendix.

Corona Personal Behaviour

The mean score of 2.309 suggests that, on average, individuals are moderately inclined towards adopting preventive behaviours. The fact that the median is 3.000 indicates that at least 50% of respondents are regularly practising preventive measures.

With a mean score of 2.422, there is a slightly stronger inclination towards adopting health practices. The median is 3.000, suggesting that a majority of respondents frequently engage in health practices.

The mean score for avoidance behaviour is 1.823, indicating that individuals are generally less likely to avoid certain behaviours in response to the pandemic. The median of 2.000 suggests that a considerable portion of respondents do engage in avoidance behaviour, though less frequently, as indicated by the 1st quartile score of 1.000. All of this can be shown in the [Graph 1.a.5](#) in the Appendix.

Corona Radical Actions

The mean of 1.264 suggests that support for mandatory vaccination is less prevalent among respondents. The 1st quartile score of 0.000 indicates that a significant portion did not engage in this action, while the 3rd quartile score of 3.000 shows some individuals took radical actions, but it was not the norm.

The mean score of 2.053 suggests a moderate inclination towards signing a petition for mandatory quarantine. The median of 3.000 indicates at least 50% of respondents have taken this action, but the 1st quartile score of 2.000 implies a significant portion has not.

The average of 1.158 for agreeing to report suspected COVID-19 cases is the lowest, indicating this support is less prevalent, this can be shown in [Graph 1.a.6](#) in the Appendix.

Corona Proximity

The data shows the total number of people in proximity reported by respondents. A significant number, 29324, reported being in proximity to no one. The total number of people in proximity varies with the highest number being "No one" (29324) and the lowest being "Myself" (530). This indicates varying degrees of social interaction among respondents, with a substantial proportion opting for minimal or no proximity to others, possibly due to social distancing requirements, this can be shown in [Graph 1.a.7](#) in the Appendix.

Corona Prosocial Behaviour

c19ProSo01, c19ProSo02, c19ProSo03, and c19ProSo04 have a range from -3 to 3, where higher values indicate more agreement towards a certain prosocial behaviour. The average scores for prosocial behaviour are relatively low, ranging from 0.552 to 0.9764. There are missing values for all four prosocial behaviour indicators, with c19ProSo03 having the highest number of missing values (138 NA values).

b. CATEGORICAL ATTRIBUTES

Country Self Report

The data includes a list of countries with a total of 109 countries reported.

COVID-19 Rank Order Life

The data consists of alphabet letters representing various aspects of life, including Beauty, Victory, and Achievement, among others. These aspects are then ranked based on their significance to the respondent's life. This ranking can be visualized in [Graph 1.a.9](#), which is presented in the Appendix.

B. PRE-PROCESSING AND DATA MANIPULATION

Before the analysis, several pre-processing steps were performed on the dataset to handle missing values and prepare the variables for the subsequent analysis.

First, a function `has_only_na()` was created to identify and remove rows that had only NA values in any of the sets of columns. By removing these rows, the analysis could focus on the observations with meaningful data.

Next, the Rank Order Life variables, which were originally coded as letters from A to F, were converted to numeric values from 1 to 6 using a custom function `convert_rank_order()`. This transformation was performed because the Rank Order Life variables were originally coded as categorical variables, which are not suitable for numerical analysis.

To address the remaining missing values in the dataset, two imputation functions were implemented:

1. `impute_zero()`: This function replaces NA values with 0 for the specified columns. Imputing missing values with 0 will be performed for Employment Status and Corona Proximity variables, where 0 is deemed as “No”.
2. `impute_mode()`: This function replaces NA values with the mode of the variable, calculated separately for each column. Imputing with the mode is appropriate when the variable is categorical (in this case, categorical data will be treated as numerical), as it preserves the distribution of the variable and does not introduce bias.

These imputation methods were chosen to maintain the integrity of the dataset and ensure that all observations could be included in the analysis, without introducing significant bias due to missing data.

II. FOCUS COUNTRY ANALYSIS

A. FOCUS COUNTRY ATTRIBUTES ANALYSIS

In this report, the focus country Argentina is identified and filtered out from the cleaned dataset from the above data processing steps (`cvbase_cleaned`), furthermore, other countries are also filtered and treated as an individual group. The attribute analysis will be performed by analysing the summary statistics of both Argentina and other countries, whose values are reported in [Table 2.a](#) in the Appendix.

Employment Status

Argentina had a significantly higher proportion of participants working 40+ hours per week and a lower proportion unemployed and looking for work compared to other countries. Argentina also had more homemakers but fewer students. This suggests the employment landscape in Argentina may be distinct, with more of the population employed or actively seeking work.

Social Isolation

Participants in Argentina report having significantly fewer in-person contacts with friends/relatives and other people compared to the other countries. However, they generally have more online contacts with friends/relatives than the other countries. This indicates that Argentinians may be more socially isolated in terms of in-person interactions, but maintain stronger online social connections towards both their friends and other people, which can be inferred that Argentina might have had stricter quarantine requirements during COVID-19.

Loneliness and Life Satisfaction

Despite slightly higher feelings of isolation, Argentinian participants reported lower overall loneliness and higher happiness, life satisfaction, and sense of purpose compared to other countries. This suggests Argentinians maintain relatively high well-being despite some social isolation.

Boredom

Argentina had significantly higher levels of boredom than other countries. Argentinians tended to wish time would go by faster but also felt more in control of their time. This points to elevated boredom during the pandemic in Argentina.

Conspiracy Beliefs

Argentinian participants exhibited stronger beliefs in conspiracy theories compared to other countries. Most of the respondents from Argentina strongly agree with all forms of conspiracy theories, including that everything is heavily monitored by the government and politicians. This could reflect differences in information environments, trust in institutions, or cultural factors.

COVID-19 Personal Behaviour and Radical Actions

Argentinians report higher levels of personal protective behaviours (c19perBeh01 to c19perBeh03) and stronger support for radical actions (c19RCA01 - c19RCA03) related to the COVID-19 pandemic. This suggests that Argentinians may be more proactive and willing to take measures, even radical ones, to address the pandemic.

Proximity to COVID-19 Cases

Participants in Argentina are less likely to know someone who has had COVID-19, including family members, close friends, and other acquaintances (coronaClose_2 - coronaClose_4). This could indicate differences in the spread of the virus or access to information about COVID-19 cases between Argentina and other countries.

Demographics

Argentina had a significantly higher proportion of female participants and Argentinian respondents are significantly older compared to the other countries. Argentina also had a significantly lower average level of education compared to the other countries.

Prosocial COVID-19 behaviours

For the outcome variables of prosocial COVID-19 behaviours (c19ProSo01 - c19ProSo04), there were no statistically significant differences between Argentina and the other countries. This suggests that the underlying drivers of these prosocial behaviours may be similar across the countries.

Rank Order of Life Priorities

There were also no significant differences in the rankings of life priorities for both Argentina and other countries. Overall, it can be concluded that priorities such as "Achievement", "Victory" and "Friendship" are deemed as the most important priorities to both Argentina and other countries' respondents.

B. ARGENTINA PROSOCIAL BEHAVIOURS

To investigate the predictors of prosocial attitudes in Argentina, we conducted a comprehensive analysis using both correlation and multiple linear regression modelling, which would provide valuable insights into the predictive factors shaping the willingness of Argentinian participants to engage in various prosocial behaviours.

Correlation Analysis

The [correlation](#) between the predictor variables and prosocial behaviours is visualised by the [correlation heatmap](#) in the Appendix.

1. Willingness to Help Others (c19ProSo01)

- The strongest positive correlations are with c19perBeh02 ($r = 0.32$), c19perBeh03 ($r = 0.31$), and c19perBeh01 ($r = 0.30$), indicating that participants who are more willing to engage in protective behaviours are also more willing to help others. Positive correlations also exist with bor03 ($r = 0.17$), happy and lifeSat ($r = 0.18$ and 0.19), and MLQ ($r = 0.17$).
- Negative correlations are observed with coronaClose_1 ($r = -0.13$) and coronaClose_3 ($r = -0.10$), suggesting that personal experiences with the virus may reduce willingness to help others.

2. Willingness to Make Donations (c19ProSo02)

- The strongest positive correlations are with c19perBeh02 ($r = 0.26$), c19perBeh03 ($r = 0.26$), and c19RCA01 ($r = 0.25$). Positive correlations are also observed with bor01 ($r = 0.16$), bor03 ($r = 0.15$), happy and lifeSat ($r = 0.16$ and 0.14), and MLQ ($r = 0.16$). This indicates that participants who are more willing to engage in protective behaviours, support public health measures and with a sense of urgency, control, and well-being are more willing to make donations.
- Negative correlations are found with employstatus_5 ($r = -0.12$) and age ($r = -0.13$), suggesting that unemployed and younger individuals are less willing to make donations.

3. Willingness to Protect Vulnerable Groups (c19ProSo03)

- The strongest positive correlations are with c19perBeh03 ($r = 0.25$), c19RCA01 ($r = 0.23$), and bor03 ($r = 0.16$). Positive correlations are also observed with happy and lifeSat ($r = 0.18$ and 0.15), and bor01 ($r = 0.13$). This infers that participants who are more willing to engage in protective behaviours feel in control of their time and with higher life satisfaction and a sense of urgency are more willing to protect vulnerable groups.
- Negative correlations are found with age ($r = -0.10$), indicating that older participants are less willing to protect vulnerable groups, potentially due to concerns about their health and safety.

4. Willingness to Make Personal Sacrifices (c19ProSo04)

- The strongest positive correlations are with c19perBeh03 ($r = 0.35$), c19RCA01 ($r = 0.34$), and c19perBeh02 ($r = 0.33$). Positive correlations are also observed with bor01 ($r = 0.11$), bor03 ($r = 0.08$), and happy ($r = 0.10$). This indicates that participants who are more willing to engage in protective behaviours, support public health measures and with a sense of urgency and control, as well as higher life satisfaction, are more willing to make personal sacrifices.
- Negative correlations are found with isoFriends_inPerson ($r = -0.10$) and isoOthPpl_inPerson ($r = -0.09$), suggesting that participants with lower levels of in-person social interaction are more willing to make personal sacrifices.

Multiple Linear Regression Analysis

Observing the [multiple linear regression model of Argentina](#), the strongest predictors of participants' willingness to help others who suffer from coronavirus in Argentina were:

1. Willingness to Help Others (c19ProSo01)

1. Feeling in control of their time (bor03): Participants who felt more in control of their time were more willing to help others. This suggests that a sense of personal agency and control may be an important factor in motivating prosocial behaviours.
2. Willingness to put themselves in quarantine (c19perBeh03): Participants who were more willing to take protective measures, such as self-quarantining, were also more likely to help others. This indicates a broader commitment to prosocial actions during the pandemic.
3. Knowing someone else with COVID-19 (coronaClose_4): Participants who knew someone else with the virus were more willing to help others, perhaps due to a greater personal connection to the impacts of the pandemic.

2. Willingness to Make Donations (c19ProSo02)

1. Employment status (employstatus_5): Participants who were not employed and not looking for work were less willing to make donations, suggesting that financial constraints may be a barrier to prosocial giving.
2. Feelings about time (bor01, bor03): Participants who wished time would go by faster but felt more in control of their time were more willing to make donations. This may reflect a sense of urgency and personal agency that motivates prosocial actions.
3. Support for mandatory vaccination (c19RCA01): Participants who were more willing to support mandatory vaccination were also more willing to make donations, indicating a broader commitment to prosocial behaviours.
4. Demographic factors (age, education, gender): Older participants, those with higher education levels, and male participants were more willing to make donations.

3. Willingness to Protect Vulnerable Groups (c19ProSo03)

1. Feelings about time (bor01, bor03): Participants who wished time would go by faster and felt more in control of their time were more willing to protect vulnerable groups.
2. Willingness to put themselves in quarantine (c19perBeh03): Participants who were more willing to take protective measures, such as self-quarantining, were also more likely to protect vulnerable groups.
3. Support for mandatory vaccination (c19RCA01): Participants who were more willing to support mandatory vaccination were also more willing to protect vulnerable groups.
4. Age: Older participants were less willing to protect vulnerable groups, which may be related to concerns about their own health and safety.

4. Willingness to Make Personal Sacrifices (c19ProSo04)

1. Employment status (employstatus_2, employstatus_3, employstatus_4): Participants who are employed, working 24 hours or more per week, were more willing to make personal sacrifices, potentially due to a greater sense of responsibility in their community due to their occupations.
2. Support for mandatory vaccination (c19RCA01): Participants who were more willing to support mandatory vaccination were also more willing to make personal sacrifices.
3. Willingness to put themselves in quarantine (c19perBeh03) and support for reporting suspected cases (c19RCA03): Participants who were more willing to take protective measures and support reporting suspected cases were also more likely to make personal sacrifices.

C. OTHER COUNTRY PROSOCIAL BEHAVIOURS

To investigate the predictors of prosocial attitudes in the other countries as a group, we would conduct the same analysis using both correlation and multiple linear regression modelling as Argentina's analysis.

Correlation Analysis

The [correlation](#) between the predictor variables and prosocial behaviours is visualised by the [correlation heatmap](#) in the Appendix.

1. Willingness to Help Others (c19ProSo01)

- The strongest positive correlations are with isoFriends_online ($r = 0.12$), isoOthPpl_online ($r = 0.09$), lifeSat ($r = 0.15$), MLQ ($r = 0.16$), and c19perBeh01 ($r = 0.18$) and c19perBeh02 ($r = 0.16$). This suggests that participants with more online social interaction, higher life satisfaction and sense of purpose, and a greater willingness to engage in protective behaviours are more willing to help others.
- Negative correlations are observed with employstatus_4 ($r = -0.02$), employstatus_5 ($r = -0.04$), employstatus_7 ($r = -0.05$), and employstatus_8 ($r = -0.04$), indicating that participants with lower employment status are less willing to help others.

2. Willingness to Make Donations (c19ProSo02)

- The strongest positive correlations are with isoFriends_online ($r = 0.14$), isoOthPpl_online ($r = 0.11$), lifeSat ($r = 0.19$), MLQ ($r = 0.21$), c19perBeh01 ($r = 0.19$), c19perBeh02 ($r = 0.18$), and c19perBeh03 ($r = 0.17$). This suggests that participants with more online social interaction, higher life satisfaction and sense of purpose, and a greater willingness to engage in protective behaviours are more willing to make donations.
- Negative correlations are observed with employstatus_4 ($r = -0.07$), employstatus_5 ($r = -0.04$), employstatus_7 ($r = -0.04$), and employstatus_8 ($r = -0.07$), indicating that participants with lower employment status are less willing to make donations. Age ($r = -0.06$) and gender ($r = -0.05$) also show negative correlations, suggesting that younger participants and females are less willing to make donations.

3. Willingness to Protect Vulnerable Groups (c19ProSo03)

- The strongest positive correlations are with isoFriends_online ($r = 0.11$), isoOthPpl_online ($r = 0.10$), lifeSat ($r = 0.14$), MLQ ($r = 0.12$), c19perBeh01 ($r = 0.15$), c19perBeh02 ($r = 0.15$), and c19perBeh03 ($r = 0.13$). This indicates that participants with more online social interaction, higher life satisfaction and sense of purpose, and a greater willingness to engage in protective behaviours are more willing to protect vulnerable groups.
- Negative correlations are observed with employstatus_7 ($r = -0.08$) and age ($r = -0.08$), suggesting that retired participants and older individuals are less willing to protect vulnerable groups.

4. Willingness to Make Personal Sacrifices (c19ProSo04)

- The strongest positive correlations are with isoFriends_online ($r = 0.11$), c19perBeh01 ($r = 0.24$), c19perBeh02 ($r = 0.28$), c19perBeh03 ($r = 0.23$), c19RCA01 ($r = 0.15$), and c19RCA02 ($r = 0.21$). This indicates that participants with more online social interaction, a greater willingness to engage in protective behaviours, and stronger support for public health measures are more willing to make personal sacrifices.

- Negative correlations are observed with isoFriends_inPerson ($r = -0.06$), isoOthPpl_inPerson ($r = -0.07$), and coronaClose_6 ($r = -0.08$), suggesting that participants with lower in-person social interaction and no personal connections to COVID-19 cases are more willing to make personal sacrifices.

Multiple Linear Regression Analysis

Observing the [multiple linear regression model of other countries](#), the strongest predictors of participants' willingness to help others who suffer from coronavirus in other countries as a group were:

1. Willingness to Help Others (c19ProSo01)

1. Employment status (employstatus_3, employstatus_7, employstatus_8, employstatus_9, employstatus_10): Participants who were employed and working 40 or more hours per week, as well as those who were students volunteering, were more willing to help others who suffer from coronavirus. In contrast, participants who were retired or disabled were less willing to help others. This suggests that potentially a greater sense of responsibility in their community motivates prosocial helping behaviours.
2. Social interaction (isoFriends_inPerson, isoOthPpl_inPerson, isoFriends_online, isoOthPpl_online): Participants with more in-person and online social contact were more willing to help others. This indicates that maintaining social connections may foster a greater sense of community and willingness to support others in need.
3. Loneliness (lone01, lone02, lone03): Participants who reported feeling less lonely were more willing to help others, suggesting that emotional well-being may be an important factor.
4. Life satisfaction (happy, lifeSat, MLQ): Participants with higher levels of life satisfaction were more willing to help others, indicating that a greater sense of well-being and purpose may motivate prosocial actions.

2. Willingness to Make Donations (c19ProSo02)

1. Employment status (employstatus_3, employstatus_4, employstatus_8, employstatus_9, employstatus_10): Participants who were employed and working 40 or more hours per week were more willing to make donations, while those not employed and looking for work were less willing. This suggests that financial resources and a sense of stability may be important factors.
2. Social interaction (isoFriends_inPerson, isoFriends_online, isoOthPpl_online): Participants with more in-person and online social contact were more willing to make donations, indicating that maintaining social connections may foster empathy and a willingness to provide financial support.
3. Loneliness (lone01, lone02, lone03): Participants who reported feeling less lonely were more willing to make donations, suggesting that emotional well-being is an important factor.
4. Life satisfaction (happy, lifeSat, MLQ): Participants with higher levels of life satisfaction were more willing to make donations, which indicates that a greater sense of well-being and purpose may motivate prosocial giving.
5. Support for public health measures (c19RCA01): Participants who were more willing to support mandatory vaccination were also more willing to make donations, suggesting that a commitment to well-being is associated with prosocial donation behaviours.

3. Willingness to Protect Vulnerable Groups (c19ProSo03)

1. Employment status (employstatus_2, employstatus_3, employstatus_7, employstatus_9, employstatus_10): Participants who were employed, working 24-39 hours per week or 40 or more hours per week, students and volunteers, were more willing to protect vulnerable groups. Those who were retired were less willing.
2. Social interaction (isoFriends_inPerson, isoOthPpl_inPerson, isoFriends_online, isoOthPpl_online): Participants with more in-person and online social contact were more willing to protect vulnerable groups, indicating that maintaining social connections may foster empathy and concern for others.

3. Loneliness (lone01, lone03): Participants who reported feeling less lonely were more willing to protect vulnerable groups, suggesting that emotional well-being is an important factor.
4. Life satisfaction (happy, lifeSat, MLQ): Participants with higher levels of life satisfaction were more willing to protect vulnerable groups.
5. Support for public health measures (c19RCA01) Participants who were more willing to support mandatory vaccination were also more willing to protect vulnerable groups.

4. Willingness to Make Personal Sacrifices (c19ProSo04)

1. Employment status (employstatus_2, employstatus_3, employstatus_7, employstatus_10): Participants who were employed, working 24-39 hours per week or 40 or more hours per week, as well as volunteers, were more willing to make personal sacrifices.
2. Social interaction (isoOthPpl_inPerson, isoFriends_online): Participants with more in-person contact with other people and more online contact with friends were more willing to make personal sacrifices, indicating that maintaining social connections may foster a willingness to make sacrifices for the benefit of others.
3. Loneliness (lone01, lone02, lone03): Participants who reported feeling less lonely were more willing to make personal sacrifices, suggesting that emotional well-being is an important factor.
4. Protective behaviours (c19perBeh02): Participants who were more willing to avoid crowded spaces to minimise their chances of getting coronavirus were also more willing to make personal sacrifices. This suggests that a broader commitment to collective well-being may underlie both protective actions and a willingness to make personal sacrifices.

Comparison to the Focus Country (Argentina)

The analysis of the predictors of prosocial COVID-19 behaviours in the focus country of Argentina and the other countries as a group reveals both similarities and notable differences:

Similarities:

1. The importance of protective behaviours and support for public health measures are observed as strong predictors of prosocial attitudes in both groups. This suggests that a broader commitment to personal health and a sense of social responsibility may be a common driver of prosocial actions during the pandemic.
2. The role of life satisfaction and feelings of control over time are also positive predictors of prosocial behaviours. This indicates that individual well-being and a sense of personal agency are important factors in shaping prosocial responses across different country contexts.

Differences:

1. The other countries show a stronger emphasis on social interaction (both in-person and online) as a predictor of prosocial behaviours, while this was not as prominent in Argentina. This suggests that maintaining social connections may be more crucial for fostering prosocial behaviours in other countries.
2. Demographic factors like age and education level also appear to play a significant role in predicting prosocial behaviours in other countries, compared to Argentina.
3. The focus country of Argentina exhibited more nuanced relationships between employment status and prosocial behaviours, while the other countries showed a more straightforward positive association between respondents who were employed and prosocial behaviours.

4. The focus country of Argentina had some unique predictors, such as knowing someone else with COVID-19 for willingness to help others for willingness to make personal sacrifices. These findings suggest that country-specific factors may shape prosocial behaviours in unique ways.

III. CLUSTERING ANALYSIS

A. CLUSTERING

To identify countries similar to the focus country of Argentina, a set of relevant indicators were selected from various external data sources. The choice of indicators was guided by a consideration of the factors that may influence prosocial behaviours during the COVID-19 pandemic. The [table of values](#) used for the clustering is attached in the Appendix. The following indicators were chosen for the clustering analysis:

1. Life expectancy: This indicator provides insights into the overall health and well-being of a population, which can be a crucial factor in shaping social and economic dynamics.
2. GDP per capita: This metric reflects the economic development and prosperity of a country, which can influence various aspects of a society, including access to resources and opportunities.
3. Health infrastructure: Specifically, we used the total number of doctors as a proxy for the availability and quality of healthcare services, which can have a significant impact on a country's ability to respond to public health crises.
4. Government effectiveness: This indicator measures the quality of public services, the capacity of the government to effectively formulate and implement policies, and the credibility of the government's commitment to such policies. These factors can play a crucial role in a country's resilience and ability to address societal challenges.
5. Education level: We utilised the adult literacy rate as a representation of the educational attainment and human capital within a country, which can shape social and economic outcomes.
6. Death rate: This metric provides insights into the overall mortality patterns within a country, which can be influenced by various socioeconomic and health-related factors.
7. COVID-19 data: Specifically, we included the cumulative number of COVID-19 cases and deaths, as these indicators can reflect a country's ability to manage and respond to the pandemic.

We gathered the data for these indicators from various reputable sources, including the World Bank, the World Health Organization, and the COVID-19 Global Data. The data was then merged into a comprehensive "country_data" dataset. To prepare the data for the clustering analysis, we standardised the numeric variables in the "country_data_scaled" dataset. This step was crucial to ensure that all indicators were on a similar scale, as the clustering algorithm would otherwise be disproportionately influenced by variables with larger numerical ranges.

Hierarchical Clustering

We then performed hierarchical clustering on the standardised "country_data_scaled" dataset, using the "ward.D" method. This approach allowed us to identify groups of countries that are similar to one another based on the selected indicators. To determine the optimal number of clusters, we utilised the "fviz_nbclust" function, which suggested the use of 5 clusters. We then proceeded to cut the dendrogram at this level, resulting in the identification of 5 distinct clusters.

The cluster containing Argentina was identified, and the 30 countries most similar to Argentina (excluding Argentina itself) were extracted. These 30 countries were considered the most similar to Argentina based on the selected

indicators and the hierarchical clustering analysis. The table of values used for the clustering analysis is provided in the Appendix. [The dendrogram showing the 5 clusters](#), with the cluster containing Argentina highlighted in red, is also provided in the Appendix. This visual representation of the clustering results can further aid in the interpretation and understanding of the similarities and differences between the countries.

B. CLUSTERING PROSOCIAL ANALYSIS

Correlation Analysis

Based on the [correlation matrix cor_cluster](#), we can identify the strongest predictors of prosocial attitudes for the cluster of countries similar to Argentina. The correlation between the predictor variables and prosocial behaviours is visualised by the [correlation heatmap](#) in the Appendix. The variables with the strongest correlations with the prosocial attitude variables are:

- Social Interaction and Isolation: Positively correlated with all four prosocial attitude variables (around 0.11-0.12).
- Psychological Factors (happy, lifeSat, MLQ): Positively correlated with all four prosocial attitude variables (around 0.11-18).
- COVID-19 Personal Behaviours (c19perBeh01 - c19perBeh04): Positively correlated with all four prosocial attitude variables (around 0.14-0.23).
- Support for COVID-19 Policies (c19RCA01 - c19RCA03): Positively correlated with all four prosocial attitude variables (around 0.15-0.24).

Multiple Linear Regression Analysis

Observing the [multiple linear regression model of similar countries](#), the strongest predictors of participants' willingness to help others who suffer from coronavirus in the clustered countries group were:

1. Willingness to Help Others (c19ProSo01)

1. Employment status (employstatus_10, p-value < 0.001): Participants who were volunteering were more willing to help others.
2. Loneliness (lone02, p-value < 0.001): Participants who reported that they felt isolated were more willing to help others.
3. Support for public health measures (c19RCA01, p-value < 0.001; c19RCA03, p-value < 0.001): Participants who were more willing to support mandatory vaccination and reporting suspected cases were more willing to help others.

2. Willingness to Make Donations (c19ProSo02)

1. Employment status (employstatus_9, p-value = 0.042; employstatus_10, p-value = 0.00216): Participants who are volunteers were more willing to make donations, while those who are students were less willing.
2. Life satisfaction (lifeSat, p-value = 0.0038): Participants with higher life satisfaction were more willing to make donations.
3. Feelings about time (bor01, p-value < 0.001; bor03, p-value < 0.001): Participants who wished time would go by faster and felt more in control of their time were more willing to make donations.
4. Protective behaviours (c19perBeh01, p-value = 0.0022) and support for public health measures (c19RCA01, p-value < 0.001; c19RCA03, p-value < 0.001): Participants who were more willing to engage in protective

behaviours such as washing their hands more often and support public health initiatives were more willing to make donations.

3. Willingness to Protect Vulnerable Groups (c19ProSo03)

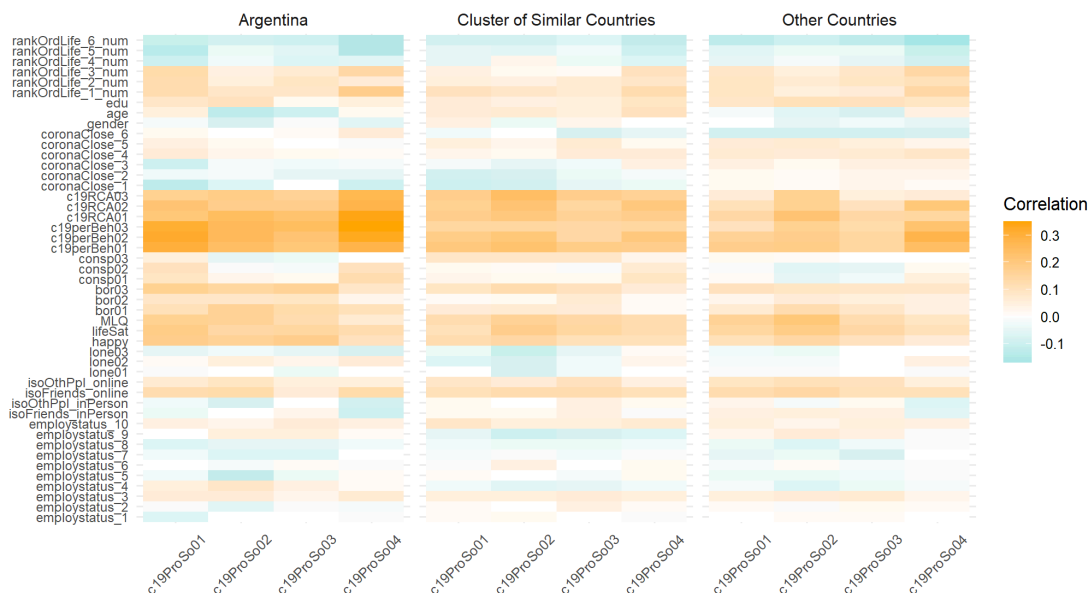
1. Employment status (employstatus_10, p-value < 0.0054): Participants who are volunteers were more willing to protect vulnerable groups.
2. Life satisfaction (lifeSat, p-value < 0.0067; MLQ): Participants with higher life satisfaction and sense of purpose were more willing to protect vulnerable groups.
3. Feelings about time (bor02, p-value = 0.00318): Participants who felt time moving very slowly were more willing to protect vulnerable groups.
4. Protective behaviours (c19perBeh01, p-value = 0.00068; c19perBeh03, p-value = 0.00068) and support for public health measures (c19RCA01, p-value = 0.00132; c19RCA03, p-value < 0.001): Participants who were more willing to engage in protective behaviours and support public health initiatives were more willing to protect vulnerable groups.

4. Willingness to Make Personal Sacrifices (c19ProSo04)

1. Employment status (employstatus_10, p-value = 0.00156): Participants with higher employment status, such as volunteers, were more willing to make personal sacrifices.
2. Life satisfaction (lifeSat, p-value = 0.027): Participants with higher life satisfaction were more willing to make personal sacrifices.
3. Protective behaviours (c19perBeh02, p-value = 0.0061) and support for public health measures (c19RCA01, p-value < 0.001; c19RCA03, p-value < 0.001): Participants who were more willing to engage in protective behaviours and support public health initiatives were more willing to make personal sacrifices.

Comparing these results to the focus country of Argentina

Comparison of Correlation Heatmaps: Argentina, Other Countries, and Cluster of Similar Countries



Graph III.b. Comparison of correlation heatmaps of Argentina, Other Countries and Cluster of Similar Countries

Similarities:

1. Importance of Social Interaction and Isolation: In both the cluster and Argentina, variables related to online social interaction, such as contact with friends and others, were strong positive predictors of prosocial attitudes. Conversely,

feelings of loneliness and in-person social interaction were negatively associated with prosocial behaviours in both groups.

2. Influence of Life Satisfaction and Psychological Factors: Variables reflecting life satisfaction, happiness, and sense of purpose were consistently positive predictors of prosocial attitudes in both the cluster and Argentina.

3. Importance of COVID-19 Protective Behaviours and Support for Public Health Measures: Participants' willingness to engage in protective behaviours (e.g., hand-washing, avoiding crowds) and support for public health measures (e.g., mandatory vaccination, mandatory quarantine) were strongly linked to prosocial attitudes in both the cluster and the focus country.

Differences:

1. Role of Employment Status and Demographic Factors: In Argentina, employment status emerged as a significant predictor of prosocial attitudes, particularly for donation-making and personal sacrifices. However, employment status was not a consistent predictor in the cluster of similar countries, with volunteering being the only employment-related variable that showed a strong positive association. Additionally, demographic factors like age and gender were more strongly predictive of prosocial attitudes in Argentina compared to the cluster.

2. Influence of Boredom and Feelings about Time: For Argentina, attributes related to boredom and feelings about time (e.g., wishing time would go by faster, feeling in control of time) were significant predictors of prosocial attitudes. In the cluster of similar countries, while feelings about time were also predictive, the specific patterns differed, with a stronger emphasis on the role of feeling that time is moving slowly (bor02).

Overall, the analysis suggests that the cluster of similar countries provides, although not significant, a better match to the important attributes for predicting prosocial attitudes in the focus country of Argentina, compared to the group of all other countries. The cluster of similar countries shows a more nuanced and country-specific set of predictors, which aligns more closely with the key drivers identified for Argentina. The multiple linear regression models for the cluster of similar countries also show a more similar set of key predictors compared to the analysis for Argentina. Factors like COVID-19 personal behaviours and support for COVID-19 policies emerge as important predictors in both the focus country and the cluster. The analysis for the group of all other countries showed some differences in the prominence of certain predictors, such as time perception, social interaction, and employment status, which did not align as closely with the focus country.

IV. APPENDIX

A. R Codes

```
rm(list = ls())
setwd("~/MONASH/SEM 01-2024/FIT3152/Assignment 1- Argentina")
set.seed(33295379)

cvbase = read.csv("PsyCoronaBaselineExtract.csv")
cvbase <- cvbase[sample(nrow(cvbase), 40000), ]
View(cvbase)

library(ggplot2)
library(gplots)
library(dplyr)
library(tidyr)
library(tibble)

#Question 1
# (a)
glimpse(cvbase)
# Dimension of the dataset
dim(cvbase)
# Summary of the entire dataset
summary(cvbase)

# Employment Status count
employment_frequency <- data.frame(colSums(cvbase[, grepl("employstatus",
names(cvbase))], na.rm = TRUE))
colnames(employment_frequency) <- ("Total number of employment")
rownames(employment_frequency) <- c("1-24 hours", "24-39 hours", "40 hours or more",
"Looking for work", "Not looking for work", "Homemaker", "Retired", "Disable",
"Student", "Volunteering")
print(employment_frequency)
# Convert the data frame to a tibble for ggplot
employment_frequency <- as.data.frame(employment_frequency)
employment_frequency$Employment_Type <- rownames(employment_frequency)

# Create the histogram using ggplot2
ggplot(employment_frequency, aes(x = Employment_Type, y = `Total number of employment`,
fill = Employment_Type)) +
  geom_bar(stat = "identity") +
  labs(title = "Employment Frequency",
       x = "Employment Type",
       y = "Number of Employment") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        axis.text = element_text(size = 10),
        axis.title = element_text(size = 12),
        plot.title = element_text(size = 16, hjust = 0.5))

# Social Isolation
offline_interaction <- cvbase[, c("isoFriends_inPerson", "isoOthPpl_inPerson")]
online_interaction <- cvbase[, c("isoFriends_online", "isoOthPpl_online")]
```

```

# Create histograms for offline and online interaction
p1 <- ggplot(offline_interaction, aes(x = isoFriends_inPerson)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Offline Interaction with Friends", x = "Days of In-Person Contact", y =
"Count")+
  theme_minimal()
p2 <- ggplot(offline_interaction, aes(x = isoOthPpl_inPerson)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Offline Interaction with Others", x = "Days of In-Person Contact", y =
"Count")+
  theme_minimal()
p3 <- ggplot(online_interaction, aes(x = isoFriends_online)) +
  geom_histogram(binwidth = 1, fill = "orange", color = "white") +
  labs(title = "Online Interaction with Friends", x = "Days of Online Contact", y =
"Count")+
  theme_minimal()
p4 <- ggplot(online_interaction, aes(x = isoOthPpl_online)) +
  geom_histogram(binwidth = 1, fill = "orange", color = "white") +
  labs(title = "Online Interaction with Others", x = "Days of Online Contact", y =
"Count")+
  theme_minimal()
# Arrange the plots using cowplot
library(cowplot)
plot_grid(p1, p2, p3, p4, ncol = 2)

# Loneliness and Life Satisfaction
loneliness <- cvbase[, c("lone01", "lone02", "lone03")]
life_satisfaction <- cvbase[, c("happy", "lifeSat", "MLQ")]
#Create histograms for loneliness and life satisfaction
p1 <- ggplot(loneliness, aes(x = lone01)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Loneliness: Feeling Lonely", x = "Rating", y = "Count")+
  theme_minimal()
p2 <- ggplot(loneliness, aes(x = lone02)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Loneliness: Feeling Isolated", x = "Rating", y = "Count")+
  theme_minimal()
p3 <- ggplot(loneliness, aes(x = lone03)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Loneliness: Feeling Left Out", x = "Rating", y = "Count")+
  theme_minimal()
p4 <- ggplot(life_satisfaction, aes(x = happy)) +
  geom_histogram(binwidth = 1, fill = "orange", color = "white") +
  labs(title = "Life Satisfaction: Happiness", x = "Rating", y = "Count")+
  theme_minimal()
p5 <- ggplot(life_satisfaction, aes(x = lifeSat)) +
  geom_histogram(binwidth = 1, fill = "orange", color = "white") +
  labs(title = "Life Satisfaction: Life Satisfaction", x = "Rating", y = "Count")+
  theme_minimal()
p6 <- ggplot(life_satisfaction, aes(x = MLQ)) +
  geom_histogram(binwidth = 1, fill = "orange", color = "white") +
  labs(title = "Life Satisfaction: Sense of Purpose", x = "Rating", y = "Count")+
  theme_minimal()
# Arrange the plots using cowplot
plot_grid(p1, p2, p3, p4, p5, p6, ncol = 2)

```



```

# Boredom
boredom <- cvbase[, c("bor01", "bor02", "bor03")]
# Create histograms for boredom
p1 <- ggplot(boredom, aes(x = bor01)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Boredom: Wish Time Would Go Faster", x = "Rating", y = "Count")+
  theme_minimal()
p2 <- ggplot(boredom, aes(x = bor02)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Boredom: Time Moving Slowly", x = "Rating", y = "Count")+
  theme_minimal()
p3 <- ggplot(boredom, aes(x = bor03)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Boredom: Feeling in Control of Time", x = "Rating", y = "Count")+
  theme_minimal()
# Arrange the plots using cowplot
plot_grid(p1, p2, p3, ncol = 2)

# Conspiracy Theories
conspiracy <- cvbase[, c("consp01", "consp02", "consp03")]
# Create histograms for conspiracy theories
p1 <- ggplot(conspiracy, aes(x = consp01)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Conspiracy Theories: Undisclosed Events", x = "Rating", y = "Count")+
  theme_minimal()
p2 <- ggplot(conspiracy, aes(x = consp02)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Conspiracy Theories: Politicians' True Motives", x = "Rating", y =
"Count")+
  theme_minimal()
p3 <- ggplot(conspiracy, aes(x = consp03)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Conspiracy Theories: Government Monitoring", x = "Rating", y =
"Count")+
  theme_minimal()
# Arrange the plots using cowplot
plot_grid(p1, p2, p3, ncol = 2)

# Rank Order Life
# Create a long format dataframe
rank_order_long <- tidyr::gather(cvbase, key = "Rank_Order_Life", value = "Value",
                                starts_with("rankOrdLife"))
# Create the plot
ggplot(rank_order_long, aes(x = Value, fill = Rank_Order_Life)) +
  geom_bar(position = "dodge") +
  labs(title = "Distribution of Rank Order Life Variables",
       x = "Rank Order Life Category",
       y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        legend.position = "bottom")

# Corona Personal Behavior
corona_personal_behavior <- cvbase[, c("c19perBeh01", "c19perBeh02", "c19perBeh03")]
# Create histograms for corona personal behavior
p1 <- ggplot(corona_personal_behavior, aes(x = c19perBeh01)) +

```

```

geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Corona Personal Behavior: Wash Hands More", x = "Rating", y = "Count")+
  theme_minimal()
p2 <- ggplot(corona_personal_behavior, aes(x = c19perBeh02)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Corona Personal Behavior: Avoid Crowded Spaces", x = "Rating", y =
"Count")+
  theme_minimal()
p3 <- ggplot(corona_personal_behavior, aes(x = c19perBeh03)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Corona Personal Behavior: Put Myself in Quarantine", x = "Rating", y =
"Count")+
  theme_minimal()
# Arrange the plots using cowplot
plot_grid(p1, p2, p3, ncol = 2)

# Corona Radical Action
corona_radical_action <- cvbase[, c("c19RCA01", "c19RCA02", "c19RCA03")]
# Create histograms for corona radical action
p1 <- ggplot(corona_radical_action, aes(x = c19RCA01)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Corona Radical Action: Support Mandatory Vaccination", x = "Rating", y
= "Count")+
  theme_minimal()
p2 <- ggplot(corona_radical_action, aes(x = c19RCA02)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Corona Radical Action: Support Mandatory Quarantine", x = "Rating", y =
"Count")+
  theme_minimal()
p3 <- ggplot(corona_radical_action, aes(x = c19RCA03)) +
  geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
  labs(title = "Corona Radical Action: Support Reporting Suspected Cases", x =
"Rating", y = "Count")+
  theme_minimal()
# Arrange the plots using cowplot
plot_grid(p1, p2, p3, ncol = 2)

# Corona Proximity
corona_proximity <- data.frame(colSums(cvbase[, grepl("coronaClose", names(cvbase))],
na.rm = TRUE))
colnames(corona_proximity) <- ("Total number of people in proximity")
rownames(corona_proximity) <- c("Myself", "Family member", "Close friend", "Someone I
know", "Someone else", "No one")
# Create a bar plot for corona proximity
ggplot(corona_proximity, aes(x = rownames(corona_proximity), y = `Total number of
people in proximity`)) +
  geom_bar(stat = "identity", fill = "cyan3") +
  labs(title = "Corona Proximity",
x = "Proximity to COVID-19 Cases",
y = "Total Number of People") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Demographic (Gender, Age, Education)
demographic <- cvbase[, c("gender", "age", "edu")]
# Create histograms for demographic variables
p1 <- ggplot(demographic, aes(x = gender)) +

```

```

geom_bar(fill = "cyan3") +
labs(title = "Gender Distribution", x = "Gender", y = "Count") +
theme_minimal()
p2 <- ggplot(demographic, aes(x = age)) +
geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
labs(title = "Age Distribution", x = "Age", y = "Count") +
theme_minimal()
p3 <- ggplot(demographic, aes(x = edu)) +
geom_bar(fill = "cyan3") +
labs(title = "Education Distribution", x = "Education Level", y = "Count") +
theme_minimal()
# Arrange the plots using cowplot
plot_grid(p1, p2, p3, ncol = 2)

# Country Self Report
country <- cvbase[, c("coded_country")]
unique(country)
table(country)

# Corona ProSocial Behavior
corona_prosocial_behavior <- cvbase[, c("c19ProSo01", "c19ProSo02", "c19ProSo03",
"c19ProSo04")]
# Create a faceted histogram
ggplot(corona_prosocial_behavior, aes(x = c19ProSo01)) +
geom_histogram(binwidth = 1, fill = "cyan3", color = "white") +
facet_wrap(~ names(corona_prosocial_behavior), ncol = 2) +
labs(title = "Corona Pro-Social Behavior",
x = "Rating",
y = "Count") +
theme_minimal()

#b)
# Function to check if a row has only NA values in a given set of columns
has_only_na <- function(data, cols) {
  rowSums(is.na(data[, cols])) == length(cols)
}

# Remove rows with only NA values in any category
cvbase_cleaned <- cvbase %>%
  filter(!has_only_na(., c("employstatus_1", "employstatus_2", "employstatus_3",
"employstatus_4",
"employstatus_5", "employstatus_6", "employstatus_7",
"employstatus_8",
"employstatus_9", "employstatus_10")),
!has_only_na(., c("isoFriends_inPerson", "isoOthPpl_inPerson",
"isoFriends_online", "isoOthPpl_online")),
!has_only_na(., c("lone01", "lone02", "lone03")),
!has_only_na(., c("happy", "lifeSat", "MLQ")),
!has_only_na(., c("bor01", "bor02", "bor03")),
!has_only_na(., c("consp01", "consp02", "consp03")),
!has_only_na(., c("rankOrdLife_1", "rankOrdLife_2", "rankOrdLife_3",
"rankOrdLife_4", "rankOrdLife_5", "rankOrdLife_6")),
!has_only_na(., c("c19perBeh01", "c19perBeh02", "c19perBeh03")),
!has_only_na(., c("c19RCA01", "c19RCA02", "c19RCA03")),

```

```

!has_only_na(., c("coronaClose_1", "coronaClose_2", "coronaClose_3",
"coronaClose_4", "coronaClose_5", "coronaClose_6")),
!has_only_na(., c("c19ProSo01", "c19ProSo02", "c19ProSo03", "c19ProSo04"))))

# Function to convert Rank Order Life variables to numeric (from A->F to 1->6)
convert_rank_order <- function(df, prefix) {
  # Get the unique values in the rank order variables
  unique_values <- c("A", "B", "C", "D", "E", "F")

  # Create new numeric attributes
  for (i in 1:length(grep(prefix, names(df)))) {
    var_name <- names(df)[grep(prefix, names(df))][i]
    df[[paste0(var_name, "_num")]] <- match(df[[var_name]], unique_values)
  }
  return(df)
}

cvbase_cleaned <- convert_rank_order(cvbase_cleaned, "rankOrdLife")
cvbase_cleaned$rankOrdLife_1 <- NULL
cvbase_cleaned$rankOrdLife_2 <- NULL
cvbase_cleaned$rankOrdLife_3 <- NULL
cvbase_cleaned$rankOrdLife_4 <- NULL
cvbase_cleaned$rankOrdLife_5 <- NULL
cvbase_cleaned$rankOrdLife_6 <- NULL

# Function to impute missing values with 0
impute_zero <- function(df, cols) {
  for (col in cols) {
    df[[col]] <- ifelse(is.na(df[[col]]), 0, df[[col]])
  }
  return(df)
}

# Function to impute missing values with mode
impute_mode <- function(df, cols) {
  for (col in cols) {
    df[[col]] <- ifelse(is.na(df[[col]]),
                        as.numeric(names(which.max(table(df[[col]]), useNA =
"always")))),
                        df[[col]])
  }
  return(df)
}

# Impute missing values with 0
cvbase_cleaned <- cvbase_cleaned %>%
  filter(!has_only_na(., c("employstatus_1", "employstatus_2", "employstatus_3",
"employstatus_4",
                        "employstatus_5", "employstatus_6", "employstatus_7",
"employstatus_8",
                        "employstatus_9", "employstatus_10",
                        "coronaClose_1", "coronaClose_2", "coronaClose_3",
"coronaClose_4", "coronaClose_5", "coronaClose_6")))) %>%

```

```

impute_zero(c("employstatus_1", "employstatus_2", "employstatus_3", "employstatus_4",
              "employstatus_5", "employstatus_6", "employstatus_7", "employstatus_8",
              "employstatus_9", "employstatus_10",
              "coronaClose_1", "coronaClose_2", "coronaClose_3", "coronaClose_4",
              "coronaClose_5", "coronaClose_6"))

# Impute other variables with mode
cvbase_cleaned <- impute_mode(cvbase_cleaned, c("isoFriends_inPerson",
"isoOthPpl_inPerson", "isoFriends_online", "isoOthPpl_online",
              "happy", "lifeSat", "MLQ",
              "bor01", "bor02", "bor03",
              "consp01", "consp02", "consp03",
              "lone01", "lone02", "lone03",
              "c19perBeh01", "c19perBeh02",
              "c19perBeh03",
              "c19RCA01", "c19RCA02", "c19RCA03",
              "gender", "age", "edu",
              "c19ProSo01", "c19ProSo02",
              "c19ProSo03", "c19ProSo04",
              "rankOrdLife_1_num",
              "rankOrdLife_2_num", "rankOrdLife_3_num",
              "rankOrdLife_4_num",
              "rankOrdLife_5_num", "rankOrdLife_6_num"))

View(cvbase_cleaned)
summary(cvbase_cleaned)

# Question 2
# Filter out data of focus country (Argentina)
cvbase_argentina <- data.frame(filter(cvbase_cleaned, coded_country == "Argentina"))
cvbase_argentina$coded_country <- NULL
View(cvbase_argentina)

cvbase_others <- data.frame(filter(cvbase_cleaned, coded_country != "Argentina"))
cvbase_others$coded_country <- NULL
View(cvbase_others)

#a)
# Summarize the distributions for each attribute
for (col in names(cvbase_argentina)) {
  print(paste0("Variable: ", col))

  print("Argentina:")
  print(summary(cvbase_argentina[[col]]))
  print("Other countries:")
  print(summary(cvbase_others[[col]]))
}

# Initialize an empty dataframe to store the summary statistics
summary_df <- data.frame(
  Variable = character(),
  Argentina_Mean = numeric(),

```

```

Argentina_Median = numeric(),
Argentina_Min = numeric(),
Argentina_Max = numeric(),
Other_Mean = numeric(),
Other_Median = numeric(),
Other_Min = numeric(),
Other_Max = numeric(),
stringsAsFactors = FALSE
)

# Summarize the distributions for each attribute
for (col in names(cvbase_argentina)) {
  arg_summary <- summary(cvbase_argentina[[col]])
  others_summary <- summary(cvbase_others[[col]])

  # Extract summary statistics
  arg_mean <- arg_summary[["Mean"]]
  arg_median <- arg_summary[["Median"]]
  arg_min <- min(cvbase_argentina[[col]], na.rm = TRUE) # Compute min value
  arg_max <- max(cvbase_argentina[[col]], na.rm = TRUE) # Compute max value

  other_mean <- others_summary[["Mean"]]
  other_median <- others_summary[["Median"]]
  other_min <- min(cvbase_others[[col]], na.rm = TRUE) # Compute min value
  other_max <- max(cvbase_others[[col]], na.rm = TRUE) # Compute max value

  # Add the summary statistics and p-value to the dataframe
  summary_df <- rbind(
    summary_df,
    data.frame(
      Variable = col,
      Argentina_Mean = arg_mean,
      Argentina_Median = arg_median,
      Argentina_Min = arg_min,
      Argentina_Max = arg_max,
      Other_Mean = other_mean,
      Other_Median = other_median,
      Other_Min = other_min,
      Other_Max = other_max
    )
  )
}
View(summary_df)
write.csv(summary_df, "summary_ARG_OTHERS.csv", row.names = FALSE)

```

```

# (b) How well do participant responses (attributes) predict pro-social attitudes
(c19ProSo01,2,3 and 4) for your focus country? Which attributes seem to be the best
predictors? Explain your reasoning.
# Multiple linear regression model Analysis
model_argentina <- lm(cbind(c19ProSo01, c19ProSo02, c19ProSo03, c19ProSo04) ~ ., data =
cvbase_argentina)
summary(model_argentina)

```

```

# Correlation Analysis
cor_argentina <- data.frame(round(cor(cvbase_argentina[, !names(cvbase_argentina) %in%
c("c19ProSo01", "c19ProSo02", "c19ProSo03", "c19ProSo04")],
                                cvbase_argentina[, c("c19ProSo01", "c19ProSo02",
"c19ProSo03", "c19ProSo04")])),
                                digits = 2))

View(cor_argentina)
cor_argentina

# Convert the correlation matrix to a long format data frame
cor_long <- cor_argentina %>%
  rownames_to_column("Variable1") %>%
  mutate(row_num = row_number()) %>%
  pivot_longer(cols = -c(Variable1, row_num),
               names_to = "Variable2",
               values_to = "Correlation")

# Create the heatmap for the correlation (Argentina countries)
ggplot(cor_long, aes(x = Variable2, y = Variable1, fill = Correlation)) +
  geom_tile() +
  scale_fill_gradient2(low = "cyan3", mid = "white", high = "orange", midpoint = 0) +
  scale_x_discrete(limits = unique(cor_long$Variable2)) +
  scale_y_discrete(limits = unique(cor_long$Variable1)) +
  theme_minimal() +
  theme(axis.text.x = element_text(vjust = 0.5, hjust = 1),
        axis.text.y = element_text(size = 8)) +
  labs(title = "Correlation Heatmap for Argentina",
       x = NULL, y = NULL,
       fill = "Correlation")

# (c) Repeat Question 2(b) for the other countries as a group. Which attributes are the
strongest predictors? How do these attributes compare to those of your focus country?
# Multiple linear regression model
model_others <- lm(cbind(c19ProSo01, c19ProSo02, c19ProSo03, c19ProSo04) ~ ., data =
cvbase_others)
summary(model_others)

# Correlation
cor_others <- data.frame(round(cor(cvbase_others[, !names(cvbase_others) %in%
c("c19ProSo01", "c19ProSo02", "c19ProSo03", "c19ProSo04")],
                                cvbase_others[, c("c19ProSo01", "c19ProSo02",
"c19ProSo03", "c19ProSo04")])),
                                digits = 2))

View(cor_others)
cor_others

# Convert the correlation matrix to a long format data frame
cor_long_o <- cor_others %>%
  rownames_to_column("Variable1") %>%
  mutate(row_num = row_number()) %>%
  pivot_longer(cols = -c(Variable1, row_num),
               names_to = "Variable2",
               values_to = "Correlation")

```



```

# Create the heatmap for other countries
ggplot(cor_long_o, aes(x = Variable2, y = Variable1, fill = Correlation)) +
  geom_tile() +
  scale_fill_gradient2(low = "cyan3", mid = "white", high = "orange", midpoint = 0) +
  scale_x_discrete(limits = unique(cor_long_o$Variable2)) +
  scale_y_discrete(limits = unique(cor_long_o$Variable1)) +
  theme_minimal() +
  theme(axis.text.x = element_text(vjust = 0.5, hjust = 1),
        axis.text.y = element_text(size = 8)) +
  labs(title = "Correlation Heatmap for Other Countries",
       x = NULL, y = NULL,
       fill = "Correlation")

#Question 3:
# (a) Clustering
life_expectancy <- read.csv("C:/Users/hothu/Downloads/life_expectancy.csv",
header=TRUE)
gpd_per_capita <- read.csv("C:/Users/hothu/Downloads/gpd_per_capita.csv", header=FALSE,
comment.char="#")
gpd_per_capita <- read.csv("C:/Users/hothu/Downloads/gpd_per_capita.csv")
health_infrastructure <-
read.csv("C:/Users/hothu/Downloads/WHO_OECD_health_infrastructure.csv")
government_effectiveness <-
read.csv("C:/Users/hothu/Downloads/recent_wb_government_effectiveness.csv")
education_statistics <-
read.csv("C:/Users/hothu/Downloads/recent_education_statistics.csv")
death_rate <- read.csv("C:/Users/hothu/Downloads/recent_fctb_death_rate.csv")
COVID.19.global.data <- read.csv("C:/Users/hothu/Downloads/death_rate_2022.csv")

colnames(gpd_per_capita)[1] <- "country"
colnames(COVID.19.global.data)[3] <- "country"

# Choosing indicators
life_expectancy_cols <- c("country", "lifeexpectancy.2102_2020")
gpd_per_capita_cols <- c("country", "X2020")
health_infrastructure_cols <- c("country", "total_n_of_doctors")
government_effectiveness_cols <- c("country",
"latest.value_estimate_control_of_corru.364")
education_cols <- c("country", "latest.value_value_adult_literacy_rate.28134")
death_rate_cols <- c("country", "latest.value_deathrate.2066")
COVI_cols <- c("country", "Cumulative_cases", "Cumulative_deaths")

# Merging columns
country_data <- life_expectancy %>% select(all_of(life_expectancy_cols)) %>%
  left_join(gpd_per_capita %>% select(all_of(gpd_per_capita_cols)), by = "country") %>%
  left_join(health_infrastructure %>% select(all_of(health_infrastructure_cols)), by =
"country") %>%
  left_join(government_effectiveness %>% select(all_of(government_effectiveness_cols)),
by = "country") %>%

```

```

left_join(education_statistics %>% select(all_of(education_cols)), by = "country")
%>%
left_join(death_rate %>% select(all_of(death_rate_cols)), by = "country") %>%
left_join(COVID.19.global.data %>% select(all_of(COVI_cols)), by = "country")
data.frame(country_data)
colnames(country_data) <- c("Country", "Life Expectancy", "GDP per Capita", "Health
Infrastructure (Doctors)",
"Government Effectiveness Score", "Education Level", "Death
Rate",
"COVID-19 Cumulative Cases", "COVID-19 Cumulative Deaths")
country_data <- na.omit(country_data)
country_data

# Saving the dataset as a CSV file
write.csv(country_data, "country_data.csv", row.names = FALSE)
getwd()

library(cluster)

# Standardize the numeric variables
country_data_scaled <- country_data
country_data_scaled[,2:9] <- scale(country_data_scaled[,2:9])
rownames(country_data_scaled) <- country_data_scaled$Country
View(country_data_scaled)

# Perform hierarchical clustering
hc_clusters <- hclust(dist(country_data_scaled[,2:9]), method = "ward.D")
hc_clusters

# Determine the optimal number of clusters
fviz_nbclust(country_data_scaled[,2:9], hcut, method = "wss")

# Cut the dendrogram to get 5 clusters
hc_clusters_5 <- cutree(hc_clusters, k = 5)

# Identify the cluster containing Argentina
argentina_cluster <- which(hc_clusters_5 == hc_clusters_5[country_data$Country ==
"Argentina"])

# Extract the 10 countries most similar to Argentina (excluding Argentina)
similar_countries <-
country_data$Country[argentina_cluster][country_data$Country[argentina_cluster] !=
"Argentina"][1:30]

# Plot the dendrogram
plot(hc_clusters, hang = -1, cex = 0.5)
rect.hclust(hc_clusters, k = 5, border = "red")

# 3b. How well do participant responses (attributes) predict pro-social attitudes
#(c19ProSo01,2,3 and 4) for this cluster of similar countries?
#Which attributes are the strongest predictors?
#How do these attributes compare to those of your focus country?

# Extract the data for the cluster of similar countries

```

```

similar_countries_data <- subset(cvbase_cleaned[cvbase_cleaned$coded_country %in%
similar_countries, ], select = - coded_country)

# Correlation Analysis
cor_cluster <- data.frame(round(cor(similar_countries_data[, !names(cvbase_others) %in%
c("c19ProSo01", "c19ProSo02", "c19ProSo03", "c19ProSo04")],
similar_countries_data[, c("c19ProSo01",
"c19ProSo02", "c19ProSo03", "c19ProSo04")])),
digits = 2))
cor_cluster

# Convert the correlation matrix to a long format data frame
cor_long_clus <- cor_cluster %>%
  rownames_to_column("Variable1") %>%
  mutate(row_num = row_number()) %>%
  pivot_longer(cols = -c(Variable1, row_num),
names_to = "Variable2",
values_to = "Correlation")
cor_long_clus

# Create the heatmap for similar countries
ggplot(cor_long_clus, aes(x = Variable2, y = Variable1, fill = Correlation)) +
  geom_tile() +
  scale_fill_gradient2(low = "cyan3", mid = "white", high = "orange", midpoint = 0) +
  scale_x_discrete(limits = unique(cor_long_clus$Variable2)) +
  scale_y_discrete(limits = unique(cor_long_clus$Variable1)) +
  theme_minimal() +
  theme(axis.text.x = element_text(vjust = 0.5, hjust = 1),
axis.text.y = element_text(size = 8)) +
  labs(title = "Correlation Heatmap for Similar Countries",
x = NULL, y = NULL,
fill = "Correlation")

# Multiple Linear Regression (Cluster)
model_similar_countries <- lm(cbind(c19ProSo01, c19ProSo02, c19ProSo03, c19ProSo04) ~
., data = similar_countries_data)
summary(model_similar_countries)

# Prepare the data for the Multivariate Graphic (the comparison correlation heatmaps)
data_for_graphic <- data.frame()

# Add Argentina data
argentina_long <- cor_argentina %>%
  rownames_to_column("Variable1") %>%
  pivot_longer(cols = -Variable1, names_to = "Variable2", values_to = "Correlation")
%>%
  mutate(Country = "Argentina")
data_for_graphic <- rbind(data_for_graphic, argentina_long)

# Add other countries data
others_long <- cor_others %>%
  rownames_to_column("Variable1") %>%

```

```

  pivot_longer(cols = -Variable1, names_to = "Variable2", values_to = "Correlation")
%>%
  mutate(Country = "Other Countries")
data_for_graphic <- rbind(data_for_graphic, others_long)

# Add cluster of similar countries data
cluster_long <- cor_cluster %>%
  rownames_to_column("Variable1") %>%
  pivot_longer(cols = -Variable1, names_to = "Variable2", values_to = "Correlation")
%>%
  mutate(Country = "Cluster of Similar Countries")
data_for_graphic <- rbind(data_for_graphic, cluster_long)
data_for_graphic

# Create the multivariate graphic
ggplot(data_for_graphic, aes(x = Variable2, y = Variable1, fill = Correlation)) +
  geom_tile() +
  facet_wrap(~ Country, ncol = 3) +
  scale_fill_gradient2(low = "cyan3", mid = "white", high = "orange", midpoint = 0) +
  scale_x_discrete(limits = unique(data_for_graphic$Variable2)) +
  scale_y_discrete(limits = unique(data_for_graphic$Variable1)) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, vjust = 0.5, hjust = 0.5),
        axis.text.y = element_text(size = 8),
        strip.text = element_text(size = 10)) +
  labs(title = "Comparison of Correlation Heatmaps: Argentina, Other Countries, and
Cluster of Similar Countries",
       x = NULL, y = NULL,
       fill = "Correlation")

```

B. R Codes Output

Argentina's Correlation Output

```

> cor_argentina

```

	c19ProSo01	c19ProSo02	c19ProSo03	c19ProSo04
employstatus_1	-0.07	0.00	0.00	-0.01
employstatus_2	-0.01	-0.06	-0.01	-0.02
employstatus_3	0.06	0.06	0.03	0.07
employstatus_4	0.05	0.08	0.04	0.01
employstatus_5	-0.03	-0.12	-0.04	0.01
employstatus_6	0.00	-0.02	0.01	-0.01
employstatus_7	-0.03	-0.07	-0.07	0.00
employstatus_8	-0.07	-0.05	-0.05	-0.03
employstatus_9	0.00	0.05	0.05	0.01
employstatus_10	0.04	0.03	0.06	0.04
isoFriends_inPerson	-0.04	0.00	0.03	-0.10
isoOthPpl_inPerson	-0.03	-0.08	0.00	-0.09
isoFriends_online	0.12	0.13	0.06	0.13
isoOthPpl_online	0.07	0.09	0.05	0.05
lone01	-0.01	0.00	-0.04	0.00
lone02	0.01	0.05	0.03	0.06
lone03	-0.05	-0.03	-0.05	-0.08
happy	0.18	0.16	0.18	0.10

lifeSat	0.19	0.14	0.15	0.12
MLQ	0.17	0.16	0.12	0.07
bor01	0.11	0.16	0.13	0.11
bor02	0.08	0.08	0.09	0.03
bor03	0.17	0.15	0.16	0.08
consp01	0.09	0.03	0.02	0.12
consp02	0.10	-0.01	-0.02	0.10
consp03	0.05	-0.05	-0.04	0.00
c19perBeh01	0.30	0.24	0.21	0.28
c19perBeh02	0.32	0.26	0.22	0.33
c19perBeh03	0.31	0.26	0.25	0.35
c19RCA01	0.21	0.25	0.23	0.34
c19RCA02	0.22	0.18	0.18	0.28
c19RCA03	0.17	0.19	0.16	0.27
coronaClose_1	-0.13	-0.07	0.00	-0.10
coronaClose_2	-0.03	-0.02	-0.05	-0.05
coronaClose_3	-0.10	-0.02	-0.03	-0.02
coronaClose_4	0.06	0.03	0.02	0.01
coronaClose_5	0.04	0.02	0.00	-0.01
coronaClose_6	0.02	0.00	0.01	0.06
gender	-0.02	-0.08	-0.01	-0.06
age	0.05	-0.13	-0.10	0.02
edu	0.08	0.10	0.02	0.05
rankOrdLife_1_num	0.12	0.08	0.08	0.18
rankOrdLife_2_num	0.12	0.05	0.09	0.06
rankOrdLife_3_num	0.13	0.04	0.07	0.14
rankOrdLife_4_num	-0.10	-0.03	-0.07	-0.06
rankOrdLife_5_num	-0.14	-0.04	-0.06	-0.15
rankOrdLife_6_num	-0.11	-0.09	-0.10	-0.15

Argentina's Multiple Linear Model Summary Output

```
> summary(model_argentina)
```

Response c19ProSo01 :

Call:

```
lm(formula = c19ProSo01 ~ employstatus_1 + employstatus_2 + employstatus_3 +
    employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
    employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
    isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
    lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
    bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
    c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
    coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
    coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
    rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
    rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_argentina)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-4.5675	-0.7966	0.2769	0.9595	3.2192

Coefficients: (1 not defined because of singularities)

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-2.1980088	0.8745025	-2.513	0.0122 *
employstatus_1	-0.1094757	0.1786801	-0.613	0.5403
employstatus_2	0.0506376	0.1963716	0.258	0.7966

employstatus_3	0.1280265	0.1951143	0.656	0.5119
employstatus_4	0.3784808	0.1960368	1.931	0.0539 .
employstatus_5	0.0577599	0.2924589	0.197	0.8435
employstatus_6	-0.0192043	0.1864598	-0.103	0.9180
employstatus_7	-0.2859959	0.2497648	-1.145	0.2525
employstatus_8	-0.5469854	0.4564469	-1.198	0.2311
employstatus_9	0.0141028	0.1866446	0.076	0.9398
employstatus_10	0.2646123	0.3677880	0.719	0.4721
isoFriends_inPerson	0.0258876	0.0328743	0.787	0.4312
isoOthPpl_inPerson	0.0067129	0.0296965	0.226	0.8212
isoFriends_online	0.0193528	0.0258767	0.748	0.4548
isoOthPpl_online	0.0129585	0.0210331	0.616	0.5380
lone01	0.0466671	0.0617593	0.756	0.4501
lone02	-0.0368271	0.0452187	-0.814	0.4157
lone03	0.0713366	0.0582874	1.224	0.2214
happy	0.0674487	0.0347030	1.944	0.0523 .
lifeSat	0.1031556	0.0544616	1.894	0.0586 .
MLQ	0.0120335	0.0445585	0.270	0.7872
bor01	0.0450416	0.0347248	1.297	0.1950
bor02	0.0301277	0.0344889	0.874	0.3826
bor03	0.1001901	0.0350762	2.856	0.0044 **
consp01	0.0046232	0.0242091	0.191	0.8486
consp02	-0.0006229	0.0249881	-0.025	0.9801
consp03	-0.0032787	0.0223449	-0.147	0.8834
c19perBeh01	0.0989703	0.0647719	1.528	0.1269
c19perBeh02	0.1361157	0.0915733	1.486	0.1376
c19perBeh03	0.1898979	0.0794426	2.390	0.0171 *
c19RCA01	-0.0059436	0.0414191	-0.143	0.8859
c19RCA02	0.0159494	0.0637712	0.250	0.8026
c19RCA03	-0.0026950	0.0479560	-0.056	0.9552
coronaClose_1	-0.0792545	0.4850159	-0.163	0.8702
coronaClose_2	0.5002991	0.5055787	0.990	0.3227
coronaClose_3	-0.4680379	0.5867983	-0.798	0.4253
coronaClose_4	0.9414363	0.4110661	2.290	0.0223 *
coronaClose_5	0.5403041	0.4553467	1.187	0.2358
coronaClose_6	0.3916039	0.4128392	0.949	0.3431
gender	0.0287459	0.1108785	0.259	0.7955
age	0.0153378	0.0430993	0.356	0.7220
edu	0.0558794	0.0393414	1.420	0.1559
rankOrdLife_1_num	-0.0194079	0.0443202	-0.438	0.6616
rankOrdLife_2_num	0.0531202	0.0502776	1.057	0.2911
rankOrdLife_3_num	0.0151829	0.0506320	0.300	0.7644
rankOrdLife_4_num	-0.0538476	0.0554120	-0.972	0.3315
rankOrdLife_5_num	-0.0301585	0.0523130	-0.577	0.5644
rankOrdLife_6_num	NA	NA	NA	NA

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.449 on 773 degrees of freedom
Multiple R-squared: 0.2047, Adjusted R-squared: 0.1574
F-statistic: 4.326 on 46 and 773 DF, p-value: < 2.2e-16

Response c19ProSo02 :

Call:

lm(formula = c19ProSo02 ~ employstatus_1 + employstatus_2 + employstatus_3 +

```

employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_argentina)

```

Residuals:

	Min	1Q	Median	3Q	Max
	-4.2819	-0.8383	0.1727	1.0767	3.8565

Coefficients: (1 not defined because of singularities)

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.2246568	0.9144277	-0.246	0.80599	
employstatus_1	-0.0479799	0.1868377	-0.257	0.79740	
employstatus_2	-0.1301211	0.2053369	-0.634	0.52647	
employstatus_3	0.1106539	0.2040222	0.542	0.58773	
employstatus_4	0.3306166	0.2049868	1.613	0.10718	
employstatus_5	-0.8279712	0.3058110	-2.707	0.00693	**
employstatus_6	-0.1276237	0.1949726	-0.655	0.51294	
employstatus_7	-0.1203497	0.2611677	-0.461	0.64506	
employstatus_8	-0.1367183	0.4772858	-0.286	0.77461	
employstatus_9	0.0248180	0.1951658	0.127	0.89884	
employstatus_10	0.3327145	0.3845792	0.865	0.38723	
isoFriends_inPerson	0.0494387	0.0343751	1.438	0.15078	
isoOthPpl_inPerson	-0.0531801	0.0310523	-1.713	0.08719	.
isoFriends_online	0.0155252	0.0270581	0.574	0.56629	
isoOthPpl_online	0.0365986	0.0219934	1.664	0.09650	.
lone01	0.0045194	0.0645789	0.070	0.94423	
lone02	-0.0192145	0.0472831	-0.406	0.68458	
lone03	0.0316582	0.0609485	0.519	0.60361	
happy	0.0573695	0.0362874	1.581	0.11429	
lifeSat	0.0357320	0.0569480	0.627	0.53055	
MLQ	0.0977673	0.0465928	2.098	0.03620	*
bor01	0.1161739	0.0363101	3.199	0.00143	**
bor02	-0.0046535	0.0360634	-0.129	0.89736	
bor03	0.0966661	0.0366776	2.636	0.00857	**
consp01	0.0118086	0.0253144	0.466	0.64100	
consp02	-0.0348427	0.0261289	-1.333	0.18276	
consp03	-0.0319272	0.0233651	-1.366	0.17220	
c19perBeh01	0.1123156	0.0677291	1.658	0.09766	.
c19perBeh02	0.1054494	0.0957541	1.101	0.27113	
c19perBeh03	0.1157429	0.0830696	1.393	0.16392	
c19RCA01	0.1143142	0.0433101	2.639	0.00847	**
c19RCA02	-0.0657754	0.0666826	-0.986	0.32425	
c19RCA03	0.0182611	0.0501454	0.364	0.71584	
coronaClose_1	-0.2985346	0.5071592	-0.589	0.55627	
coronaClose_2	-0.0616221	0.5286608	-0.117	0.90724	
coronaClose_3	0.5065525	0.6135885	0.826	0.40931	
coronaClose_4	0.2151316	0.4298332	0.501	0.61687	
coronaClose_5	0.0455417	0.4761354	0.096	0.92382	
coronaClose_6	-0.1312778	0.4316873	-0.304	0.76113	
gender	-0.2306153	0.1159406	-1.989	0.04704	*

age	-0.1852602	0.0450670	-4.111	4.37e-05 ***
edu	0.0917878	0.0411376	2.231	0.02595 *
rankOrdLife_1_num	0.0005234	0.0463437	0.011	0.99099
rankOrdLife_2_num	0.0193253	0.0525730	0.368	0.71328
rankOrdLife_3_num	-0.0107236	0.0529436	-0.203	0.83954
rankOrdLife_4_num	-0.0082256	0.0579418	-0.142	0.88715
rankOrdLife_5_num	0.0236351	0.0547013	0.432	0.66581
rankOrdLife_6_num	NA	NA	NA	NA

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.515 on 773 degrees of freedom

Multiple R-squared: 0.2231, Adjusted R-squared: 0.1768

F-statistic: 4.825 on 46 and 773 DF, p-value: < 2.2e-16

Response c19ProSo03 :

Call:

```
lm(formula = c19ProSo03 ~ employstatus_1 + employstatus_2 + employstatus_3 +
    employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
    employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
    isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
    lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
    bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
    c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
    coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
    coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
    rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
    rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_argentina)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-4.1414	-0.9089	0.1474	1.1090	2.8963

Coefficients: (1 not defined because of singularities)

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-1.273966	0.914909	-1.392	0.16419
employstatus_1	0.100415	0.186936	0.537	0.59131
employstatus_2	0.208830	0.205445	1.016	0.30972
employstatus_3	0.174801	0.204130	0.856	0.39208
employstatus_4	0.295861	0.205095	1.443	0.14955
employstatus_5	-0.039681	0.305972	-0.130	0.89685
employstatus_6	0.146504	0.195075	0.751	0.45287
employstatus_7	-0.031231	0.261305	-0.120	0.90489
employstatus_8	-0.154693	0.477537	-0.324	0.74607
employstatus_9	0.164627	0.195269	0.843	0.39944
employstatus_10	0.597715	0.384782	1.553	0.12074
isoFriends_inPerson	0.054862	0.034393	1.595	0.11109
isoOthPpl_inPerson	0.027535	0.031069	0.886	0.37576
isoFriends_online	-0.022910	0.027072	-0.846	0.39768
isoOthPpl_online	0.018235	0.022005	0.829	0.40755
lone01	-0.063848	0.064613	-0.988	0.32338
lone02	0.018960	0.047308	0.401	0.68870
lone03	0.038643	0.060981	0.634	0.52646
happy	0.092003	0.036307	2.534	0.01147 *
lifeSat	0.057340	0.056978	1.006	0.31456

MLQ	0.005378	0.046617	0.115	0.90819
bor01	0.095668	0.036329	2.633	0.00862 **
bor02	0.019251	0.036082	0.534	0.59381
bor03	0.114450	0.036697	3.119	0.00188 **
consp01	0.013650	0.025328	0.539	0.59008
consp02	-0.026593	0.026143	-1.017	0.30937
consp03	-0.038863	0.023377	-1.662	0.09684 .
c19perBeh01	0.063690	0.067765	0.940	0.34758
c19perBeh02	0.027156	0.095804	0.283	0.77691
c19perBeh03	0.227184	0.083113	2.733	0.00641 **
c19RCA01	0.107339	0.043333	2.477	0.01346 *
c19RCA02	0.022726	0.066718	0.341	0.73348
c19RCA03	-0.034089	0.050172	-0.679	0.49705
coronaClose_1	0.756819	0.507426	1.491	0.13624
coronaClose_2	-0.383195	0.528939	-0.724	0.46900
coronaClose_3	-0.152026	0.613911	-0.248	0.80448
coronaClose_4	0.322210	0.430059	0.749	0.45395
coronaClose_5	-0.097696	0.476386	-0.205	0.83757
coronaClose_6	0.011034	0.431914	0.026	0.97963
gender	0.040071	0.116002	0.345	0.72986
age	-0.136265	0.045091	-3.022	0.00259 **
edu	-0.007034	0.041159	-0.171	0.86436
rankOrdLife_1_num	-0.002910	0.046368	-0.063	0.94998
rankOrdLife_2_num	0.055270	0.052601	1.051	0.29370
rankOrdLife_3_num	0.036490	0.052971	0.689	0.49112
rankOrdLife_4_num	-0.010710	0.057972	-0.185	0.85347
rankOrdLife_5_num	0.006383	0.054730	0.117	0.90719
rankOrdLife_6_num	NA	NA	NA	NA

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.516 on 773 degrees of freedom
Multiple R-squared: 0.178, Adjusted R-squared: 0.1291
F-statistic: 3.639 on 46 and 773 DF, p-value: 7.658e-14

Response c19ProSo04 :

Call:

```
lm(formula = c19ProSo04 ~ employstatus_1 + employstatus_2 + employstatus_3 +
  employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
  employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
  isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
  lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
  bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
  c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
  coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
  coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
  rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
  rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_argentina)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-4.7185	-0.7010	0.2649	0.9698	3.6388

Coefficients: (1 not defined because of singularities)

	Estimate	Std. Error	t value	Pr(> t)
--	----------	------------	---------	----------

(Intercept)	-2.317e+00	8.688e-01	-2.668	0.00780	**
employstatus_1	3.408e-01	1.775e-01	1.920	0.05521	.
employstatus_2	4.151e-01	1.951e-01	2.128	0.03365	*
employstatus_3	5.172e-01	1.938e-01	2.668	0.00779	**
employstatus_4	3.277e-01	1.948e-01	1.682	0.09289	.
employstatus_5	4.561e-01	2.905e-01	1.570	0.11688	
employstatus_6	7.018e-02	1.852e-01	0.379	0.70491	
employstatus_7	2.646e-01	2.481e-01	1.066	0.28665	
employstatus_8	1.539e-01	4.535e-01	0.339	0.73436	
employstatus_9	1.521e-01	1.854e-01	0.820	0.41240	
employstatus_10	3.531e-01	3.654e-01	0.966	0.33410	
isoFriends_inPerson	7.821e-03	3.266e-02	0.239	0.81081	
isoOthPpl_inPerson	-1.779e-02	2.950e-02	-0.603	0.54679	
isoFriends_online	2.190e-02	2.571e-02	0.852	0.39447	
isoOthPpl_online	1.316e-02	2.090e-02	0.630	0.52908	
lone01	2.846e-02	6.135e-02	0.464	0.64291	
lone02	6.541e-02	4.492e-02	1.456	0.14581	
lone03	-6.392e-02	5.791e-02	-1.104	0.26997	
happy	3.110e-02	3.448e-02	0.902	0.36730	
lifeSat	5.591e-02	5.410e-02	1.033	0.30173	
MLQ	-5.170e-02	4.427e-02	-1.168	0.24319	
bor01	3.777e-02	3.450e-02	1.095	0.27389	
bor02	-1.681e-02	3.426e-02	-0.491	0.62376	
bor03	1.185e-02	3.485e-02	0.340	0.73385	
consp01	4.494e-02	2.405e-02	1.869	0.06205	.
consp02	3.285e-05	2.482e-02	0.001	0.99894	
consp03	-4.088e-02	2.220e-02	-1.842	0.06590	.
c19perBeh01	-2.145e-02	6.435e-02	-0.333	0.73899	
c19perBeh02	1.372e-01	9.097e-02	1.508	0.13202	
c19perBeh03	1.883e-01	7.892e-02	2.386	0.01729	*
c19RCA01	1.699e-01	4.115e-02	4.130	4.02e-05	***
c19RCA02	-5.032e-02	6.335e-02	-0.794	0.42726	
c19RCA03	1.058e-01	4.764e-02	2.220	0.02668	*
coronaClose_1	2.930e-01	4.818e-01	0.608	0.54328	
coronaClose_2	9.653e-02	5.023e-01	0.192	0.84764	
coronaClose_3	9.001e-01	5.830e-01	1.544	0.12301	
coronaClose_4	6.026e-01	4.084e-01	1.476	0.14043	
coronaClose_5	1.868e-01	4.524e-01	0.413	0.67974	
coronaClose_6	2.617e-01	4.101e-01	0.638	0.52357	
gender	4.348e-02	1.102e-01	0.395	0.69312	
age	4.083e-03	4.282e-02	0.095	0.92406	
edu	3.842e-03	3.908e-02	0.098	0.92172	
rankOrdLife_1_num	7.725e-02	4.403e-02	1.754	0.07976	.
rankOrdLife_2_num	1.684e-02	4.995e-02	0.337	0.73608	
rankOrdLife_3_num	8.724e-02	5.030e-02	1.734	0.08326	.
rankOrdLife_4_num	6.955e-02	5.505e-02	1.263	0.20684	
rankOrdLife_5_num	-8.176e-03	5.197e-02	-0.157	0.87503	
rankOrdLife_6_num	NA	NA	NA	NA	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.439 on 773 degrees of freedom
Multiple R-squared: 0.2167, Adjusted R-squared: 0.1701
F-statistic: 4.648 on 46 and 773 DF, p-value: < 2.2e-16

Other countries' Correlation Output

```
> cor_others
```

	c19ProSo01	c19ProSo02	c19ProSo03	c19ProSo04
employstatus_1	0.00	0.01	0.01	0.00
employstatus_2	0.01	-0.01	0.02	0.01
employstatus_3	0.05	0.06	0.07	0.03
employstatus_4	-0.02	-0.07	-0.04	-0.02
employstatus_5	-0.04	-0.04	-0.03	-0.01
employstatus_6	-0.02	0.01	-0.02	-0.01
employstatus_7	-0.05	-0.04	-0.08	0.00
employstatus_8	-0.04	-0.07	-0.03	-0.01
employstatus_9	0.03	0.06	0.04	-0.01
employstatus_10	0.05	0.03	0.05	0.04
isoFriends_inPerson	0.04	0.05	0.04	-0.06
isoOthPpl_inPerson	0.03	-0.02	0.02	-0.07
isoFriends_online	0.12	0.14	0.11	0.11
isoOthPpl_online	0.09	0.11	0.10	0.05
lone01	-0.01	-0.01	0.00	-0.01
lone02	-0.02	-0.02	0.00	0.04
lone03	-0.03	-0.04	0.00	0.00
happy	0.11	0.14	0.10	0.06
lifeSat	0.15	0.19	0.14	0.11
MLQ	0.16	0.21	0.12	0.09
bor01	0.07	0.12	0.08	0.04
bor02	0.03	0.06	0.05	0.04
bor03	0.10	0.09	0.08	0.08
consp01	0.01	-0.05	-0.03	0.05
consp02	-0.01	-0.06	-0.05	0.02
consp03	0.02	0.01	0.00	0.00
c19perBeh01	0.18	0.19	0.15	0.24
c19perBeh02	0.16	0.18	0.15	0.28
c19perBeh03	0.10	0.17	0.13	0.23
c19RCA01	0.14	0.22	0.14	0.15
c19RCA02	0.11	0.17	0.10	0.21
c19RCA03	0.06	0.17	0.05	0.06
coronaClose_1	0.02	0.01	0.03	0.01
coronaClose_2	0.02	0.01	0.03	0.03
coronaClose_3	0.04	0.02	0.04	0.04
coronaClose_4	0.07	0.06	0.07	0.08
coronaClose_5	0.06	0.07	0.05	0.03
coronaClose_6	-0.09	-0.09	-0.09	-0.08
gender	0.00	-0.05	-0.03	-0.05
age	-0.02	-0.06	-0.08	0.04
edu	0.08	0.11	0.10	0.09
rankOrdLife_1_num	0.09	0.05	0.06	0.14
rankOrdLife_2_num	0.09	0.07	0.09	0.11
rankOrdLife_3_num	0.08	0.05	0.08	0.14
rankOrdLife_4_num	-0.05	-0.02	-0.05	-0.09
rankOrdLife_5_num	-0.06	-0.04	-0.04	-0.11
rankOrdLife_6_num	-0.13	-0.10	-0.13	-0.17

Other countries' Multiple Linear Model Summary Output

```
> summary(model_others)
Response c19ProSo01 :
```

Call:

```
lm(formula = c19ProSo01 ~ employstatus_1 + employstatus_2 + employstatus_3 +
```

```

employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_others)

```

Residuals:

Min	1Q	Median	3Q	Max
-5.2106	-0.7471	0.1965	0.9550	4.2318

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.1875366	0.2976738	-0.630	0.528694
employstatus_1	-0.0068507	0.0265550	-0.258	0.796424
employstatus_2	0.0230538	0.0273904	0.842	0.399975
employstatus_3	0.0954418	0.0263570	3.621	0.000294 ***
employstatus_4	0.0629198	0.0309715	2.032	0.042208 *
employstatus_5	-0.0836643	0.0355588	-2.353	0.018636 *
employstatus_6	-0.1050765	0.0301079	-3.490	0.000484 ***
employstatus_7	-0.2401953	0.0359540	-6.681	2.41e-11 ***
employstatus_8	-0.1496095	0.0557094	-2.686	0.007245 **
employstatus_9	0.0817696	0.0261789	3.123	0.001789 **
employstatus_10	0.3944387	0.0475311	8.299	< 2e-16 ***
isoFriends_inPerson	0.0187086	0.0033841	5.528	3.26e-08 ***
isoOthPpl_inPerson	0.0238416	0.0038383	6.211	5.31e-10 ***
isoFriends_online	0.0258716	0.0033205	7.792	6.80e-15 ***
isoOthPpl_online	0.0085133	0.0030654	2.777	0.005485 **
lone01	0.0562366	0.0092720	6.065	1.33e-09 ***
lone02	-0.0292574	0.0081965	-3.570	0.000358 ***
lone03	0.0300847	0.0088577	3.396	0.000683 ***
happy	0.0240619	0.0051907	4.636	3.57e-06 ***
lifeSat	0.0499260	0.0090138	5.539	3.07e-08 ***
MLQ	0.0738149	0.0059664	12.372	< 2e-16 ***
bor01	0.0373015	0.0052061	7.165	7.93e-13 ***
bor02	0.0055271	0.0052025	1.062	0.288064
bor03	0.0449759	0.0048310	9.310	< 2e-16 ***
consp01	0.0078650	0.0037577	2.093	0.036352 *
consp02	-0.0194966	0.0039365	-4.953	7.35e-07 ***
consp03	0.0163488	0.0030123	5.427	5.76e-08 ***
c19perBeh01	0.1289057	0.0087913	14.663	< 2e-16 ***
c19perBeh02	0.0787093	0.0105268	7.477	7.78e-14 ***
c19perBeh03	0.0007304	0.0061053	0.120	0.904779
c19RCA01	0.0686883	0.0046370	14.813	< 2e-16 ***
c19RCA02	0.0077211	0.0074846	1.032	0.302269
c19RCA03	-0.0140718	0.0049932	-2.818	0.004832 **
coronaClose_1	0.2126266	0.0715929	2.970	0.002981 **
coronaClose_2	0.0788377	0.0470877	1.674	0.094085 .
coronaClose_3	0.1490589	0.0417260	3.572	0.000354 ***
coronaClose_4	0.1541440	0.0347140	4.440	9.01e-06 ***
coronaClose_5	0.0874763	0.0352261	2.483	0.013022 *
coronaClose_6	-0.0472795	0.0360051	-1.313	0.189146
gender	0.0914153	0.0155634	5.874	4.30e-09 ***

age	0.0070682	0.0065651	1.077	0.281650	
edu	0.0359911	0.0054695	6.580	4.76e-11	***
rankOrdLife_1_num	0.0025132	0.0144295	0.174	0.861731	
rankOrdLife_2_num	0.0078870	0.0146712	0.538	0.590868	
rankOrdLife_3_num	-0.0118536	0.0148620	-0.798	0.425122	
rankOrdLife_4_num	-0.0477938	0.0146333	-3.266	0.001091	**
rankOrdLife_5_num	-0.0208943	0.0144999	-1.441	0.149593	
rankOrdLife_6_num	-0.1059712	0.0142636	-7.429	1.11e-13	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.372 on 35733 degrees of freedom

Multiple R-squared: 0.1139, Adjusted R-squared: 0.1128

F-statistic: 97.76 on 47 and 35733 DF, p-value: < 2.2e-16

Response c19ProSo2 :

Call:

```
lm(formula = c19ProSo2 ~ employstatus_1 + employstatus_2 + employstatus_3 +
    employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
    employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
    isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
    lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
    bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
    c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
    coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
    coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
    rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
    rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_others)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-5.3280	-0.8667	0.2279	1.0685	4.9358

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.9004163	0.3253457	-2.768	0.005651	**
employstatus_1	0.0216075	0.0290236	0.744	0.456590	
employstatus_2	-0.0092548	0.0299366	-0.309	0.757212	
employstatus_3	0.1552783	0.0288072	5.390	7.08e-08	***
employstatus_4	-0.1903938	0.0338507	-5.625	1.87e-08	***
employstatus_5	-0.1131750	0.0388644	-2.912	0.003593	**
employstatus_6	0.0539864	0.0329068	1.641	0.100892	
employstatus_7	-0.0709654	0.0392963	-1.806	0.070942	.
employstatus_8	-0.3428006	0.0608882	-5.630	1.82e-08	***
employstatus_9	0.0984047	0.0286125	3.439	0.000584	***
employstatus_10	0.2719088	0.0519496	5.234	1.67e-07	***
isoFriends_inPerson	0.0369895	0.0036987	10.001	< 2e-16	***
isoOthPpl_inPerson	-0.0007064	0.0041952	-0.168	0.866279	
isoFriends_online	0.0242747	0.0036291	6.689	2.28e-11	***
isoOthPpl_online	0.0209294	0.0033504	6.247	4.23e-10	***
lone01	0.0562216	0.0101339	5.548	2.91e-08	***
lone02	-0.0398192	0.0089584	-4.445	8.82e-06	***
lone03	0.0394186	0.0096811	4.072	4.68e-05	***
happy	0.0208839	0.0056733	3.681	0.000233	***
lifeSat	0.1056437	0.0098517	10.723	< 2e-16	***

MLQ	0.0965536	0.0065210	14.807	< 2e-16	***
bor01	0.0663092	0.0056901	11.654	< 2e-16	***
bor02	0.0007093	0.0056862	0.125	0.900732	
bor03	0.0300854	0.0052801	5.698	1.22e-08	***
consp01	-0.0181096	0.0041070	-4.409	1.04e-05	***
consp02	-0.0312622	0.0043025	-7.266	3.77e-13	***
consp03	0.0150617	0.0032923	4.575	4.78e-06	***
c19perBeh01	0.1001884	0.0096086	10.427	< 2e-16	***
c19perBeh02	0.0774649	0.0115054	6.733	1.69e-11	***
c19perBeh03	0.0558569	0.0066728	8.371	< 2e-16	***
c19RCA01	0.1114271	0.0050681	21.986	< 2e-16	***
c19RCA02	-0.0059668	0.0081804	-0.729	0.465759	
c19RCA03	0.0627525	0.0054573	11.499	< 2e-16	***
coronaClose_1	0.0854426	0.0782482	1.092	0.274866	
coronaClose_2	0.0776876	0.0514650	1.510	0.131174	
coronaClose_3	0.0224209	0.0456048	0.492	0.622982	
coronaClose_4	0.0753030	0.0379410	1.985	0.047181	*
coronaClose_5	0.1257524	0.0385007	3.266	0.001091	**
coronaClose_6	-0.0913946	0.0393521	-2.322	0.020213	*
gender	-0.0508722	0.0170102	-2.991	0.002785	**
age	-0.0319439	0.0071753	-4.452	8.54e-06	***
edu	0.0764633	0.0059779	12.791	< 2e-16	***
rankOrdLife_1_num	-0.0001282	0.0157709	-0.008	0.993512	
rankOrdLife_2_num	0.0494392	0.0160351	3.083	0.002049	**
rankOrdLife_3_num	-0.0074405	0.0162436	-0.458	0.646915	
rankOrdLife_4_num	-0.0083369	0.0159936	-0.521	0.602187	
rankOrdLife_5_num	0.0109600	0.0158478	0.692	0.489205	
rankOrdLife_6_num	-0.0754361	0.0155895	-4.839	1.31e-06	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.499 on 35733 degrees of freedom

Multiple R-squared: 0.1685, Adjusted R-squared: 0.1674

F-statistic: 154.1 on 47 and 35733 DF, p-value: < 2.2e-16

Response c19ProSo03 :

Call:

```
lm(formula = c19ProSo03 ~ employstatus_1 + employstatus_2 + employstatus_3 +
  employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
  employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
  isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
  lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
  bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
  c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
  coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
  coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
  rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
  rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_others)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-5.0388	-0.9823	0.1802	1.1759	4.9705

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
--	----------	------------	---------	----------

(Intercept)	-1.260194	0.340827	-3.697	0.000218	***
employstatus_1	0.045519	0.030405	1.497	0.134377	
employstatus_2	0.083354	0.031361	2.658	0.007867	**
employstatus_3	0.205876	0.030178	6.822	9.12e-12	***
employstatus_4	-0.017354	0.035461	-0.489	0.624570	
employstatus_5	-0.042603	0.040714	-1.046	0.295382	
employstatus_6	-0.058972	0.034473	-1.711	0.087149	.
employstatus_7	-0.219396	0.041166	-5.330	9.91e-08	***
employstatus_8	-0.075684	0.063786	-1.187	0.235419	
employstatus_9	0.089655	0.029974	2.991	0.002782	**
employstatus_10	0.395058	0.054422	7.259	3.97e-13	***
isoFriends_inPerson	0.024111	0.003875	6.223	4.95e-10	***
isoOthPpl_inPerson	0.020844	0.004395	4.743	2.12e-06	***
isoFriends_online	0.019781	0.003802	5.203	1.97e-07	***
isoOthPpl_online	0.020491	0.003510	5.838	5.32e-09	***
lone01	0.024261	0.010616	2.285	0.022303	*
lone02	-0.020936	0.009385	-2.231	0.025697	*
lone03	0.080599	0.010142	7.947	1.96e-15	***
happy	0.012971	0.005943	2.183	0.029078	*
lifeSat	0.105217	0.010320	10.195	< 2e-16	***
MLQ	0.043737	0.006831	6.402	1.55e-10	***
bor01	0.031563	0.005961	5.295	1.20e-07	***
bor02	0.023416	0.005957	3.931	8.47e-05	***
bor03	0.048953	0.005531	8.850	< 2e-16	***
consp01	-0.005475	0.004302	-1.273	0.203155	
consp02	-0.040635	0.004507	-9.016	< 2e-16	***
consp03	0.015472	0.003449	4.486	7.28e-06	***
c19perBeh01	0.089143	0.010066	8.856	< 2e-16	***
c19perBeh02	0.087376	0.012053	7.249	4.27e-13	***
c19perBeh03	0.053976	0.006990	7.721	1.18e-14	***
c19RCA01	0.080046	0.005309	15.077	< 2e-16	***
c19RCA02	0.009502	0.008570	1.109	0.267505	
c19RCA03	-0.024934	0.005717	-4.361	1.30e-05	***
coronaClose_1	0.320163	0.081972	3.906	9.41e-05	***
coronaClose_2	0.087832	0.053914	1.629	0.103299	
coronaClose_3	0.112244	0.047775	2.349	0.018807	*
coronaClose_4	0.077477	0.039746	1.949	0.051268	.
coronaClose_5	-0.036428	0.040333	-0.903	0.366432	
coronaClose_6	-0.141191	0.041225	-3.425	0.000616	***
gender	0.027853	0.017820	1.563	0.118051	
age	-0.055912	0.007517	-7.438	1.04e-13	***
edu	0.060445	0.006262	9.652	< 2e-16	***
rankOrdLife_1_num	0.028423	0.016521	1.720	0.085373	.
rankOrdLife_2_num	0.066016	0.016798	3.930	8.51e-05	***
rankOrdLife_3_num	0.034006	0.017017	1.998	0.045679	*
rankOrdLife_4_num	-0.012175	0.016755	-0.727	0.467424	
rankOrdLife_5_num	0.028699	0.016602	1.729	0.083879	.
rankOrdLife_6_num	-0.071330	0.016331	-4.368	1.26e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.571 on 35733 degrees of freedom
Multiple R-squared: 0.1138, Adjusted R-squared: 0.1126
F-statistic: 97.6 on 47 and 35733 DF, p-value: < 2.2e-16

Response c19ProSo04 :

Call:

```
lm(formula = c19ProSo04 ~ employstatus_1 + employstatus_2 + employstatus_3 +  
  employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +  
  employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +  
  isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +  
  lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +  
  bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +  
  c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +  
  coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +  
  coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +  
  rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +  
  rankOrdLife_5_num + rankOrdLife_6_num, data = cvbase_others)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-5.5801	-0.7046	0.3032	1.0194	4.9148

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-1.0661141	0.3086093	-3.455	0.000552	***
employstatus_1	0.0277945	0.0275305	1.010	0.312699	
employstatus_2	0.1045809	0.0283966	3.683	0.000231	***
employstatus_3	0.1489302	0.0273253	5.450	5.06e-08	***
employstatus_4	0.0476255	0.0321093	1.483	0.138022	
employstatus_5	0.0388550	0.0368651	1.054	0.291900	
employstatus_6	-0.0443477	0.0312140	-1.421	0.155394	
employstatus_7	-0.0869763	0.0372749	-2.333	0.019634	*
employstatus_8	0.0887811	0.0577560	1.537	0.124259	
employstatus_9	0.0133395	0.0271406	0.491	0.623080	
employstatus_10	0.3003270	0.0492773	6.095	1.11e-09	***
isoFriends_inPerson	0.0009731	0.0035085	0.277	0.781507	
isoOthPpl_inPerson	0.0081779	0.0039794	2.055	0.039879	*
isoFriends_online	0.0217488	0.0034425	6.318	2.68e-10	***
isoOthPpl_online	-0.0007323	0.0031780	-0.230	0.817757	
lone01	-0.0196045	0.0096126	-2.039	0.041412	*
lone02	0.0444599	0.0084976	5.232	1.69e-07	***
lone03	0.0563071	0.0091831	6.132	8.79e-10	***
happy	0.0001215	0.0053814	0.023	0.981982	
lifeSat	0.0745525	0.0093449	7.978	1.53e-15	***
MLQ	0.0138097	0.0061856	2.233	0.025584	*
bor01	-0.0046864	0.0053973	-0.868	0.385243	
bor02	0.0312844	0.0053937	5.800	6.68e-09	***
bor03	0.0417479	0.0050085	8.335	< 2e-16	***
consp01	0.0230253	0.0038957	5.910	3.44e-09	***
consp02	-0.0267335	0.0040811	-6.551	5.81e-11	***
consp03	0.0011586	0.0031229	0.371	0.710631	
c19perBeh01	0.0916902	0.0091143	10.060	< 2e-16	***
c19perBeh02	0.1824270	0.0109135	16.716	< 2e-16	***
c19perBeh03	0.0963566	0.0063296	15.223	< 2e-16	***
c19RCA01	0.0465945	0.0048074	9.692	< 2e-16	***
c19RCA02	0.1170028	0.0077596	15.078	< 2e-16	***
c19RCA03	-0.0491343	0.0051766	-9.492	< 2e-16	***
coronaClose_1	0.2568239	0.0742230	3.460	0.000540	***
coronaClose_2	0.0999014	0.0488175	2.046	0.040722	*
coronaClose_3	0.1865883	0.0432589	4.313	1.61e-05	***
coronaClose_4	0.1213899	0.0359893	3.373	0.000744	***

coronaClose_5	-0.0490759	0.0365202	-1.344	0.179021	
coronaClose_6	-0.1386920	0.0373278	-3.716	0.000203	***
gender	0.0065912	0.0161351	0.409	0.682908	
age	0.0313268	0.0068062	4.603	4.19e-06	***
edu	0.0355131	0.0056704	6.263	3.82e-10	***
rankOrdLife_1_num	0.0630870	0.0149596	4.217	2.48e-05	***
rankOrdLife_2_num	0.0441862	0.0152102	2.905	0.003674	**
rankOrdLife_3_num	0.0538916	0.0154080	3.498	0.000470	***
rankOrdLife_4_num	-0.0163347	0.0151708	-1.077	0.281614	
rankOrdLife_5_num	-0.0021540	0.0150326	-0.143	0.886061	
rankOrdLife_6_num	-0.0579351	0.0147876	-3.918	8.95e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.422 on 35733 degrees of freedom

Multiple R-squared: 0.1568, Adjusted R-squared: 0.1556

F-statistic: 141.3 on 47 and 35733 DF, p-value: < 2.2e-16=

Similar Countries's Correlation Output

```
> cor_cluster
```

	c19ProSo01	c19ProSo02	c19ProSo03	c19ProSo04
employstatus_1	0.01	0.02	0.00	-0.01
employstatus_2	0.01	0.00	0.04	0.01
employstatus_3	0.05	0.05	0.06	0.05
employstatus_4	-0.03	-0.06	-0.05	-0.03
employstatus_5	0.01	0.00	-0.02	0.02
employstatus_6	-0.01	0.04	0.00	0.02
employstatus_7	-0.02	-0.01	-0.03	-0.01
employstatus_8	-0.03	-0.04	-0.04	-0.03
employstatus_9	-0.05	-0.10	-0.08	-0.07
employstatus_10	0.08	0.05	0.05	0.07
isoFriends_inPerson	0.02	0.02	0.04	-0.01
isoOthPpl_inPerson	0.02	0.00	0.04	0.02
isoFriends_online	0.11	0.12	0.12	0.11
isoOthPpl_online	0.08	0.06	0.10	0.04
lone01	0.00	-0.08	-0.03	0.00
lone02	-0.07	-0.08	-0.03	0.03
lone03	-0.04	-0.11	-0.05	0.01
happy	0.12	0.14	0.11	0.11
lifeSat	0.11	0.18	0.15	0.12
MLQ	0.12	0.16	0.14	0.12
bor01	0.06	0.07	0.06	0.01
bor02	0.01	0.02	0.07	0.01
bor03	0.09	0.12	0.10	0.06
consp01	0.03	0.02	0.02	0.09
consp02	0.02	0.01	-0.01	0.07
consp03	0.08	0.08	0.08	0.03
c19perBeh01	0.20	0.23	0.19	0.18
c19perBeh02	0.19	0.21	0.14	0.20
c19perBeh03	0.15	0.15	0.14	0.15
c19RCA01	0.18	0.20	0.16	0.18
c19RCA02	0.17	0.22	0.15	0.20
c19RCA03	0.18	0.24	0.18	0.16
coronaClose_1	-0.10	-0.09	-0.05	-0.04
coronaClose_2	-0.09	-0.08	-0.04	-0.02
coronaClose_3	-0.02	-0.05	-0.03	0.04

coronaClose_4	0.03	0.02	0.06	0.06
coronaClose_5	0.05	0.03	0.07	0.02
coronaClose_6	-0.03	0.00	-0.08	-0.05
gender	0.04	-0.04	0.03	0.00
age	0.06	0.07	0.05	0.10
edu	0.06	0.04	0.05	0.09
rankOrdLife_1_num	0.10	0.08	0.07	0.12
rankOrdLife_2_num	0.05	0.04	0.07	0.08
rankOrdLife_3_num	0.04	0.02	0.01	0.10
rankOrdLife_4_num	-0.05	0.03	-0.04	-0.07
rankOrdLife_5_num	-0.05	-0.06	-0.03	-0.10
rankOrdLife_6_num	-0.09	-0.09	-0.07	-0.12

Similar Countries's Multiple Linear Model Summary Output

```
> summary(model_similar_countries)
```

Response c19ProSo01 :

Call:

```
lm(formula = c19ProSo01 ~ employstatus_1 + employstatus_2 + employstatus_3 +
  employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
  employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
  isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
  lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
  bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
  c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
  coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
  coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
  rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
  rankOrdLife_5_num + rankOrdLife_6_num, data = similar_countries_data)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-5.3851	-0.7066	0.2792	0.9517	3.4809

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	6.479457	14.538240	0.446	0.655878
employstatus_1	0.093417	0.103739	0.901	0.367971
employstatus_2	0.080840	0.112097	0.721	0.470901
employstatus_3	0.136754	0.103365	1.323	0.185995
employstatus_4	-0.036653	0.129562	-0.283	0.777285
employstatus_5	0.248327	0.165264	1.503	0.133111
employstatus_6	-0.007535	0.119371	-0.063	0.949673
employstatus_7	-0.190733	0.176261	-1.082	0.279346
employstatus_8	0.231983	0.376315	0.616	0.537667
employstatus_9	-0.007980	0.113947	-0.070	0.944176
employstatus_10	0.658248	0.162651	4.047	5.4e-05 ***
isoFriends_inPerson	0.011231	0.013887	0.809	0.418777
isoOthPpl_inPerson	0.011058	0.016917	0.654	0.513384
isoFriends_online	0.023847	0.014952	1.595	0.110899
isoOthPpl_online	0.007220	0.013383	0.539	0.589632
lone01	0.092449	0.037611	2.458	0.014061 *
lone02	-0.123304	0.036300	-3.397	0.000696 ***
lone03	0.044319	0.037624	1.178	0.238975
happy	0.037857	0.020911	1.810	0.070396 .
lifeSat	0.013738	0.038833	0.354	0.723555

MLQ	0.010166	0.026119	0.389	0.697163
bor01	0.022427	0.020899	1.073	0.283349
bor02	0.001180	0.018338	0.064	0.948715
bor03	0.026248	0.021404	1.226	0.220240
consp01	0.019416	0.015526	1.251	0.211259
consp02	-0.028482	0.016104	-1.769	0.077111 .
consp03	0.022823	0.012109	1.885	0.059607 .
c19perBeh01	0.114462	0.038000	3.012	0.002630 **
c19perBeh02	0.062294	0.053764	1.159	0.246752
c19perBeh03	0.056659	0.032635	1.736	0.082707 .
c19RCA01	0.085475	0.024123	3.543	0.000405 ***
c19RCA02	-0.011872	0.043608	-0.272	0.785474
c19RCA03	0.102791	0.030901	3.326	0.000897 ***
coronaClose_1	-0.689465	0.408209	-1.689	0.091389 .
coronaClose_2	-0.623516	0.242575	-2.570	0.010236 *
coronaClose_3	0.018598	0.227499	0.082	0.934855
coronaClose_4	0.064251	0.168623	0.381	0.703222
coronaClose_5	0.036529	0.167591	0.218	0.827481
coronaClose_6	-0.153710	0.171763	-0.895	0.370958
gender	0.181142	0.068371	2.649	0.008133 **
age	0.023514	0.033332	0.705	0.480622
edu	0.035713	0.025730	1.388	0.165307
rankOrdLife_1_num	-0.298155	0.692083	-0.431	0.666658
rankOrdLife_2_num	-0.332148	0.691435	-0.480	0.631017
rankOrdLife_3_num	-0.328831	0.692044	-0.475	0.634730
rankOrdLife_4_num	-0.384269	0.692594	-0.555	0.579082
rankOrdLife_5_num	-0.326485	0.691672	-0.472	0.636966
rankOrdLife_6_num	-0.400397	0.692027	-0.579	0.562939

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.364 on 1843 degrees of freedom
Multiple R-squared: 0.1306, Adjusted R-squared: 0.1085
F-statistic: 5.892 on 47 and 1843 DF, p-value: < 2.2e-16

Response c19ProSo02 :

Call:

```
lm(formula = c19ProSo02 ~ employstatus_1 + employstatus_2 + employstatus_3 +
  employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
  employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
  isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
  lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
  bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
  c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
  coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
  coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
  rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
  rankOrdLife_5_num + rankOrdLife_6_num, data = similar_countries_data)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-5.2603	-0.6393	0.2011	0.8261	2.9773

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
--	----------	------------	---------	----------

(Intercept)	5.021904	13.167621	0.381	0.70296	
employstatus_1	0.034330	0.093959	0.365	0.71487	
employstatus_2	-0.048203	0.101529	-0.475	0.63501	
employstatus_3	0.084436	0.093620	0.902	0.36723	
employstatus_4	-0.246366	0.117347	-2.099	0.03591	*
employstatus_5	0.190532	0.149683	1.273	0.20321	
employstatus_6	0.044083	0.108118	0.408	0.68352	
employstatus_7	-0.164784	0.159643	-1.032	0.30211	
employstatus_8	0.196348	0.340838	0.576	0.56464	
employstatus_9	-0.295792	0.103204	-2.866	0.00420	**
employstatus_10	0.452415	0.147317	3.071	0.00216	**
isoFriends_inPerson	0.014467	0.012578	1.150	0.25019	
isoOthPpl_inPerson	0.001475	0.015322	0.096	0.92331	
isoFriends_online	0.026292	0.013542	1.941	0.05235	.
isoOthPpl_online	-0.008540	0.012121	-0.705	0.48120	
lone01	-0.032216	0.034065	-0.946	0.34442	
lone02	-0.016478	0.032877	-0.501	0.61630	
lone03	-0.017715	0.034077	-0.520	0.60323	
happy	-0.003024	0.018940	-0.160	0.87315	
lifeSat	0.101425	0.035172	2.884	0.00398	**
MLQ	0.014104	0.023656	0.596	0.55111	
bor01	0.008404	0.018929	0.444	0.65709	
bor02	0.022051	0.016609	1.328	0.18447	
bor03	0.035537	0.019386	1.833	0.06695	.
consp01	0.016993	0.014062	1.208	0.22704	
consp02	-0.017258	0.014585	-1.183	0.23687	
consp03	0.011397	0.010967	1.039	0.29882	
c19perBeh01	0.105548	0.034418	3.067	0.00220	**
c19perBeh02	0.056371	0.048696	1.158	0.24717	
c19perBeh03	0.023371	0.029559	0.791	0.42923	
c19RCA01	0.091445	0.021848	4.185	2.98e-05	***
c19RCA02	0.002968	0.039497	0.075	0.94011	
c19RCA03	0.138136	0.027988	4.936	8.71e-07	***
coronaClose_1	-0.348037	0.369725	-0.941	0.34665	
coronaClose_2	-0.420278	0.219706	-1.913	0.05591	.
coronaClose_3	-0.097879	0.206051	-0.475	0.63483	
coronaClose_4	0.209251	0.152726	1.370	0.17082	
coronaClose_5	0.119500	0.151791	0.787	0.43123	
coronaClose_6	0.050754	0.155569	0.326	0.74428	
gender	-0.053390	0.061925	-0.862	0.38871	
age	-0.000445	0.030190	-0.015	0.98824	
edu	-0.001173	0.023304	-0.050	0.95986	
rankOrdLife_1_num	-0.211173	0.626836	-0.337	0.73624	
rankOrdLife_2_num	-0.226464	0.626249	-0.362	0.71768	
rankOrdLife_3_num	-0.238889	0.626800	-0.381	0.70315	
rankOrdLife_4_num	-0.199954	0.627299	-0.319	0.74995	
rankOrdLife_5_num	-0.230074	0.626463	-0.367	0.71347	
rankOrdLife_6_num	-0.293338	0.626785	-0.468	0.63984	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.235 on 1843 degrees of freedom
Multiple R-squared: 0.1585, Adjusted R-squared: 0.137
F-statistic: 7.386 on 47 and 1843 DF, p-value: < 2.2e-16

Response c19ProSo03 :

Call:

```
lm(formula = c19ProSo03 ~ employstatus_1 + employstatus_2 + employstatus_3 +  
  employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +  
  employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +  
  isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +  
  lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +  
  bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +  
  c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +  
  coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +  
  coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +  
  rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +  
  rankOrdLife_5_num + rankOrdLife_6_num, data = similar_countries_data)
```

Residuals:

Min	1Q	Median	3Q	Max
-4.4726	-0.8137	0.1621	1.0349	3.9953

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-37.145233	15.055581	-2.467	0.013707	*
employstatus_1	-0.026843	0.107431	-0.250	0.802719	
employstatus_2	0.059937	0.116086	0.516	0.605695	
employstatus_3	0.056941	0.107043	0.532	0.594828	
employstatus_4	-0.183601	0.134173	-1.368	0.171355	
employstatus_5	0.067577	0.171145	0.395	0.692996	
employstatus_6	-0.034005	0.123619	-0.275	0.783290	
employstatus_7	-0.270210	0.182533	-1.480	0.138954	
employstatus_8	-0.016750	0.389706	-0.043	0.965721	
employstatus_9	-0.227300	0.118002	-1.926	0.054228	.
employstatus_10	0.468191	0.168439	2.780	0.005498	**
isoFriends_inPerson	0.016344	0.014381	1.136	0.255900	
isoOthPpl_inPerson	0.018570	0.017519	1.060	0.289274	
isoFriends_online	0.030481	0.015484	1.969	0.049159	*
isoOthPpl_online	0.004664	0.013859	0.337	0.736517	
lone01	0.015688	0.038949	0.403	0.687163	
lone02	-0.021023	0.037591	-0.559	0.576059	
lone03	-0.002134	0.038963	-0.055	0.956335	
happy	-0.013277	0.021655	-0.613	0.539867	
lifeSat	0.109105	0.040214	2.713	0.006728	**
MLQ	0.026435	0.027048	0.977	0.328534	
bor01	-0.016446	0.021643	-0.760	0.447432	
bor02	0.056085	0.018991	2.953	0.003185	**
bor03	0.037190	0.022166	1.678	0.093557	.
consp01	0.022118	0.016078	1.376	0.169091	
consp02	-0.036800	0.016677	-2.207	0.027459	*
consp03	0.017905	0.012540	1.428	0.153490	
c19perBeh01	0.133826	0.039353	3.401	0.000686	***
c19perBeh02	-0.049004	0.055678	-0.880	0.378896	
c19perBeh03	0.097751	0.033797	2.892	0.003869	**
c19RCA01	0.080319	0.024981	3.215	0.001326	**
c19RCA02	-0.017498	0.045160	-0.387	0.698453	
c19RCA03	0.122174	0.032001	3.818	0.000139	***
coronaClose_1	-0.307511	0.422735	-0.727	0.467055	
coronaClose_2	-0.409169	0.251207	-1.629	0.103523	
coronaClose_3	-0.298692	0.235595	-1.268	0.205022	
coronaClose_4	0.057981	0.174623	0.332	0.739901	

coronaClose_5	-0.040924	0.173555	-0.236	0.813615
coronaClose_6	-0.359697	0.177875	-2.022	0.043301 *
gender	0.121844	0.070804	1.721	0.085444 .
age	-0.010155	0.034518	-0.294	0.768639
edu	0.022366	0.026646	0.839	0.401356
rankOrdLife_1_num	1.783327	0.716711	2.488	0.012927 *
rankOrdLife_2_num	1.792613	0.716040	2.504	0.012383 *
rankOrdLife_3_num	1.739742	0.716670	2.428	0.015297 *
rankOrdLife_4_num	1.714428	0.717240	2.390	0.016934 *
rankOrdLife_5_num	1.783690	0.716285	2.490	0.012855 *
rankOrdLife_6_num	1.696993	0.716653	2.368	0.017990 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.412 on 1843 degrees of freedom
Multiple R-squared: 0.1308, Adjusted R-squared: 0.1086
F-statistic: 5.899 on 47 and 1843 DF, p-value: < 2.2e-16

Response c19ProSo04 :

Call:

```
lm(formula = c19ProSo04 ~ employstatus_1 + employstatus_2 + employstatus_3 +
  employstatus_4 + employstatus_5 + employstatus_6 + employstatus_7 +
  employstatus_8 + employstatus_9 + employstatus_10 + isoFriends_inPerson +
  isoOthPpl_inPerson + isoFriends_online + isoOthPpl_online +
  lone01 + lone02 + lone03 + happy + lifeSat + MLQ + bor01 +
  bor02 + bor03 + consp01 + consp02 + consp03 + c19perBeh01 +
  c19perBeh02 + c19perBeh03 + c19RCA01 + c19RCA02 + c19RCA03 +
  coronaClose_1 + coronaClose_2 + coronaClose_3 + coronaClose_4 +
  coronaClose_5 + coronaClose_6 + gender + age + edu + rankOrdLife_1_num +
  rankOrdLife_2_num + rankOrdLife_3_num + rankOrdLife_4_num +
  rankOrdLife_5_num + rankOrdLife_6_num, data = similar_countries_data)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-4.9088	-0.7890	0.2942	1.0006	2.9429

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-13.593120	14.909101	-0.912	0.362028
employstatus_1	0.002816	0.106385	0.026	0.978889
employstatus_2	0.024591	0.114956	0.214	0.830636
employstatus_3	0.087915	0.106002	0.829	0.407004
employstatus_4	-0.062771	0.132867	-0.472	0.636673
employstatus_5	0.314084	0.169480	1.853	0.064010 .
employstatus_6	-0.007627	0.122416	-0.062	0.950325
employstatus_7	-0.295333	0.180757	-1.634	0.102458
employstatus_8	0.109179	0.385915	0.283	0.777277
employstatus_9	-0.042454	0.116854	-0.363	0.716416
employstatus_10	0.528193	0.166800	3.167	0.001567 **
isoFriends_inPerson	0.005140	0.014241	0.361	0.718184
isoOthPpl_inPerson	0.024573	0.017348	1.416	0.156801
isoFriends_online	0.039882	0.015333	2.601	0.009369 **
isoOthPpl_online	-0.019698	0.013724	-1.435	0.151394
lone01	-0.018378	0.038570	-0.476	0.633785
lone02	0.045981	0.037226	1.235	0.216918

lone03	0.093821	0.038584	2.432	0.015127	*
happy	0.043109	0.021445	2.010	0.044550	*
lifeSat	0.059279	0.039823	1.489	0.136774	
MLQ	0.031948	0.026785	1.193	0.233117	
bor01	-0.013212	0.021432	-0.616	0.537679	
bor02	0.005143	0.018806	0.273	0.784518	
bor03	0.009317	0.021950	0.424	0.671283	
consp01	0.046702	0.015922	2.933	0.003396	**
consp02	-0.024245	0.016514	-1.468	0.142252	
consp03	-0.010716	0.012418	-0.863	0.388253	
c19perBeh01	0.029232	0.038970	0.750	0.453274	
c19perBeh02	0.151395	0.055136	2.746	0.006094	**
c19perBeh03	0.049113	0.033468	1.467	0.142416	
c19RCA01	0.088292	0.024738	3.569	0.000367	***
c19RCA02	0.073133	0.044721	1.635	0.102151	
c19RCA03	0.074627	0.031689	2.355	0.018629	*
coronaClose_1	0.216560	0.418623	0.517	0.604998	
coronaClose_2	-0.098759	0.248763	-0.397	0.691412	
coronaClose_3	0.528659	0.233302	2.266	0.023568	*
coronaClose_4	0.286653	0.172924	1.658	0.097553	.
coronaClose_5	0.039486	0.171867	0.230	0.818313	
coronaClose_6	0.049288	0.176144	0.280	0.779650	
gender	0.076848	0.070115	1.096	0.273212	
age	0.074037	0.034183	2.166	0.030446	*
edu	0.042053	0.026387	1.594	0.111171	
rankOrdLife_1_num	0.624767	0.709738	0.880	0.378823	
rankOrdLife_2_num	0.586583	0.709073	0.827	0.408201	
rankOrdLife_3_num	0.611190	0.709697	0.861	0.389241	
rankOrdLife_4_num	0.536029	0.710262	0.755	0.450531	
rankOrdLife_5_num	0.571571	0.709316	0.806	0.420459	
rankOrdLife_6_num	0.519239	0.709680	0.732	0.464474	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.398 on 1843 degrees of freedom

Multiple R-squared: 0.1371, Adjusted R-squared: 0.1151

F-statistic: 6.232 on 47 and 1843 DF, p-value: < 2.2e-16

C. Tables - Graphs/Plots

Table 1.a.1. Employment Frequency

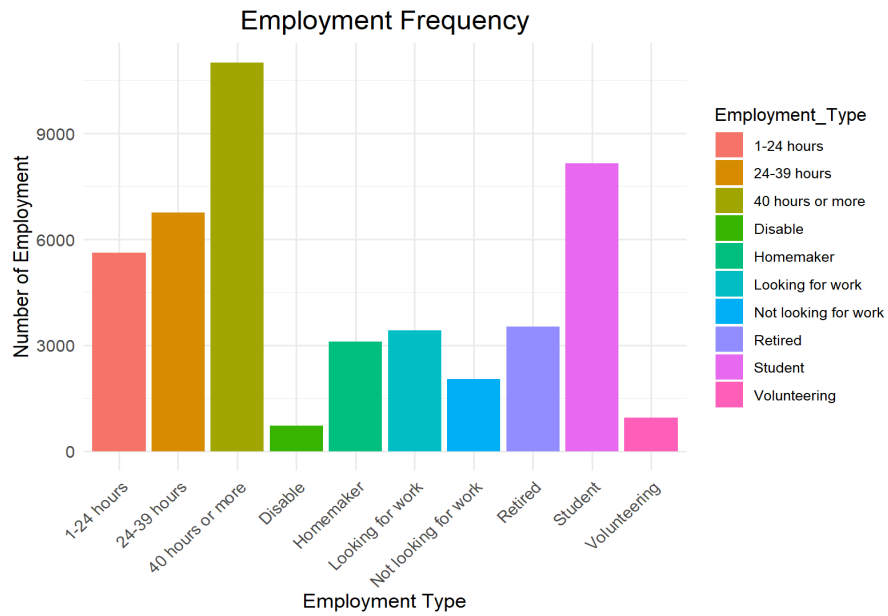


Table 1.a.2. Social Interaction

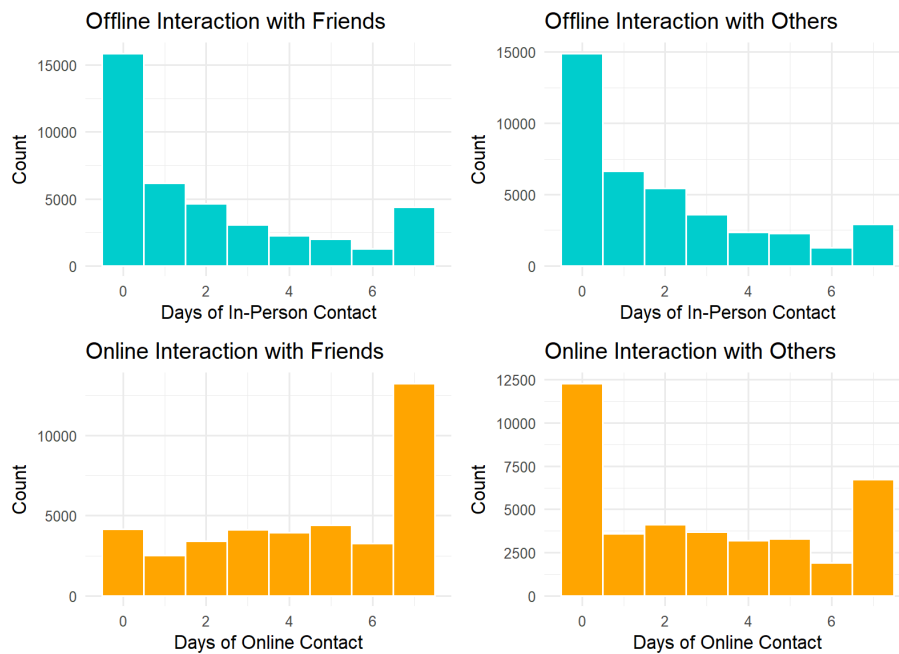


Table 1.a.3. Boredom



Table 1.a.4. Conspiracy Theories

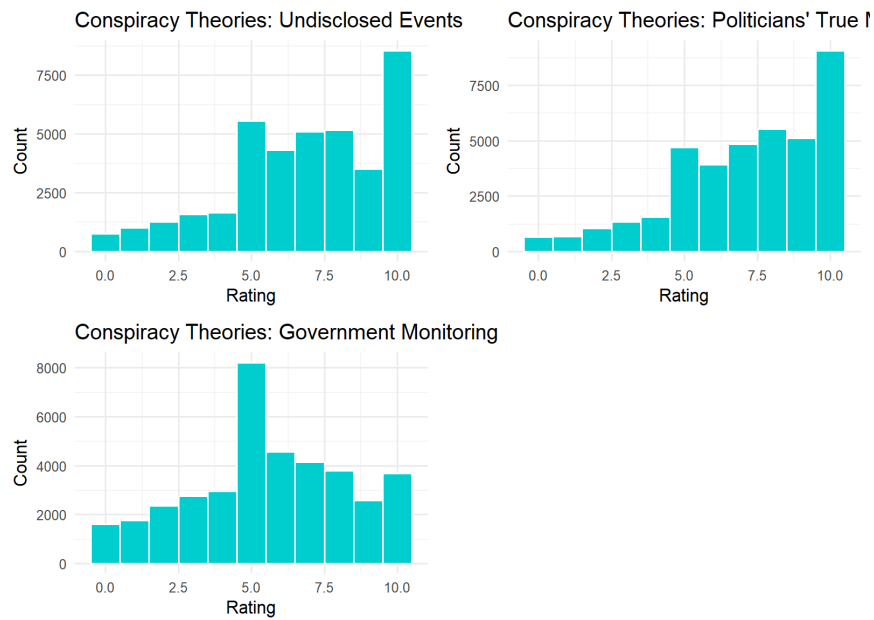


Table 1.a.5. Corona Personal Behaviors



Table 1.a.6. Corona Radical Actions

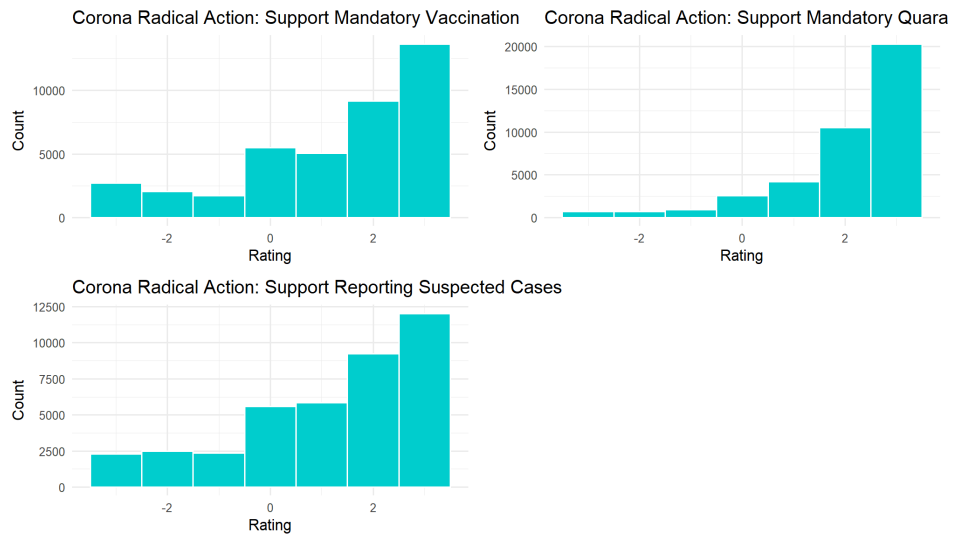


Table 1.a.7. Corona Proximity

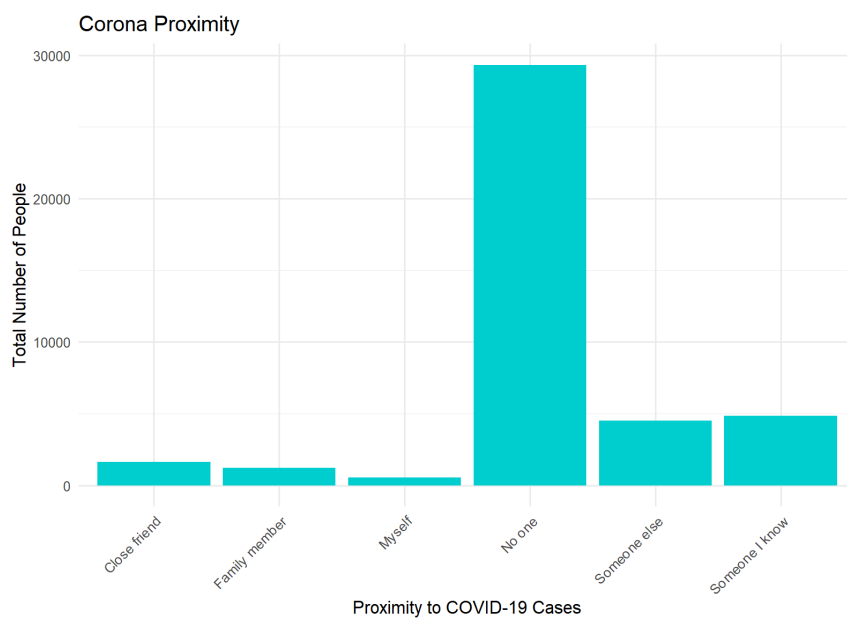


Table 1.a.8. Demographic Factors

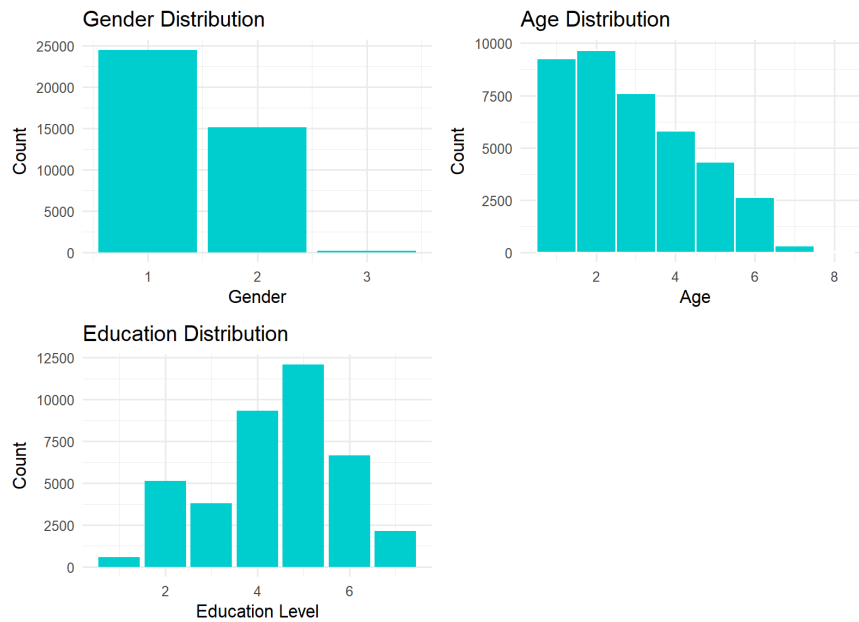


Table 1.a.9. Rank Order Life

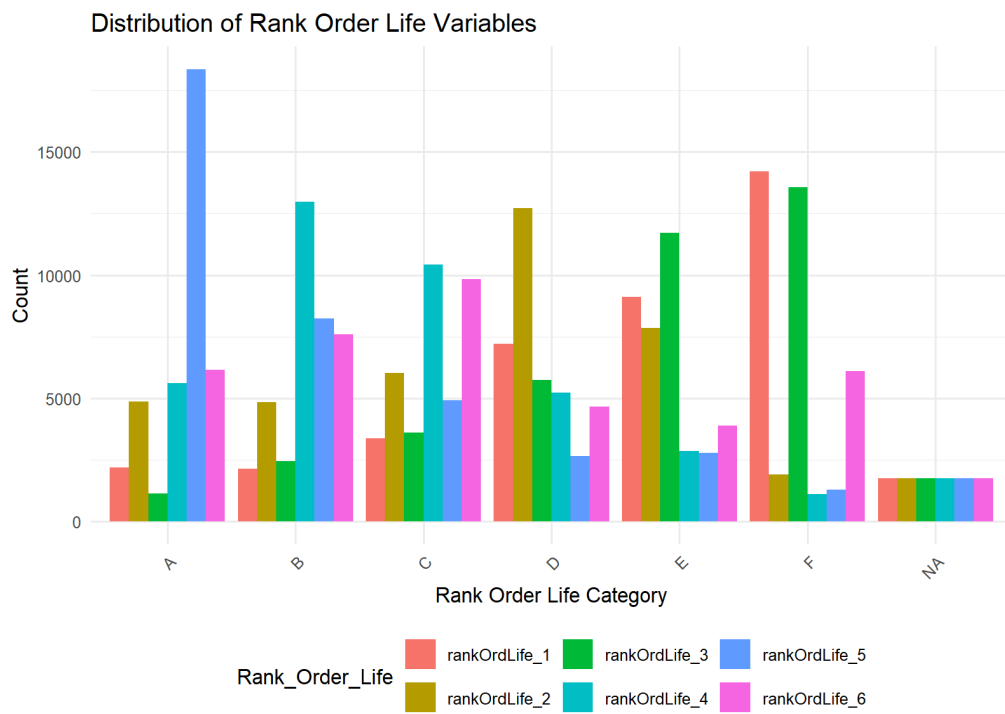


Table 2.a. Argentina and Other Country's Descriptive Statistics Table

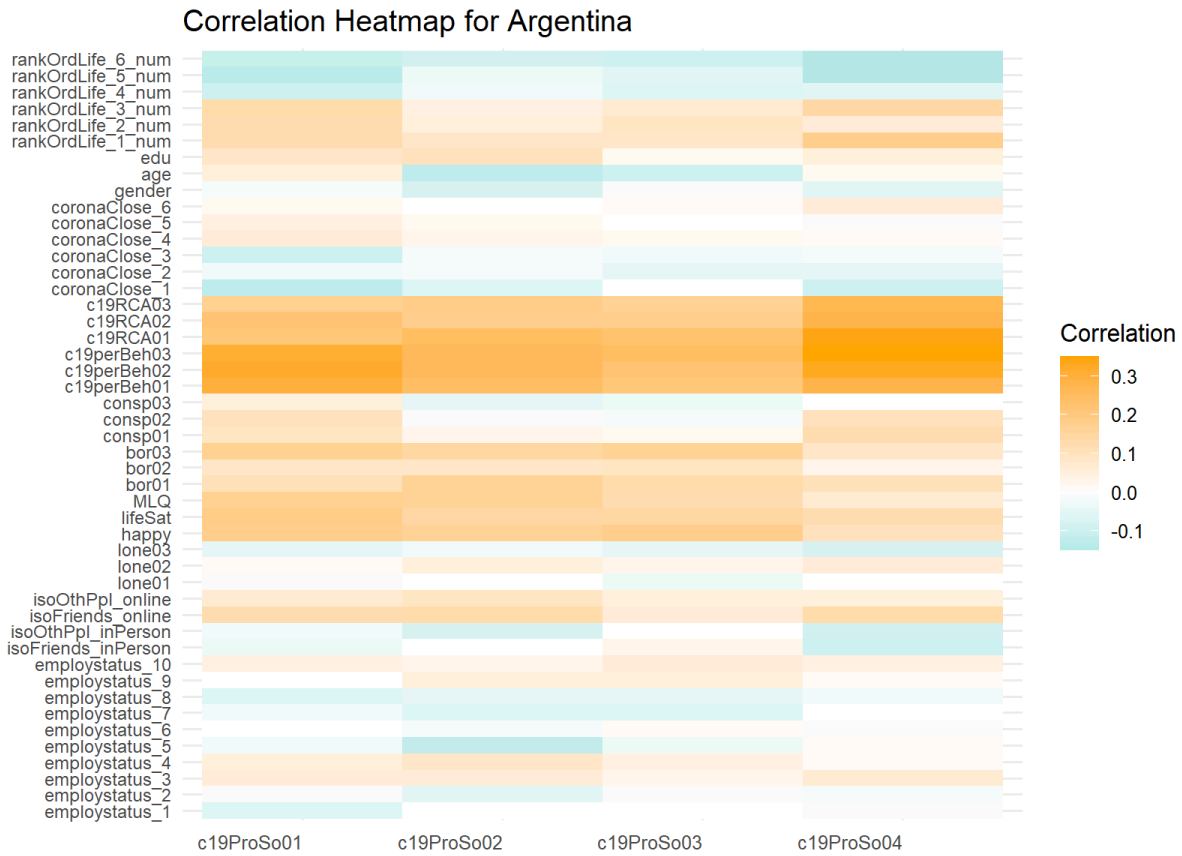
Variable	Argentina_ Mean	Argentina_ Median	Argentina_ Min	Argentina_ _Max	Other_ Mean	Other_M edian	Other_ Min	Other_ Max
employstatus_ 1	0.235366	0	0	1	0.14152 8	0	0	1
employstatus_ 2	0.184146	0	0	1	0.16928	0	0	1

employstatus_ 3	0.240244	0	0	1	0.27632	0	0	1
employstatus_ 4	0.137805	0	0	1	0.08605 1	0	0	1
employstatus_ 5	0.039024	0	0	1	0.05245 8	0	0	1
employstatus_ 6	0.104878	0	0	1	0.07828 2	0	0	1
employstatus_ 7	0.082927	0	0	1	0.09270 3	0	0	1
employstatus_ 8	0.013415	0	0	1	0.01872 5	0	0	1
employstatus_ 9	0.115854	0	0	1	0.20759 6	0	0	1
employstatus_ 10	0.020732	0	0	1	0.02453 8	0	0	1
isoFriends_in Person	0.973171	0	0	7	1.98809 4	1	0	7
isoOthPpl_in Person	1.554878	1	0	7	1.89706 8	1	0	7
isoFriends_on line	5.035366	6	0	7	4.46127 8	5	0	7
isoOthPpl_on line	2.813415	2	0	7	2.79164 9	2	0	7
lone01	2.170732	2	1	5	2.41351 6	2	1	5
lone02	2.782927	3	1	5	2.67387 7	3	1	5
lone03	1.932927	2	1	5	2.06509	2	1	5
happy	6.813415	7	1	10	6.34090 7	7	1	10
lifeSat	4.243902	5	1	6	4.15611 6	4	1	6

MLQ	1.019512	1	-3	3	0.85333	1	-3	3
bor01	0.581707	1	-3	3	0.29934 9	0	-3	3
bor02	0.241463	0	-3	3	0.03392 9	0	-3	3
bor03	0.768293	1	-3	3	0.29593 9	0	-3	3
consp01	7.220732	8	0	10	6.89089 2	7	0	10
consp02	7.428049	8	0	10	7.21793 7	8	0	10
consp03	6.186585	6	0	10	5.59140 3	5	0	10
c19perBeh01	2.35122	3	-3	3	2.34523 9	3	-3	3
c19perBeh02	2.518293	3	-3	3	2.46161 4	3	-3	3
c19perBeh03	2.47561	3	-3	3	1.83474 5	2	-3	3
c19RCA01	1.904878	3	-3	3	1.28059 6	2	-3	3
c19RCA02	2.360976	3	-3	3	2.08756	3	-3	3
c19RCA03	1.890244	2	-3	3	1.12123 8	2	-3	3
coronaClose_ 1	0.017073	0	0	1	0.01131 9	0	0	1
coronaClose_ 2	0.013415	0	0	1	0.03093 8	0	0	1
coronaClose_ 3	0.010976	0	0	1	0.04024 5	0	0	1
coronaClose_ 4	0.067073	0	0	1	0.12579 3	0	0	1

coronaClose_5	0.045122	0	0	1	0.116375	0	0	1
coronaClose_6	0.864634	1	0	1	0.729354	1	0	1
gender	1.42439	1	1	3	1.379615	1	1	3
age	3.220732	3	1	7	2.919566	3	1	8
edu	3.858537	4	1	7	4.42802	5	1	7
c19ProSo01	0.926829	1	-3	3	0.99265	1	-3	3
c19ProSo02	0.631707	1	-3	3	0.666667	1	-3	3
c19ProSo03	0.537805	1	-3	3	0.550627	1	-3	3
c19ProSo04	1.363415	2	-3	3	1.345183	2	-3	3
rankOrdLife_1_num	4.793902	5	1	6	4.610771	5	1	6
rankOrdLife_2_num	3.347561	4	1	6	3.545737	4	1	6
rankOrdLife_3_num	4.558537	5	1	6	4.738576	5	1	6
rankOrdLife_4_num	2.640244	2	1	6	2.726335	3	1	6
rankOrdLife_5_num	2.110976	1	1	6	2.118247	2	1	6
rankOrdLife_6_num	3.54878	3	1	6	3.245549	3	1	6

Graph 2.b. Correlation Heatmap of Argentina



Graph 2.c. Correlation Heatmap of Other Countries

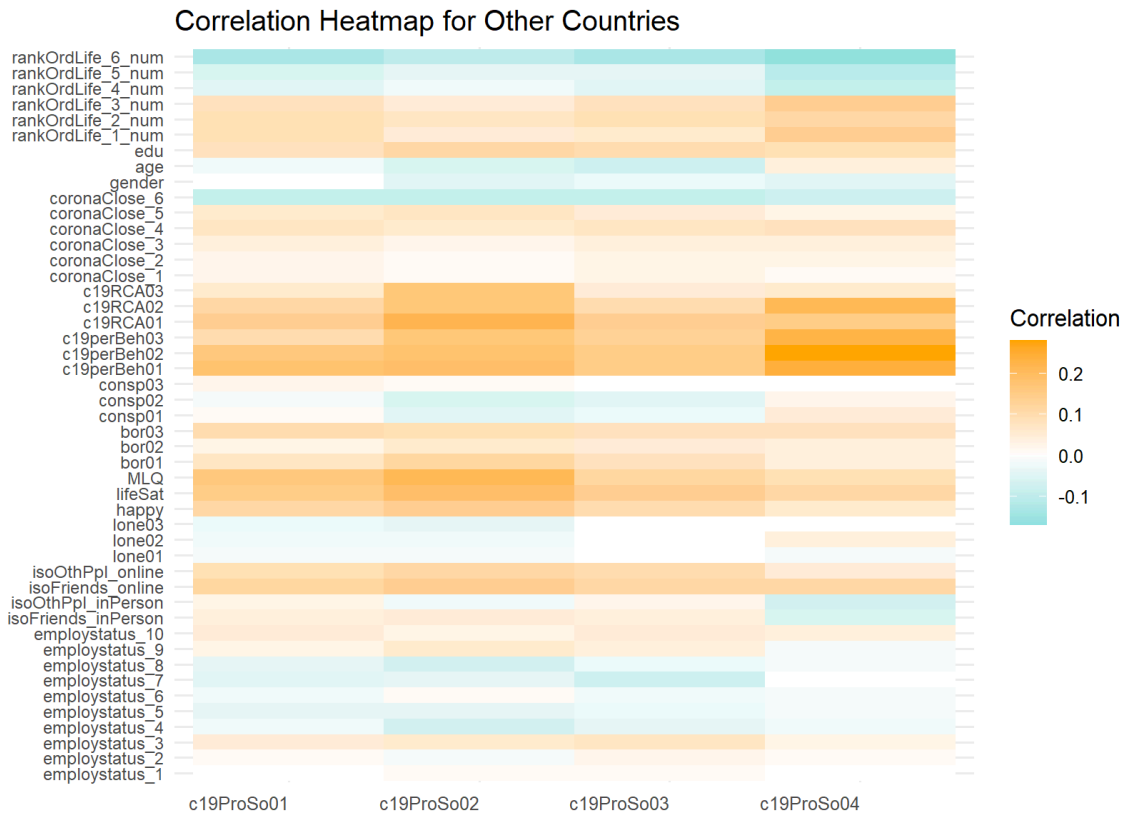


Table 3.a. Clustering Indicators Values Table

Country	Life Expectancy	GDP per Capita	Health Infrastructure (Doctors)	Government Effectiveness Score	Education Level	Death Rate	COVID-19 Cumulative Cases	COVID-19 Cumulative Deaths
Singapore	85.2	61273.99166	12967	2.174524	0.97034	3.5	1318984	1393
Andorra	82.9	37207.23887	260	1.238614	1	7.3	43067	153
Italy	82.3	31922.91916	241136	0.2356188	0.99616	10.4	17490451	166922
Spain	81.8	26984.29628	180633	0.613507	0.99038	9.1	12520475	108488
Greece	80.7	17617.29151	57909	-0.0660259	0.9887	11.3	3476433	29942
Malta	80.5	29597.63616	1240	0.5799018	1.03203	9.4	95286	744
Portugal	79.4	22242.40642	52718	0.8498304	0.97657	11.1	4827263	23424
Bahrain	79	23433.18724	1270	-0.1472867	0.96138	2.8	588070	1488
Chile	78.9	13173.78479	48531	1.012118	0.99848	6.2	3739796	57955
Qatar	78.9	52315.66008	6913	0.7248945	1.01682	1.5	369636	677
Cyprus	78.8	28281.42578	2283	0.6399662	0.991760015	6.8	491777	1067
Panama	78.8	13293.3332	6333	-0.567027	0.98867	4.9	868796	8267
Cuba	78.8	9499.572504	95487	0.1654153	1.001150012	8.7	1105443	8529
Costa Rica	78.7	12179.25667	14468	0.5517608	1.00125	4.7	904934	8525

Albania	78.5	5343.03 7704	3511	-0.5218667	0.99236	6.8	276274	3497
Dominican Republic	78.3	7167.91 4974	14983	-0.74949	0.99969	4.7	586099	4377
Slovenia	78.3	25558.4 2905	6408	0.8702175	0.999660 015	11.6	1026403	7812
Kuwait	78.2	24297.7 108	10150	-0.2894283	0.98178	2.2	634167	2555
Poland	77.8	15816.8 204	90284	0.6414219	0.997529 984	10.4	6008153	116347
Lebanon	77.8	5599.95 7523	14431	-1.108917	0.96335	5	1099745	10435
United Arab Emirates	77.7	37629.1 7417	24345	1.151608	1.02746	1.9	910338	2305
Uruguay	77.4	15650.4 993	17456	1.265534	1.00647	9.4	934961	7262
Paraguay	77.4	5353.34 8065	9421	-0.8474646	0.98963	4.8	651268	18911
Argentina	77.3	8500.83 7939	175313	-0.0834675	1.00126	7.5	9276618	128973
Morocco	77.1	3258.26 9043	26003	-0.2164034	0.77539	4.9	1169920	16079
Algeria	77	3354.15 3164	72604	-0.636465	0.86159	4.3	265896	6875
Ecuador	77	5645.19 929	33589	-0.5617972	0.98195	5.1	883224	35649
Bosnia and Herzegovina	76.9	6095.10 4237	7413	-0.5718023	0.978569 984	10	377979	15788
Sri Lanka	76.9	3852.38 9091	21316	-0.3355435	0.97869	6.2	663869	16518

Estonia	76.9	23595.2 4368	5931	1.506318	0.999589 98	12.6	562614	2458
Antigua and Barbuda	76.7	15224.8 5859	282	0.2766346	1.01037	5.7	8332	138
Libya	76.7	7034.65 8364	13757	-1.552711	0.884670 019	3.6	502040	6430
Georgia	76.4	4255.74 2993	28501	0.7079911	0.99856	10.9	1657729	16778
Tonga	76.4	4605.97 0841	55	-0.0708953	1.00125	4.9	11769	12
Croatia	76.1	14269.9 0885	12624	0.1316391	0.992649 972	12.2	1137864	15998
Mexico	76.1	8894.89 065	297307	-0.8628517	0.98312	5.3	5825774	326143
Hungary	76.1	16125.6 0941	33078	0.053347	0.999750 018	12.8	1919840	46547
Colombi a	75.9	5304.28 9129	108499	-0.3014929	1.00492	5.5	6109105	139867
Maldives	75.8	7216.81 6371	2353	-0.8930011	1.00838	4	179855	299
Mauritiu s	75.8	9011.04 2884	3210	0.2696345	0.95725	7.1	227500	998
Oman	75.7	16707.6 2301	9674	0.2460828	0.95571	3.3	389723	4628
Serbia	75.7	7733.80 3469	27563	-0.3702148	0.98722	13.6	2018437	16087
Tunisia	75.7	3497.71 9027	14892	-0.0534863	0.811789 989	6.3	1042872	28641
China	75.7	10408.7 1955	2828999	-0.2712442	0.96641	7.8	3392302	17702
Saudi Arabia	75.5	20398.0 6099	88023	0.3596962	0.95472	3.4	770650	9155

Romania	75.4	13047.4 5666	58583	-0.1216504	0.99487	12	2910392	65691
Malaysia	75.2	10164.3 4443	46491	0.3139765	0.97276	5.1	4514989	35690
Lithuania	75	20381.8 5578	17796	0.4978957	1.000399 947	14.6	1155572	9149
Armenia	74.9	4505.86 7742	12964	-0.3491127	0.99871	9.4	422963	8625
El Salvador	74.9	3961.72 6633	9955	-0.5911077	0.95754	5.8	162755	4132
Thailand	74.9	7001.78 546	55890	-0.3988041	0.97086	8	4466793	30171
Iraq	74.9	4251.33 7253	27208	-1.399408	0.8761	3.8	2328582	25220
Seychelles	74.9	12020.0 2106	203	0.7026863	1.00984	7	44192	167
Jordan	74.8	3998.67 3138	22739	0.1495421	0.99207	3.4	1697271	14068
Bulgaria	74.7	10148.3 424	29038	-0.1515335	0.993269 98	14.5	1165807	37163
Latvia	74.7	18096.2 0271	6225	0.3285871	1.00038	14.5	826960	6451
Samoa	74	4042.72 2752	67	0.6423859	1.00292	5.3	14212	27
Peru	74	6063.62 6923	40352	-0.5401052	0.94421	6.1	3583403	213228
Uzbekistan	74	1759.30 7471	72237	-1.068714	0.99986	5.3	157537	1016
Brazil	74	6923.69 9912	453351	-0.4196956	1.00447	6.7	31137479	666971
Jamaica	73.7	4897.26 475	3815	-0.1643905	1.108850 002	6.8	138374	3073

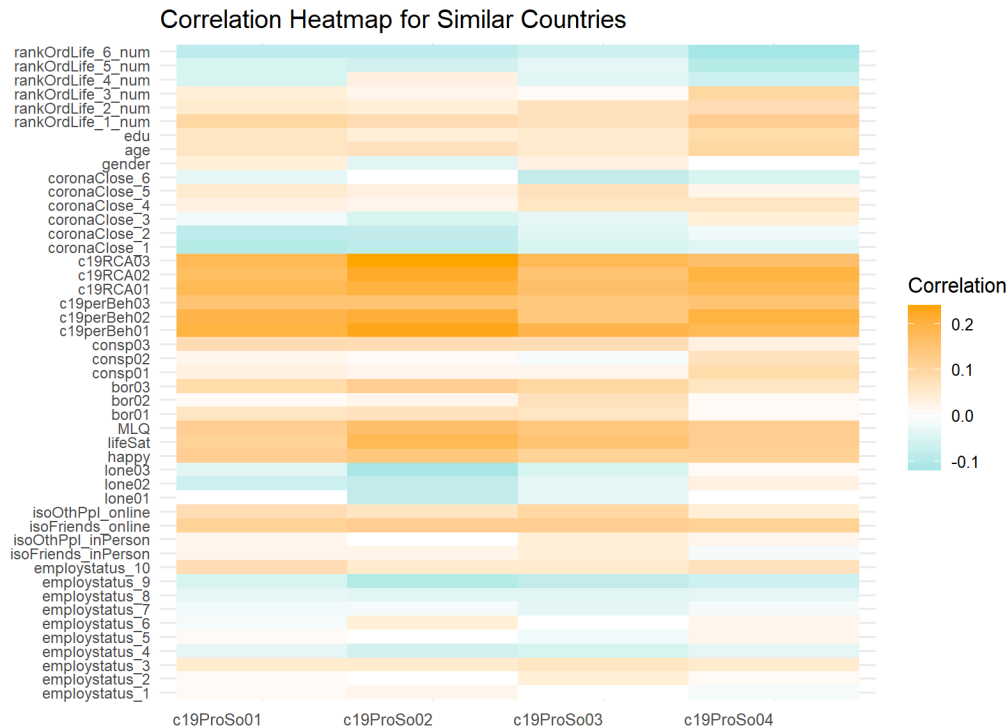
Vanuatu	73.7	2917.75 6849	46	-0.1629424	0.98188	4	10117	14
Nicaragua	73.5	1876.60 7378	6320	-1.06336	1.00413	5.1	14538	239
Palau	73.4	14349.3 1682	25	-0.5539093	0.99512	8.1	5083	6
Bangladesh	73.4	2233.30 5901	93741	-0.9050215	0.92843	5.4	1953623	29131
Marshall Islands	73.4	5545.60 0267	24	-0.0740994	0.998758 078	4.2	18	0
Trinidad and Tobago	73.1	13705.9 0023	5792	-0.317267	0.994499 981	8.8	162441	3927
Fiji	73	4815.68 9148	747	0.3809974	1.00007	6.1	65062	864
Belarus	73	6542.86 454	48995	-0.1922756	0.99931	13.2	982867	6978
Indonesia	73	3895.61 8152	114271	-0.2515447	0.96569	6.5	6056800	156615
Azerbaijan	72.8	4229.91 0649	32756	-0.8286031	0.99858	7.1	792804	9713
Guatemala	72.6	4609.89 7258	6122	-0.8228126	0.872600 019	4.7	863595	18196
Suriname	72.5	4796.53 3314	697	-0.2114844	0.96501	6.1	80547	1350
Cabo Verde	72.4	3126.39 9859	410	0.7682196	0.89476	6	56556	402
Ukraine	72.1	3751.73 7305	134986	-0.8736908	0.999459 982	14.4	4972664	106041
Honduras	71.2	2354.12 1434	2913	-0.6164857	1.00147	5.3	425471	10900
Kazakhstan	71.1	9121.63 6409	68864	-0.5017262	0.99909	8.1	1394957	19016

Nepal	71	1139.18 9892	21033	-0.6736505	0.75994	5.6	979199	11952
Bhutan	70.6	3181.33 9747	320	1.646514	0.76091	6.5	59636	21
Turkme nistan	70.4	7330.36 6288	12161	-1.357742	0.998700 023	6.1	0	0
Mongoli a	69.9	4041.17 4146	8739	-0.4277897	1.00471	6.3	927272	2116
Philippin es	69.4	3224.42 2811	63141	-0.5448154	1.00121	6.1	3691545	60456
Belize	68.9	5185.15 807	422	-0.138192	1.013200 045	6	59788	678
India	68.8	1913.21 9733	1159309	-0.186293	0.79875	7.3	43176817	524692
Guyana	68.6	6863.07 4346	625	-0.2266977	1.039510 012	7.4	65148	1237
Timor-L este	68.4	1663.55 9629	916	-0.4735851	0.89345	5.9	22925	131
Pakistan	68.1	1322.31 4785	208007	-0.7907338	0.65341	6.3	1530650	30379
Tajikista n	68.1	852.330 2296	17352	-1.415102	0.999109 983	6	17786	125
Papua New Guinea	67.3	2446.08 4687	602	-0.8760095	0.949479 997	6.6	44638	651
Ghana	67	2176.57 6218	3957	-0.1149039	0.89165	7	161841	1445
Madagas car	66.3	462.404 2288	4275	-1.000727	0.93671	6.5	64478	1396
Togo	65.4	886.699 5115	611	-0.7275374	0.66324	6.9	37126	273
Sao Tome	65.3	2155.26 5868	11	0.1838712	0.93088	6.8	5991	73

and Principe								
Cambodia	64.9	1577.91 174	2944	-1.325572	0.86712	7.5	136262	3056
Comoros	64.6	1519.58 678	216	-0.8164125	0.8192	7.2	8131	160
Equatorial Guinea	64.6	6198.94 2524	507	-1.559684	0.954209 983	7.8	15924	183
Sudan	64.4	608.332 5195	10683	-1.426933	0.85678	7.3	62427	4950
Kenya	64.3	1936.25 0755	8042	-0.8520129	0.91999	6.7	325442	5651
Rwanda	64.3	773.773 2609	1648	0.5782577	0.89473	6.4	130179	1459
Haiti	64.2	1283.14 1228	2606	-1.265189	0.89312	7.6	30963	835
Namibia	64	4252.04 172	1024	0.3399599	0.99792	7.9	164645	4040
South Africa	63.8	5753.06 6494	51616	-0.021569	0.9861	9.4	3967078	101313
Mauritania	63.4	1836.29 2411	821	-0.8072538	0.68008	7.9	59183	982
Botswana	63.3	5875.07 0606	1138	0.7505108	1.022799 969	9.6	310409	2701
Liberia	63.3	597.529 6919	168	-0.8509958	0.54377	7.6	7458	294
Ethiopia	62.6	918.652 5941	8395	-0.4861672	0.74987	7.7	474715	7515
Benin	62.3	1240.73 3155	908	-0.3833744	0.57565	7.9	26914	163
Senegal	62.1	1492.47 5903	1066	-0.0247014	0.61406	8.1	86133	1966

Malawi	61.7	622.184 5913	649	-0.7433892	0.79141	7.9	86001	2642
Guinea	61	1073.65 9339	977	-1.041717	0.600440 025	9	36817	442
Burundi	60.9	216.827 4175	1084	-1.450633	0.80245	8.8	42205	15
Zimbabwe	60.4	1372.69 6674	3026	-1.235616	0.963150 024	10.2	253338	5510
Mali	60.3	822.906 1368	2454	-0.695331	0.55723	9.8	31109	735
Angola	60.2	1450.90 5112	6400	-1.144541	0.741069 973	9.2	99839	1900
Cameroon	59	1539.13 0545	1842	-1.149748	0.86637	9.6	120028	1931
Sierra Leone	58.6	493.432 2406	165	-0.4921698	0.67481	10.4	7682	126
Burkina Faso	55.9	823.552 4109	1626	-0.112395	0.65278	11.2	20899	384
Uganda	55.9	846.881 1992	6918	-1.037357	0.85702	10.2	164679	3602
Niger	55.9	564.841 6623	900	-0.5798146	0.403800 011	11.8	9056	310
Nigeria	53.8	2074.61 3747	74543	-1.04489	0.73898	12.4	256148	3143
Mozambique	53.7	456.581 929	2473	-0.7813797	0.69278	11.6	225933	2204
Lesotho	53	917.356 3813	138	-0.1033081	1.260050 058	15	33659	699
Central African Republic	52.8	435.469 2478	324	-1.233395	0.52018	13.2	14371	113
Zambia	52.7	956.831 729	20591	-0.6561365	0.91702	12.2	322289	3989

Graph 3.b.2 Correlation Heatmap of Similar Countries



D. Generative AI Declaration

(1) The technology used: ChatGPT

(2) The information that was generated:

To identify columns with similar names that differ only by a suffix, you can use regular expressions with the `grep` or `grepl` functions in R.

Here's an example using `grep` to identify columns in the iris data that start with "Sepal.":

```
matching_columns <- grep("Sepal.", names(iris), value = TRUE)
```

'`grep`' returns a logical vector indicating whether each element in `names(iris)` matches the specified pattern. We then use this logical vector to subset `names(iris)` and obtain the names of the matching columns.

(3) The prompts used: How to identify columns that have the same name? (for example: `employment_1`, `employment_2`, `employment_3`, etc.)

(4) How the output was used in my work:

```
employment_frequency <- data.frame(colSums(cvbase[, grepl("employment", names(cvbase))], na.rm = TRUE))
```

(1) The technology used: ChatGPT

(2) The information that was generated:

To check if a set of columns in a data frame will only have NA values, you can use the `all` function in combination with `is.na` and column subsetting.

Here's a function that accomplishes this:

```
has_only_na <- function(data, cols) {  
  all(is.na(data[, cols]))  
}
```

This `has_only_na` function takes two arguments:

data: The data frame you want to check.

cols: A vector of column names (or indices) in data that you want to check for NA values.

The function works as follows:

Subsets data to include only the specified columns using data[, cols].

Uses is.na to create a logical matrix indicating NA values in the subsetted data.

Uses all to check if all values in the logical matrix are TRUE, indicating that all values in the specified columns are NA.

(3) The prompts used: How to check whether a set of columns will only have NA values?

(4) How the output was used in my work:

```
has_only_na <- function(data, cols) {  
  rowSums(is.na(data[, cols])) == length(cols)  
}
```

(1) The technology used: ChatGPT

(2) The information that was generated:

You can iterate over column names in a dataframe that match a specified prefix using a for loop along with grep or startsWith functions to identify the matching column names. Here's how you can do it:

Using grep to Match Column Names

Sample dataframe

```
df <- data.frame(  
  prefix_var1 = c(1, 2, 3),  
  prefix_var2 = c(4, 5, 6),  
  other_var = c(7, 8, 9)  
)
```

Specify the prefix

```
prefix <- "prefix_"
```

Get column names that match the prefix

```
matching_cols <- grep(paste0("^", prefix), names(df), value = TRUE)
```

Iterate over matching column names

```
for (col_name in matching_cols) {  
  print(paste("Processing column:", col_name))  
  # Add your processing code here  
}
```

In this example:

grep(paste0("^", prefix), names(df), value = TRUE) finds column names in df that start with the specified prefix.

The for loop iterates over the matching_cols vector containing the names of the columns that match the prefix.

(3) The prompts used: How to iterate over column names in a dataframe that match the specified prefix?

(4) How the output was used in my work:

Function to convert Rank Order Life variables to numeric (from A->F to 1->6)

```
convert_rank_order <- function(df, prefix) {  
  # Get the unique values in the rank order variables  
  unique_values <- c("A", "B", "C", "D", "E", "F")  
  # Create new numeric attributes  
  for (i in 1:length(grep(prefix, names(df)))) {  
    var_name <- names(df)[grep(prefix, names(df))][i]  
    df[[paste0(var_name, "_num")]] <- match(df[[var_name]], unique_values)
```

```

}
return(df)
}

```

(1) The technology used: ChatGPT

(2) The information that was generated:

To impute NAs in a column with the mode (most frequent value) of that column, you can use the following approach using base R functions:

```

impute_mode <- function(column) {
  mode_value <- as.numeric(names(which.max(table(column, useNA = "always"))))
  column[is.na(column)] <- mode_value
  return(column)
}

```

Here's how the function works:

`table(column, useNA = "always")`: This creates a frequency table of the values in the column, including NAs.

`which.max(...)`: This finds the value with the highest frequency in the frequency table.

`names(...)`: This extracts the name of the value with the highest frequency (i.e., the mode).

`as.numeric(...)`: This converts the mode value to numeric format.

`column[is.na(column)] <- mode_value`: This replaces NAs in the column with the mode value.

(3) The prompts used: how to impute NAs in a column with the mode of that column?

(4) How the output was used in my work:

Function to impute missing values with mode

```

impute_mode <- function(df, cols) {
  for (col in cols) {
    df[[col]] <- ifelse(is.na(df[[col]]),
                      as.numeric(names(which.max(table(df[[col]], useNA = "always")))),
                      df[[col]])
  }
  return(df)
}

```

(1) The technology used: ChatGPT

(2) The information that was generated:

To convert a matrix to a long format suitable for plotting a heatmap, you can use the tidyverse package, specifically the `tidyr` and `dplyr` packages, to reshape the matrix into a data frame. Here's a step-by-step guide on how to do this:

Steps to Convert a Matrix to Long Format:

Convert Matrix to Data Frame: Convert the matrix to a data frame using `as.data.frame()`.

Add Row Names as a New Column: Use `rownames_to_column()` to add row names as a new column.

Reshape Data to Long Format: Use `pivot_longer()` to reshape the data from wide to long format.

Example:

Let's say you have a sample matrix `mat`:

```

# Sample matrix
mat <- matrix(c(1, 0.5, 0.2,
               0.5, 1, -0.3,
               0.2, -0.3, 1),
              nrow = 3,

```

```
dimnames = list(c("VarA", "VarB", "VarC"),
c("VarA", "VarB", "VarC"))
```

Convert Matrix to Long Format:

```
library(tidyr)
library(dplyr)
```

```
# Convert matrix to data frame
df <- as.data.frame(mat)
# Add row names as a new column
df <- df %>%
  rownames_to_column("Variable1")
# Reshape data to long format
df_long <- df %>%
  mutate(row_num = row_number()) %>%
  pivot_longer(cols = -c(Variable1, row_num),
    names_to = "Variable2",
    values_to = "Value")

# Print the long-format data frame
print(df_long)
```

After executing this code, `df_long` will be a data frame in long format suitable for plotting a heatmap. The resulting data frame will have three columns: `Variable1`, `Variable2`, and `Value`, where `Variable1` and `Variable2` represent the row and column names of the original matrix, and `Value` represents the corresponding values in the matrix.

(3) The prompts used: how to convert a matrix to a long data format (one that i can use to plot a heatmap)?

(4) How the output was used in my work:

```
# Convert the correlation matrix to a long format data frame
cor_long <- cor_argentina %>%
  rownames_to_column("Variable1") %>%
  mutate(row_num = row_number()) %>%
  pivot_longer(cols = -c(Variable1, row_num),
    names_to = "Variable2",
    values_to = "Correlation")
```