Regional Well Being

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Abstract

This project aims to **estimate the effect of various factors such as health, education, and income among others, on the life satisfaction of people in different regions from different countries**. For this, we carried out a robust approach with MEMs & Robust Estimators. Also, we performed a robust clustering of various factors into different clusters of life satisfacton.

Introduction

For this project, we utilized the OECD database focusing on **indicators and life-satisfaction scores across various regions within different countries**. This comprehensive dataset captures diverse dimensions of well-being, such as education, employment, health, environment, and social support, which together contribute to a region's overall quality of life. The indicators allow for meaningful comparisons between regions, highlighting disparities and trends. Although the data reflects different years depending on the country, for consistency we adopted the **latest available data**.

It is essential to acknowledge that while some variability exists in the timing of the data, we assumed that any changes within a year or two would be minimal and unlikely to significantly alter policies or life-satisfaction scores. This approach enables us to draw relevant conclusions about the factors influencing regional well-being. By examining key metrics such as income, safety, health, and life satisfaction, this report aims to present a clear picture of well-being across OECD regions and highlight patterns that can inform future policies and initiatives.

Original Dataset

To execute this project, a dataset containing the different metrics regarding well-being was downloaded and linked to a variable named **df_wb**.

The variable **df_wb** contains 447 tuples and 28 columns (25 are the attributes to analyze).

```
## [1] 447  28
```

The variables included are the following:

1. **Country:** Includes the name of all the countries included in the results.
2. **Region:** Includes the name of all the cities from the countries included in the results.
3. **Code:** Code associated to each pair country-city.
4. **Population.with.at.least.secondary.education.(%):** Percentage of the population completing secondary education.
5. **Employment rate (%):** Percentage of the working-age population employed.
6. **Unemploy-ment rate (%):** Percentage of people without jobs actively seeking work.
7. **Household disposable income per capita (USD PPP):** Average income available per person, in USD.
8. **Homicide rate (per 100k):** Number of homicides per 100.000 people.
9. **Mortality rate (per 1k):** Deaths per 1,000 people annually.
10. **Life expectancy:** Average expected lifespan (years).
11. **Air pollution (level of PM2.5, µg/m^3):** Fine particulate air pollution levels.
12. **Voter turnout (%):** Share of voters participating in elections.
13. **Broadband access (% of household):** Percentage of households with internet access.
14. **Internet download speed 2021-Q4 (%):** Internet speed growth/decline in 2021-Q4.
15. **Number of rooms per person:** Average living space per person.
16. **Perceived social network support (%):** Percentage of people with available social support.
17. **Self assessment of life satisfaction (0-10):** Subjective rating of overall happiness.
18. **Education (0-10):** Regional score for education.
19. **Jobs (0-10):** Score based on employment indicators.
20. **Income (0-10):** Score for household income.
21. **Safety (0-10):** Regional score for personal safety.
22. **Health (0-10):** Score for health indicators.
23. **Environment (0-10):** Score for environmental quality.
24. **Civic engagement (0-10):** Score for public participation.
25. **Accessibility to services (0-10):** Availability of public services.
26. **Housing (0-10):** Score for housing quality and affordability.
27. **Community (0-10):** Score for social cohesion.
28. **Life satisfaction (0-10):** Overall happiness score.

The value type of each attribute appeared to be character, so further data pre-processing and data manipulation will be done.

Data Manipulation and EDA

Null values

Before analyzing the hypothesis and attributes, a check on the data structure was conducted to prevent potential errors in the future. This involved examining both data types and null values.

First we checked the **null values** to determine their significance and understand which is the best action to take regaridng this matter. After checking that there were no null values, but yet we couldn't perform some calculations on the attributes, we did a more detailed analysis to realize that there were null values which were replaced by the **character ".."**.

```
##                                                    wb_missing_values
## Country                                                   0.0000000
## Region                                                    0.0000000
## Code                                                      0.0000000
## Population.with.at.least.secondary.education.(%)          5.3691275
## Employment.rate.(%)                                       3.3557047
## Unemploy-ment.rate.(%)                                    3.5794183
## Household.disposable.income.per.capita.(USD.PPP)          2.6845638
## Homicide.rate.(per.100k)                                  0.6711409
## Mortality.rate.(per.1k)                                   0.0000000
## Life.expectancy                                           1.7897092
## Air.pollution.(level.of.PM2.5,.µg/m³)                     0.0000000
## Voter.turnout.(%)                                         0.2237136
## Broadband.access.(%.of.household)                         1.3422819
## Internet.download.speed.2021-Q4.(%)                       0.6711409
## Number.of.rooms.per.person                                0.6711409
## Perceived.social.network.support.(%)                      2.2371365
## Self.assessment.of.life.satisfaction.(0-10)               2.2371365
## Education.(0-10)                                          5.3691275
## Jobs.(0-10)                                               3.3557047
## Income.(0-10)                                             2.6845638
## Safety.(0-10)                                             0.6711409
## Health.(0-10)                                             0.0000000
## Environment.(0-10)                                        0.0000000
## Civic.engagement.(0-10)                                   0.2237136
## Accessiblity.to.services.(0-10)                           0.0000000
## Housing.(0-10)                                            0.6711409
## Community.(0-10)                                          2.2371365
## Life.satisfaction.(0-10)                                  2.2371365
```

Taking this into account, we concluded that there were no significance level of null values (in the form of ".."), so for the moment we decided to keep all the information and look for further actions regarding null values.

```
##        Country n_cities n_missing      p_na
## 1       Canada       13         3  23.07692
## 2        Chile       16         1   6.25000
## 3     Colombia       33         9  27.27273
## 4   Costa Rica        6         6 100.00000
## 5      Finland        5         1  20.00000
## 6       France       18         5  27.77778
## 7      Iceland        2         2 100.00000
## 8       Israel        6         1  16.66667
## 9        Japan       10        10 100.00000
## 10   Lithuania       10         1  10.00000
## 11 New Zealand       14         2  14.28571
```

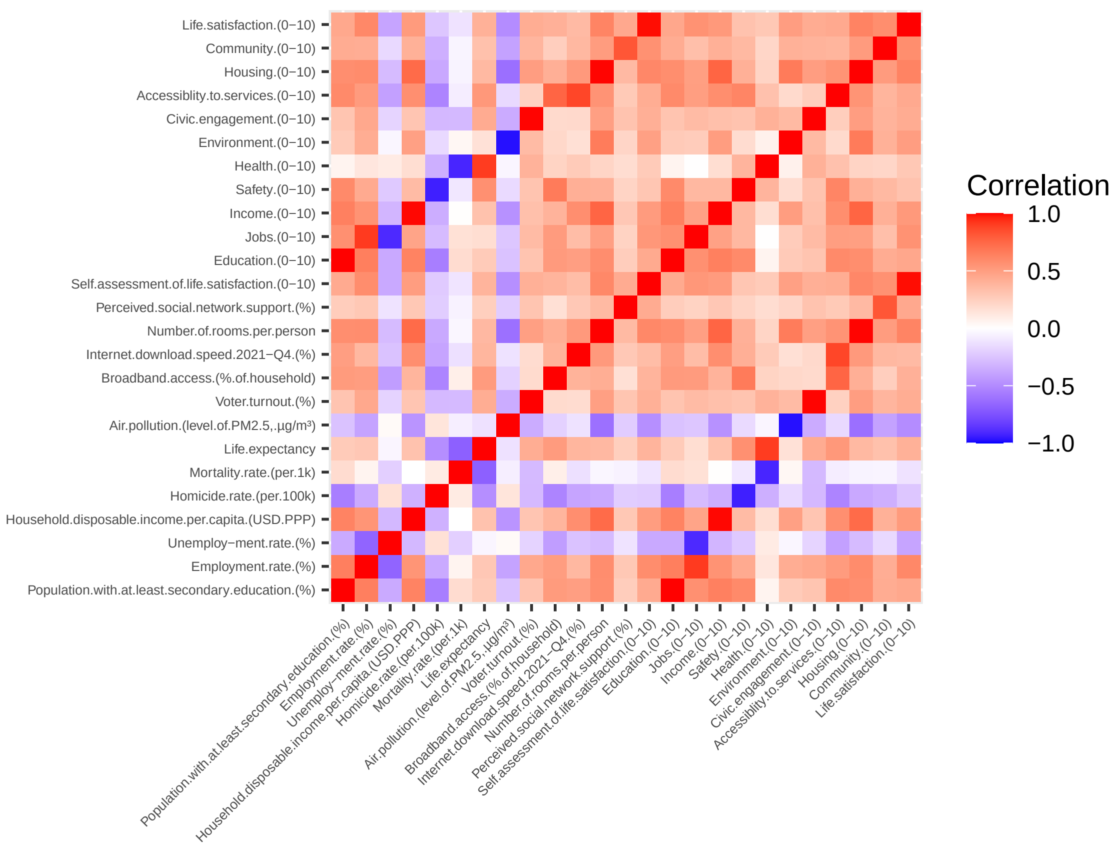
Also, we can see that, when analyzing the null values by country, there were some cases that have 100% of missing values in some attributes. This is why, we decided to drop **Costa Rica, Iceland and Japan** as they had attributes without values, and this would have not been useful for our project. In addition to them, we also decided to exclude Türkiye as we found poor the information contained in the Life.Satisfaction.(0-10) attribute.

Moreover, for those cases with some null values, we decided to replace them with the **median of the country**. We decided this because the data is divided by city, so we could use the median of the rest cities of the country for those cities with null values. Furthermore, the median is a better option than the mean as we can avoid the influence of any possible outlier.

Finally, after all this data manipulation, we have the correct data type for each attribute.

Variables and Correlation

Continuing with the data manipulation, we decided to carry out a correlation analysis to determine the need of any further removal of attributes. For this, we decided to plot a correlation heatmap to rapidly see any pair of attributes highly correlated, and with thise, determine the removal of one of them.



As a result of this analysis, we decided to drop the following variables, because they can be explained by others (high correlation) and probably have less information than other correlated variables (this was checked manually with the dataset):

1. **Unemploy-ment.rate.(%):** -0.9 of correlation with Jobs.(0-10).
2. **Life.expectancy:** 0.9 of correlation with Health.(0-10).
3. **Internet.download.speed.2021-Q4.(%):** 0.87 of correlation with Accessiblity.to.services.(0-10).
4. **Perceived.social.network.support.(%):** 0.83 of correlation with Community.(0-10).
5. **Voter.turnout.(%):** 0.99 of correlation with Civic.engagement.(0-10).
6. **Air.pollution.(level.of.PM2.5,.µg/m³):** -0.97 of correlation with Environment.(0-10).
7. **Population.with.at.least.secondary.education.(%):** 0.99 of correlation with Education.(0-10).
8. **Household.disposable.income.per.capita.(USD.PPP):** 0.99 of correlation with Income.(0-10).
9. **Employment.rate.(%):** 0.92 of correlation with Jobs.(0-10).

Additionally, we decided to remove also Homicide.rate.(per.100k) and Mortality.rate.(per.1k) because we assumed that can be represented by Safety (0-10). Also we removed Broadband.access.(%.of.household) and

Number.of.rooms.per.person as we did not consider it useful for the project. Last but not least, we removed Self.assessment.of.life.satisfaction.(0-10) as we directly used Life.satisfaction.(0-10).

Taking into account the resulting dataset, we decided to exclude those countries that have less than 10 cities in the dataset, as we have 10 variables plus the main variable (life satisfaction).

The last step of the data manipulation was to set the upper bound of the scale to 10, as there were some cases with decimals that ended up being a little bit over 10.

So the final dataset used in the models was the following, containing 295 tuples and 14 columns (10 are the attributes to analyze, plus the life satisfaction attribute):

```
## [1] 285  14
```

```
##    Country             Region              Code           Education.(0-10)
##  Length:285         Length:285         Length:285         Min.   : 0.009965
##  Class :character   Class :character   Class :character   1st Qu.: 4.239527
##  Mode  :character   Mode  :character   Mode  :character   Median : 7.247493
##                                                           Mean   : 6.388977
##                                                           3rd Qu.: 9.079590
##                                                           Max.   :10.000000
##   Jobs.(0-10)        Income.(0-10)       Safety.(0-10)      Health.(0-10)
##  Min.   : 0.008579   Min.   : 0.002448   Min.   : 0.00077   Min.   :0.009284
##  1st Qu.: 4.394316   1st Qu.: 0.814674   1st Qu.: 7.63587   1st Qu.:3.422444
##  Median : 6.881235   Median : 3.393236   Median : 9.48370   Median :6.089307
##  Mean   : 6.183821   Mean   : 3.514659   Mean   : 8.04128   Mean   :5.618996
##  3rd Qu.: 8.286467   3rd Qu.: 4.421304   3rd Qu.: 9.80978   3rd Qu.:7.759107
##  Max.   :10.000000   Max.   :10.000000   Max.   :10.00000   Max.   :9.504940
##  Environment.(0-10) Civic.engagement.(0-10) Accessiblity.to.services.(0-10)
##  Min.   : 0.00532   Min.   :0.009971        Min.   :0.008148
##  1st Qu.: 5.47264   1st Qu.:3.200993        1st Qu.:4.219586
##  Median : 7.26368   Median :5.113918        Median :6.666018
##  Mean   : 6.85327   Mean   :4.955544        Mean   :5.972564
##  3rd Qu.: 8.55721   3rd Qu.:7.103542        3rd Qu.:7.980286
##  Max.   :10.00000   Max.   :9.246560        Max.   :9.888185
##  Housing.(0-10)      Community.(0-10)   Life.satisfaction.(0-10)
##  Min.   : 0.008387   Min.   : 0.00998   Min.   : 0.009778
##  1st Qu.: 1.516854   1st Qu.: 4.41441   1st Qu.: 4.615385
##  Median : 4.550562   Median : 7.07207   Median : 6.538462
##  Mean   : 4.609031   Mean   : 6.31863   Mean   : 6.059621
##  3rd Qu.: 7.359551   3rd Qu.: 8.37838   3rd Qu.: 8.076923
##  Max.   :10.000000   Max.   :10.00000   Max.   :10.000000
```

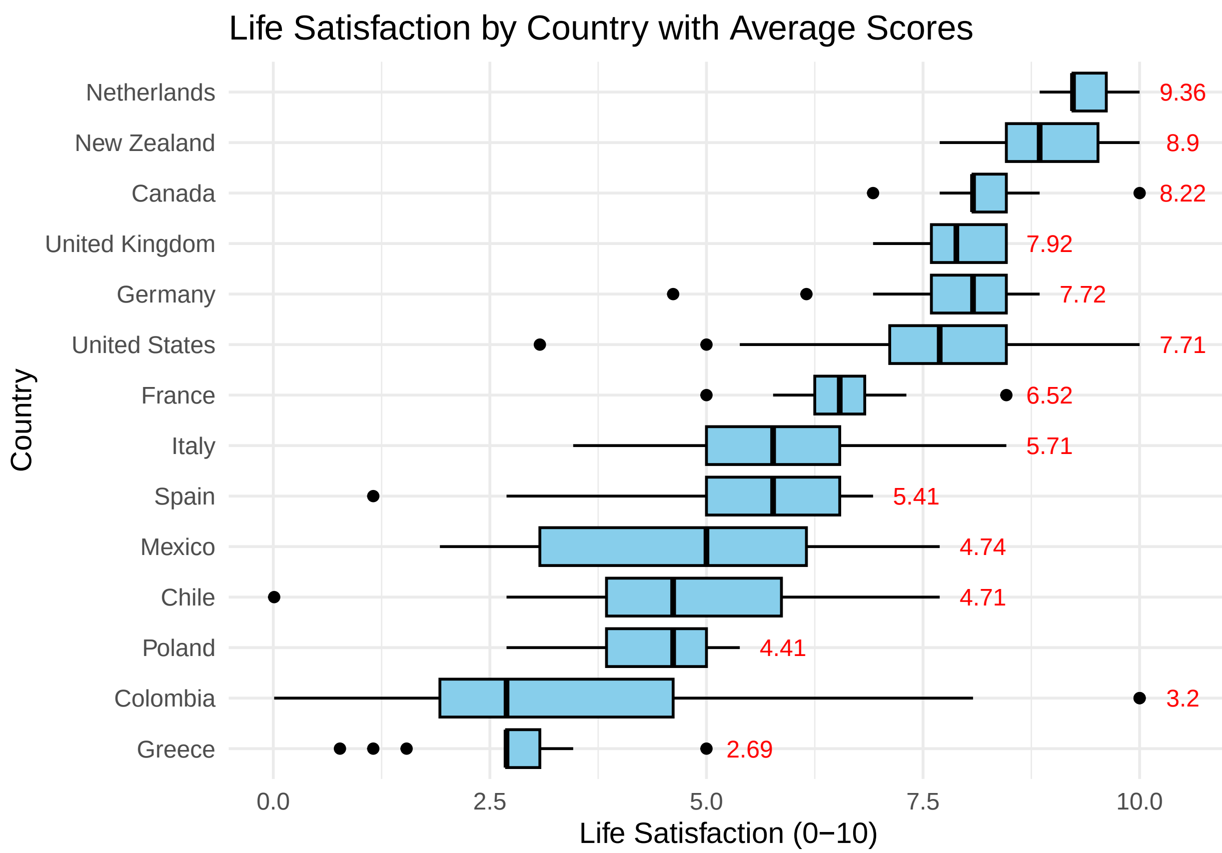
Exploratory Data Analysis

After completing a rigorous data cleaning process to remove redundancies and address multicollinearity, we continued with an Exploratory Data Analysis (EDA) to obtain insights about the factors influencing life satisfaction across 15 countries.

Life Satisfaction Distribution Across Countries

We began by analyzing how life satisfaction varies from one country to another. As illustrated in the box plot below, countries like the Netherlands, New Zealand, and Canada stood out with the highest average life satisfaction scores (9.36, 8.9, and 8.22, respectively). On the other hand, countries such as Greece, and Colombia reported the lowest scores.

Interestingly, in countries like Mexico and Colombia, we observed wide variability, suggesting significant regional differences within these nations. This led us to our **first key insight**: life satisfaction is not equally distributed across countries, and economic or social disparities likely play a role.



Understanding Relationships Between Metrics (Correlation Analysis)

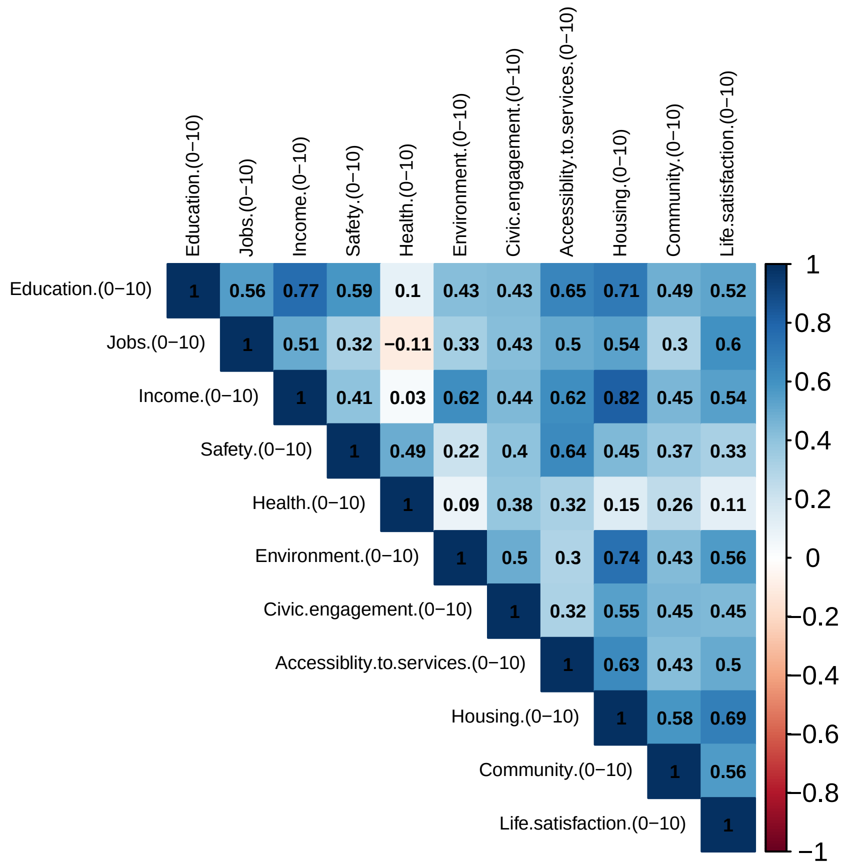
Deeper in our analysis, we explored the correlations between life satisfaction and other well-being metrics using a heatmap:

1. **Housing** had the strongest correlation with life satisfaction (0.69), showing that access to adequate housing and living conditions significantly influences well-being.
2. **Jobs** metric followed closely at 0.6, highlighting the importance of employment opportunities.

3. **Environemnt** and **Community** stood out with a correlation of 0.56 both, highlighting that a clean and sustainable environment and, connectedness and solidarity among groups in society are also an important part of life.

Surprisingly, **Income** showed a slightly lower correlation at 0.54, suggesting that while important, economic wealth is not the sole driver of life satisfaction.

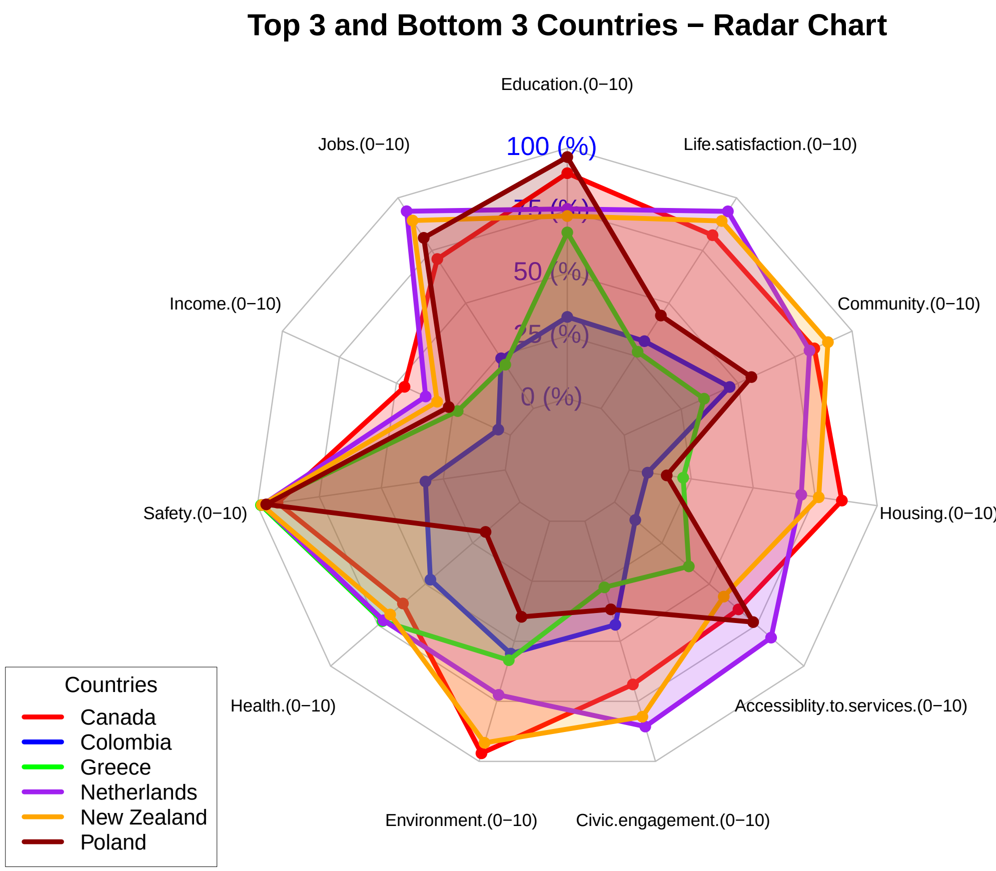
This analysis revealed that housing conditions, employment opportunities, environment and community are more influential for life satisfaction than income alone.



A Holistic Comparison of Countries (Radar Chart)

The radar chart highlights the Top 3 countries (Netherlands, Canada, and New Zealand) and the Bottom 3 countries (Poland, Greece, and Colombia) based on key life attributes. Netherlands leads in Jobs, Civic Engagement, and Accessibility to Services, achieving the highest Life Satisfaction. Canada excels in Housing, Environment, and Income, demonstrating a strong economic and living standard. New Zealand stands out with the best Community scores, fostering a strong sense of belonging.

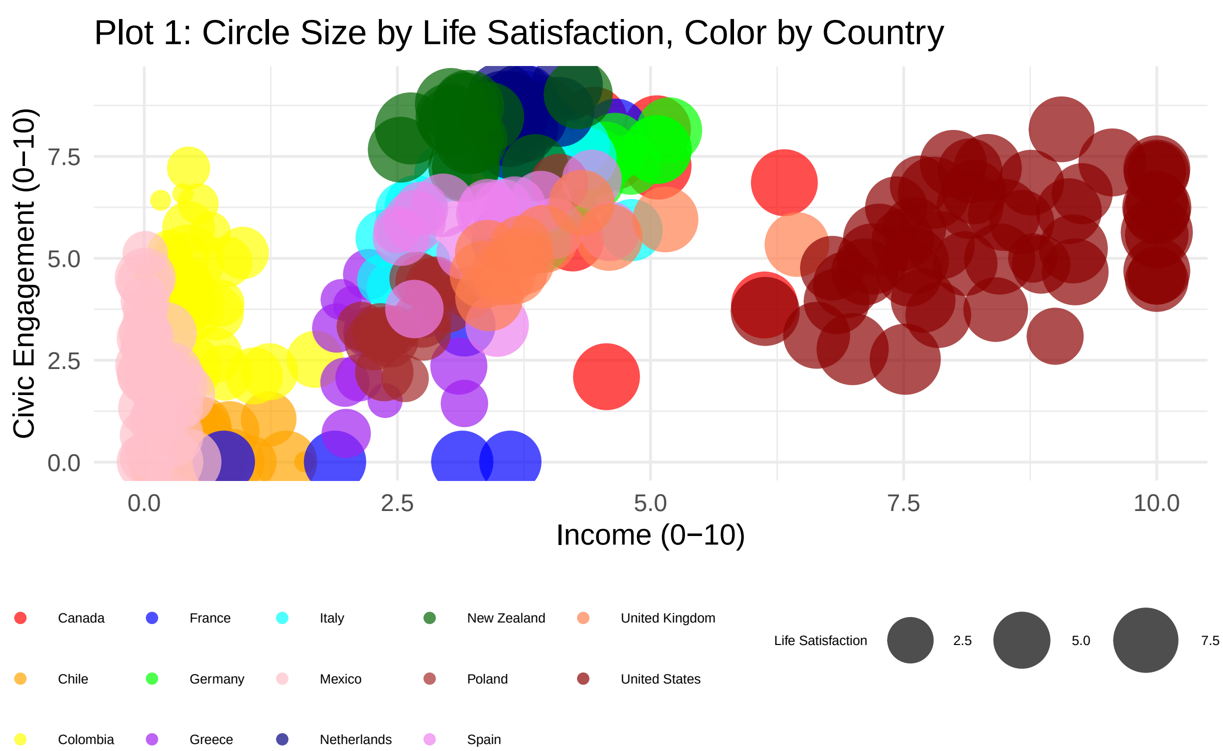
Among the lowest countries, Poland performs well in Education but struggles with Environment and Housing. Colombia, despite having a better Environment than expected, lags in Housing, Accessibility to Services, and especially Safety, making it the least secure. This highlights how gaps in infrastructure, safety, and education can lead to lower life satisfaction across these countries.



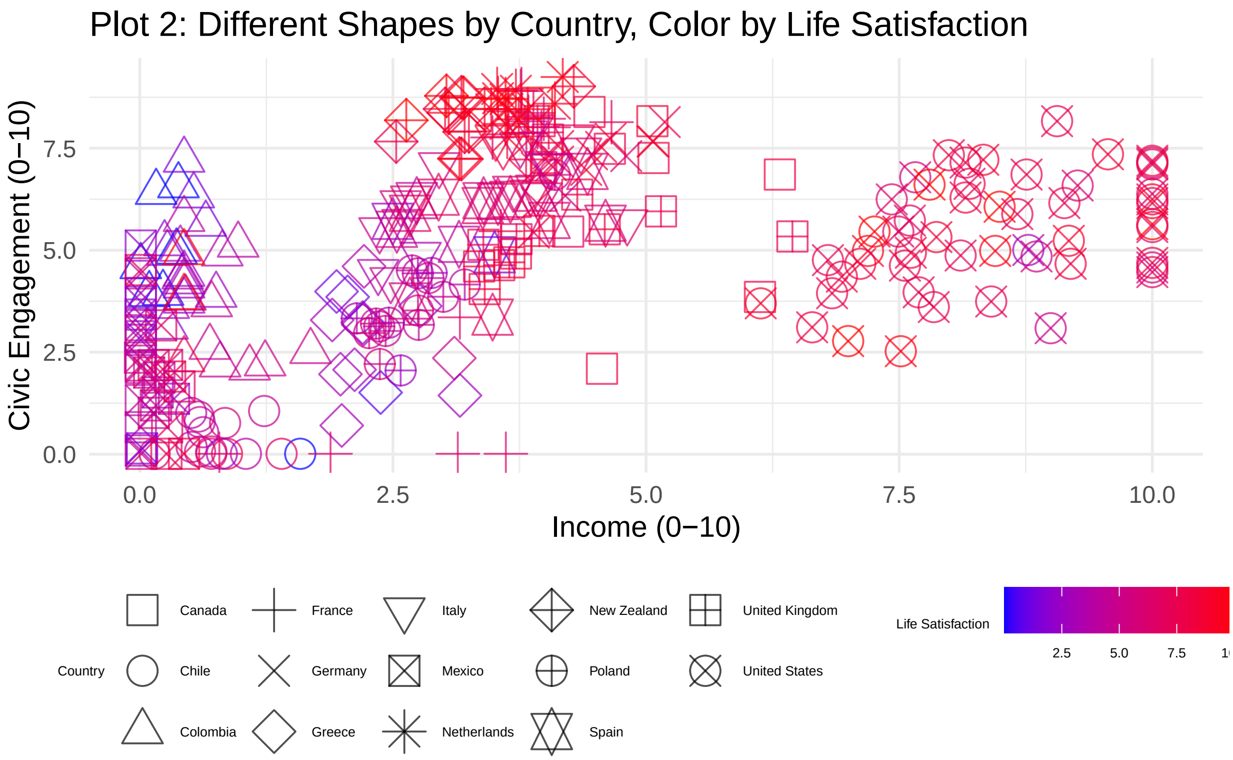
Visualizing Patterns Through Scatter Plots

Finally, we created two plots to explore the relationships between Income, Civic Engagement, and Life Satisfaction:

1. **Plot 1: Circle Size by Life Satisfaction, Color by Country:** This plot revealed that countries with larger circles (higher life satisfaction) tend to have higher income and civic engagement levels. For instance, the Netherlands and the United States dominate the upper-right region of the plot. Conversely, smaller circles in the lower-left region highlight countries like Greece, where income and civic engagement remain low.



2. **Plot 2: Different Shapes by Country, Color by Life Satisfaction:** Here, each country is represented with a unique shape, and colors reflect their life satisfaction. Countries with higher satisfaction are visibly clustered in red, whereas lower-satisfaction countries are more dispersed, particularly toward the lower income range. These visualizations allowed us to see the clear relationships between income, civic engagement, and well-being, while also identifying disparities and regional patterns.



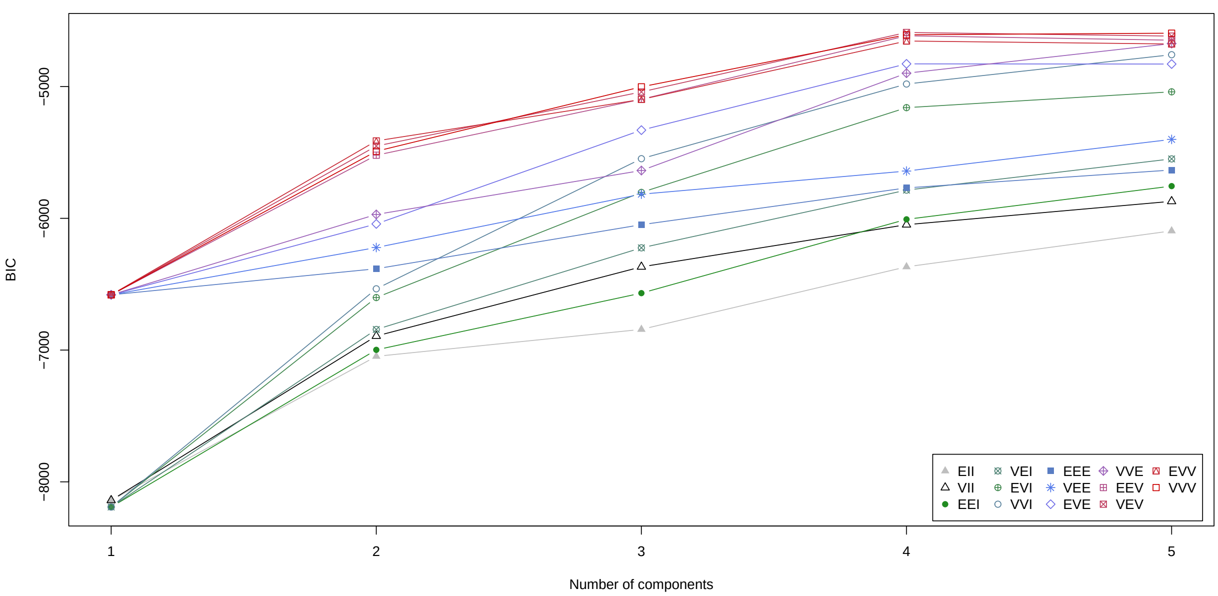
Clustering

Performing the Model Based Clustering.

For this model, we used **Mclust (Model Based Clustering)**, which employs **Gaussian Mixture Models (GMM)** to perform the clustering. It automatically selects the optimal number of clusters and model type based on criteria such as the **Bayesian Information Criterion (BIC)**. This approach ensures both accuracy and interpretability in clustering. The summary shows that the ***optimal number of clusters is 4*** **(Appendix A)**.

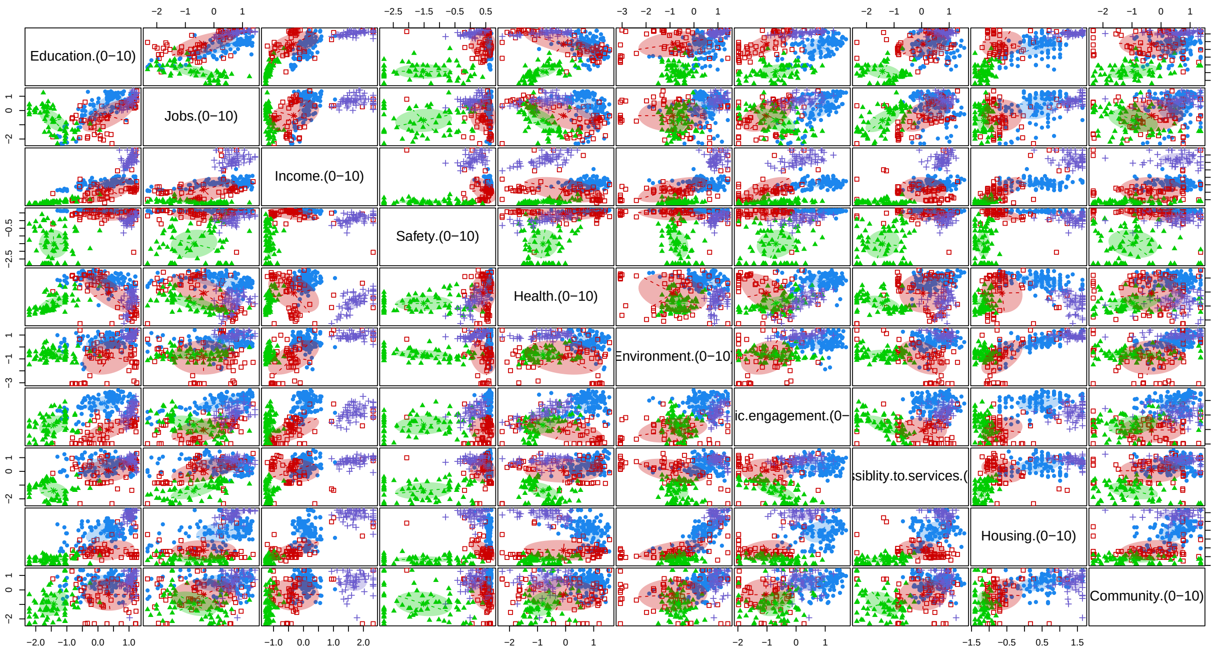
Once we got the 4 clusters, we created a Classification and Uncertainty plots for the different clusters:

BIC and Number of Components Used for Clustering



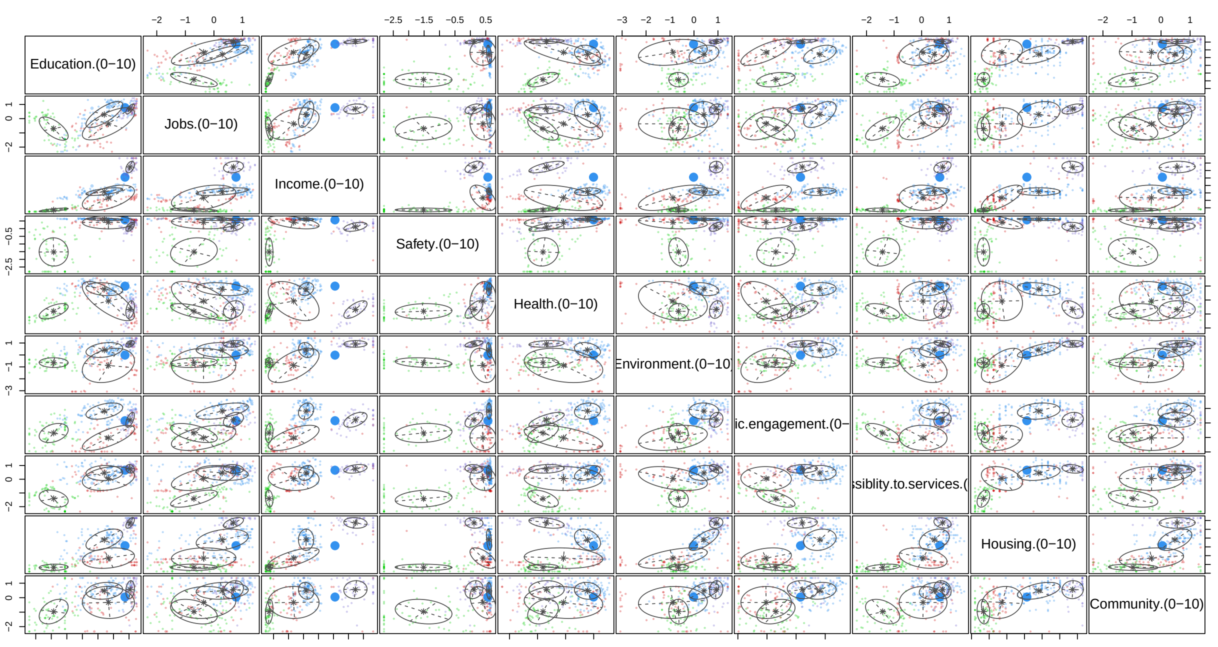
By evaluating the fit of models with different numbers of clusters and covariance structures, the BIC plot confirmed that the **VEV model with four components** was the most appropriate. This indicated a good balance between model complexity and interpretability. This result reassures us that the identified clusters capture meaningful differences in well-being metrics while avoiding overfitting.

Classification of Data Points



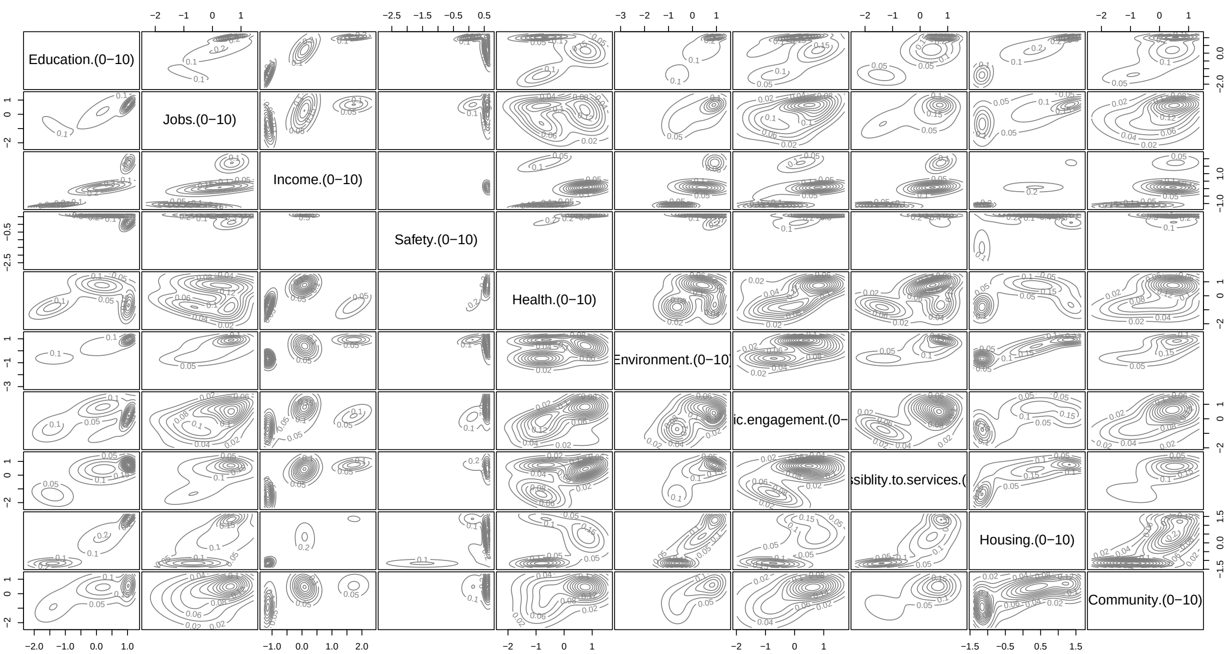
The classification plot of data points across clusters visualized the **assignment of regions to the four clusters based on their scores in the different attributes**. The plot highlighted distinct separations between clusters, emphasizing the significant variations in regional well-being. We can see some clear separation between clusters as for example in Education, Income and Safety, among others. This visualization effectively communicated how regions with similar well-being conditions are grouped together, providing a clear understanding of how specific attributes define life satisfaction levels.

Uncertainty



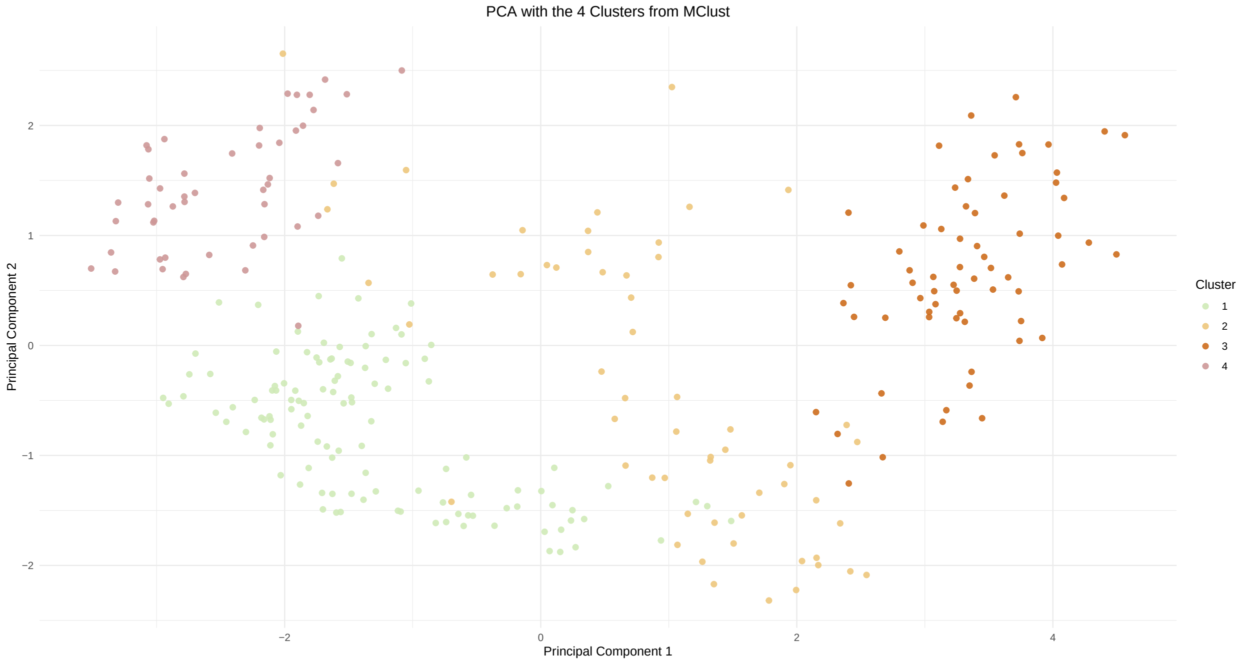
Furthermore, the uncertainty plot offered an additional layer of insight by visualizing the **degree of confidence in assigning data points to their respective clusters**. Most regions exhibited low uncertainty, indicating that the GMM model reliably classified regions into distinct clusters. However, a few regions displayed higher uncertainty, suggesting they share characteristics with multiple clusters.

Density Distribution of Data Within Clusters

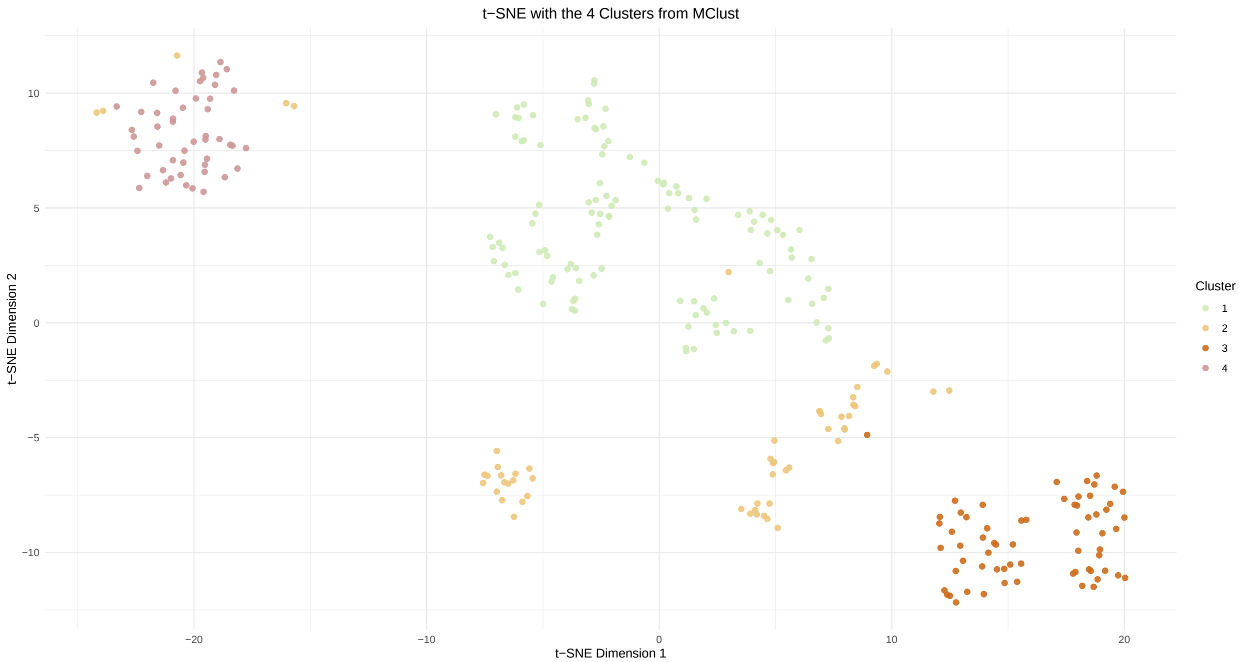


Last but not least, the density distribution plot for data within clusters provide an in-depth look at how key well-being attributes are distributed across the identified clusters. These plots enable a better understanding of the internal variability and the distinctiveness of each cluster. For example, metrics such as **education, income, and safety exhibit unique distributions within clusters**, highlighting the degree of homogeneity or disparity among regions in each grouping.

After this, we applied Principal Component Analysis (PCA) to ***reduce the dataset's dimensionality***. This allowed us to plot the identified clusters in a two-dimensional space, providing a clear and intuitive representation of their separation and structure.



Furthermore, we employed t-SNE (t-Distributed Stochastic Neighbor Embedding) for a better visualization. This technique maps high-dimensional data into a lower-dimensional space while preserving the local structure (cluster), offering an alternative perspective on the clustering results.

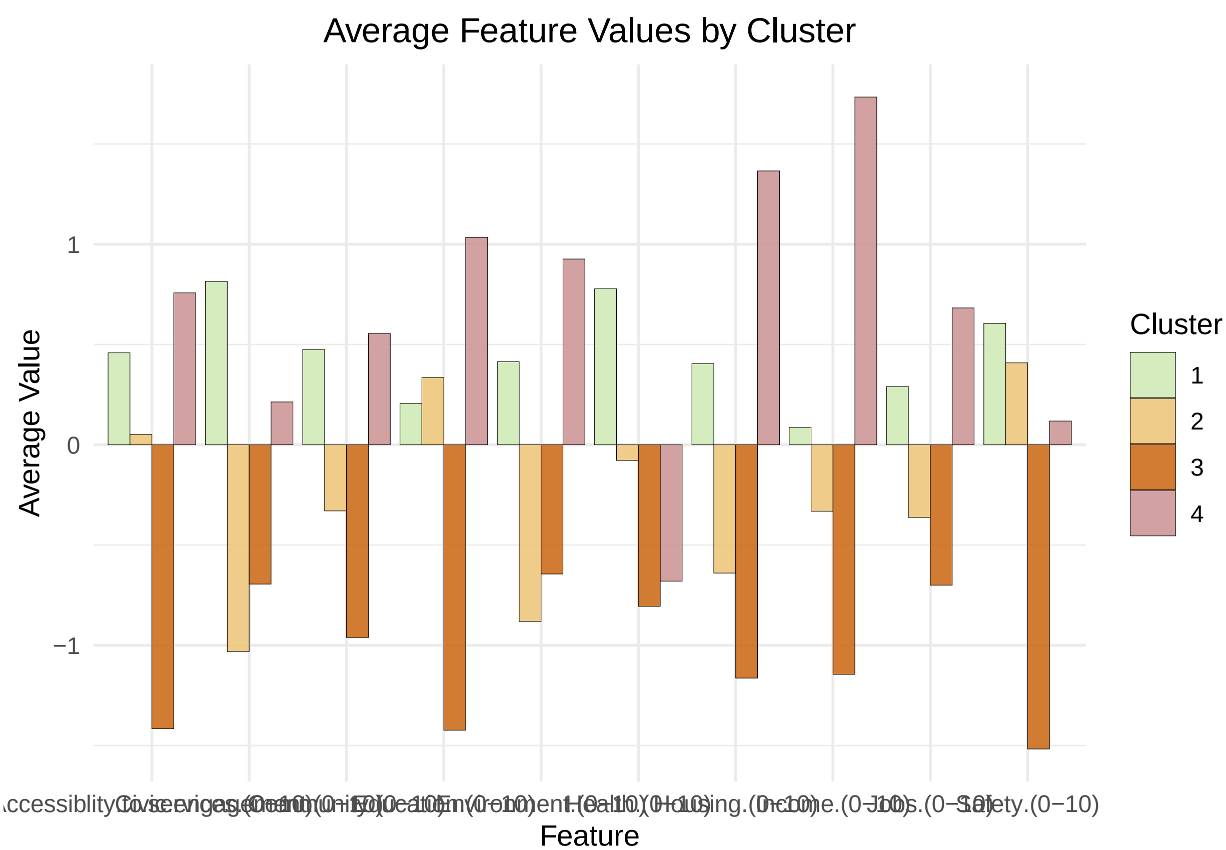


Analysis of Clusters

After obtaining the 4 clusters, we added the assigned clusters to the original dataframe. We then calculated the means for each cluster to better understand the characteristics of the data points within each group. This step helps identify patterns and differences between the clusters.

```
## # A tibble: 4 x 11
##   Cluster `Education.(0-10)` `Jobs.(0-10)` `Income.(0-10)` `Safety.(0-10)`
##   <fct>                <dbl>         <dbl>           <dbl>           <dbl>
## 1 1                    0.206         0.290          0.0875           0.606
## 2 2                    0.335        -0.362         -0.331            0.409
## 3 3                   -1.42         -0.700         -1.14            -1.52
## 4 4                    1.03          0.682          1.73             0.118
## # i 6 more variables: `Health.(0-10)` <dbl>, `Environment.(0-10)` <dbl>,
## #   `Civic.engagement.(0-10)` <dbl>, `Accessiblity.to.services.(0-10)` <dbl>,
## #   `Housing.(0-10)` <dbl>, `Community.(0-10)` <dbl>
```

We used a bar plot to show the contribution of each feature in every cluster, with base reference to the average (mean) value of the feature. We can mainly see that for cluster 1, all the features have a positive value, more than the average value for all parameters.

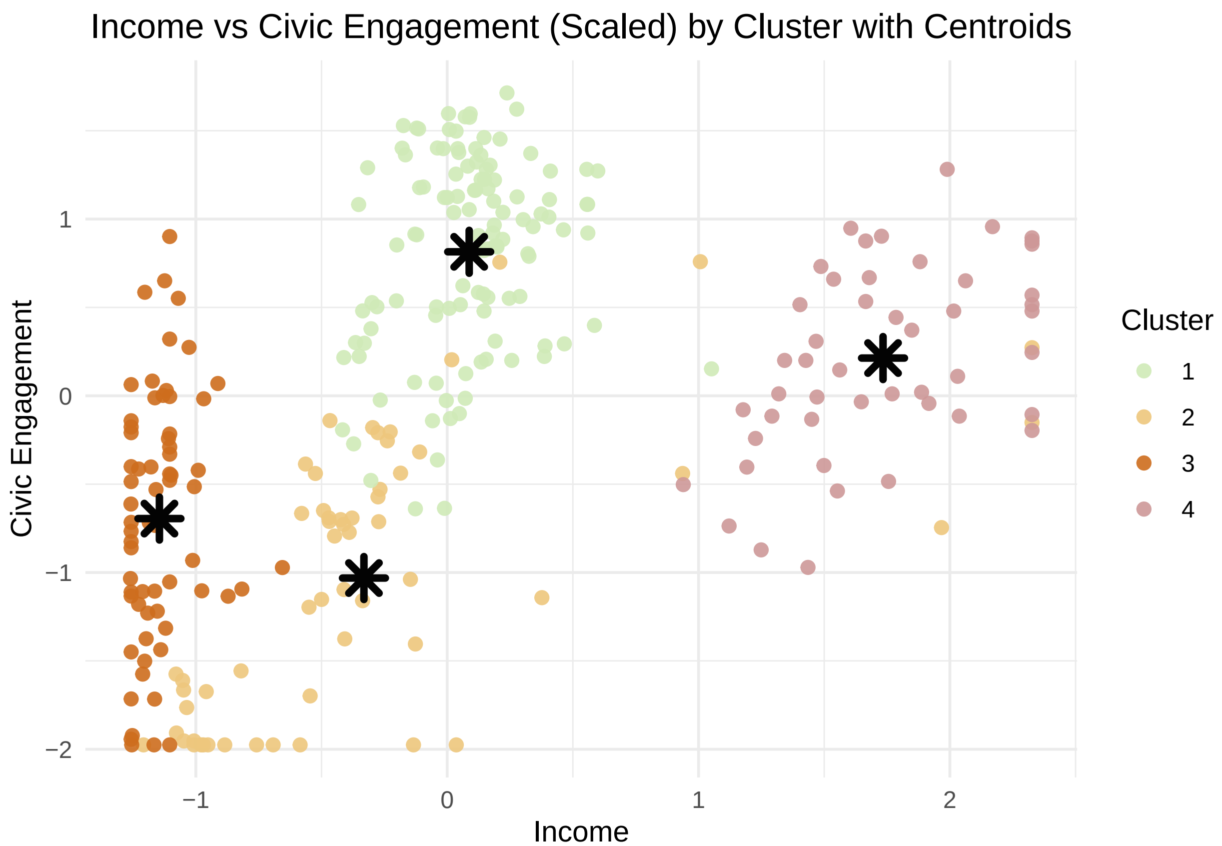


From this table we can clearly conclude that the data highlights a clear disparity in well-being across the clusters.:

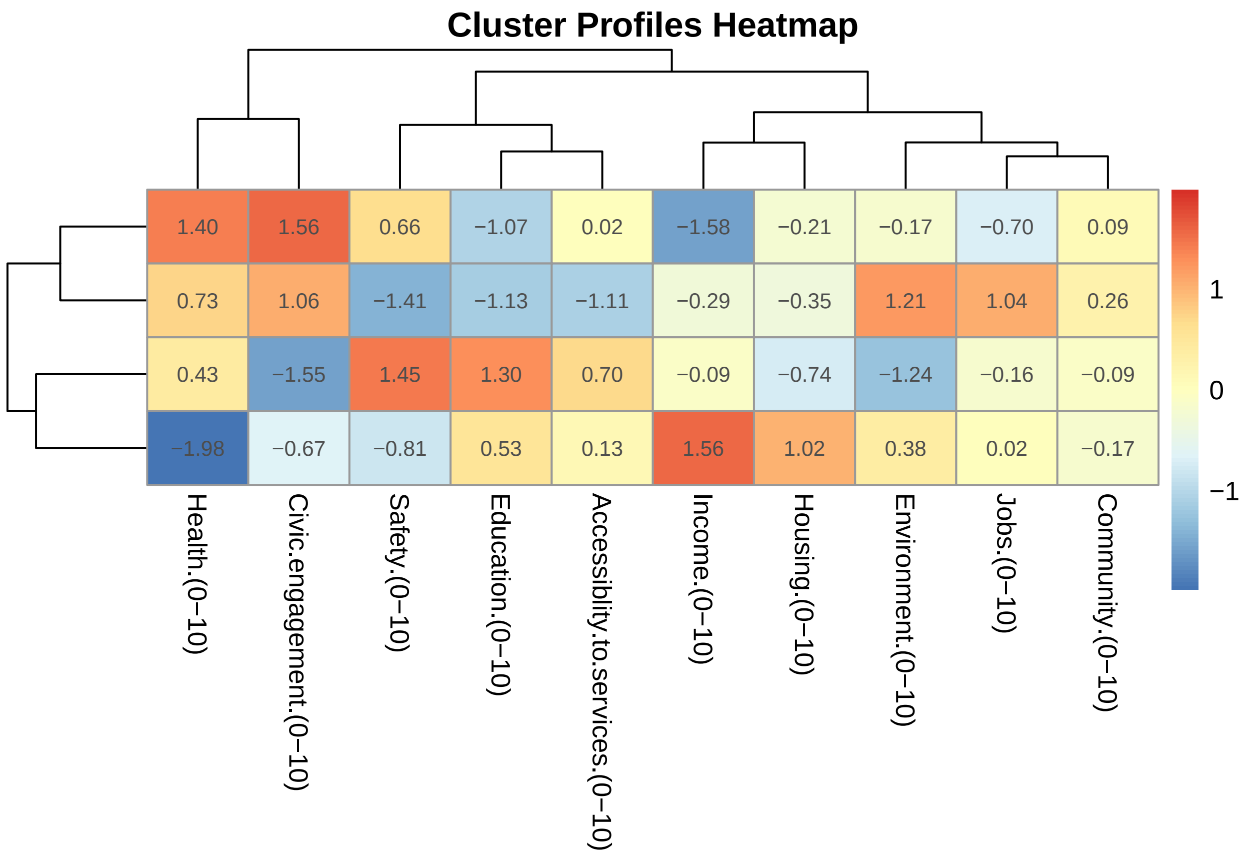
- **Cluster 1** performs relatively well in safety (0.606).
- **Clsuter 2** shows mixed results, including negative scores in jobs (-0.362) and income (-0.331).

- **Cluster 3** exhibits significantly lower scores across all attributes, with particularly negative values in safety (-1.52) and income (-1.14).
- **Cluster 4** consistently shows the highest scores in most attributes, such as income (1.73) and jobs (0.682).

Moreover, we generated a scatter plot of **Income vs Civic Engagement** for the four clusters, highlighting the distribution of each cluster based on these two variables.



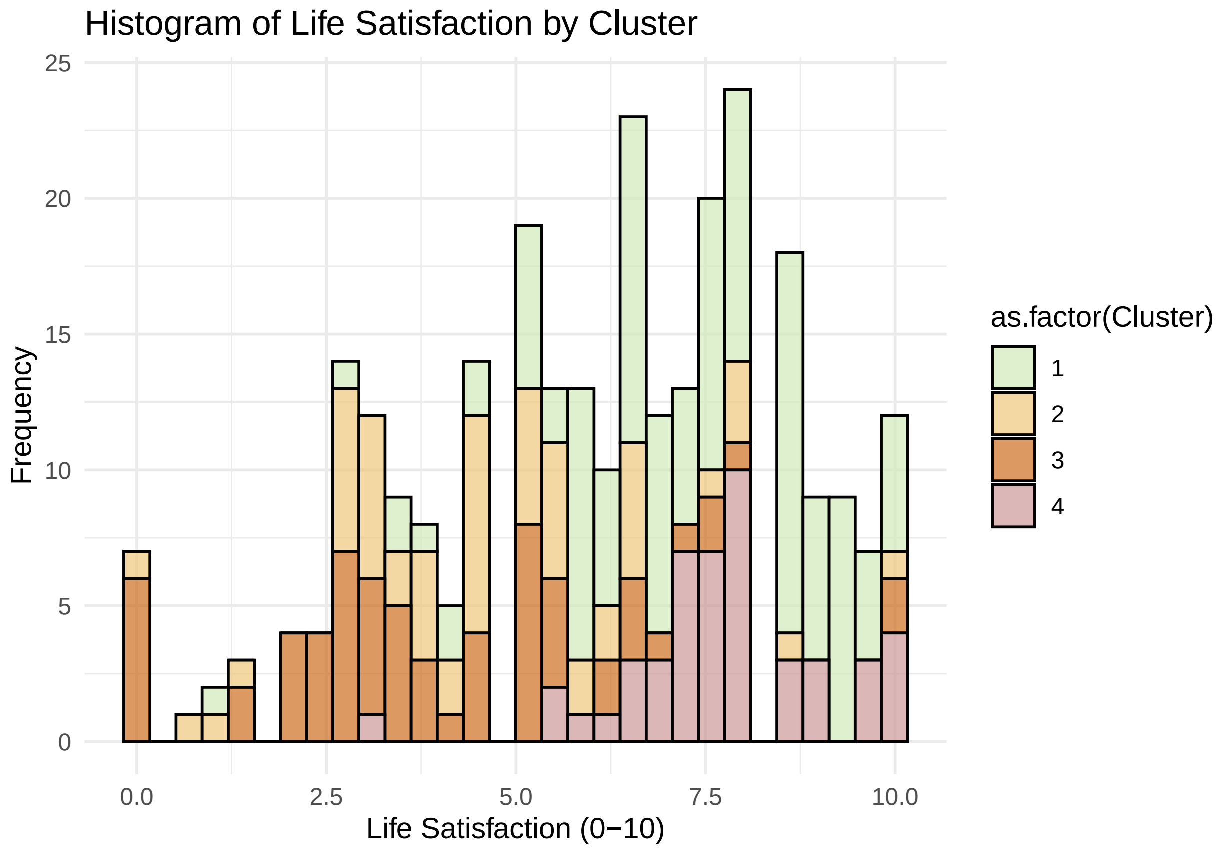
We also created a heatmap displaying the average values of factors in each cluster, with the data scaled to a baseline of 0. This plot is presented alongside the average plot to provide a clear comparison of the cluster characteristics.

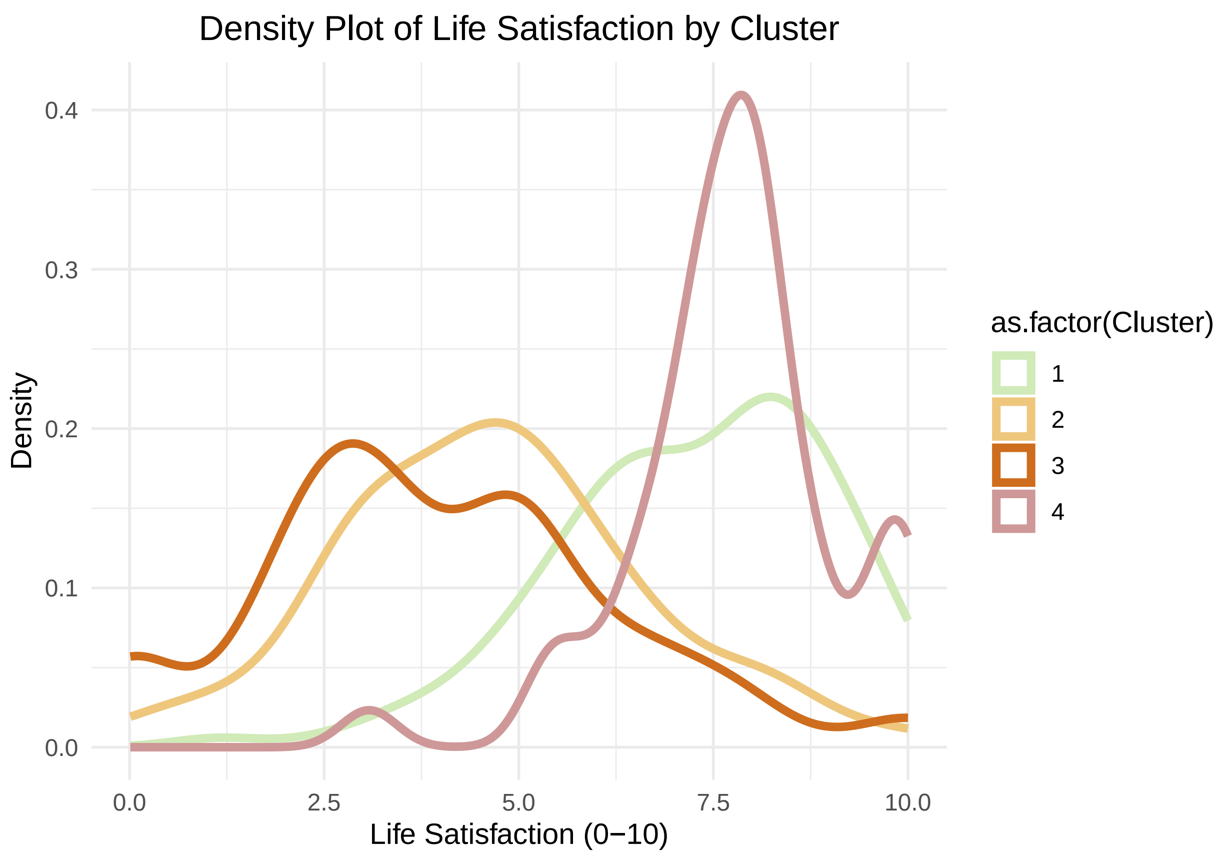


Later on, we went into more detail by plotting the **average Life Satisfaction Score** in each cluster.

```
## # A tibble: 4 x 2
##   Cluster Average_Life_Satisfaction
##     <dbl>                     <dbl>
## 1       1                      7.24
## 2       2                      4.64
## 3       3                      3.95
## 4       4                      7.76
```

Finally, we created a histogram and a density plot for the four clusters to explore how **Life Satisfaction** behaves and its distribution within each cluster.

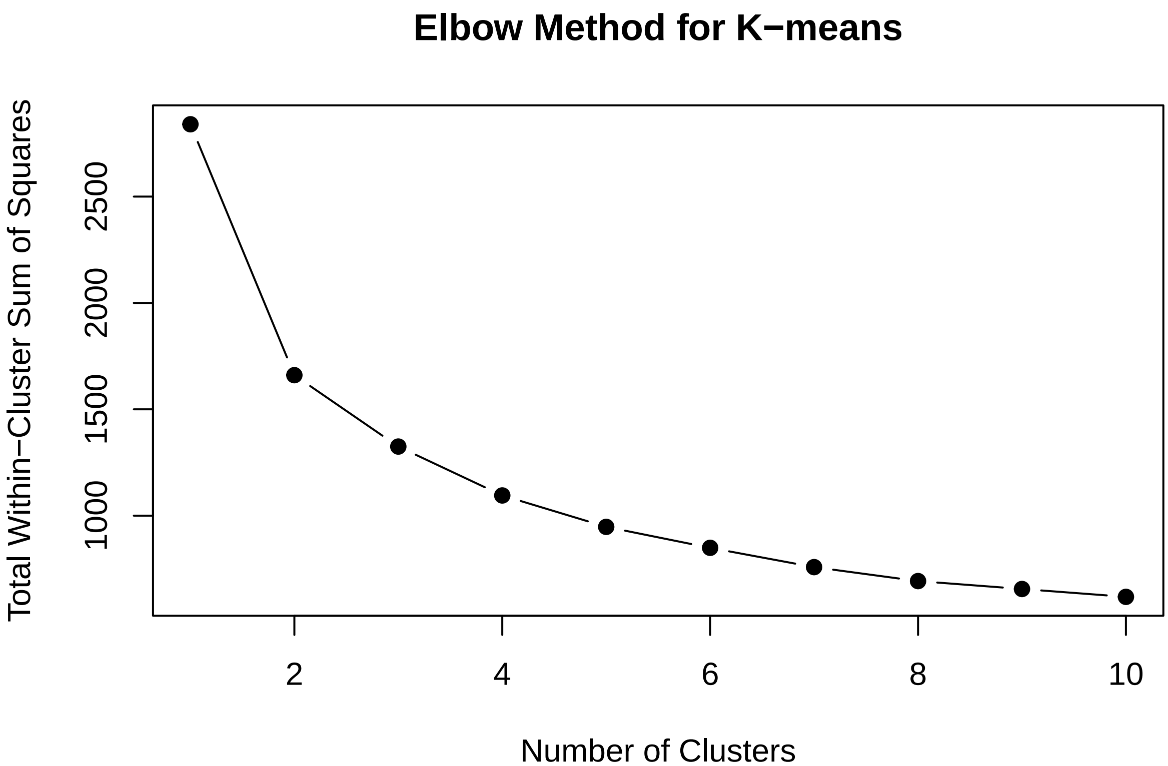

Histogram of Life Satisfaction by Cluster
Frequency
0
5
10
15
20
25
0.0
2.5
5.0
7.5
10.0
Life Satisfaction (0−10)
as.factor(Cluster)
1
2
3
4



K-Means

Continuing with our clustering analysis, we decided to do a K-Means clustering to cross check.

When analysing the number of k clusters, we used the **Elbow Method**, and we concluded that there is a kink at k=2, but we move ahead to choose up to 4 clusters, after which the within-cluster sum of squares starts to fade off.



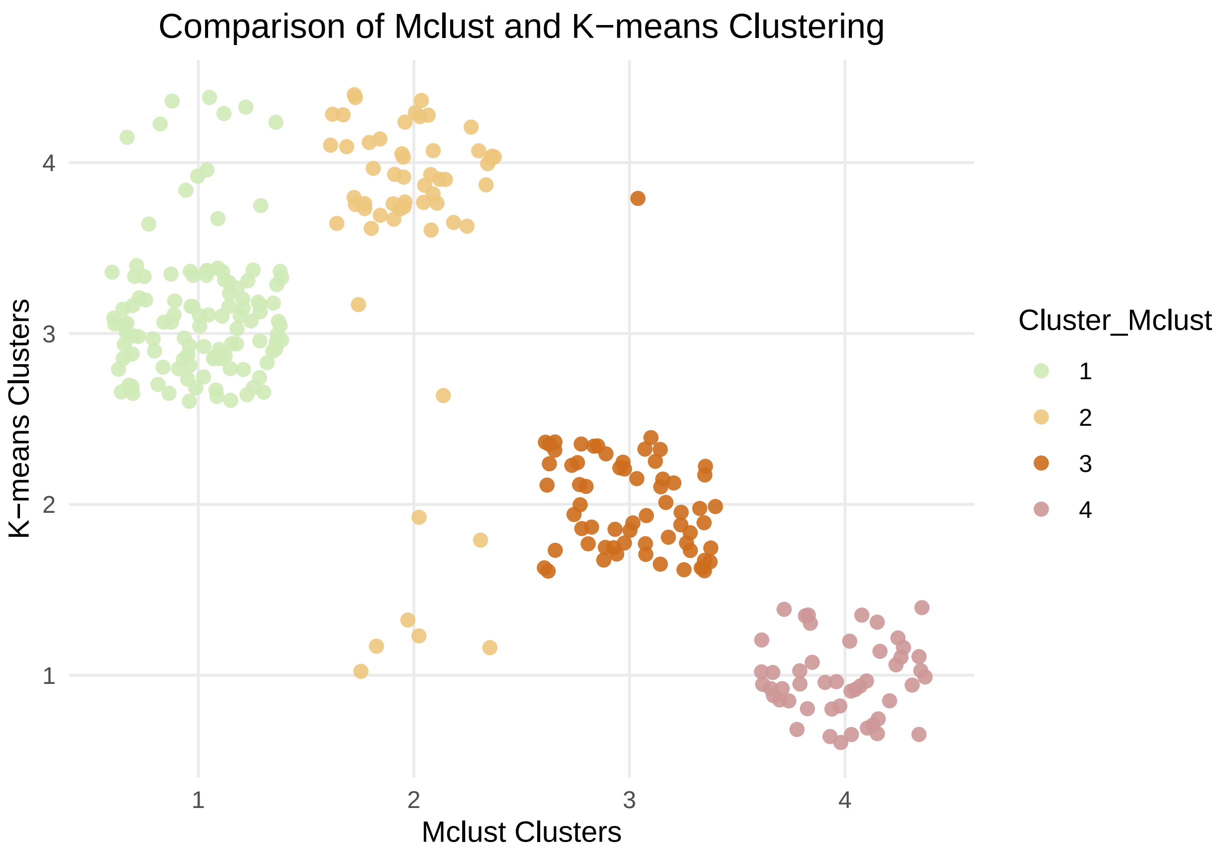

```
## Count of Cities in Each Cluster from K-Means

##
##   1   2   3   4
##  53  66 104  62
```

Comparing K-Means vs MCLUSt

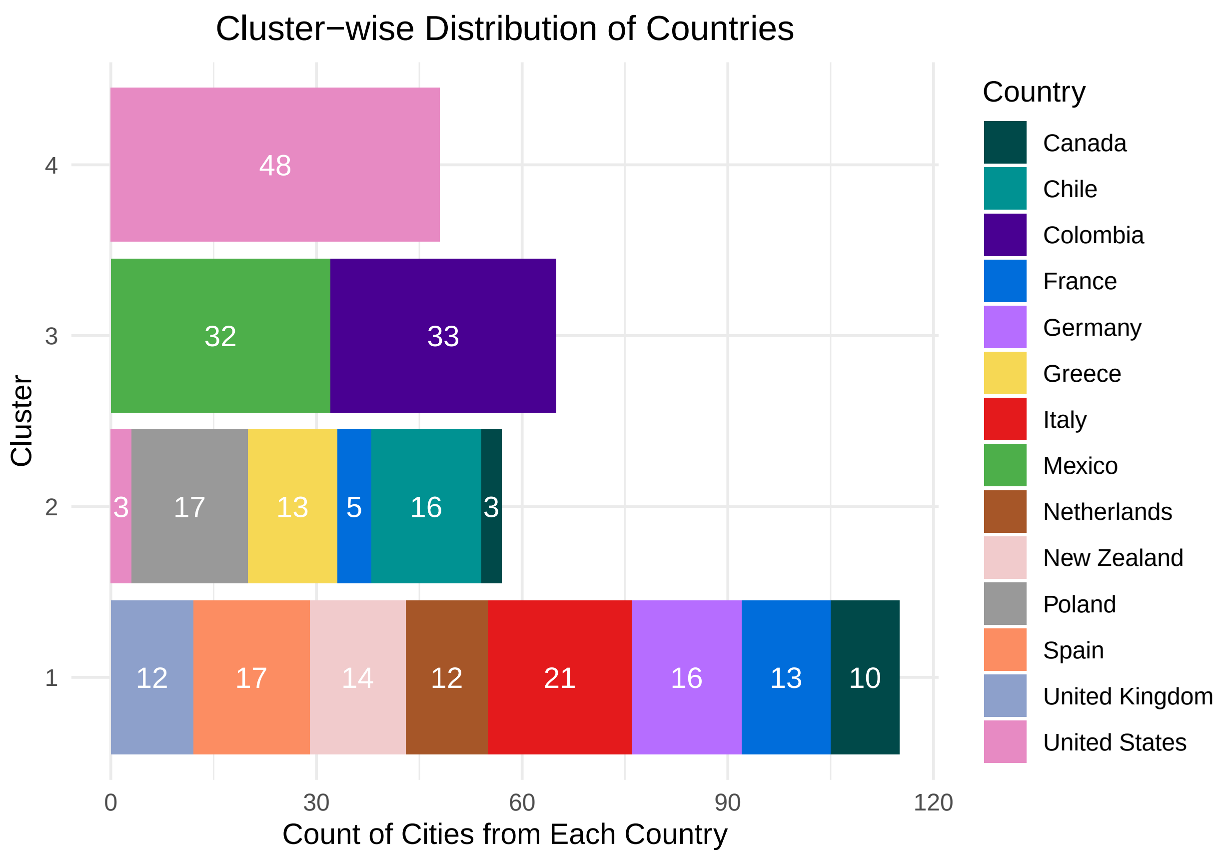
First, we did a **contingency table** to quickly compare both models:

```
##
## Contingency Table: Mclust and K-means Clusters Comparison

##
## Rows: Mclust Clusters
## Columns: K-means Clusters

##
##           1   2   3   4 Sum
##   1       0   0 102  13 115
##   2       5   2   2  48  57
##   3       0  64   0   1  65
##   4      48   0   0   0  48
##   Sum    53  66 104  62 285
```

Additionally, we created a scatter plot for comparing the clusters of both models.



Moreover, This plot shows how the different cities of the countries are segregated/distributed in the 5 clusters.



The **Rand Index Comparison** is:

```
## [1] 0.807066
```

This demonstrates a strong agreement between the two clustering solutions, with a notable overlap of the clusters identified by both techniques.

Further Analysis for Clustering

After all the analysis done, we decided to further analyse **Life Satisfaction**, so we manually divided it in 4 clusters. We divided the range 0-10 into 4 groups:

1. **0-2.5**
2. **2.5-5**
3. **5-7.5**
4. **7.5-10**

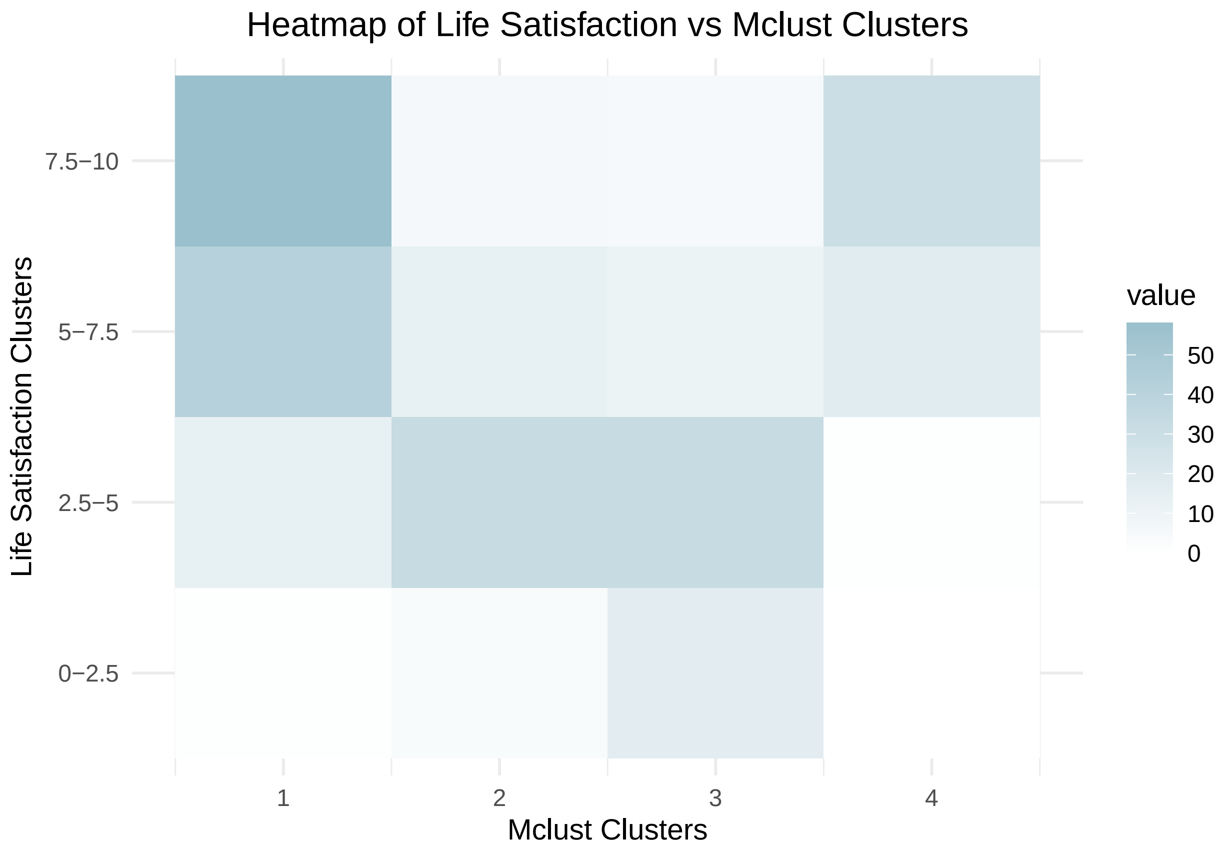
```
##
##  0-2.5  2.5-5  5-7.5 7.5-10
##     21     81     84     99
```

We compared this **manual clustering** vs **the M-Clust model** and the **K-Mean model**.

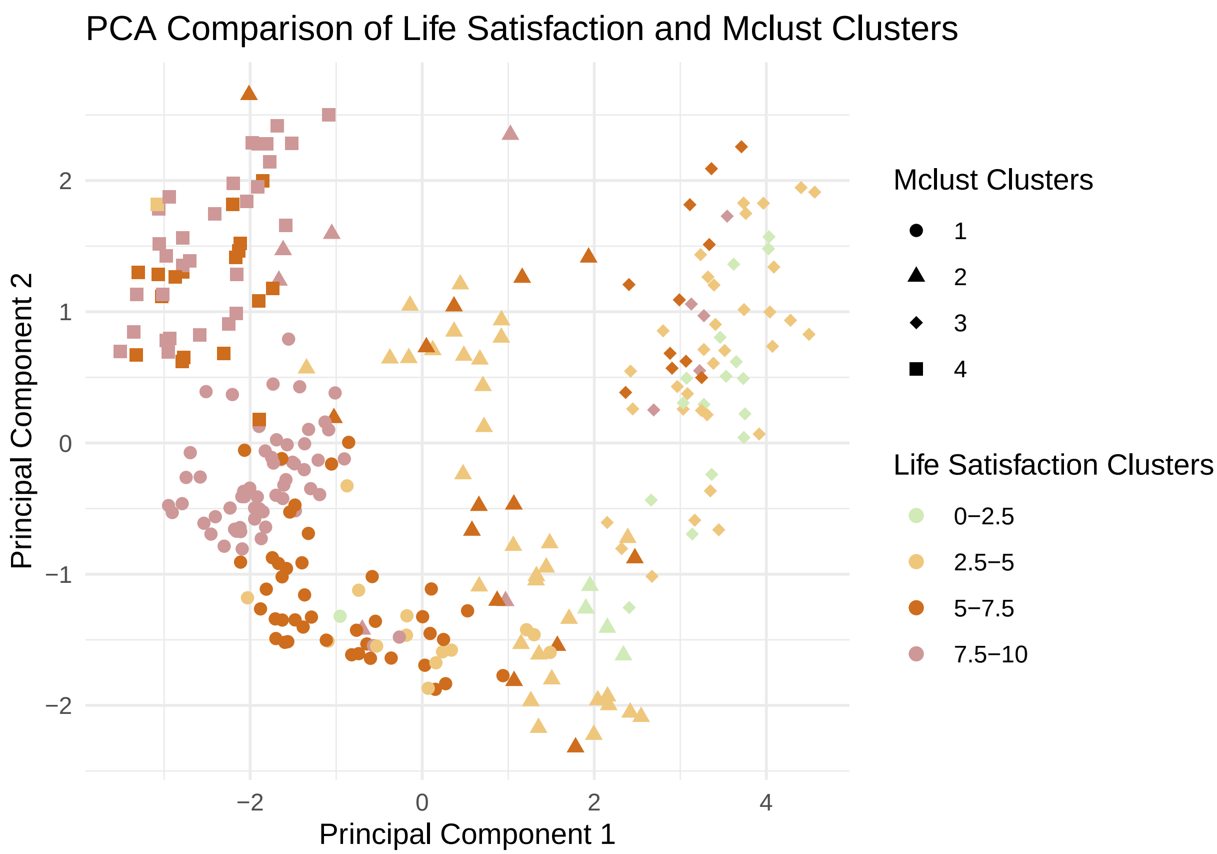
Manual clustering vs M-Clust model

```
##          mclust_clusters
##            1  2  3  4
##   0-2.5    1  4 16  0
##   2.5-5   14 33 33  1
##   5-7.5   42 14 11 17
##   7.5-10  58  6  5 30
```

For complementing this table, we used a heatmap to compare both ways of clustering:



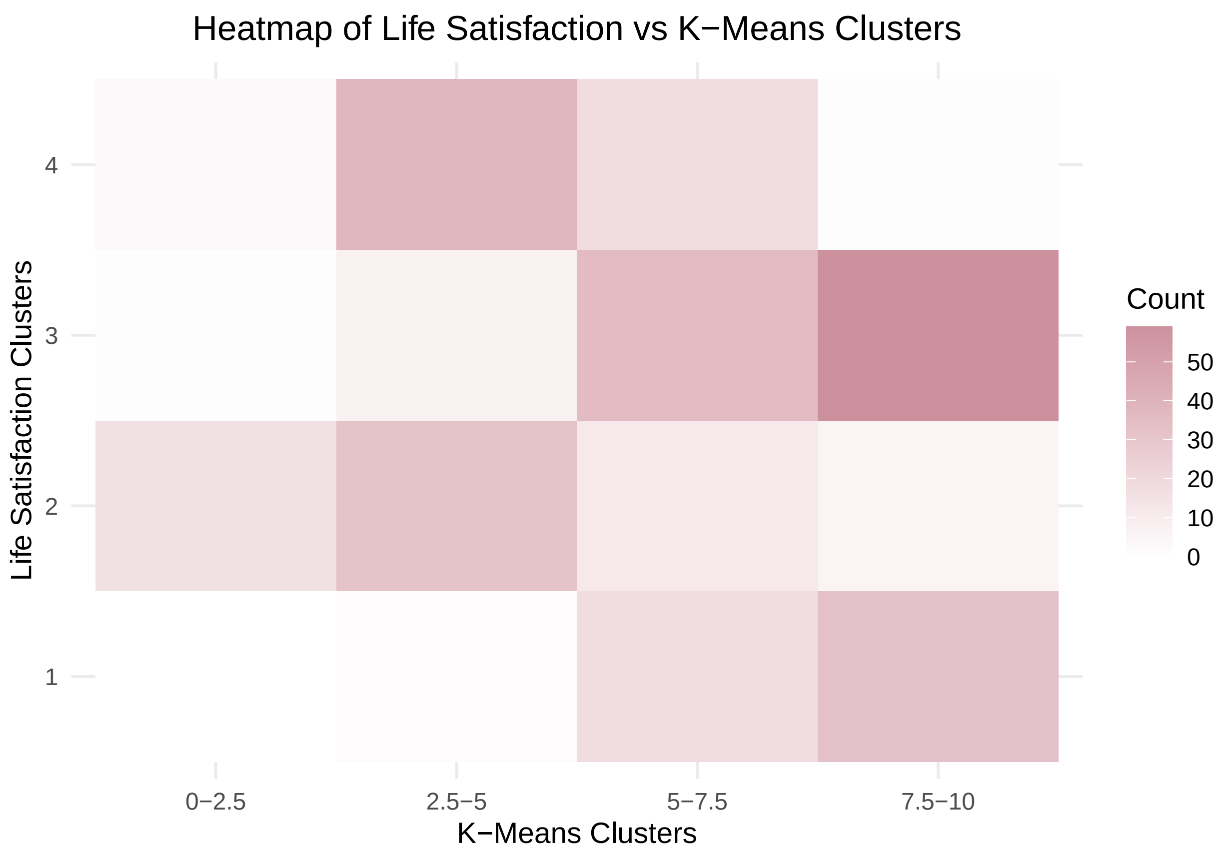
Additionally, we used a PCA visualization for further comparison between these two clustering methods.



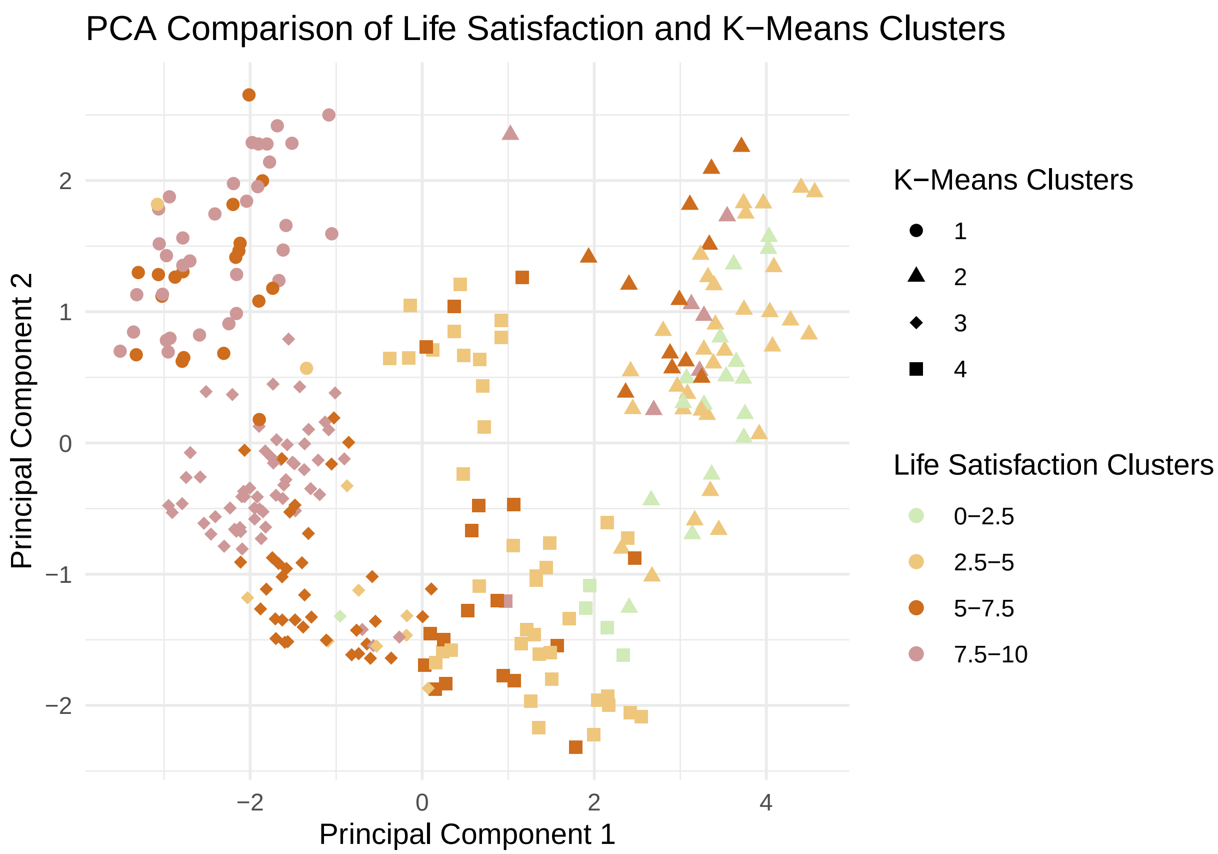
Manual clustering vs K-Means Cluster

```
##
##             1  2  3  4
##    0-2.5    0 16  1  4
##    2.5-5    2 32  8 39
##    5-7.5   18 12 36 18
##    7.5-10 33  6 59  1
```

Again we used a heatmap for complementing the table.



Additionally we did used the PCA visualization for further comparison.



The clusters divided manually **don't overlap** the clusters made by K-Means and M-Clust. The is probably because the scores are subjective, and different people measure life satisfaction scores in different perspectives. For some income would be a major factor, and for others community would be a major factor. However, statistically, we see that the **clustering using M-Clust and K-Means show a good overlap for the 4 clusters with a rand index 0.80**.

Fitting the Regression Models

Model 1:Linear Regression

```
##
## Call:
## lm(formula = ‘Life.satisfaction.(0-10)‘ ~ ., data = df_wb %>%
##     select(-Country, -Region, -Code))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.74515 -0.60416 -0.04097  0.58376  1.85999
##
## Coefficients:
##                                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         0.9281478  0.5356474   1.733   0.0843 .
## ‘Education.(0-10)‘                 -0.0269646  0.0312393  -0.863   0.3888
## ‘Jobs.(0-10)‘                       0.0311250  0.0269075   1.157   0.2484
## ‘Income.(0-10)‘                    -0.0247918  0.0441355  -0.562   0.5748
## ‘Safety.(0-10)‘                    -0.0386604  0.0263350  -1.468   0.1433
## ‘Health.(0-10)‘                    -0.0092182  0.0291554  -0.316   0.7521
## ‘Environment.(0-10)‘                0.0001279  0.0362010   0.004   0.9972
## ‘Civic.engagement.(0-10)‘           0.0426075  0.0288788   1.475   0.1413
## ‘Accessiblity.to.services.(0-10)‘  0.0814921  0.0349788   2.330   0.0206 *
## ‘Housing.(0-10)‘                    0.0271973  0.0363601   0.748   0.4551
## ‘Community.(0-10)‘                  0.0318094  0.0228166   1.394   0.1644
## Cluster                            -0.0056113  0.0821042  -0.068   0.9456
## LifeSatisfactionCluster2.5-5        2.6266549  0.2014153  13.041   <2e-16 ***
## LifeSatisfactionCluster5-7.5        4.7828907  0.2330951  20.519   <2e-16 ***
## LifeSatisfactionCluster7.5-10       6.8858235  0.2527388  27.245   <2e-16 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Residual standard error: 0.7632 on 270 degrees of freedom
## Multiple R-squared:  0.9065, Adjusted R-squared:  0.9017
## F-statistic: 187.1 on 14 and 270 DF,  p-value: < 2.2e-16
```

The **basic regression model** shows that Jobs, Community, Environment, Civic Engagement, Health and Housing are significant for the Life satisfaction score.

Model 2: Linear Regression using Pairwise Interaction effects

For this second model we used a pairwise interaction effect which can be seen in **Anex B**.

For individual attributes, we can conclude that:

- **Education.(0-10)**: has a positive coefficient (1.52), suggesting that as education increases, life satisfaction tends to increase.
- **Income.(0-10)**: has a negative coefficient (-0.53), indicating that higher income is associated with lower life satisfaction in this model, which might be counterintuitive and could require further exploration.
- **Health.(0-10)**: has a negative coefficient (-0.71), suggesting that higher health scores correlate with lower life satisfaction in this dataset.

When checking the effects by cluster, we can see that:

- **Cluster 7.5-10**: is the strongest positive cluster (estimate = 6.23).
- **Cluster 2.5-5**: has a notable negative impact (-0.57).

On the other hand, although those values represent an important impact to the dependent variable, we can see that none of them is significant in any level.

Nevertheless, in this case we observe that some variables might have interaction effects, so we build a different model, and compare with the original one using ANOVA.

Model 3: Model with Interaction effects based on relevance of factors.

```
##
## Call:
## lm(formula = `Life.satisfaction.(0-10)` ~ `Education.(0-10)` +
##     `Jobs.(0-10)` + `Income.(0-10)` + `Safety.(0-10)` + `Health.(0-10)` +
##     `Environment.(0-10)` + `Civic.engagement.(0-10)` + `Accessiblity.to.services.(0-10)` +
##     `Housing.(0-10)` + `Community.(0-10)` + `Education.(0-10)`:`Safety.(0-10)` +
##     `Education.(0-10)`:`Accessiblity.to.services.(0-10)` + `Education.(0-10)`:`Housing.(0-10)` +
##     `Jobs.(0-10)`:`Income.(0-10)` + `Jobs.(0-10)`:`Safety.(0-10)` +
##     `Jobs.(0-10)`:`Civic.engagement.(0-10)` + `Jobs.(0-10)`:`Accessiblity.to.services.(0-10)` +
##     `Jobs.(0-10)`:`Housing.(0-10)` + `Safety.(0-10)`:`Environment.(0-10)` +
##     `Safety.(0-10)`:`Civic.engagement.(0-10)` + `Safety.(0-10)`:`Accessiblity.to.services.(0-10)` +
##     `Safety.(0-10)`:`Housing.(0-10)` + `Accessiblity.to.services.(0-10)`:`Community.(0-10)` +
##     `Education.(0-10)`:`Jobs.(0-10)`:`Income.(0-10)`, data = df_wb %>%
##     select(-Country, -Region, -Code))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8756 -0.6815  0.0888  0.6933  3.7682
##
## Coefficients:
##                                                       Estimate Std. Error
## (Intercept)                                           8.937159   1.832009
## `Education.(0-10)`                                    0.527538   0.248658
## `Jobs.(0-10)`                                         0.030748   0.190232
## `Income.(0-10)`                                       0.565472   0.279209
## `Safety.(0-10)`                                      -1.029663   0.196845
## `Health.(0-10)`                                      -0.062124   0.052722
## `Environment.(0-10)`                                 -0.883211   0.274572
## `Civic.engagement.(0-10)`                            -1.276137   0.214451
## `Accessiblity.to.services.(0-10)`                    -0.008574   0.313844
## `Housing.(0-10)`                                      0.399813   0.354916
## `Community.(0-10)`                                    0.518839   0.074370
## `Education.(0-10)`:`Safety.(0-10)`                   -0.052642   0.025547
## `Education.(0-10)`:`Accessiblity.to.services.(0-10)` -0.052203   0.028172
## `Education.(0-10)`:`Housing.(0-10)`                   0.060829   0.023305
## `Jobs.(0-10)`:`Income.(0-10)`                        -0.028055   0.066604
## `Jobs.(0-10)`:`Safety.(0-10)`                        -0.007618   0.022614
## `Jobs.(0-10)`:`Civic.engagement.(0-10)`               0.076665   0.017629
## `Jobs.(0-10)`:`Accessiblity.to.services.(0-10)`       0.013846   0.024977
## `Jobs.(0-10)`:`Housing.(0-10)`                        0.045218   0.021726
```

```
## `Safety.(0-10)`:`Environment.(0-10)`                      0.123750   0.029860
## `Safety.(0-10)`:`Civic.engagement.(0-10)`                 0.092178   0.023223
## `Safety.(0-10)`:`Accessiblity.to.services.(0-10)`         0.095767   0.031939
## `Safety.(0-10)`:`Housing.(0-10)`                         -0.114082   0.035121
## `Accessiblity.to.services.(0-10)`:`Community.(0-10)` -0.067782   0.012406
## `Education.(0-10)`:`Jobs.(0-10)`:`Income.(0-10)`         -0.006949   0.004434
##                                                      t value Pr(>|t|)
## (Intercept)                                            4.878 1.87e-06 ***
## `Education.(0-10)`                                     2.122  0.03482 *
## `Jobs.(0-10)`                                          0.162  0.87172
## `Income.(0-10)`                                        2.025  0.04386 *
## `Safety.(0-10)`                                       -5.231 3.47e-07 ***
## `Health.(0-10)`                                       -1.178  0.23974
## `Environment.(0-10)`                                  -3.217  0.00146 **
## `Civic.engagement.(0-10)`                             -5.951 8.60e-09 ***
## `Accessiblity.to.services.(0-10)`                     -0.027  0.97823
## `Housing.(0-10)`                                       1.127  0.26099
## `Community.(0-10)`                                     6.976 2.50e-11 ***
## `Education.(0-10)`:`Safety.(0-10)`                    -2.061  0.04034 *
## `Education.(0-10)`:`Accessiblity.to.services.(0-10)`  -1.853  0.06502 .
## `Education.(0-10)`:`Housing.(0-10)`                    2.610  0.00958 **
## `Jobs.(0-10)`:`Income.(0-10)`                         -0.421  0.67394
## `Jobs.(0-10)`:`Safety.(0-10)`                         -0.337  0.73649
## `Jobs.(0-10)`:`Civic.engagement.(0-10)`                4.349 1.97e-05 ***
## `Jobs.(0-10)`:`Accessiblity.to.services.(0-10)`        0.554  0.57981
## `Jobs.(0-10)`:`Housing.(0-10)`                         2.081  0.03838 *
## `Safety.(0-10)`:`Environment.(0-10)`                   4.144 4.61e-05 ***
## `Safety.(0-10)`:`Civic.engagement.(0-10)`              3.969 9.34e-05 ***
## `Safety.(0-10)`:`Accessiblity.to.services.(0-10)`      2.998  0.00298 **
## `Safety.(0-10)`:`Housing.(0-10)`                      -3.248  0.00131 **
## `Accessiblity.to.services.(0-10)`:`Community.(0-10)`  -5.464 1.09e-07 ***
## `Education.(0-10)`:`Jobs.(0-10)`:`Income.(0-10)`      -1.567  0.11834
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.258 on 260 degrees of freedom
## Multiple R-squared:  0.7556, Adjusted R-squared:  0.7331
## F-statistic:  33.5 on 24 and 260 DF,  p-value: < 2.2e-16
```

This model shows that Education, Environment, "Education & Housing", "Jobs & Civic Engagement", "Safety & Environment", "Safety & Civic Engagement", "Safety and Accessibility to Services", "Accessibility to Services & Community", "Safety & Housing" and "Education & Safety", "Education & Accessibility to Services", "Jobs & Housing" and "Education & Jobs & Income", **are all significant and contribute towards life satisfaction scores**.

Furthermore, the model has a **low MSE as compared to the simple model**.

Parameters from the Three Models

Adjusted R-square

```
## [1] "Model 1: 0.901686237642046"
```

```
## [1] "Model 2: 0.934655589047462"
```

```
## [1] "Model 3: 0.733087895430447"
```

AIC

```
## [1] "Model 1: 671.371611208139"
```

```
## [1] "Model 2: 618.543007528791"
```

```
## [1] "Model 3: 965.260902982299"
```

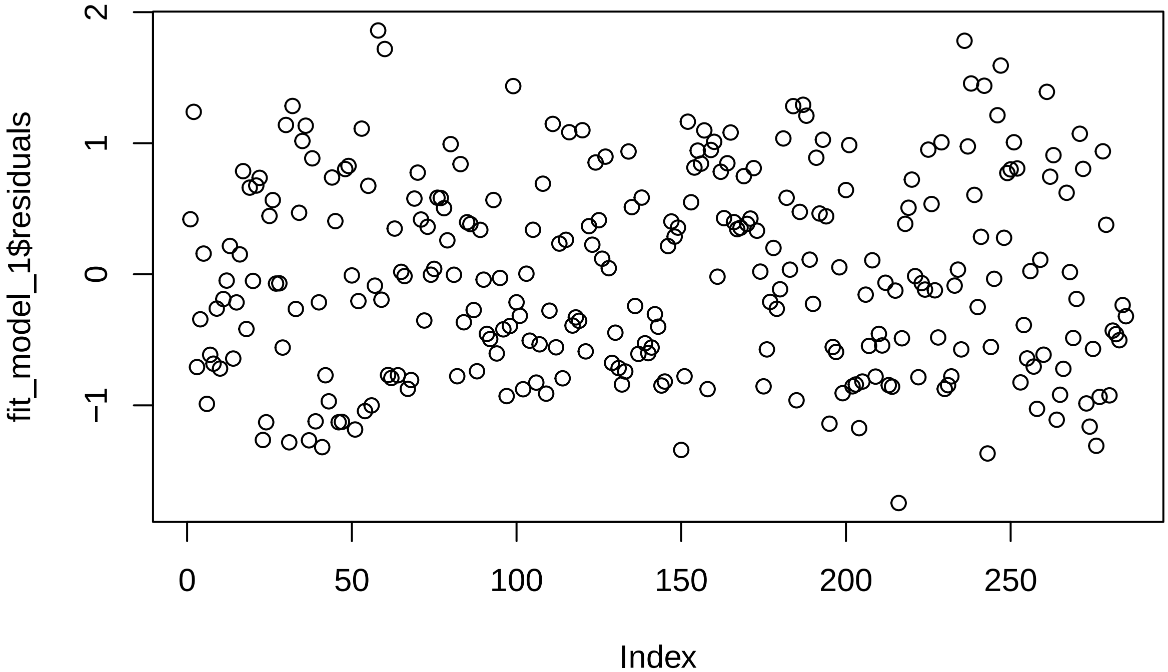
BIC

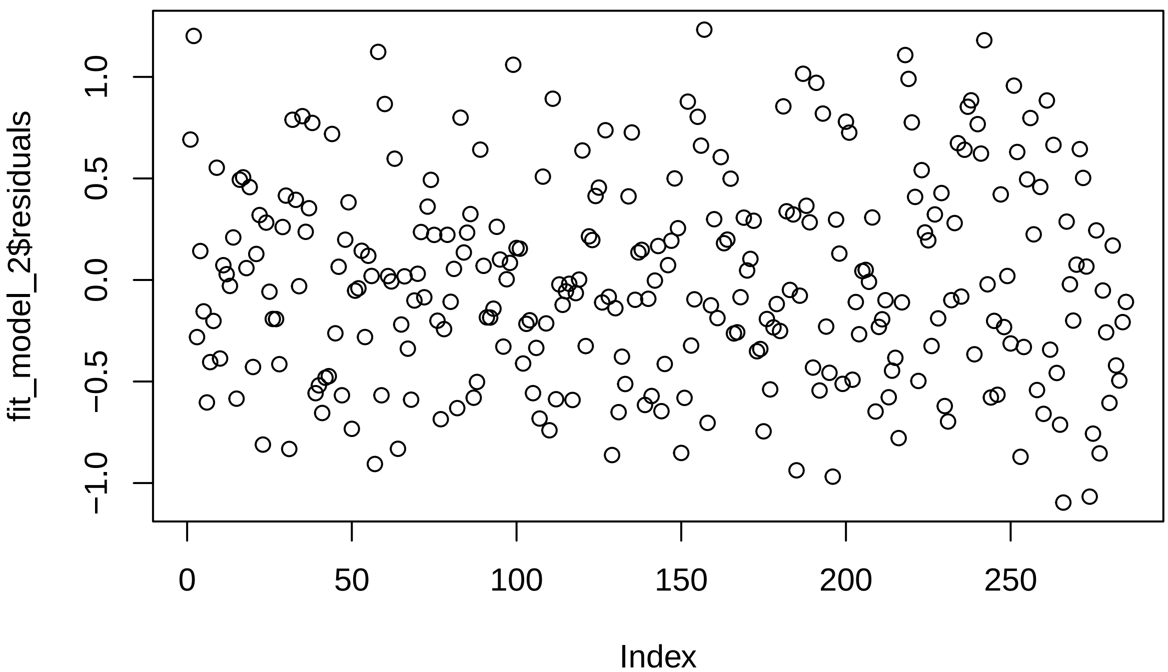
```
## [1] "Model 1: 729.811438092438"
```

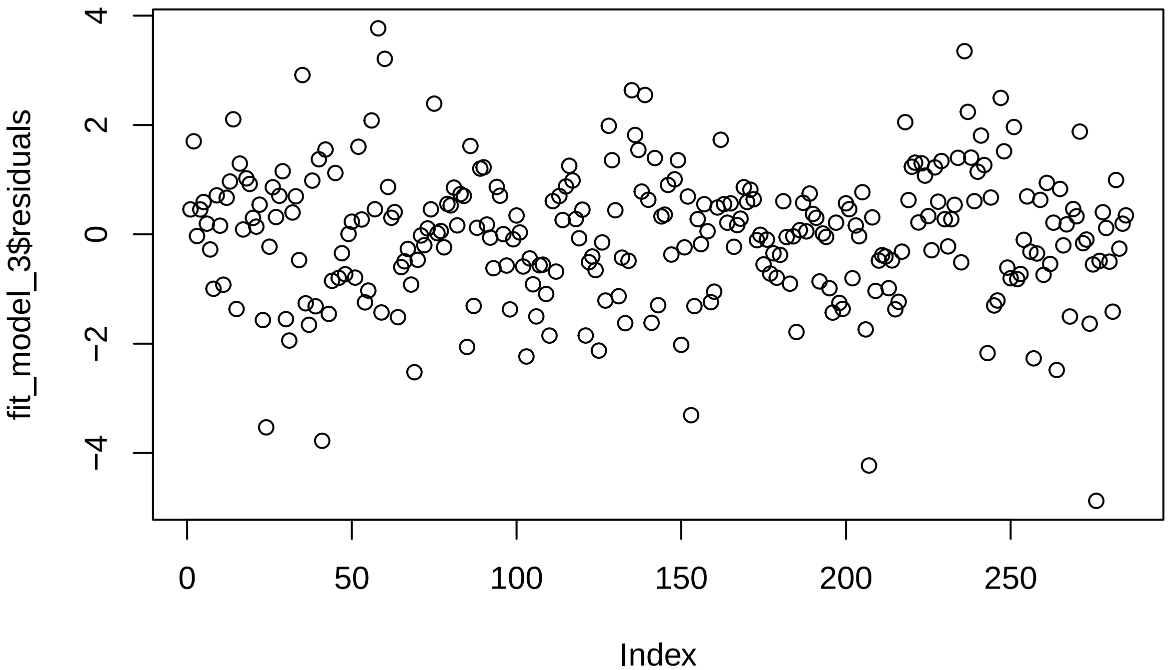
```
## [1] "Model 2: 998.401882276731"
```

```
## [1] "Model 3: 1060.22562166928"
```

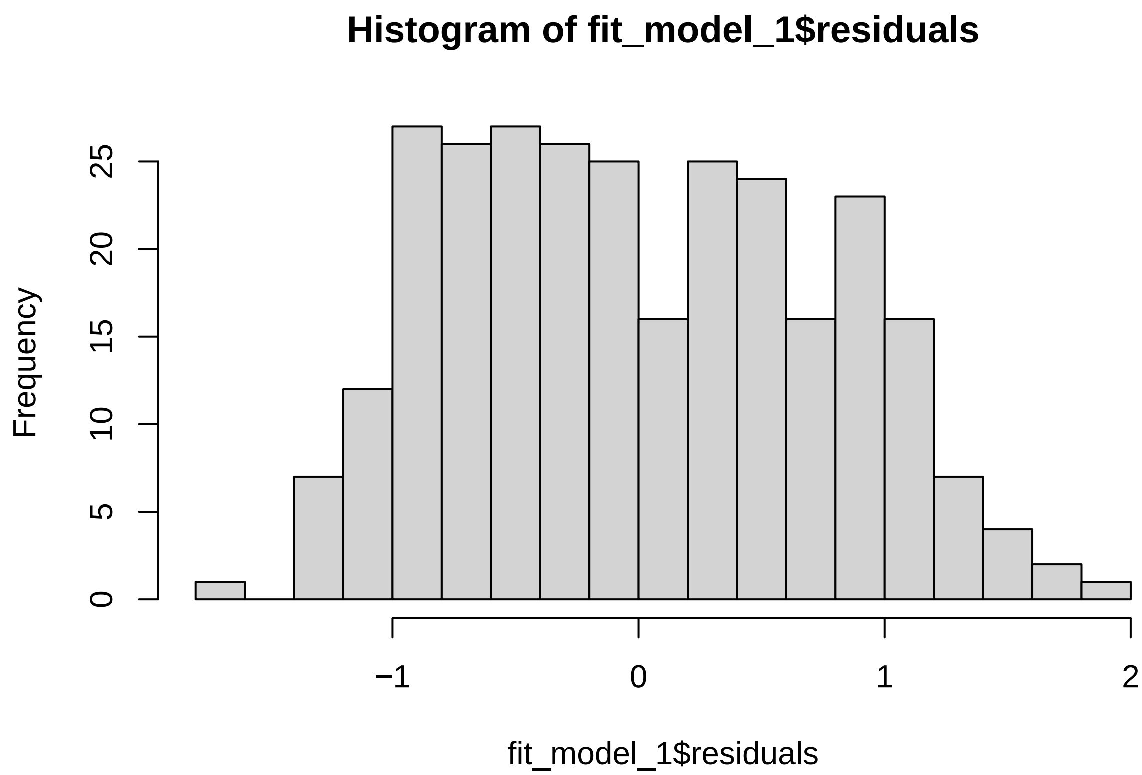
Residuals

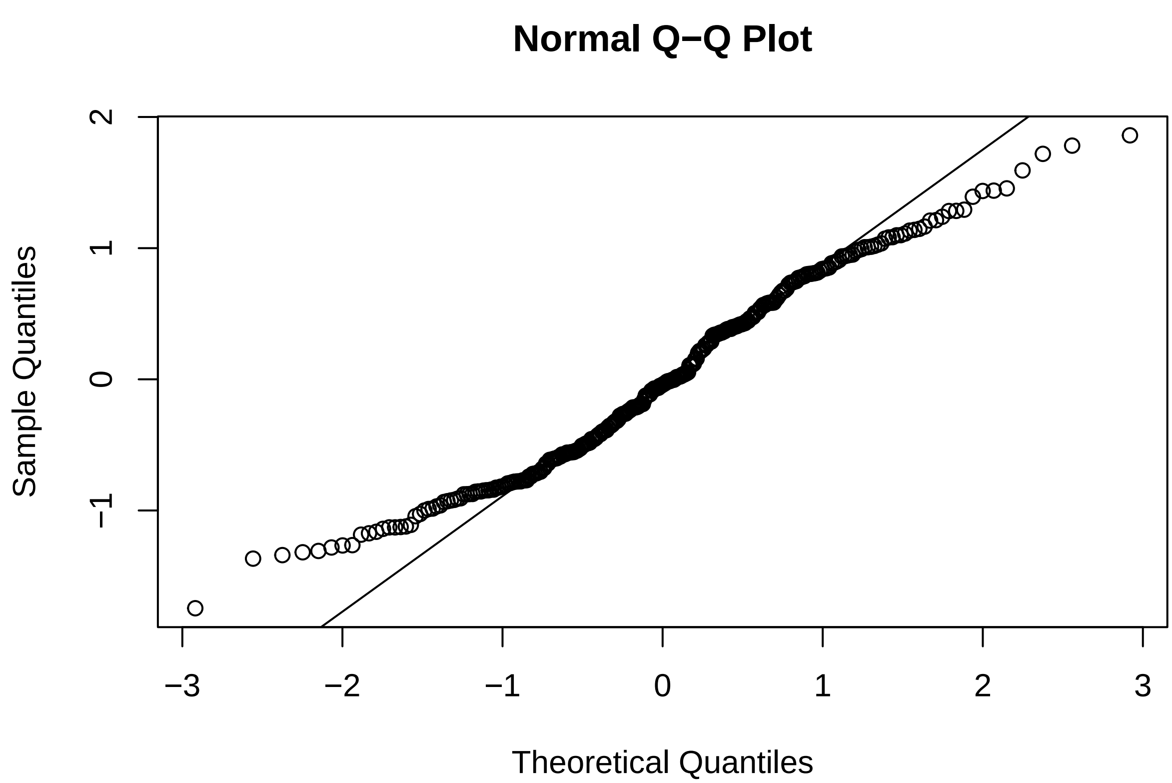


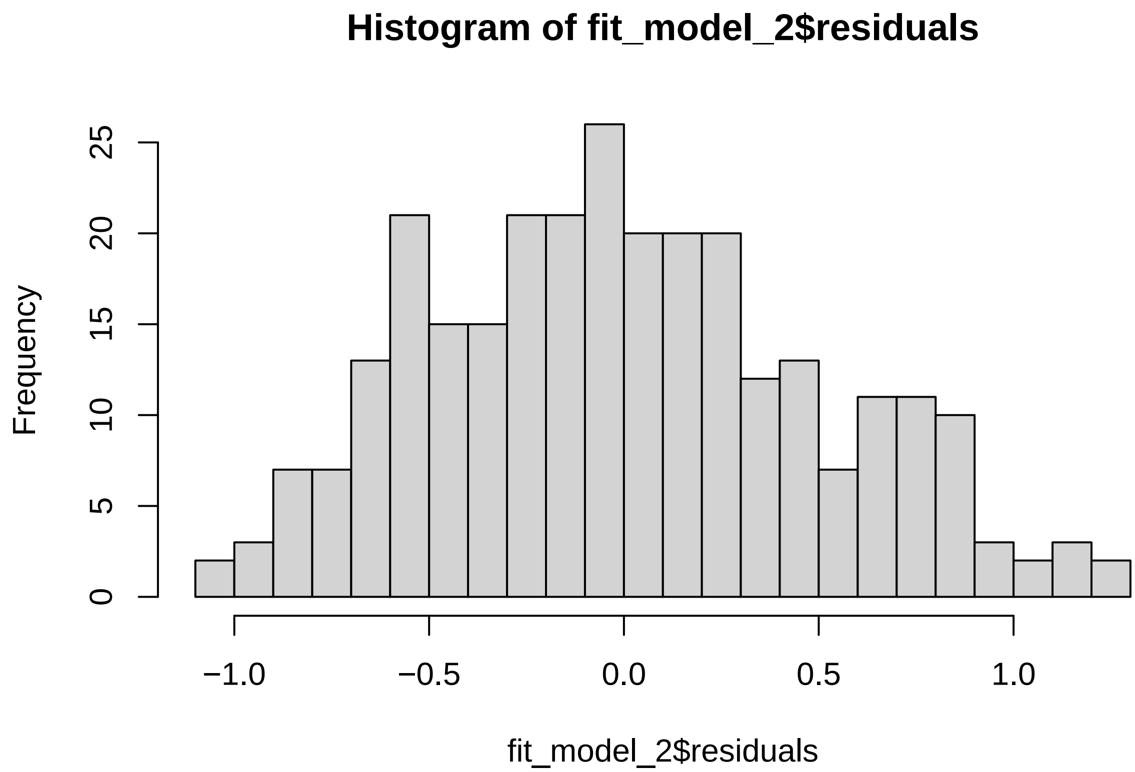


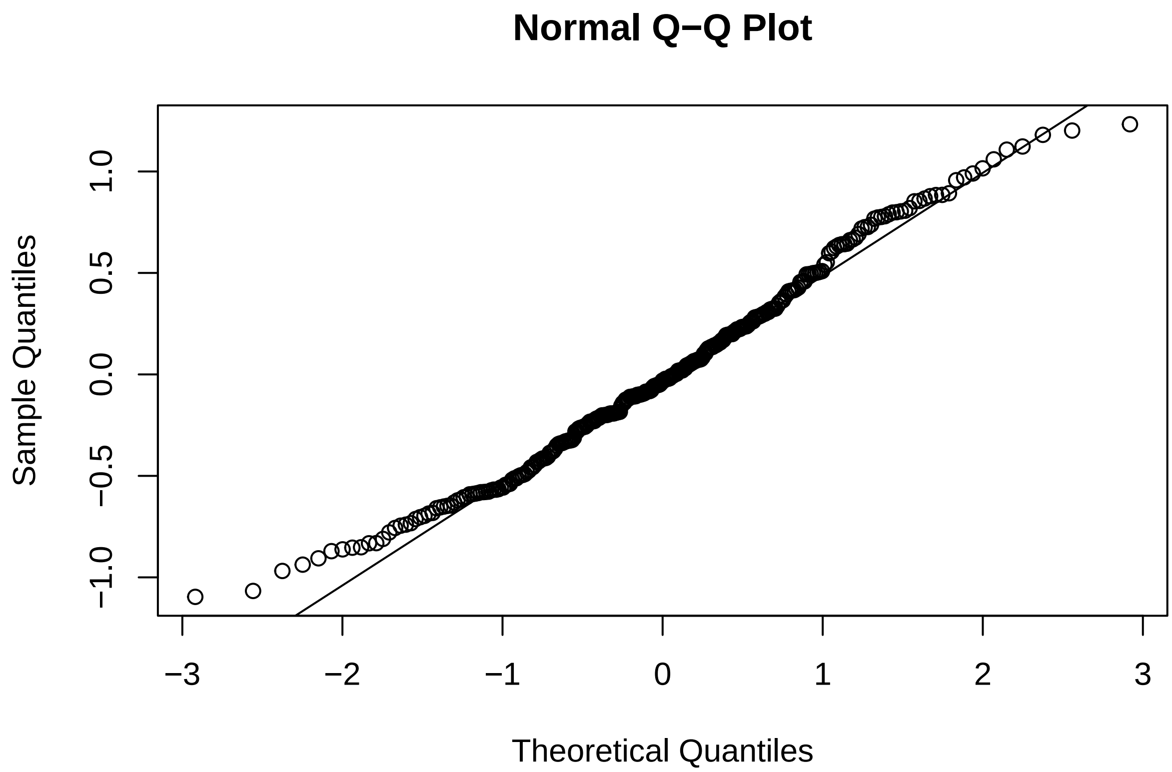

fit_model_3$residuals
Index
4
2
0
−2
−4
0
50
100
150
200
250

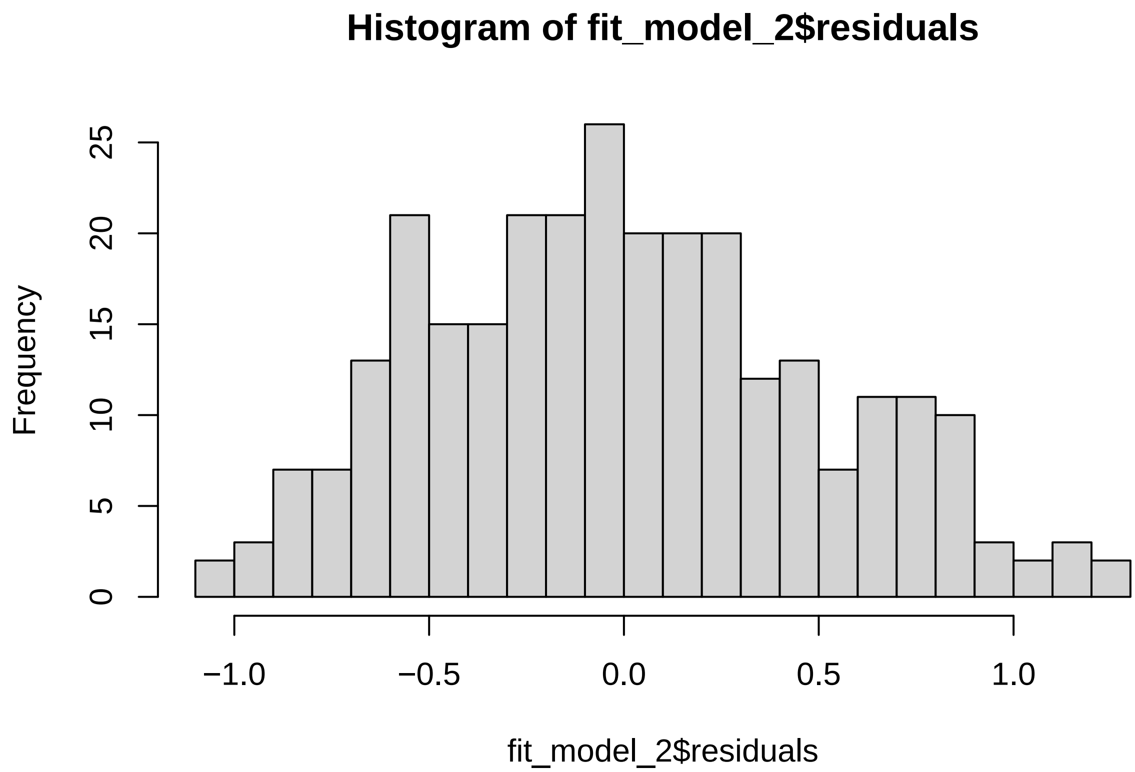
Normality using Q-Q Plots

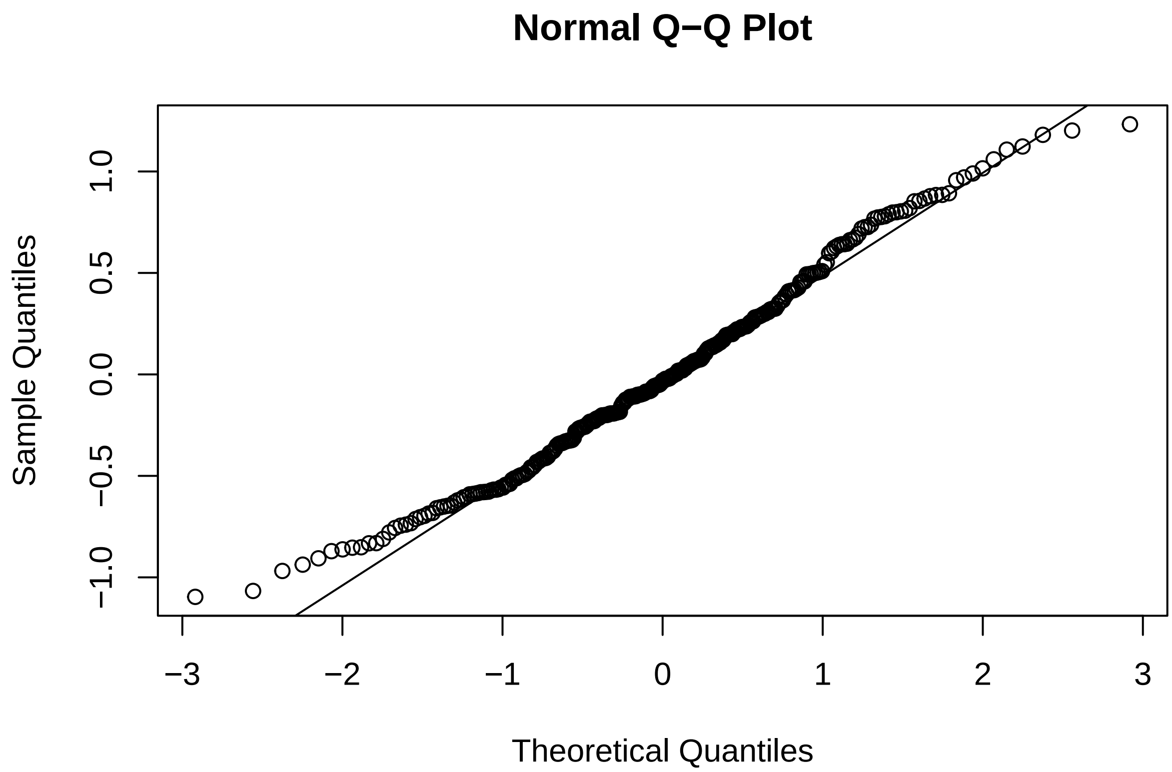





Histogram of fit_model_2$residuals
Frequency
0
5
10
15
20
25
−1.0
−0.5
0.0
0.5
1.0
fit_model_2$residuals


Normal Q−Q Plot
Sample Quantiles
Theoretical Quantiles
−1.0
−0.5
0.0
0.5
1.0
−3
−2
−1
0
1
2
3


Histogram of fit_model_2$residuals
Frequency
0
5
10
15
20
25
−1.0
−0.5
0.0
0.5
1.0
fit_model_2$residuals



ANOVA

We used ANOVA to check which model is better from Model 1 and Model 3:

```
## Analysis of Variance Table
##
## Model 1: ‘Life.satisfaction.(0-10)‘ ~ ‘Education.(0-10)‘ + ‘Jobs.(0-10)‘ +
##     ‘Income.(0-10)‘ + ‘Safety.(0-10)‘ + ‘Health.(0-10)‘ + ‘Environment.(0-10)‘ +
##     ‘Civic.engagement.(0-10)‘ + ‘Accessiblity.to.services.(0-10)‘ +
##     ‘Housing.(0-10)‘ + ‘Community.(0-10)‘ + Cluster + LifeSatisfactionCluster
## Model 2: ‘Life.satisfaction.(0-10)‘ ~ ‘Education.(0-10)‘ + ‘Jobs.(0-10)‘ +
##     ‘Income.(0-10)‘ + ‘Safety.(0-10)‘ + ‘Health.(0-10)‘ + ‘Environment.(0-10)‘ +
##     ‘Civic.engagement.(0-10)‘ + ‘Accessiblity.to.services.(0-10)‘ +
##     ‘Housing.(0-10)‘ + ‘Community.(0-10)‘ + ‘Education.(0-10)‘:‘Safety.(0-10)‘ +
##     ‘Education.(0-10)‘:‘Accessiblity.to.services.(0-10)‘ + ‘Education.(0-10)‘:‘Housing.(0-10)‘ +
##     ‘Jobs.(0-10)‘:‘Income.(0-10)‘ + ‘Jobs.(0-10)‘:‘Safety.(0-10)‘ +
##     ‘Jobs.(0-10)‘:‘Civic.engagement.(0-10)‘ + ‘Jobs.(0-10)‘:‘Accessiblity.to.services.(0-10)‘ +
##     ‘Jobs.(0-10)‘:‘Housing.(0-10)‘ + ‘Safety.(0-10)‘:‘Environment.(0-10)‘ +
##     ‘Safety.(0-10)‘:‘Civic.engagement.(0-10)‘ + ‘Safety.(0-10)‘:‘Accessiblity.to.services.(0-10)‘ +
##     ‘Safety.(0-10)‘:‘Housing.(0-10)‘ + ‘Accessiblity.to.services.(0-10)‘:‘Community.(0-10)‘ +
##     ‘Education.(0-10)‘:‘Jobs.(0-10)‘:‘Income.(0-10)‘
##   Res.Df    RSS Df Sum of Sq F Pr(>F)
## 1    270 157.28
## 2    260 411.18 10    -253.9
```

Since the **p-value is 2.2e-16 < 0.05**, we reject the Null Hypothesis and conclude that the **Model 3 with Interaction Terms is the preferred model**.

Random Intercept Model

Since the data has hierarchical structure, we fitted the random intercept model:

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: `Life.satisfaction.(0-10)` ~ `Education.(0-10)` + `Jobs.(0-10)` +
##     `Income.(0-10)` + `Safety.(0-10)` + `Health.(0-10)` + `Environment.(0-10)` +
##     `Civic.engagement.(0-10)` + `Accessiblity.to.services.(0-10)` +
##     `Housing.(0-10)` + `Community.(0-10)` + (1 | Country)
##    Data: df_wb %>% select(-Region, -Code)
##
## REML criterion at convergence: 1056.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.0049 -0.3837  0.0287  0.4401  4.1670
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Country  (Intercept) 1.760    1.327
##  Residual             1.903    1.380
## Number of obs: 285, groups:  Country, 14
##
## Fixed effects:
##                                   Estimate Std. Error t value
## (Intercept)                        1.99349    0.90626   2.200
## `Education.(0-10)`                 0.24477    0.10371   2.360
## `Jobs.(0-10)`                      0.09457    0.07077   1.336
## `Income.(0-10)`                   -0.01267    0.12532  -0.101
## `Safety.(0-10)`                   -0.08039    0.05615  -1.432
## `Health.(0-10)`                   -0.01965    0.08048  -0.244
## `Environment.(0-10)`               0.16097    0.07002   2.299
## `Civic.engagement.(0-10)`         -0.13851    0.07074  -1.958
## `Accessiblity.to.services.(0-10)`  0.11535    0.08865   1.301
## `Housing.(0-10)`                   0.10318    0.08786   1.174
## `Community.(0-10)`                 0.19783    0.04225   4.682
##
## Correlation of Fixed Effects:
##             (Intr) `Ed.(0-10)` `J.(0- `I.(0- `S.(0- `Hl.(0-10)` `En.(0-10)`
## `Ed.(0-10)` -0.136
## `Jb.(0-10)` -0.145 -0.241
## `In.(0-10)`  0.026 -0.290      -0.187
## `Sf.(0-10)` -0.385 -0.148       0.085  0.033
## `Hl.(0-10)` -0.107  0.058       0.004 -0.206 -0.189
## `En.(0-10)` -0.444 -0.030      -0.058 -0.063  0.039 -0.027
## `C..(0-10)`  0.078  0.031      -0.333 -0.060 -0.169 -0.282       0.111
## `A...(0-10) -0.214 -0.279       0.075 -0.075  0.063 -0.377       0.076
## `Hs.(0-10)`  0.003 -0.284      -0.022  0.081 -0.014  0.139      -0.227
## `Cm.(0-10)` -0.258 -0.080       0.001 -0.003  0.072  0.004       0.005
##             `C..(0 `A...( `Hs.(0-10)`
```

```
## `Ed.(0-10)`
## `Jb.(0-10)`
## `In.(0-10)`
## `Sf.(0-10)`
## `Hl.(0-10)`
## `En.(0-10)`
## `C..(0-10)`
## `A...(0-10) -0.028
## `Hs.(0-10)` -0.222 -0.139
## `Cm.(0-10)` -0.034  0.073 -0.129
```

Taking into account this:

- **Significant Effects**: Education, Environment, Community (+ve), and Civic engagement (-ve).
- **Non-significant Effects**: Jobs, Income, Safety, Health, Housing, and Accessibility to services.
- **REML Criterion**: 1,131.8. Measure of model fit for restricted maximum likelihood (REML) estimation. Lower values of the REML criterion indicate a better-fitting model.

Fitting the Random Slope and Random Intercept Model

Random Intercept Model with Random Slope for Education

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: `Life.satisfaction.(0-10)` ~ `Education.(0-10)` + `Jobs.(0-10)` +
##     `Income.(0-10)` + `Safety.(0-10)` + `Health.(0-10)` + `Environment.(0-10)` +
##     `Civic.engagement.(0-10)` + `Accessiblity.to.services.(0-10)` +
##     `Housing.(0-10)` + `Community.(0-10)` + (1 + `Education.(0-10)` |
##     Country)
##    Data: df_wb %>% select(-Region, -Code)
##
## REML criterion at convergence: 1048.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.0770 -0.4608  0.0149  0.3999  4.1388
##
## Random effects:
##  Groups   Name               Variance Std.Dev. Corr
##  Country  (Intercept)        3.9988   1.9997
##           `Education.(0-10)` 0.1283   0.3582   -0.91
##  Residual                    1.8175   1.3482
## Number of obs: 285, groups:  Country, 14
##
## Fixed effects:
##                                  Estimate Std. Error t value
## (Intercept)                       2.71979    1.00237   2.713
## `Education.(0-10)`                0.18365    0.14257   1.288
## `Jobs.(0-10)`                     0.15170    0.07254   2.091
## `Income.(0-10)`                  -0.01495    0.12780  -0.117
## `Safety.(0-10)`                  -0.11387    0.05482  -2.077
## `Health.(0-10)`                  -0.07032    0.07799  -0.902
```

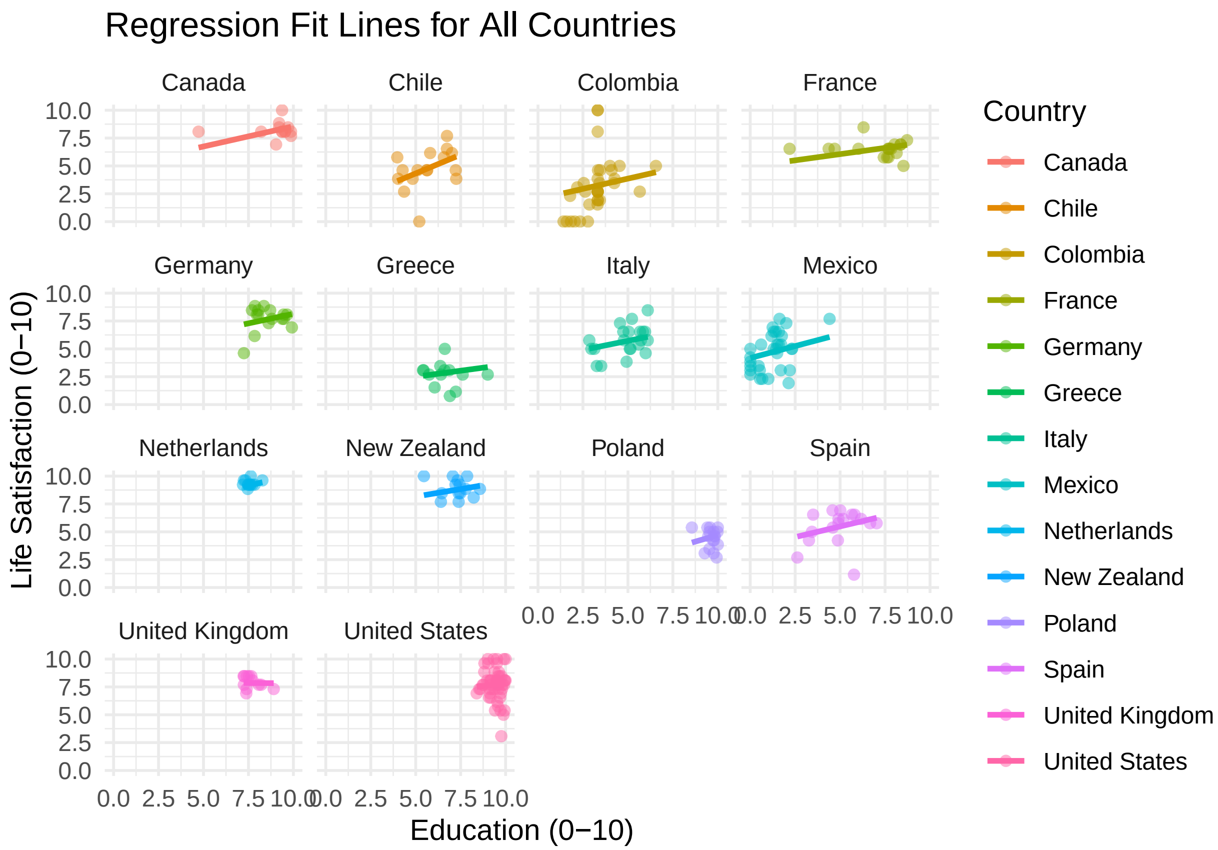
```
## `Environment.(0-10)`               0.18495    0.07071   2.616
## `Civic.engagement.(0-10)`         -0.03511    0.07111  -0.494
## `Accessiblity.to.services.(0-10)`  0.06419    0.08633   0.744
## `Housing.(0-10)`                   0.11566    0.09025   1.282
## `Community.(0-10)`                 0.18027    0.04148   4.346
##
## Correlation of Fixed Effects:
##             (Intr) `Ed.(0-10)` `J.(0- `I.(0- `S.(0- `Hl.(0-10)` `En.(0-10)`
## `Ed.(0-10)` -0.506
## `Jb.(0-10)`  0.003 -0.213
## `In.(0-10)`  0.118 -0.261      -0.134
## `Sf.(0-10)` -0.304 -0.080       0.036  0.033
## `Hl.(0-10)` -0.190  0.055       0.000 -0.166 -0.220
## `En.(0-10)` -0.391 -0.002      -0.076 -0.139  0.012  0.026
## `C..(0-10)`  0.091  0.021      -0.248 -0.152 -0.189 -0.249       0.080
## `A...(0-10) -0.202 -0.121      -0.038 -0.116  0.067 -0.378       0.101
## `Hs.(0-10)`  0.044 -0.202      -0.108  0.096 -0.071  0.213      -0.234
## `Cm.(0-10)` -0.234 -0.024      -0.018 -0.014  0.086 -0.003      -0.011
##             `C..(0 `A...( `Hs.(0-10)`
## `Ed.(0-10)`
## `Jb.(0-10)`
## `In.(0-10)`
## `Sf.(0-10)`
## `Hl.(0-10)`
## `En.(0-10)`
## `C..(0-10)`
## `A...(0-10) -0.027
## `Hs.(0-10)` -0.175 -0.183
## `Cm.(0-10)` -0.072  0.083 -0.166
```

Random Intercept Model with Random Slope for Community

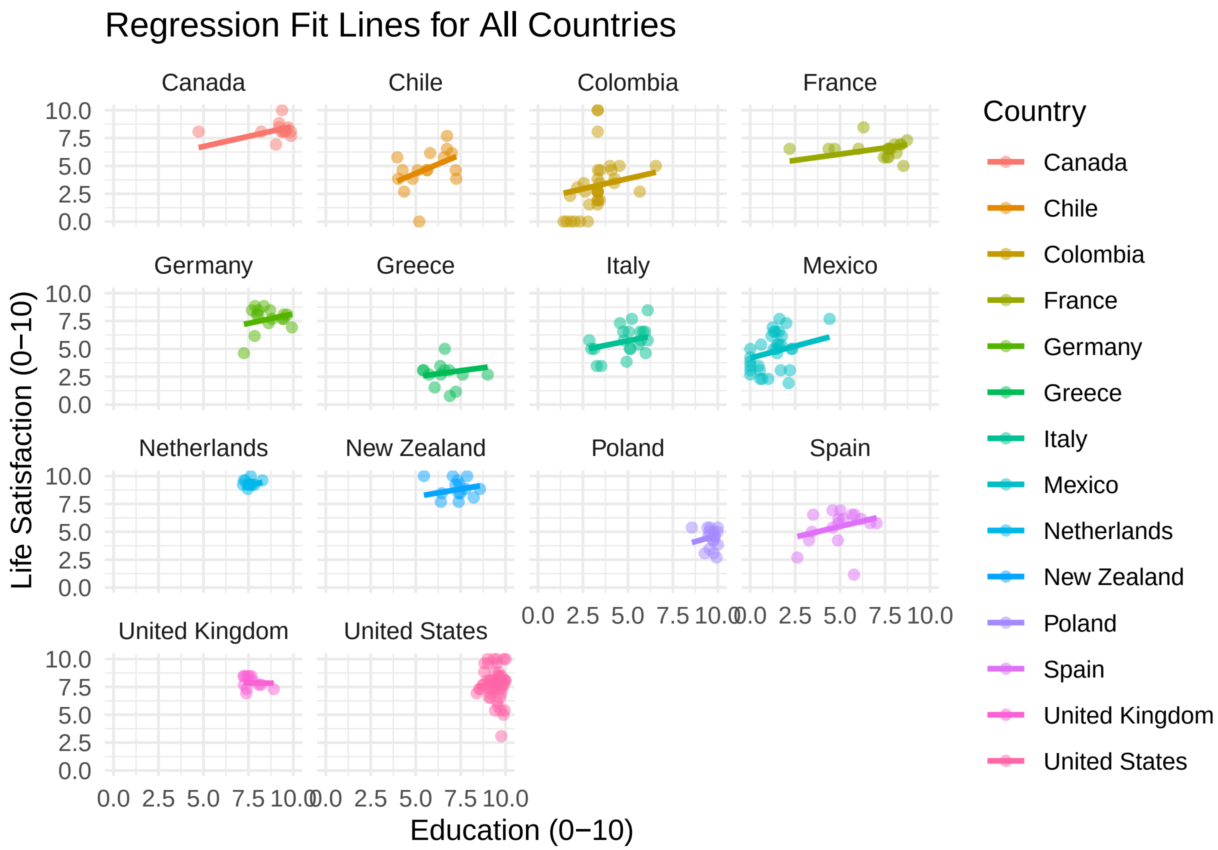
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: `Life.satisfaction.(0-10)` ~ `Education.(0-10)` + `Jobs.(0-10)` +
##     `Income.(0-10)` + `Safety.(0-10)` + `Health.(0-10)` + `Environment.(0-10)` +
##     `Civic.engagement.(0-10)` + `Accessiblity.to.services.(0-10)` +
##     `Housing.(0-10)` + `Community.(0-10)` + (1 + `Community.(0-10)` |
##     Country)
##    Data: df_wb %>% select(-Region, -Code)
##
## REML criterion at convergence: 1045.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8163 -0.3721  0.0712  0.4790  3.6315
##
## Random effects:
##  Groups   Name                Variance Std.Dev. Corr
##  Country  (Intercept)         3.257    1.8047
##           `Community.(0-10)` 0.029    0.1703   -0.75
##  Residual                     1.782    1.3351
## Number of obs: 285, groups:  Country, 14
##
```

```
## Fixed effects:
##                                    Estimate Std. Error t value
## (Intercept)                         2.05779    0.97012   2.121
## `Education.(0-10)`                  0.20139    0.10045   2.005
## `Jobs.(0-10)`                       0.13475    0.06885   1.957
## `Income.(0-10)`                    -0.04688    0.11898  -0.394
## `Safety.(0-10)`                    -0.06680    0.05419  -1.233
## `Health.(0-10)`                    -0.01616    0.07737  -0.209
## `Environment.(0-10)`                0.15195    0.06775   2.243
## `Civic.engagement.(0-10)`          -0.15918    0.06870  -2.317
## `Accessiblity.to.services.(0-10)`   0.10479    0.08517   1.230
## `Housing.(0-10)`                    0.14577    0.08442   1.727
## `Community.(0-10)`                  0.20786    0.06982   2.977
##
## Correlation of Fixed Effects:
##             (Intr) `Ed.(0-10)` `J.(0- `I.(0- `S.(0- `Hl.(0-10)` `En.(0-10)`
## `Ed.(0-10)` -0.134
## `Jb.(0-10)` -0.129 -0.252
## `In.(0-10)`  0.032 -0.285      -0.183
## `Sf.(0-10)` -0.337 -0.150       0.090  0.027
## `Hl.(0-10)` -0.107  0.063       0.011 -0.190 -0.185
## `En.(0-10)` -0.384 -0.022      -0.063 -0.071  0.035 -0.026
## `C..(0-10)`  0.074  0.030      -0.341 -0.060 -0.172 -0.290       0.112
## `A...(0-10) -0.197 -0.274       0.062 -0.075  0.053 -0.376       0.083
## `Hs.(0-10)`  0.020 -0.283      -0.006  0.054 -0.012  0.144      -0.245
## `Cm.(0-10)` -0.501 -0.048       0.008  0.000  0.040 -0.008      -0.023
##             `C..(0 `A...( `Hs.(0-10)`
## `Ed.(0-10)`
## `Jb.(0-10)`
## `In.(0-10)`
## `Sf.(0-10)`
## `Hl.(0-10)`
## `En.(0-10)`
## `C..(0-10)`
## `A...(0-10) -0.016
## `Hs.(0-10)` -0.231 -0.143
## `Cm.(0-10)` -0.021  0.049 -0.077
```

Plots for Random Intercept Model

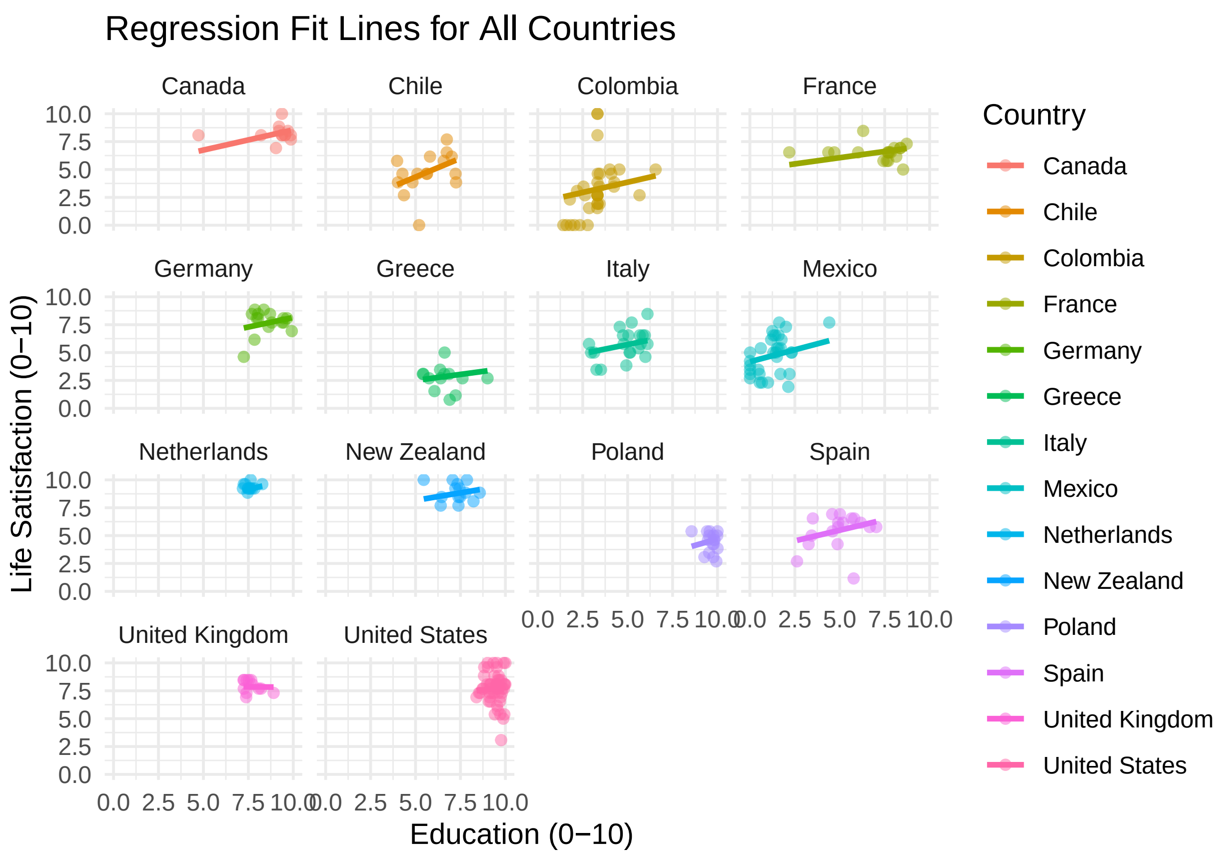


Plots for Random Intercept Model with Random Slope for Education



Plots for Random Intercept Model with Random Slope for Community

```
## `geom_smooth()` using formula = 'y ~ x'
```

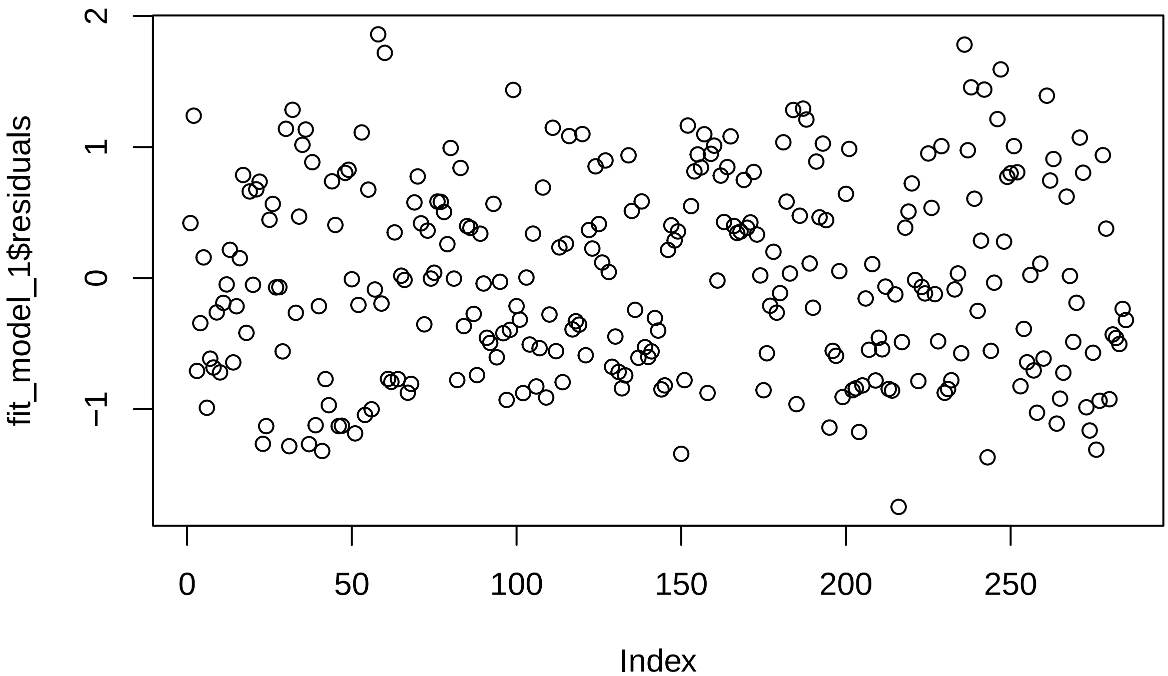


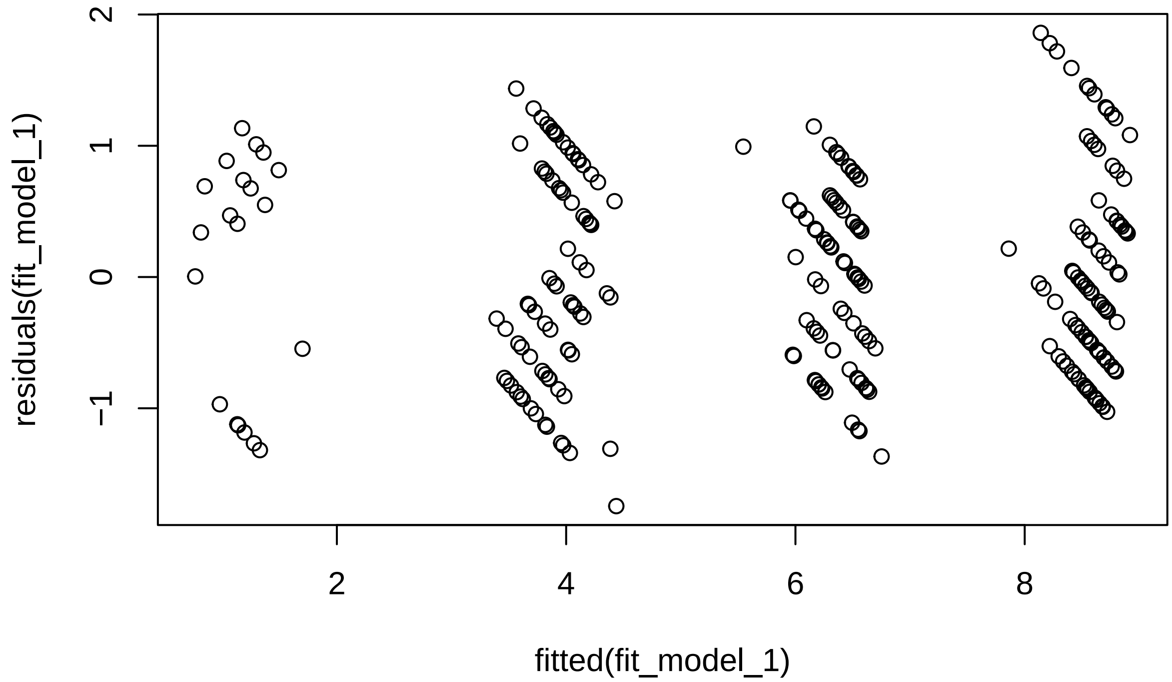
R Squared

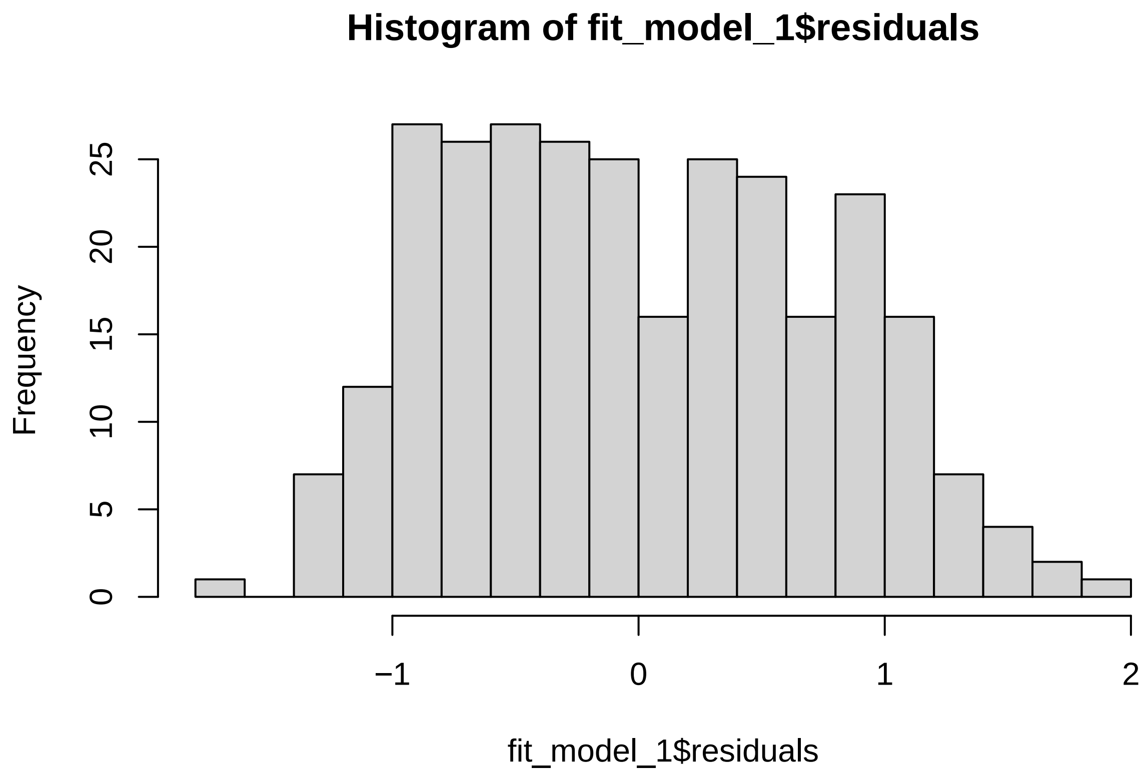
```
##                                          Model R_Squared_Marginal
## 1                       Random Intercept Model          0.4164078
## 2 Random Intercept with Random Slope for Education          0.4034987
## 3 Random Intercept with Random Slope for Community          0.4276506
##   R_Squared_Conditional
## 1             0.6968376
## 2             0.7139324
## 3             0.7065214
```

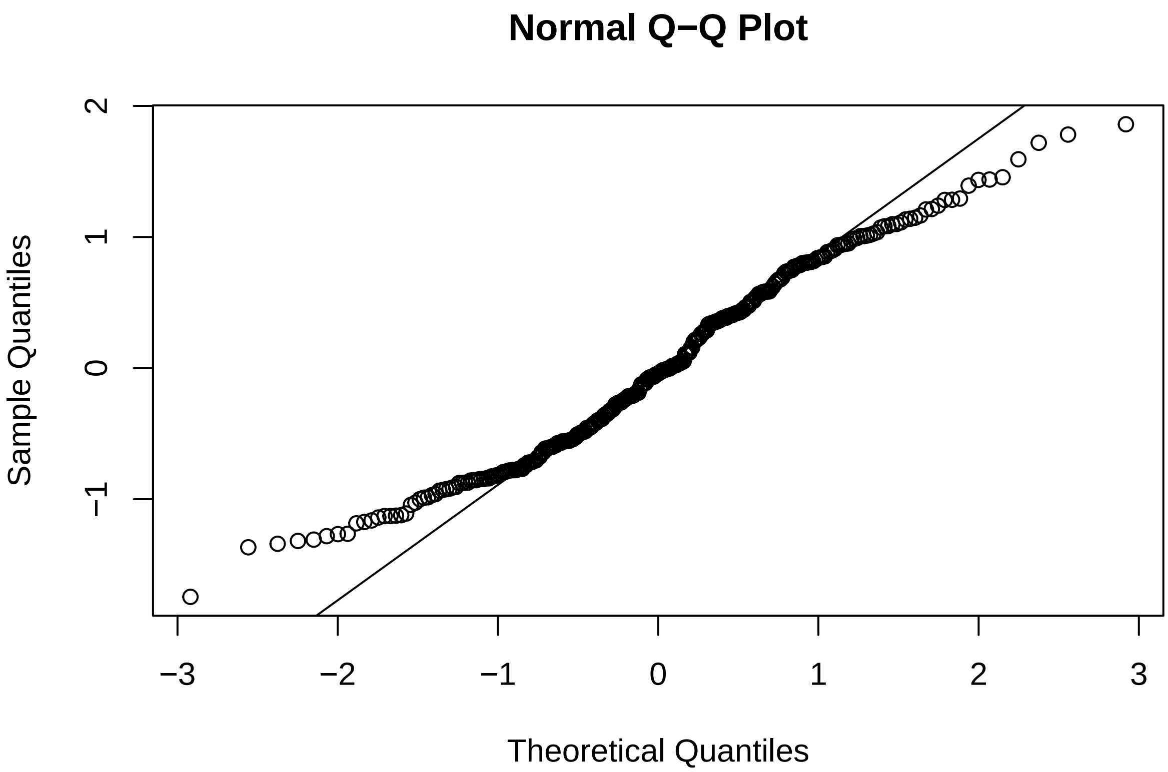
The table shows improvement in explanation of variables by the model with a random slope for Community. Further, it is noteworthy that the improvement over base models is not significant.

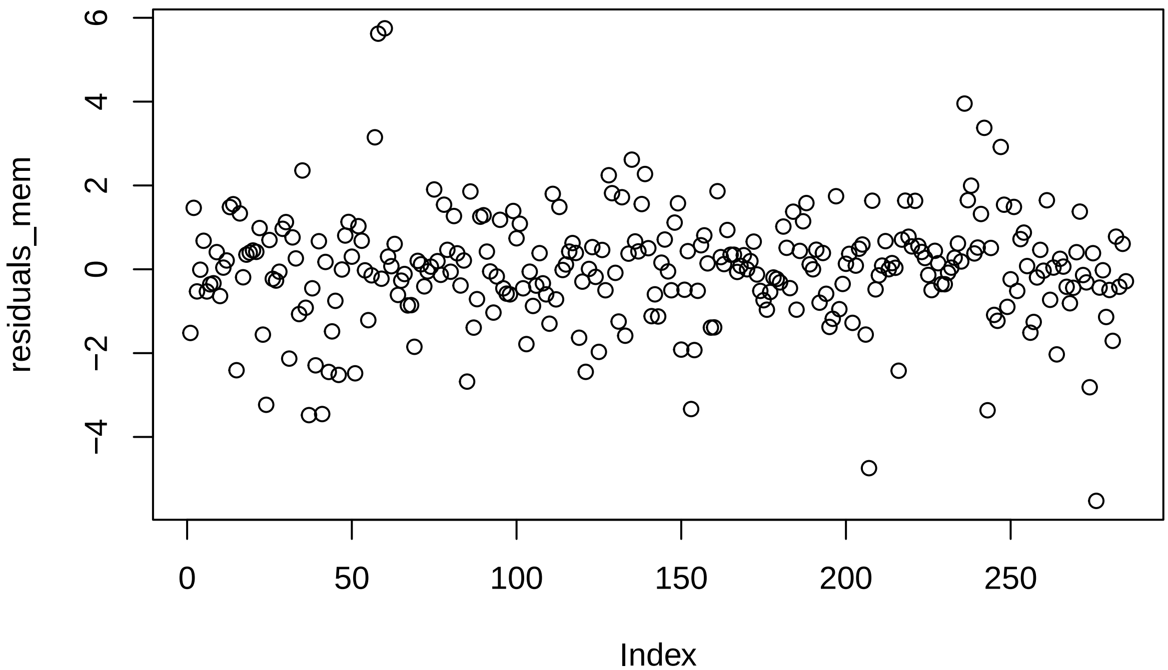
Residual Analysis

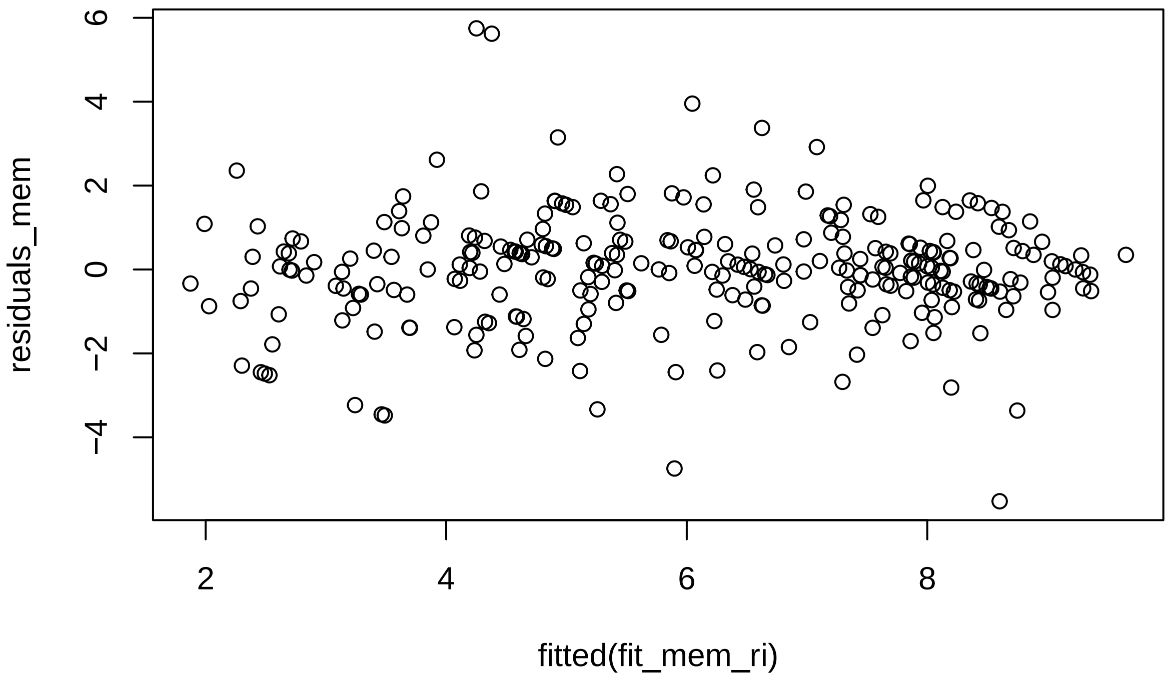


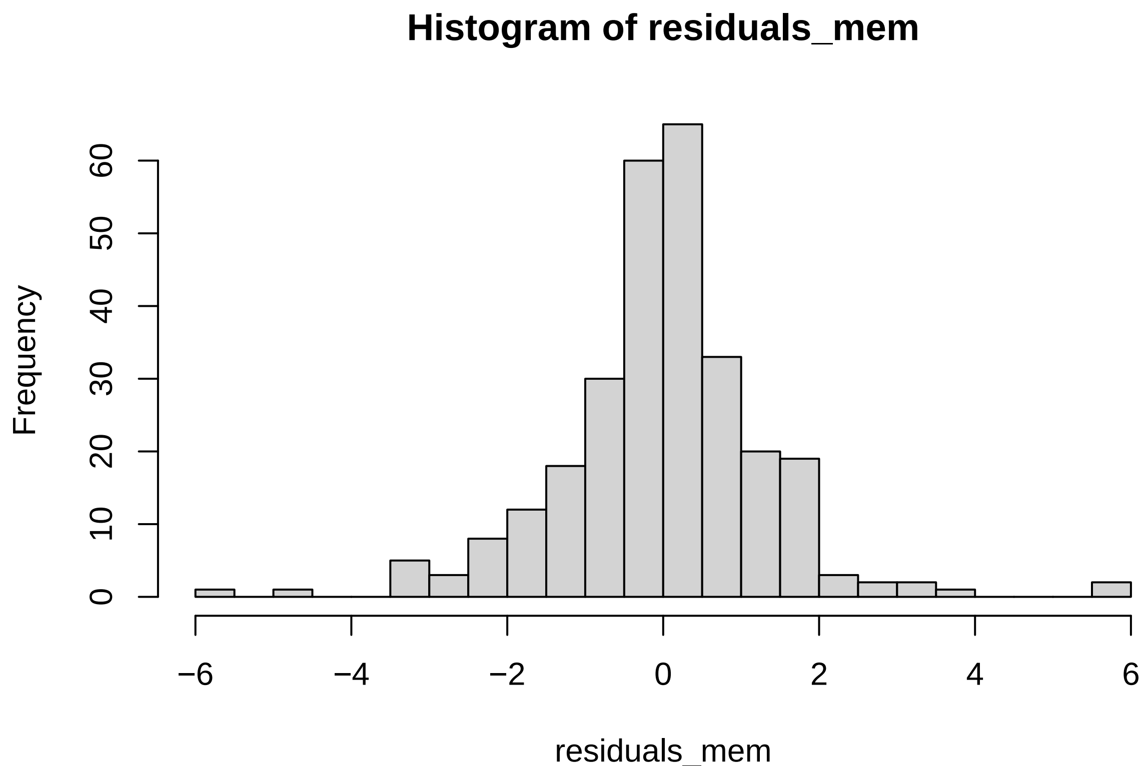

residuals(fit_model_1)
fitted(fit_model_1)
2
1
0
−1
2
4
6
8

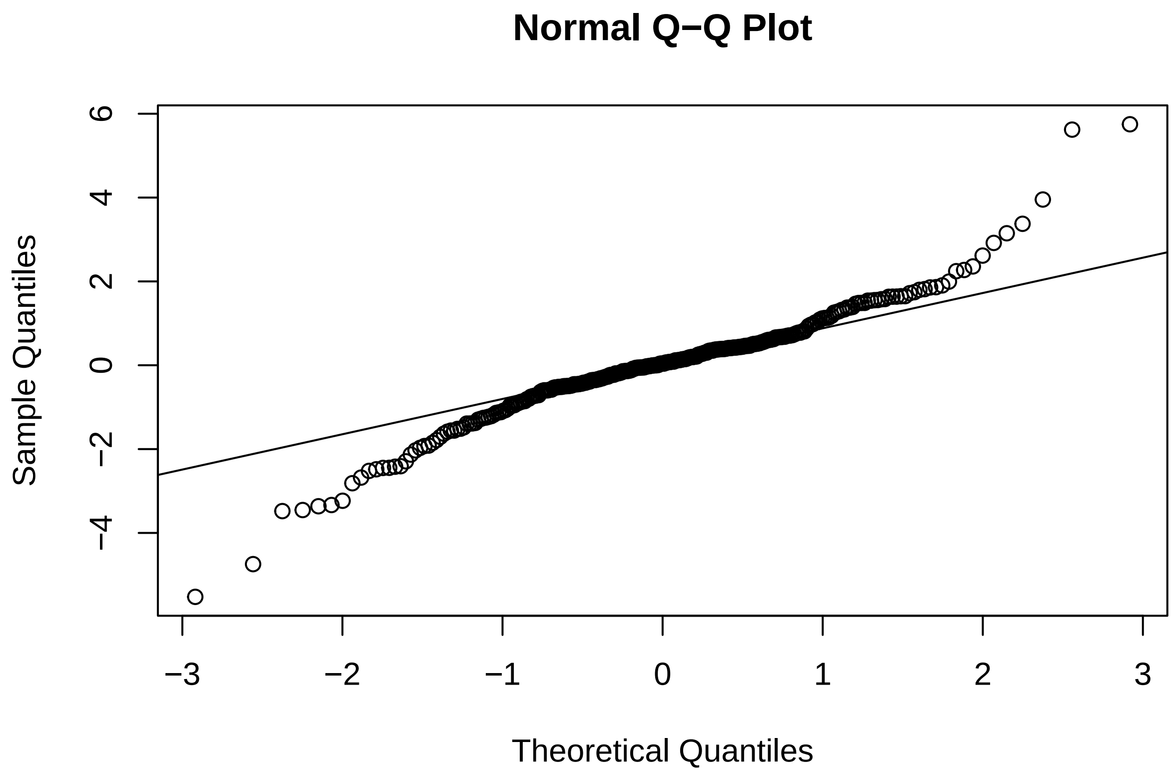

Histogram of fit_model_1$residuals
Frequency
0
5
10
15
20
25
−1
0
1
2
fit_model_1$residuals

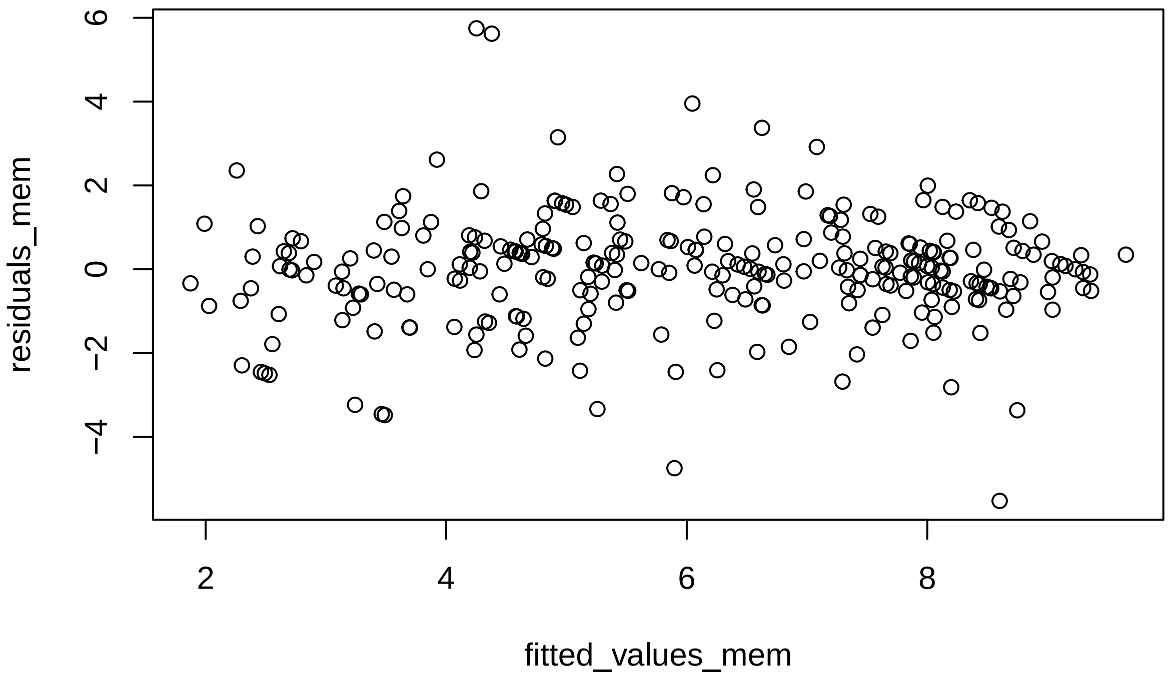

Normal Q−Q Plot
Sample Quantiles
Theoretical Quantiles
−3
−2
−1
0
1
2
3
−1
0
1
2


residuals_mem
Index
6
4
2
0
−2
−4
0
50
100
150
200
250


residuals_mem
fitted(fit_mem_ri)
6
4
2
0
−2
−4
2
4
6
8

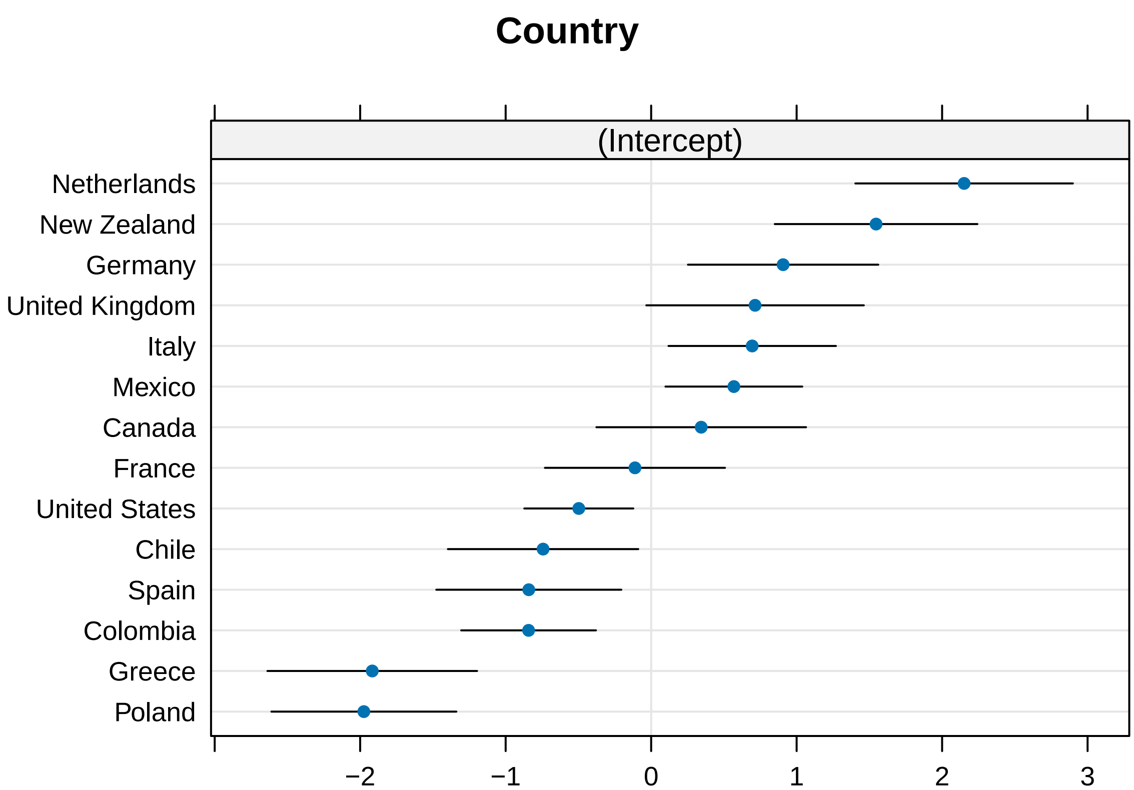

Histogram of residuals_mem
Frequency
0
10
20
30
40
50
60
−6
−4
−2
0
2
4
6
residuals_mem


Normal Q−Q Plot
Sample Quantiles
Theoretical Quantiles
6
4
2
0
−2
−4
−3
−2
−1
0
1
2
3



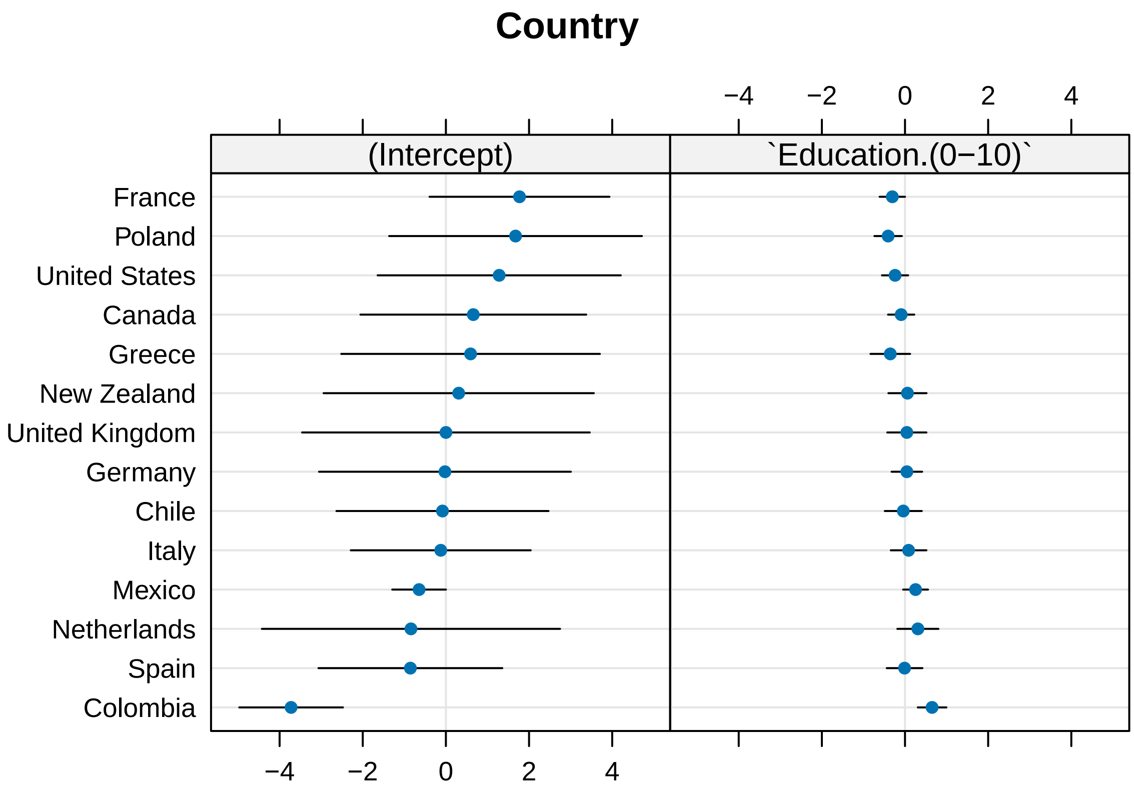
Creating Dot Plots

```
## $Country
```

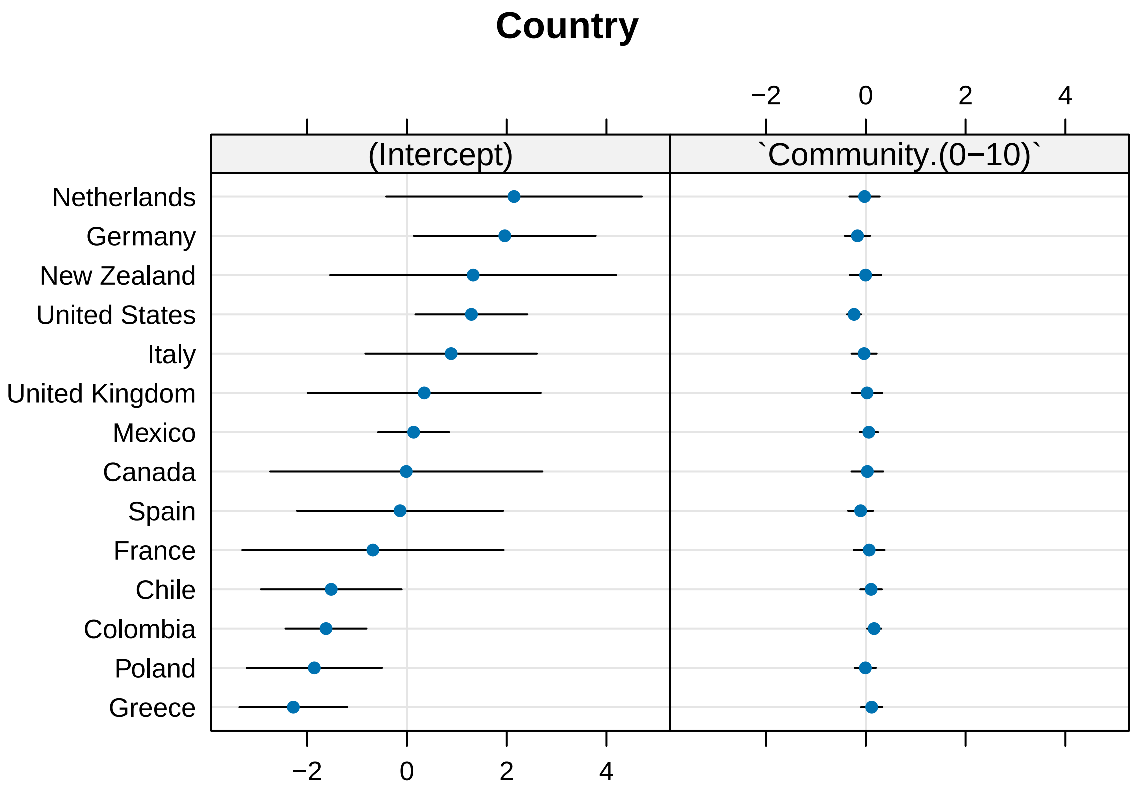


Country
(Intercept)
Netherlands
New Zealand
Germany
United Kingdom
Italy
Mexico
Canada
France
United States
Chile
Spain
Colombia
Greece
Poland
−2
−1
0
1
2
3


```
## $Country
```


Country
(Intercept)
`Education.(0−10)`
France
Poland
United States
Canada
Greece
New Zealand
United Kingdom
Germany
Chile
Italy
Mexico
Netherlands
Spain
Colombia
−4
−2
0
2
4

```
## $Country
```



AIC and BIC of the four models

```
##                         Model       AIC       BIC
## 1                     Model 1  671.3716  729.8114
## 2                     Model 2  618.5430  998.4019
## 3                     Model 3  965.2609 1060.2256
## 4 Model 4 (Random Intercept) 1082.4098 1129.8922
## 5          Model 5 (RI+S_Edu 1078.2695 1133.0569
## 6         Model 6 (RI+S_Comm) 1075.2022 1129.9896
```

From this comparison, we see that the **Interaction effect no group model** gives a better fit for the data, instead of the complex models. This can be due to the fact that we lack enough data points in each category, thus making the complex models work poorly.

Conclusion

To conclude, we can say that.......

Appendix

A: Summary of Clusters with Model Fitted

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VEV (ellipsoidal, equal shape) model with 4 components:
##
##  log-likelihood   n  df       BIC       ICL
##       -1627.609 285 236 -4589.206 -4589.333
##
## Clustering table:
##   1   2   3   4
## 115  57  65  48
##
## Mixing probabilities:
##         1         2         3         4
## 0.4032620 0.2002456 0.2280711 0.1684213
##
## Means:
##                                   [,1]        [,2]       [,3]       [,4]
## Education.(0-10)                0.2059389  0.33610881 -1.4232941  1.0346704
## Jobs.(0-10)                     0.2901518 -0.36102661 -0.7000418  0.6824914
## Income.(0-10)                   0.0869365 -0.32957114 -1.1448790  1.7340488
## Safety.(0-10)                   0.6056543  0.40874312 -1.5171713  0.1183728
## Health.(0-10)                   0.7777678 -0.07678917 -0.8056766 -0.6799380
## Environment.(0-10)              0.4146131 -0.88000950 -0.6445377  0.9263714
## Civic.engagement.(0-10)         0.8150896 -1.02976944 -0.6947396  0.2135245
## Accessiblity.to.services.(0-10) 0.4584912  0.05241932 -1.4161384  0.7575726
## Housing.(0-10)                  0.4050547 -0.63898592 -1.1635679  1.3655462
## Community.(0-10)                0.4754022 -0.32931839 -0.9612754  0.5549891
##
## Variances:
## [,,1]
##                                 Education.(0-10)  Jobs.(0-10) Income.(0-10)
## Education.(0-10)                      0.34980136  0.407182085   0.092807170
## Jobs.(0-10)                           0.40718209  0.834731225   0.119791045
## Income.(0-10)                         0.09280717  0.119791045   0.065108587
## Safety.(0-10)                        -0.01655527 -0.006133159  -0.003876554
## Health.(0-10)                        -0.05879976 -0.115383455   0.025958817
## Environment.(0-10)                    0.10349335 -0.009294753  -0.030499331
## Civic.engagement.(0-10)               0.14509401  0.281653439   0.032168567
## Accessiblity.to.services.(0-10)       0.02158839 -0.098242664   0.033742609
## Housing.(0-10)                        0.18503138  0.170892287   0.001044623
## Community.(0-10)                      0.06030100  0.059233844  -0.022023868
##                                 Safety.(0-10) Health.(0-10) Environment.(0-10)
## Education.(0-10)                 -0.016555274   -0.05879976        0.103493347
## Jobs.(0-10)                      -0.006133159   -0.11538346       -0.009294753
## Income.(0-10)                    -0.003876554    0.02595882       -0.030499331
## Safety.(0-10)                     0.006718398    0.00822568       -0.015635688
## Health.(0-10)                     0.008225680    0.21609910       -0.078631354
## Environment.(0-10)               -0.015635688   -0.07863135        0.387884547
```

```
## Civic.engagement.(0-10)          -0.001524007    0.02423316       -0.015511267
## Accessiblity.to.services.(0-10)  -0.006549369    0.11456670        0.040168215
## Housing.(0-10)                   -0.016589154   -0.08974164        0.274621107
## Community.(0-10)                 -0.005168471   -0.02580432        0.167395605
##                                 Civic.engagement.(0-10)
## Education.(0-10)                             0.145094013
## Jobs.(0-10)                                  0.281653439
## Income.(0-10)                                0.032168567
## Safety.(0-10)                               -0.001524007
## Health.(0-10)                                0.024233157
## Environment.(0-10)                          -0.015511267
## Civic.engagement.(0-10)                      0.312758868
## Accessiblity.to.services.(0-10)              0.009385007
## Housing.(0-10)                               0.062255648
## Community.(0-10)                             0.056006849
##                                 Accessiblity.to.services.(0-10) Housing.(0-10)
## Education.(0-10)                                     0.021588389    0.185031378
## Jobs.(0-10)                                         -0.098242664    0.170892287
## Income.(0-10)                                        0.033742609    0.001044623
## Safety.(0-10)                                       -0.006549369   -0.016589154
## Health.(0-10)                                        0.114566698   -0.089741638
## Environment.(0-10)                                   0.040168215    0.274621107
## Civic.engagement.(0-10)                              0.009385007    0.062255648
## Accessiblity.to.services.(0-10)                      0.297895467    0.098310627
## Housing.(0-10)                                       0.098310627    0.368370397
## Community.(0-10)                                     0.056802692    0.169917710
##                                 Community.(0-10)
## Education.(0-10)                      0.060300996
## Jobs.(0-10)                           0.059233844
## Income.(0-10)                        -0.022023868
## Safety.(0-10)                        -0.005168471
## Health.(0-10)                        -0.025804318
## Environment.(0-10)                    0.167395605
## Civic.engagement.(0-10)               0.056006849
## Accessiblity.to.services.(0-10)       0.056802692
## Housing.(0-10)                        0.169917710
## Community.(0-10)                      0.340576918
## [,,2]
##                                 Education.(0-10)  Jobs.(0-10) Income.(0-10)
## Education.(0-10)                      0.704440177  0.645273600    0.37880250
## Jobs.(0-10)                           0.645273600  1.273236111    0.38020307
## Income.(0-10)                         0.378802504  0.380203066    0.72351089
## Safety.(0-10)                         0.001136638 -0.045726193   -0.18315198
## Health.(0-10)                        -0.864678917 -1.025965923   -0.54759686
## Environment.(0-10)                    0.339637297  0.001309143    0.73086258
## Civic.engagement.(0-10)               0.529657744  0.472669503    0.46917669
## Accessiblity.to.services.(0-10)       0.191802268  0.490562370   -0.04139288
## Housing.(0-10)                        0.110166160  0.033336242    0.34737005
## Community.(0-10)                     -0.024431717  0.114990735   -0.01293922
##                                 Safety.(0-10) Health.(0-10) Environment.(0-10)
## Education.(0-10)                  0.001136638   -0.86467892        0.339637297
## Jobs.(0-10)                      -0.045726193   -1.02596592        0.001309143
## Income.(0-10)                    -0.183151982   -0.54759686        0.730862577
## Safety.(0-10)                     0.177700880    0.07287982       -0.155290192
```

```
## Health.(0-10)                     0.072879818    1.96342448       -0.532833668
## Environment.(0-10)               -0.155290192   -0.53283367        2.070902923
## Civic.engagement.(0-10)          -0.010952974   -0.64797029        0.388072287
## Accessiblity.to.services.(0-10)  -0.040980803   -0.02348970       -0.513211345
## Housing.(0-10)                   -0.150007073   -0.08468139        0.471642398
## Community.(0-10)                 -0.184290447   -0.19951018        0.089476918
##                                 Civic.engagement.(0-10)
## Education.(0-10)                             0.529657744
## Jobs.(0-10)                                  0.472669503
## Income.(0-10)                                0.469176690
## Safety.(0-10)                               -0.010952974
## Health.(0-10)                               -0.647970295
## Environment.(0-10)                           0.388072287
## Civic.engagement.(0-10)                      0.753461869
## Accessiblity.to.services.(0-10)             -0.025272599
## Housing.(0-10)                               0.138877483
## Community.(0-10)                            -0.003184435
##                                 Accessiblity.to.services.(0-10) Housing.(0-10)
## Education.(0-10)                                     0.191802268     0.11016616
## Jobs.(0-10)                                          0.490562370     0.03333624
## Income.(0-10)                                       -0.041392877     0.34737005
## Safety.(0-10)                                       -0.040980803    -0.15000707
## Health.(0-10)                                       -0.023489700    -0.08468139
## Environment.(0-10)                                  -0.513211345     0.47164240
## Civic.engagement.(0-10)                             -0.025272599     0.13887748
## Accessiblity.to.services.(0-10)                      0.755407352    -0.16356952
## Housing.(0-10)                                      -0.163569521     0.34007860
## Community.(0-10)                                     0.002148064     0.11500946
##                                 Community.(0-10)
## Education.(0-10)                    -0.024431717
## Jobs.(0-10)                          0.114990735
## Income.(0-10)                       -0.012939225
## Safety.(0-10)                       -0.184290447
## Health.(0-10)                       -0.199510185
## Environment.(0-10)                   0.089476918
## Civic.engagement.(0-10)             -0.003184435
## Accessiblity.to.services.(0-10)      0.002148064
## Housing.(0-10)                       0.115009461
## Community.(0-10)                     1.225117273
## [,,3]
##                                 Education.(0-10)  Jobs.(0-10) Income.(0-10)
## Education.(0-10)                     0.218292478 -0.249089461   0.042661919
## Jobs.(0-10)                         -0.249089461  0.669576935  -0.047674565
## Income.(0-10)                        0.042661919 -0.047674565   0.015622258
## Safety.(0-10)                       -0.010498767  0.107953617  -0.004919550
## Health.(0-10)                        0.155340032 -0.282051158   0.039814031
## Environment.(0-10)                  -0.003886977  0.060657513  -0.001295857
## Civic.engagement.(0-10)              0.101859301 -0.296383550   0.015421809
## Accessiblity.to.services.(0-10)     -0.078066048  0.329833103  -0.011416315
## Housing.(0-10)                       0.007779135  0.001859178   0.005790162
## Community.(0-10)                     0.151245621 -0.262665963   0.023542835
##                                 Safety.(0-10) Health.(0-10) Environment.(0-10)
## Education.(0-10)                 -0.010498767   0.155340032      -0.0038869767
## Jobs.(0-10)                       0.107953617  -0.282051158       0.0606575128
```

```
## Income.(0-10)                    -0.004919550  0.039814031     -0.0012958570
## Safety.(0-10)                     0.849739159  0.042503745     -0.0925500706
## Health.(0-10)                     0.042503745  0.299712175      0.0023038611
## Environment.(0-10)               -0.092550071  0.002303861      0.1666364139
## Civic.engagement.(0-10)           0.086947473  0.190595793     -0.0346634692
## Accessiblity.to.services.(0-10)   0.102055221 -0.165786860     -0.0247877003
## Housing.(0-10)                   -0.006502189  0.010872885     -0.0003924336
## Community.(0-10)                 -0.149741117  0.132660767     -0.0136392994
##                                 Civic.engagement.(0-10)
## Education.(0-10)                             0.10185930
## Jobs.(0-10)                                 -0.29638355
## Income.(0-10)                                0.01542181
## Safety.(0-10)                                0.08694747
## Health.(0-10)                                0.19059579
## Environment.(0-10)                          -0.03466347
## Civic.engagement.(0-10)                      0.43308331
## Accessiblity.to.services.(0-10)             -0.26609935
## Housing.(0-10)                              -0.03514126
## Community.(0-10)                             0.17591681
##                                 Accessiblity.to.services.(0-10) Housing.(0-10)
## Education.(0-10)                                     -0.07806605   0.0077791349
## Jobs.(0-10)                                           0.32983310   0.0018591777
## Income.(0-10)                                        -0.01141631   0.0057901620
## Safety.(0-10)                                         0.10205522  -0.0065021886
## Health.(0-10)                                        -0.16578686   0.0108728849
## Environment.(0-10)                                   -0.02478770  -0.0003924336
## Civic.engagement.(0-10)                              -0.26609935  -0.0351412570
## Accessiblity.to.services.(0-10)                       0.38617419   0.0416321848
## Housing.(0-10)                                        0.04163218   0.0324726173
## Community.(0-10)                                     -0.20336860  -0.0175575090
##                                 Community.(0-10)
## Education.(0-10)                      0.15124562
## Jobs.(0-10)                          -0.26266596
## Income.(0-10)                         0.02354284
## Safety.(0-10)                        -0.14974112
## Health.(0-10)                         0.13266077
## Environment.(0-10)                   -0.01363930
## Civic.engagement.(0-10)               0.17591681
## Accessiblity.to.services.(0-10)      -0.20336860
## Housing.(0-10)                       -0.01755751
## Community.(0-10)                      0.72232047
## [,,4]
##                                 Education.(0-10) Jobs.(0-10) Income.(0-10)
## Education.(0-10)                     0.019020781  0.03488645   0.022812218
## Jobs.(0-10)                          0.034886450  0.12245668   0.024135948
## Income.(0-10)                        0.022812218  0.02413595   0.151095287
## Safety.(0-10)                        0.021338578  0.03942980   0.050384797
## Health.(0-10)                        0.029617392  0.04709618   0.164715557
## Environment.(0-10)                   0.014435187  0.02236032   0.002246519
## Civic.engagement.(0-10)              0.042495061  0.05846904   0.099841828
## Accessiblity.to.services.(0-10)     -0.007249655 -0.01310691   0.040136487
## Housing.(0-10)                       0.024885177  0.05468386  -0.014590003
## Community.(0-10)                     0.015451488  0.03948197   0.013357092
##                                 Safety.(0-10) Health.(0-10) Environment.(0-10)
```

```
## Education.(0-10)                  0.021338578    0.02961739        0.014435187
## Jobs.(0-10)                       0.039429803    0.04709618        0.022360316
## Income.(0-10)                     0.050384797    0.16471556        0.002246519
## Safety.(0-10)                     0.085072399    0.12070134        0.040667466
## Health.(0-10)                     0.120701339    0.39759859        0.037280729
## Environment.(0-10)                0.040667466    0.03728073        0.078381753
## Civic.engagement.(0-10)           0.070935696    0.22898453        0.029828024
## Accessiblity.to.services.(0-10)  -0.013360516    0.02983863       -0.040759637
## Housing.(0-10)                   -0.007441072   -0.07947989        0.010579484
## Community.(0-10)                  0.033961317    0.00983620        0.014585084
##                                 Civic.engagement.(0-10)
## Education.(0-10)                             0.04249506
## Jobs.(0-10)                                  0.05846904
## Income.(0-10)                                0.09984183
## Safety.(0-10)                                0.07093570
## Health.(0-10)                                0.22898453
## Environment.(0-10)                           0.02982802
## Civic.engagement.(0-10)                      0.26696445
## Accessiblity.to.services.(0-10)              0.02307354
## Housing.(0-10)                               0.02013529
## Community.(0-10)                            -0.02692342
##                                 Accessiblity.to.services.(0-10) Housing.(0-10)
## Education.(0-10)                                   -0.007249655    0.024885177
## Jobs.(0-10)                                        -0.013106907    0.054683862
## Income.(0-10)                                       0.040136487   -0.014590003
## Safety.(0-10)                                      -0.013360516   -0.007441072
## Health.(0-10)                                       0.029838633   -0.079479892
## Environment.(0-10)                                 -0.040759637    0.010579484
## Civic.engagement.(0-10)                             0.023073541    0.020135289
## Accessiblity.to.services.(0-10)                     0.098684022   -0.024229531
## Housing.(0-10)                                     -0.024229531    0.092641409
## Community.(0-10)                                   -0.034832576    0.006234386
##                                 Community.(0-10)
## Education.(0-10)                      0.015451488
## Jobs.(0-10)                           0.039481971
## Income.(0-10)                         0.013357092
## Safety.(0-10)                         0.033961317
## Health.(0-10)                         0.009836200
## Environment.(0-10)                    0.014585084
## Civic.engagement.(0-10)              -0.026923419
## Accessiblity.to.services.(0-10)      -0.034832576
## Housing.(0-10)                        0.006234386
## Community.(0-10)                      0.386789965
```

B: Summary of Linear Regression using Pairwise Interaction effects

```
##
## Call:
## lm(formula = `Life.satisfaction.(0-10)` ~ .^2, data = df_wb %>%
##     select(-Country, -Region, -Code))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -1.09611 -0.36605 -0.03063  0.31955  1.23265
##
## Coefficients:
##                                                               Estimate
## (Intercept)                                                 -8.3026458
## `Education.(0-10)`                                           1.5234003
## `Jobs.(0-10)`                                                0.2406282
## `Income.(0-10)`                                             -0.5338477
## `Safety.(0-10)`                                              0.0330612
## `Health.(0-10)`                                             -0.7064951
## `Environment.(0-10)`                                         0.2500438
## `Civic.engagement.(0-10)`                                   -0.3499145
## `Accessiblity.to.services.(0-10)`                            0.5425568
## `Housing.(0-10)`                                             0.0618109
## `Community.(0-10)`                                           0.5122832
## Cluster                                                      3.0154832
## LifeSatisfactionCluster2.5-5                                 2.8267989
## LifeSatisfactionCluster5-7.5                                 1.8502394
## LifeSatisfactionCluster7.5-10                                6.2256178
## `Education.(0-10)`:`Jobs.(0-10)`                             0.0001758
## `Education.(0-10)`:`Income.(0-10)`                           0.0618977
## `Education.(0-10)`:`Safety.(0-10)`                          -0.0615710
## `Education.(0-10)`:`Health.(0-10)`                          -0.0177132
## `Education.(0-10)`:`Environment.(0-10)`                      0.0318438
## `Education.(0-10)`:`Civic.engagement.(0-10)`                -0.0862557
## `Education.(0-10)`:`Accessiblity.to.services.(0-10)`         0.0145184
## `Education.(0-10)`:`Housing.(0-10)`                          0.0588407
## `Education.(0-10)`:`Community.(0-10)`                        0.0220960
## `Education.(0-10)`:Cluster                                  -0.1709954
## `Education.(0-10)`:LifeSatisfactionCluster2.5-5             -1.0259508
## `Education.(0-10)`:LifeSatisfactionCluster5-7.5             -1.1521283
## `Education.(0-10)`:LifeSatisfactionCluster7.5-10            -1.1560547
## `Jobs.(0-10)`:`Income.(0-10)`                               -0.0153609
## `Jobs.(0-10)`:`Safety.(0-10)`                               -0.0325196
## `Jobs.(0-10)`:`Health.(0-10)`                                0.0077391
## `Jobs.(0-10)`:`Environment.(0-10)`                          -0.0098039
## `Jobs.(0-10)`:`Civic.engagement.(0-10)`                      0.0325799
## `Jobs.(0-10)`:`Accessiblity.to.services.(0-10)`             -0.0182378
## `Jobs.(0-10)`:`Housing.(0-10)`                               0.0985468
## `Jobs.(0-10)`:`Community.(0-10)`                            -0.0248100
## `Jobs.(0-10)`:Cluster                                       -0.0462812
## `Jobs.(0-10)`:LifeSatisfactionCluster2.5-5                  -0.0480993
## `Jobs.(0-10)`:LifeSatisfactionCluster5-7.5                   0.1303739
## `Jobs.(0-10)`:LifeSatisfactionCluster7.5-10                 -0.1645694
## `Income.(0-10)`:`Safety.(0-10)`                              0.0520013
## `Income.(0-10)`:`Health.(0-10)`                             -0.0490305
## `Income.(0-10)`:`Environment.(0-10)`                        -0.0242222
## `Income.(0-10)`:`Civic.engagement.(0-10)`                   -0.0274103
## `Income.(0-10)`:`Accessiblity.to.services.(0-10)`           -0.0074923
## `Income.(0-10)`:`Housing.(0-10)`                            -0.1504574
## `Income.(0-10)`:`Community.(0-10)`                          -0.0162743
## `Income.(0-10)`:Cluster                                      0.0296444
## `Income.(0-10)`:LifeSatisfactionCluster2.5-5                 0.7705041
## `Income.(0-10)`:LifeSatisfactionCluster5-7.5                 1.1367036
```

```
## `Income.(0-10)`:LifeSatisfactionCluster7.5-10                  1.3721030
## `Safety.(0-10)`:`Health.(0-10)`                                -0.0013248
## `Safety.(0-10)`:`Environment.(0-10)`                            0.0035969
## `Safety.(0-10)`:`Civic.engagement.(0-10)`                       0.0621985
## `Safety.(0-10)`:`Accessiblity.to.services.(0-10)`               0.0514590
## `Safety.(0-10)`:`Housing.(0-10)`                               -0.0305515
## `Safety.(0-10)`:`Community.(0-10)`                              0.0128350
## `Safety.(0-10)`:Cluster                                        -0.0687200
## `Safety.(0-10)`:LifeSatisfactionCluster2.5-5                    0.0206238
## `Safety.(0-10)`:LifeSatisfactionCluster5-7.5                    0.0529117
## `Safety.(0-10)`:LifeSatisfactionCluster7.5-10                   0.0603829
## `Health.(0-10)`:`Environment.(0-10)`                           -0.0121420
## `Health.(0-10)`:`Civic.engagement.(0-10)`                       0.0285231
## `Health.(0-10)`:`Accessiblity.to.services.(0-10)`              -0.0105407
## `Health.(0-10)`:`Housing.(0-10)`                                0.0608130
## `Health.(0-10)`:`Community.(0-10)`                             -0.0372515
## `Health.(0-10)`:Cluster                                         0.0879618
## `Health.(0-10)`:LifeSatisfactionCluster2.5-5                    0.7397151
## `Health.(0-10)`:LifeSatisfactionCluster5-7.5                    0.9122106
## `Health.(0-10)`:LifeSatisfactionCluster7.5-10                   0.7719480
## `Environment.(0-10)`:`Civic.engagement.(0-10)`                 -0.0067331
## `Environment.(0-10)`:`Accessiblity.to.services.(0-10)`         -0.0152411
## `Environment.(0-10)`:`Housing.(0-10)`                           0.0220474
## `Environment.(0-10)`:`Community.(0-10)`                        -0.0300236
## `Environment.(0-10)`:Cluster                                   -0.0658057
## `Environment.(0-10)`:LifeSatisfactionCluster2.5-5               0.0573317
## `Environment.(0-10)`:LifeSatisfactionCluster5-7.5               0.2273317
## `Environment.(0-10)`:LifeSatisfactionCluster7.5-10             -0.0418219
## `Civic.engagement.(0-10)`:`Accessiblity.to.services.(0-10)`     0.0101297
## `Civic.engagement.(0-10)`:`Housing.(0-10)`                      0.0017670
## `Civic.engagement.(0-10)`:`Community.(0-10)`                    0.0129049
## `Civic.engagement.(0-10)`:Cluster                               0.0602317
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster2.5-5         -0.0707680
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster5-7.5         -0.2643189
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster7.5-10        -0.0201933
## `Accessiblity.to.services.(0-10)`:`Housing.(0-10)`             -0.0424945
## `Accessiblity.to.services.(0-10)`:`Community.(0-10)`           -0.0664558
## `Accessiblity.to.services.(0-10)`:Cluster                      -0.0776084
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster2.5-5  0.2036494
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster5-7.5  0.0180805
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster7.5-10 0.2614342
## `Housing.(0-10)`:`Community.(0-10)`                             0.0388052
## `Housing.(0-10)`:Cluster                                        0.1155528
## `Housing.(0-10)`:LifeSatisfactionCluster2.5-5                  -0.8767178
## `Housing.(0-10)`:LifeSatisfactionCluster5-7.5                  -0.9067667
## `Housing.(0-10)`:LifeSatisfactionCluster7.5-10                 -1.1343786
## `Community.(0-10)`:Cluster                                     -0.0814317
## `Community.(0-10)`:LifeSatisfactionCluster2.5-5                 0.2303806
## `Community.(0-10)`:LifeSatisfactionCluster5-7.5                 0.3340625
## `Community.(0-10)`:LifeSatisfactionCluster7.5-10                0.2238037
## Cluster:LifeSatisfactionCluster2.5-5                           -0.5722182
## Cluster:LifeSatisfactionCluster5-7.5                           -0.2132606
## Cluster:LifeSatisfactionCluster7.5-10                          -0.1161588
##                                                                Std. Error
```

```
## (Intercept)                                                    9.7975950
## `Education.(0-10)`                                             0.7082404
## `Jobs.(0-10)`                                                  0.5022796
## `Income.(0-10)`                                                1.4315522
## `Safety.(0-10)`                                                0.4423181
## `Health.(0-10)`                                                0.4629910
## `Environment.(0-10)`                                           0.5001203
## `Civic.engagement.(0-10)`                                      0.4330903
## `Accessiblity.to.services.(0-10)`                              0.5094257
## `Housing.(0-10)`                                               0.7791232
## `Community.(0-10)`                                             0.3084778
## Cluster                                                        2.7184179
## LifeSatisfactionCluster2.5-5                                   9.0236978
## LifeSatisfactionCluster5-7.5                                   9.1836678
## LifeSatisfactionCluster7.5-10                                  8.9442196
## `Education.(0-10)`:`Jobs.(0-10)`                               0.0234906
## `Education.(0-10)`:`Income.(0-10)`                             0.0536177
## `Education.(0-10)`:`Safety.(0-10)`                             0.0318366
## `Education.(0-10)`:`Health.(0-10)`                             0.0334777
## `Education.(0-10)`:`Environment.(0-10)`                        0.0289460
## `Education.(0-10)`:`Civic.engagement.(0-10)`                   0.0274611
## `Education.(0-10)`:`Accessiblity.to.services.(0-10)`           0.0349920
## `Education.(0-10)`:`Housing.(0-10)`                            0.0346637
## `Education.(0-10)`:`Community.(0-10)`                          0.0167971
## `Education.(0-10)`:Cluster                                     0.1432287
## `Education.(0-10)`:LifeSatisfactionCluster2.5-5                0.3538779
## `Education.(0-10)`:LifeSatisfactionCluster5-7.5                0.3738374
## `Education.(0-10)`:LifeSatisfactionCluster7.5-10               0.4116904
## `Jobs.(0-10)`:`Income.(0-10)`                                  0.0422987
## `Jobs.(0-10)`:`Safety.(0-10)`                                  0.0235518
## `Jobs.(0-10)`:`Health.(0-10)`                                  0.0258990
## `Jobs.(0-10)`:`Environment.(0-10)`                             0.0302121
## `Jobs.(0-10)`:`Civic.engagement.(0-10)`                        0.0205985
## `Jobs.(0-10)`:`Accessiblity.to.services.(0-10)`                0.0292603
## `Jobs.(0-10)`:`Housing.(0-10)`                                 0.0286838
## `Jobs.(0-10)`:`Community.(0-10)`                               0.0156543
## `Jobs.(0-10)`:Cluster                                          0.0908453
## `Jobs.(0-10)`:LifeSatisfactionCluster2.5-5                     0.1891996
## `Jobs.(0-10)`:LifeSatisfactionCluster5-7.5                     0.2104402
## `Jobs.(0-10)`:LifeSatisfactionCluster7.5-10                    0.2258316
## `Income.(0-10)`:`Safety.(0-10)`                                0.0454663
## `Income.(0-10)`:`Health.(0-10)`                                0.0435968
## `Income.(0-10)`:`Environment.(0-10)`                           0.0462026
## `Income.(0-10)`:`Civic.engagement.(0-10)`                      0.0392772
## `Income.(0-10)`:`Accessiblity.to.services.(0-10)`              0.0465504
## `Income.(0-10)`:`Housing.(0-10)`                               0.0497760
## `Income.(0-10)`:`Community.(0-10)`                             0.0271151
## `Income.(0-10)`:Cluster                                        0.0799981
## `Income.(0-10)`:LifeSatisfactionCluster2.5-5                   1.3871965
## `Income.(0-10)`:LifeSatisfactionCluster5-7.5                   1.3853752
## `Income.(0-10)`:LifeSatisfactionCluster7.5-10                  1.4005294
## `Safety.(0-10)`:`Health.(0-10)`                                0.0311967
## `Safety.(0-10)`:`Environment.(0-10)`                           0.0326717
## `Safety.(0-10)`:`Civic.engagement.(0-10)`                      0.0234496
```

```
## `Safety.(0-10)`:`Accessiblity.to.services.(0-10)`              0.0316161
## `Safety.(0-10)`:`Housing.(0-10)`                                0.0466776
## `Safety.(0-10)`:`Community.(0-10)`                              0.0130767
## `Safety.(0-10)`:Cluster                                         0.1136758
## `Safety.(0-10)`:LifeSatisfactionCluster2.5-5                    0.1334563
## `Safety.(0-10)`:LifeSatisfactionCluster5-7.5                    0.1615644
## `Safety.(0-10)`:LifeSatisfactionCluster7.5-10                   0.1810701
## `Health.(0-10)`:`Environment.(0-10)`                            0.0233539
## `Health.(0-10)`:`Civic.engagement.(0-10)`                       0.0244045
## `Health.(0-10)`:`Accessiblity.to.services.(0-10)`               0.0242606
## `Health.(0-10)`:`Housing.(0-10)`                                0.0275776
## `Health.(0-10)`:`Community.(0-10)`                              0.0163317
## `Health.(0-10)`:Cluster                                         0.0821763
## `Health.(0-10)`:LifeSatisfactionCluster2.5-5                    0.2177887
## `Health.(0-10)`:LifeSatisfactionCluster5-7.5                    0.2303647
## `Health.(0-10)`:LifeSatisfactionCluster7.5-10                   0.2287563
## `Environment.(0-10)`:`Civic.engagement.(0-10)`                  0.0308462
## `Environment.(0-10)`:`Accessiblity.to.services.(0-10)`          0.0361455
## `Environment.(0-10)`:`Housing.(0-10)`                           0.0324159
## `Environment.(0-10)`:`Community.(0-10)`                         0.0203448
## `Environment.(0-10)`:Cluster                                    0.0963545
## `Environment.(0-10)`:LifeSatisfactionCluster2.5-5               0.2226726
## `Environment.(0-10)`:LifeSatisfactionCluster5-7.5               0.2615090
## `Environment.(0-10)`:LifeSatisfactionCluster7.5-10              0.2995334
## `Civic.engagement.(0-10)`:`Accessiblity.to.services.(0-10)`     0.0281496
## `Civic.engagement.(0-10)`:`Housing.(0-10)`                      0.0311019
## `Civic.engagement.(0-10)`:`Community.(0-10)`                    0.0181876
## `Civic.engagement.(0-10)`:Cluster                               0.0720760
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster2.5-5          0.1930670
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster5-7.5          0.2149595
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster7.5-10         0.2493473
## `Accessiblity.to.services.(0-10)`:`Housing.(0-10)`              0.0324829
## `Accessiblity.to.services.(0-10)`:`Community.(0-10)`            0.0259025
## `Accessiblity.to.services.(0-10)`:Cluster                       0.0875621
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster2.5-5  0.2829313
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster5-7.5  0.3200200
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster7.5-10 0.3191709
## `Housing.(0-10)`:`Community.(0-10)`                             0.0252498
## `Housing.(0-10)`:Cluster                                        0.1124941
## `Housing.(0-10)`:LifeSatisfactionCluster2.5-5                   0.4675876
## `Housing.(0-10)`:LifeSatisfactionCluster5-7.5                   0.4868450
## `Housing.(0-10)`:LifeSatisfactionCluster7.5-10                  0.4948592
## `Community.(0-10)`:Cluster                                      0.0475326
## `Community.(0-10)`:LifeSatisfactionCluster2.5-5                 0.1063623
## `Community.(0-10)`:LifeSatisfactionCluster5-7.5                 0.1226581
## `Community.(0-10)`:LifeSatisfactionCluster7.5-10                0.1344764
## Cluster:LifeSatisfactionCluster2.5-5                            2.4825965
## Cluster:LifeSatisfactionCluster5-7.5                            2.4946183
## Cluster:LifeSatisfactionCluster7.5-10                           2.4477655
##                                                                t value
## (Intercept)                                                     -0.847
## `Education.(0-10)`                                               2.151
## `Jobs.(0-10)`                                                    0.479
## `Income.(0-10)`                                                 -0.373
```

```
## `Safety.(0-10)`                                                 0.075
## `Health.(0-10)`                                                -1.526
## `Environment.(0-10)`                                            0.500
## `Civic.engagement.(0-10)`                                      -0.808
## `Accessiblity.to.services.(0-10)`                               1.065
## `Housing.(0-10)`                                                0.079
## `Community.(0-10)`                                              1.661
## Cluster                                                         1.109
## LifeSatisfactionCluster2.5-5                                    0.313
## LifeSatisfactionCluster5-7.5                                    0.201
## LifeSatisfactionCluster7.5-10                                   0.696
## `Education.(0-10)`:`Jobs.(0-10)`                                0.007
## `Education.(0-10)`:`Income.(0-10)`                              1.154
## `Education.(0-10)`:`Safety.(0-10)`                             -1.934
## `Education.(0-10)`:`Health.(0-10)`                             -0.529
## `Education.(0-10)`:`Environment.(0-10)`                         1.100
## `Education.(0-10)`:`Civic.engagement.(0-10)`                   -3.141
## `Education.(0-10)`:`Accessiblity.to.services.(0-10)`            0.415
## `Education.(0-10)`:`Housing.(0-10)`                             1.697
## `Education.(0-10)`:`Community.(0-10)`                           1.315
## `Education.(0-10)`:Cluster                                     -1.194
## `Education.(0-10)`:LifeSatisfactionCluster2.5-5                -2.899
## `Education.(0-10)`:LifeSatisfactionCluster5-7.5                -3.082
## `Education.(0-10)`:LifeSatisfactionCluster7.5-10               -2.808
## `Jobs.(0-10)`:`Income.(0-10)`                                  -0.363
## `Jobs.(0-10)`:`Safety.(0-10)`                                  -1.381
## `Jobs.(0-10)`:`Health.(0-10)`                                   0.299
## `Jobs.(0-10)`:`Environment.(0-10)`                             -0.325
## `Jobs.(0-10)`:`Civic.engagement.(0-10)`                         1.582
## `Jobs.(0-10)`:`Accessiblity.to.services.(0-10)`                -0.623
## `Jobs.(0-10)`:`Housing.(0-10)`                                  3.436
## `Jobs.(0-10)`:`Community.(0-10)`                               -1.585
## `Jobs.(0-10)`:Cluster                                          -0.509
## `Jobs.(0-10)`:LifeSatisfactionCluster2.5-5                     -0.254
## `Jobs.(0-10)`:LifeSatisfactionCluster5-7.5                      0.620
## `Jobs.(0-10)`:LifeSatisfactionCluster7.5-10                    -0.729
## `Income.(0-10)`:`Safety.(0-10)`                                 1.144
## `Income.(0-10)`:`Health.(0-10)`                                -1.125
## `Income.(0-10)`:`Environment.(0-10)`                           -0.524
## `Income.(0-10)`:`Civic.engagement.(0-10)`                      -0.698
## `Income.(0-10)`:`Accessiblity.to.services.(0-10)`              -0.161
## `Income.(0-10)`:`Housing.(0-10)`                               -3.023
## `Income.(0-10)`:`Community.(0-10)`                             -0.600
## `Income.(0-10)`:Cluster                                         0.371
## `Income.(0-10)`:LifeSatisfactionCluster2.5-5                    0.555
## `Income.(0-10)`:LifeSatisfactionCluster5-7.5                    0.821
## `Income.(0-10)`:LifeSatisfactionCluster7.5-10                   0.980
## `Safety.(0-10)`:`Health.(0-10)`                                -0.042
## `Safety.(0-10)`:`Environment.(0-10)`                            0.110
## `Safety.(0-10)`:`Civic.engagement.(0-10)`                       2.652
## `Safety.(0-10)`:`Accessiblity.to.services.(0-10)`               1.628
## `Safety.(0-10)`:`Housing.(0-10)`                               -0.655
## `Safety.(0-10)`:`Community.(0-10)`                              0.982
## `Safety.(0-10)`:Cluster                                        -0.605
```

```
## `Safety.(0-10)`:LifeSatisfactionCluster2.5-5                          0.155
## `Safety.(0-10)`:LifeSatisfactionCluster5-7.5                          0.327
## `Safety.(0-10)`:LifeSatisfactionCluster7.5-10                         0.333
## `Health.(0-10)`:`Environment.(0-10)`                                 -0.520
## `Health.(0-10)`:`Civic.engagement.(0-10)`                             1.169
## `Health.(0-10)`:`Accessiblity.to.services.(0-10)`                    -0.434
## `Health.(0-10)`:`Housing.(0-10)`                                      2.205
## `Health.(0-10)`:`Community.(0-10)`                                   -2.281
## `Health.(0-10)`:Cluster                                               1.070
## `Health.(0-10)`:LifeSatisfactionCluster2.5-5                          3.396
## `Health.(0-10)`:LifeSatisfactionCluster5-7.5                          3.960
## `Health.(0-10)`:LifeSatisfactionCluster7.5-10                         3.375
## `Environment.(0-10)`:`Civic.engagement.(0-10)`                       -0.218
## `Environment.(0-10)`:`Accessiblity.to.services.(0-10)`               -0.422
## `Environment.(0-10)`:`Housing.(0-10)`                                 0.680
## `Environment.(0-10)`:`Community.(0-10)`                              -1.476
## `Environment.(0-10)`:Cluster                                         -0.683
## `Environment.(0-10)`:LifeSatisfactionCluster2.5-5                     0.257
## `Environment.(0-10)`:LifeSatisfactionCluster5-7.5                     0.869
## `Environment.(0-10)`:LifeSatisfactionCluster7.5-10                   -0.140
## `Civic.engagement.(0-10)`:`Accessiblity.to.services.(0-10)`           0.360
## `Civic.engagement.(0-10)`:`Housing.(0-10)`                            0.057
## `Civic.engagement.(0-10)`:`Community.(0-10)`                          0.710
## `Civic.engagement.(0-10)`:Cluster                                     0.836
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster2.5-5               -0.367
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster5-7.5               -1.230
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster7.5-10              -0.081
## `Accessiblity.to.services.(0-10)`:`Housing.(0-10)`                   -1.308
## `Accessiblity.to.services.(0-10)`:`Community.(0-10)`                 -2.566
## `Accessiblity.to.services.(0-10)`:Cluster                            -0.886
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster2.5-5        0.720
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster5-7.5        0.056
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster7.5-10       0.819
## `Housing.(0-10)`:`Community.(0-10)`                                   1.537
## `Housing.(0-10)`:Cluster                                              1.027
## `Housing.(0-10)`:LifeSatisfactionCluster2.5-5                        -1.875
## `Housing.(0-10)`:LifeSatisfactionCluster5-7.5                        -1.863
## `Housing.(0-10)`:LifeSatisfactionCluster7.5-10                       -2.292
## `Community.(0-10)`:Cluster                                           -1.713
## `Community.(0-10)`:LifeSatisfactionCluster2.5-5                       2.166
## `Community.(0-10)`:LifeSatisfactionCluster5-7.5                       2.724
## `Community.(0-10)`:LifeSatisfactionCluster7.5-10                      1.664
## Cluster:LifeSatisfactionCluster2.5-5                                 -0.230
## Cluster:LifeSatisfactionCluster5-7.5                                 -0.085
## Cluster:LifeSatisfactionCluster7.5-10                                -0.047
##                                                                     Pr(>|t|)
## (Intercept)                                                         0.397876
## `Education.(0-10)`                                                  0.032798 *
## `Jobs.(0-10)`                                                       0.632462
## `Income.(0-10)`                                                     0.709645
## `Safety.(0-10)`                                                     0.940499
## `Health.(0-10)`                                                     0.128761
## `Environment.(0-10)`                                                0.617702
## `Civic.engagement.(0-10)`                                           0.420175
```

```
## `Accessiblity.to.services.(0-10)`                                0.288270
## `Housing.(0-10)`                                                 0.936854
## `Community.(0-10)`                                               0.098499 .
## Cluster                                                          0.268774
## LifeSatisfactionCluster2.5-5                                     0.754439
## LifeSatisfactionCluster5-7.5                                     0.840556
## LifeSatisfactionCluster7.5-10                                    0.487286
## `Education.(0-10)`:`Jobs.(0-10)`                                 0.994037
## `Education.(0-10)`:`Income.(0-10)`                               0.249839
## `Education.(0-10)`:`Safety.(0-10)`                               0.054668 .
## `Education.(0-10)`:`Health.(0-10)`                               0.597377
## `Education.(0-10)`:`Environment.(0-10)`                          0.272736
## `Education.(0-10)`:`Civic.engagement.(0-10)`                     0.001965 **
## `Education.(0-10)`:`Accessiblity.to.services.(0-10)`             0.678699
## `Education.(0-10)`:`Housing.(0-10)`                              0.091316 .
## `Education.(0-10)`:`Community.(0-10)`                            0.190008
## `Education.(0-10)`:Cluster                                       0.234086
## `Education.(0-10)`:LifeSatisfactionCluster2.5-5                  0.004202 **
## `Education.(0-10)`:LifeSatisfactionCluster5-7.5                  0.002377 **
## `Education.(0-10)`:LifeSatisfactionCluster7.5-10                 0.005528 **
## `Jobs.(0-10)`:`Income.(0-10)`                                    0.716912
## `Jobs.(0-10)`:`Safety.(0-10)`                                    0.169043
## `Jobs.(0-10)`:`Health.(0-10)`                                    0.765421
## `Jobs.(0-10)`:`Environment.(0-10)`                               0.745930
## `Jobs.(0-10)`:`Civic.engagement.(0-10)`                          0.115462
## `Jobs.(0-10)`:`Accessiblity.to.services.(0-10)`                  0.533871
## `Jobs.(0-10)`:`Housing.(0-10)`                                   0.000732 ***
## `Jobs.(0-10)`:`Community.(0-10)`                                 0.114733
## `Jobs.(0-10)`:Cluster                                            0.611054
## `Jobs.(0-10)`:LifeSatisfactionCluster2.5-5                       0.799609
## `Jobs.(0-10)`:LifeSatisfactionCluster5-7.5                       0.536342
## `Jobs.(0-10)`:LifeSatisfactionCluster7.5-10                      0.467106
## `Income.(0-10)`:`Safety.(0-10)`                                  0.254237
## `Income.(0-10)`:`Health.(0-10)`                                  0.262226
## `Income.(0-10)`:`Environment.(0-10)`                             0.600736
## `Income.(0-10)`:`Civic.engagement.(0-10)`                        0.486151
## `Income.(0-10)`:`Accessiblity.to.services.(0-10)`                0.872311
## `Income.(0-10)`:`Housing.(0-10)`                                 0.002867 **
## `Income.(0-10)`:`Community.(0-10)`                               0.549125
## `Income.(0-10)`:Cluster                                          0.711394
## `Income.(0-10)`:LifeSatisfactionCluster2.5-5                     0.579276
## `Income.(0-10)`:LifeSatisfactionCluster5-7.5                     0.413003
## `Income.(0-10)`:LifeSatisfactionCluster7.5-10                    0.328533
## `Safety.(0-10)`:`Health.(0-10)`                                  0.966173
## `Safety.(0-10)`:`Environment.(0-10)`                             0.912458
## `Safety.(0-10)`:`Civic.engagement.(0-10)`                        0.008697 **
## `Safety.(0-10)`:`Accessiblity.to.services.(0-10)`                0.105335
## `Safety.(0-10)`:`Housing.(0-10)`                                 0.513601
## `Safety.(0-10)`:`Community.(0-10)`                               0.327640
## `Safety.(0-10)`:Cluster                                          0.546247
## `Safety.(0-10)`:LifeSatisfactionCluster2.5-5                     0.877358
## `Safety.(0-10)`:LifeSatisfactionCluster5-7.5                     0.743669
## `Safety.(0-10)`:LifeSatisfactionCluster7.5-10                    0.739157
## `Health.(0-10)`:`Environment.(0-10)`                             0.603757
```

```
## `Health.(0-10)`:`Civic.engagement.(0-10)`                         0.244029
## `Health.(0-10)`:`Accessiblity.to.services.(0-10)`                  0.664455
## `Health.(0-10)`:`Housing.(0-10)`                                   0.028696 *
## `Health.(0-10)`:`Community.(0-10)`                                 0.023711 *
## `Health.(0-10)`:Cluster                                            0.285855
## `Health.(0-10)`:LifeSatisfactionCluster2.5-5                       0.000838 ***
## `Health.(0-10)`:LifeSatisfactionCluster5-7.5                       0.000107 ***
## `Health.(0-10)`:LifeSatisfactionCluster7.5-10                      0.000904 ***
## `Environment.(0-10)`:`Civic.engagement.(0-10)`                     0.827456
## `Environment.(0-10)`:`Accessiblity.to.services.(0-10)`             0.673772
## `Environment.(0-10)`:`Housing.(0-10)`                              0.497279
## `Environment.(0-10)`:`Community.(0-10)`                            0.141742
## `Environment.(0-10)`:Cluster                                       0.495505
## `Environment.(0-10)`:LifeSatisfactionCluster2.5-5                  0.797106
## `Environment.(0-10)`:LifeSatisfactionCluster5-7.5                  0.385824
## `Environment.(0-10)`:LifeSatisfactionCluster7.5-10                 0.889112
## `Civic.engagement.(0-10)`:`Accessiblity.to.services.(0-10)`        0.719375
## `Civic.engagement.(0-10)`:`Housing.(0-10)`                         0.954757
## `Civic.engagement.(0-10)`:`Community.(0-10)`                       0.478894
## `Civic.engagement.(0-10)`:Cluster                                  0.404437
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster2.5-5             0.714383
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster5-7.5             0.220426
## `Civic.engagement.(0-10)`:LifeSatisfactionCluster7.5-10            0.935543
## `Accessiblity.to.services.(0-10)`:`Housing.(0-10)`                 0.192451
## `Accessiblity.to.services.(0-10)`:`Community.(0-10)`               0.011105 *
## `Accessiblity.to.services.(0-10)`:Cluster                          0.376612
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster2.5-5     0.472581
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster5-7.5     0.955007
## `Accessiblity.to.services.(0-10)`:LifeSatisfactionCluster7.5-10 0.413798
## `Housing.(0-10)`:`Community.(0-10)`                                0.126067
## `Housing.(0-10)`:Cluster                                           0.305694
## `Housing.(0-10)`:LifeSatisfactionCluster2.5-5                      0.062397 .
## `Housing.(0-10)`:LifeSatisfactionCluster5-7.5                      0.064139 .
## `Housing.(0-10)`:LifeSatisfactionCluster7.5-10                     0.023031 *
## `Community.(0-10)`:Cluster                                         0.088383 .
## `Community.(0-10)`:LifeSatisfactionCluster2.5-5                    0.031612 *
## `Community.(0-10)`:LifeSatisfactionCluster5-7.5                    0.007088 **
## `Community.(0-10)`:LifeSatisfactionCluster7.5-10                   0.097781 .
## Cluster:LifeSatisfactionCluster2.5-5                               0.817968
## Cluster:LifeSatisfactionCluster5-7.5                               0.931967
## Cluster:LifeSatisfactionCluster7.5-10                              0.962203
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6222 on 182 degrees of freedom
## Multiple R-squared:  0.9581, Adjusted R-squared:  0.9347
## F-statistic: 40.83 on 102 and 182 DF,  p-value: < 2.2e-16
```