The impact of alcohol consumption and average BMI on life expectancy across countries

Svenja Mikłaszewska, Joanna Pokora

Abstract

In this study, we explore the impact of average BMI and alcohol consumption on life expectancy across countries, using various parametric and semiparametric regression models. We begin by analyzing quadratic regression models, followed by penalized spline regression to better capture the trends. To investigate the joint effects of BMI and alcohol consumption on life expectancy, we extend our analysis to simple semiparametric regression and bivariate smoothing models. Our results indicate that higher BMI and alcohol consumption in a country are generally associated with increased life expectancy. We select the most optimal models based on AIC, BIC, and R^2 criteria. The findings highlight the advantages of smoothing techniques and emphasize the need for careful interpretation when analyzing life expectancy.

1 Historical Outline

Life expectancy, or life expectancy, is an important indicator of a population's health and quality of life. The history of life expectancy is a fascinating topic that shows how advances in medicine, public health and living conditions have affected our lives.

1.1 Early Times

In ancient times, life expectancy was much lower than today. Studies indicate that during the Paleolithic period (about 12,000 years ago) life expectancy was about 33 years. High death rates in childhood, as well as infectious diseases, wars and other dangers significantly reduced life expectancy.

1.2 The Middle Ages and the Renaissance

In the Middle Ages and Renaissance, life expectancy was still low, but the first changes began to appear. In the 15th century, life expectancy was about 48 years. The introduction of new agricultural techniques, improved nutrition and the development of medicine contributed to a gradual increase in life expectancy.

1.3 Industrialization

Industrialization has brought significant changes in living conditions and health. In the nineteenth century, life expectancy began to increase, despite some industrial health challenges. The introduction of vaccines, better sanitation and hygiene, and medical developments contributed to a significant reduction in mortality, especially among children.

1.4 Contemporaneity

In the 20th century, life expectancy increased significantly due to advances in medicine, such as the development of modern drugs, diagnostic and surgical techniques. In 2019, life expectancy worldwide was about 73.3 years. Today, life expectancy varies by region and living conditions, but is generally higher than ever before.

1.5 Challenges and Prospects

Despite progress, life expectancy still faces challenges, such as chronic diseases, neurodegenerative diseases and health problems associated with an aging population. Research on life expectancy and public health remains key to developing effective health strategies and improving quality of life.

2 Introduction

Alcohol is one of the most significant risk factors for health problems and mortality. According to the WHO estimates, in 2016 alcohol consumption contributed to 3 million deaths and was responsible for 5.1% of the global burden of disease and injury [1].

On the other hand, it is well known that severe obesity and underweight can deeply affect health and quality of life. This issue is particularly concerning today, as unhealthy weight trends continue to rise in many countries [2]. To measure them, the body mass index (BMI) is commonly used, calculated as the ratio of weight in kilograms to height squared in meters. A BMI between 18.5 and 25 is considered healthy [3].

The question that arises is how these two factors affect the mean life expectancy across countries. As many studies have shown, these relationships are not always straightforward and may deviate from expectations based on common sense [4]. Therefore, this article employs both parametric and semi-parametric approaches to model the impact of mean BMI, alcohol consumption and their combined effects on life expectancy across countries.

3 Methodology

3.1 Data characteristics

Dataset used in the study contains aggregated life expectancy averaged over multiple years for 179 countries, along with associated socio-economic and health-related factors.

- Country & Region: Includes data from a diverse range of countries across continents, categorized by their respective regions.
- Life Expectancy: The average life expectancy in years for each country.
- Socio-economic Indicators:
  - GDP per capita
  - Schooling (average years of education)
  - Alcohol consumption
  - Economy status (developed or developing)
- Health Indicators:
  - Infant mortality
  - Adult mortality
  - HIV prevalence
  - Immunization rates (e.g., Hepatitis B, Polio)
  - Incidence of diseases like measles and diphtheria
  - BMI (Body Mass Index) data
  - Thinness prevalence among children and adolescents

3.2 Quadratic regression with one predictor

First model used in the study is a quadratic regression with one independent variable. For n observations it can be written as

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i, \ \ i \in \{1, ..., n\},$$

where

- y_i is the dependent variable for the observation i,
- x_i is the independent variable for the observation$i$,
- β_0 is a fixed word free,
- β_1 is the coefficient of linear slope
- β_2 is the square factor
- ϵ_i is the random error for observations i, derived from a normal distribution.

It can be also written in a matrix form as

$$Y = X\beta + \epsilon,$$

where

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}, \quad X = \begin{bmatrix} 1 & x_1 & x_1^2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}, \quad \epsilon = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}.$$

Then, the expected value of independent variable takes form

$$\mathbb{E}Y = X\beta.$$

3.3 General Form of Semiparametric Model.

The general form of the semiparametric model can be written as:

$$y = X\beta + f(z) + \epsilon$$

where:

- y is the dependent variable,
- X is the covariance matrix for the parametric part,
- β is a vector of coefficients for the parametric part,
- $f(z)$ is a nonparametric function that models the nonlinear relationship between the independent variable z and the dependent variable y,
- ϵ is a random error.

3.3.1 Parametric Part

The parametric part of the model describes the linear relationship between the independent variables and the dependent variable:

$$X\beta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p$$

where

- $\beta_0, \beta_1, \ldots, \beta_p$ are coefficients,
- $x_1, x_2, \ldots, x_p$ are independent variables.

3.3.2 Non-Parametric Part

The nonparametric part of the model describes a more flexible, nonlinear relationship $f(z)$. This function can be modeled using various techniques, such as splines, kernel smoothing or local regression.

3.3.3 Model Estimation

Estimation of a semiparametric model involves simultaneously fitting the parametric part using traditional methods (such as least squares) and the nonparametric part using smoothing techniques.

3.4 Penalized Spline Regression

Penalized spline regression, often called P-spline regression, is a technique used to model non-linear relationships by fitting splines (piecewise polynomials) with a penalty on their roughness. It combines the flexibility of splines with the smoothness of regularization to prevent overfitting.

3.4.1 General Form of the Model

The general form of the spline regression model with a penalty is:

$$y = \sum_{i=1}^{k} \beta_i B_i(x) + \epsilon$$

where:

- y is the dependent variable,
- $B_i(x)$ are basis functions of splines (B-splines),
- β_i are coefficients to be estimated,
- ϵ is a random error

3.4.2 Cubic Regression Spline

Cubic regression splines use cubic polynomials as basis functions. The model can be expressed as:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \sum_{j=1}^{m} \gamma_j (x - \xi_j)_+^3 + \epsilon$$

where $(x - \xi_j)_+^3$ is a cubic basis spline function.

3.4.3 Gaussian Process Basis Functions

Gaussian processes (GP) are non-parametric probabilistic models that define a distribution over functions. The GP model is defined by its mean function and covariance function (kernel):

$$f(x) \sim GP(m(x), k(x, x'))$$

where:

- $m(x)$ is a function of the average,
- $k(x, x')$ is the covariance function

3.5 Regularization

To prevent over-fitting, a spline roughness penalty term is added to the loss function. The most common penalty is a penalty on the second derivative of the spline, which measures the curvature:

$$\lambda \int \left(\frac{d^2 f(x)}{dx^2} \right)^2 dx$$

where λ is a smoothing parameter that controls the balance between model fit and smoothness.

3.6 Estimation of the Smoothing Parameter

In our study, we consider two methods for estimating the smoothing parameter. These are GCV and REML, shown below.

3.6.1 Generalized Cross-Validation (GCV)

Smoothing parameter λ can be estimated using generalized cross-validation (GCV):

$$\text{GCV}(\lambda) = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - \hat{f}_{-i}(x_i; \lambda)}{1 - S_{\lambda,ii}} \right)^2$$

3.6.2 Restricted Maximum Likelihood (REML)

Smoothing parameter λ can also be estimated using restricted maximum likelihood (REML):

$$R(G, R) = P(G, R) - \frac{1}{2} \log |X^T V^{-1} X|$$

where

- $V = \sigma_u^2 Z Z^T + \sigma_\epsilon^2 I$.

3.7 Bivariate Smooth Models

Bivariate smooth models extend the idea of smoothing to two-dimensional spaces by modeling relationships involving two predictors. These models are particularly useful when the relationships between variables are complex and nonlinear.

3.7.1 General Form of the Model

The general form of the two-dimensional smoothing model can be written as:

$$y = f(x_1, x_2) + \epsilon$$

where:

- y is the dependent variable,
- $f(x_1, x_2)$ is a smooth function of two predictors x_1 i x_2,
- ϵ is a random error

3.7.2 Base Functions

One popular approach to modeling $f(x_1, x_2)$ is to use tensor splines. Function $f(x_1, x_2)$ can be written as:

$$f(x_1, x_2) = \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} \beta_{ij} B_i(x_1) B_j(x_2)$$

where:

- $B_i(x_1)$ are the base functions for the predictor x_1,
- $B_j(x_2)$ are the base functions for the predictor x_2,
- β_{ij} are coefficients to be estimated

3.8 Akaike Information Criterion (AIC)

Akaike Information Criterion (AIC) is a statistical model selection criterion that balances the complexity of the model with its fit to the data. The AIC value is calculated as:

$$\text{AIC} = 2k - 2\ln(L)$$

where:

- k is the number of parameters in the model,
- L is the value of the maximum reliability function of the model

A model with a smaller AIC value is considered better because it suggests that the model fits the data better with fewer parameters.

3.9 Bayesian Information Criterion (BIC)

Bayesian Information Criterion (BIC), also known as Schwarz Criterion, is similar to AIC, but includes a stronger penalty for the number of parameters in the model. The BIC value is calculated as:

$$\mathrm{BIC} = \ln(n)k - 2\ln(L)$$

where:

- n is the number of observations,
- k is the number of parameters in the model,
- L is the value of the maximum reliability function of the model

A model with a smaller BIC value is considered better because it indicates a better fit given the number of parameters and the number of observations.

3.10 Determination Factor (R^2)

Coefficient of determination (R^2) jest measure that indicates how much of the variability in the dependent variable y is explained by the independent variables X in the regression model. ValueR^2 is calculated as:

$$R^2 = 1 - \frac{SS_{\mathrm{res}}}{SS_{\mathrm{tot}}}$$

where:

- SS_{res} is the sum of the squares of the residuals,
- SS_{tot} is the total sum of squares

Value R^2 ranges from 0 to 1, where a value closer to 1 indicates a better fit of the model to the data.

4 Results

In this section, we present data visualizations that illustrate the key findings of our study. The graphs were designed to better illustrate the relationships between variables.

In particular, we focus on:

- Analyze the impact of health and social factors on life expectancy.
- Visualize the results of advanced statistical models, such as spline regression with penalty and semiparametric models.
- Presentation of relationships between variables using graphs of two-dimensional smoothing models.

4.1 Quadratic models

We fit two quadratic models with life expectancy as a dependent variable and BMI and alcohol consumption as the regressors. Let's examine the plots of residuals against fitted values shown in Figure 1, to assess the appropriateness of the models.

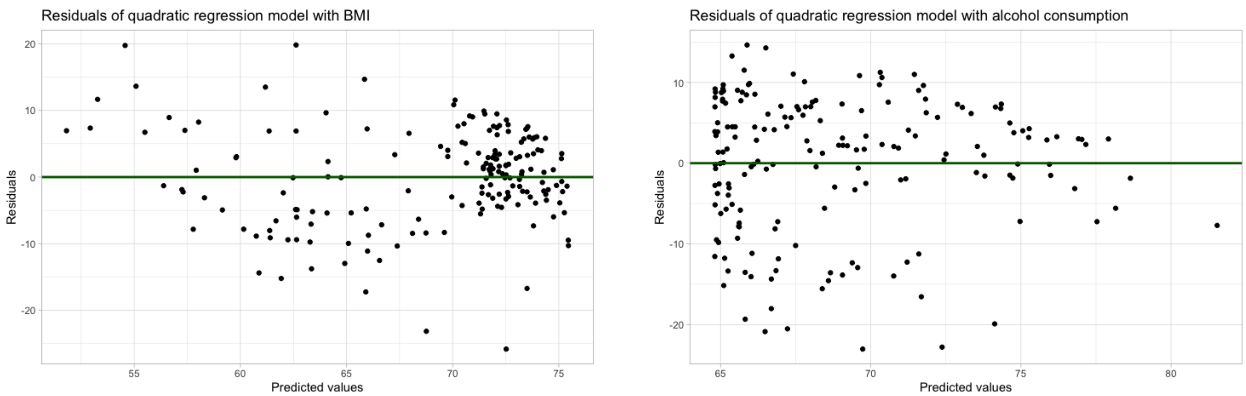

Figure 1: Plots of residuals against fitted values for quadratic regression models.

In both cases, the residuals cluster rather than being randomly spread. Moreover, they are not evenly distributed around 0 with respect to the predicted values, indicating that the variance of the residuals is not constant. For the model involving alcohol consumption, the residuals are also not symmetrically spread around 0, which may suggest that their mean differs from 0.

In conclusion, these quadratic models are unlikely to be optimal fits. To further assess this, we examine the data plots with fitted curves and 95% confidence intervals, shown in Figure 2.

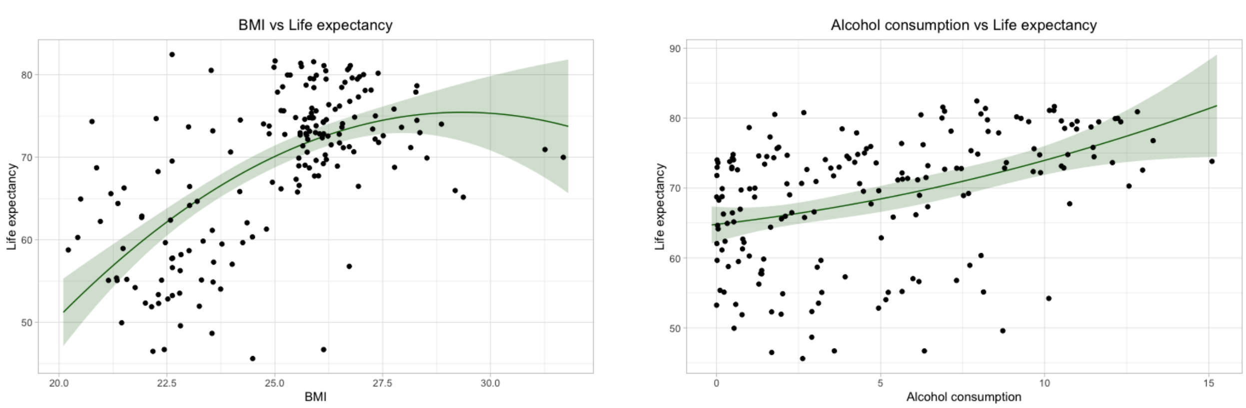

Figure 2: Data plots with fitted quadratic regression curves and 95% confidence intervals.

The first graph in Figure 2 illustrates the relationship between body mass index (BMI) and life expectancy. The overall trend suggests a correlation between BMI and life expectancy. According to the plot, the predicted life expectancy is highest at a BMI of approximately 29 and decreases for both lower and slightly higher BMI values. Moreover, the data scatter and the shape of the fitted curve indicate considerable variability in life expectancy across different BMI values.

The shaded area around the trend line represents the 95% confidence interval, indicating greater uncertainty in predictions for low and high BMI values. This is expected, as fewer observations are available at both ends of the BMI range.

The second graph in Figure 2 shows the relationship between alcohol consumption and life expectancy. There is a visible relationship between alcohol consumption and life expectancy. The graph indicates that in countries where alcohol consumption is higher, people live longer. Alcohol consumption around 0 can be associated with lower life expectancy, although some countries with low average alcohol consumption still have high life expectancy.

Overall, the data are widely scattered, indicating high variability in life expectancy for different levels of alcohol consumption. As in the first graph in Figure 2, the shaded area around the trend line represents the 95% confidence interval, which shows the greater uncertainty of forecasts for extreme values of alcohol consumption, particularly high ones.

Both curves follow the general patterns in the data. However, based on Figure 2, the fits could likely be improved. Table 1 presents the model selection criteria for both.

Model	R^2	AIC	BIC
Quadratic BMI	0.390	1220.590	1233.340
Quadratic Alcohol	0.176	1274.618	1287.368

Table 1: Model selection criteria values for quadratic regressions.

The R^2 values are approximately 0.390 for the BMI model and 0.176 for the alcohol consumption model. This indicates that about 39% of the variation in life expectancy is explained by BMI, which is fairly reasonable given the nature of the data. In contrast, only about 18% is explained by average alcohol consumption, suggesting a weaker fit for the latter.

The same conclusion can be drawn from the AIC and BIC values, which are both lower for the model involving Body Mass Index.

4.2 Penalized splines models

Next, we fit the penalized spline regression to the data used in our study. Once again, we obtain two models - one with the average BMI in a country as the explanatory variable and another with alcohol consumption. The introduction of spline roughness penalties and regularization allows for smoother and more stable estimations, which remain well-fitted. In both scenarios, we consider multiple models with

- 3, 30 and 100 knots,
- cubic regression and Gaussian process basis functions,
- smoothing parameter estimated using Generalized Cross Validation and restricted maximum likelihood.

Once again, we analyze the obtained results by examining data plots with fitted curves and 95% confidence intervals as well as residual plots against fitted values.

4.2.1 BMI

Figure 3 shows the plots based on the model with BMI as an independent variable.

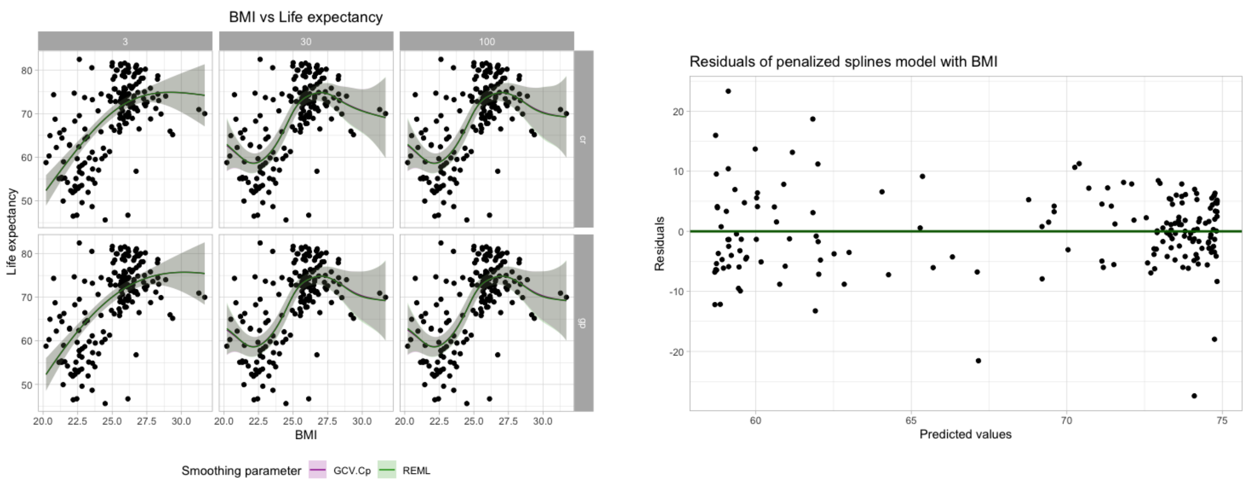

Figure 3: Data plots with fitted curves and a plot of residuals against fitted values based on the most optimal model involving BMI.

The residual plot was generated using the optimal model, shown in Table 2, which features 30 knots, a smoothing parameter estimated via GCV, and Gaussian process basis functions.

Residuals cluster around the lowest and, especially, the highest predicted values. They are fairly evenly distributed around 0; however, some outliers are still present. Their variance appears more stable compared to the residual plot from the quadratic regression with BMI in Figure 1.

The obtained fits do not differ significantly based on the choice of smoothing parameter estimator or type of basis functions. Models with three knots produce curves that closely resemble the results from quadratic regression. With 30 knots, the fit improves noticeably for the most extreme BMI values. However, introducing 100 knots does not lead to substantial improvement, which explains why models with 30 knots are preferable - they are much less complex while yielding similar results.

Examining the most optimal fit, we observe that life expectancy is highest for individuals with a BMI of approximately 27. Both low and high BMI values are associated with lower life expectancy; however, the minimum life expectancy occurs around a BMI of 22 rather than 20, like for the quadratic regression.

The shaded regions around the smoothing curves represent 95% confidence intervals, highlighting the uncertainty of the predictions. For the lowest and highest BMI values, the confidence intervals are broader, indicating greater uncertainty in the predictions for these ranges.

4.2.2 Alcohol consumption

Figure 4 shows the same plots as Figure 3 but for models with alcohol consumption as an explanatory variable.

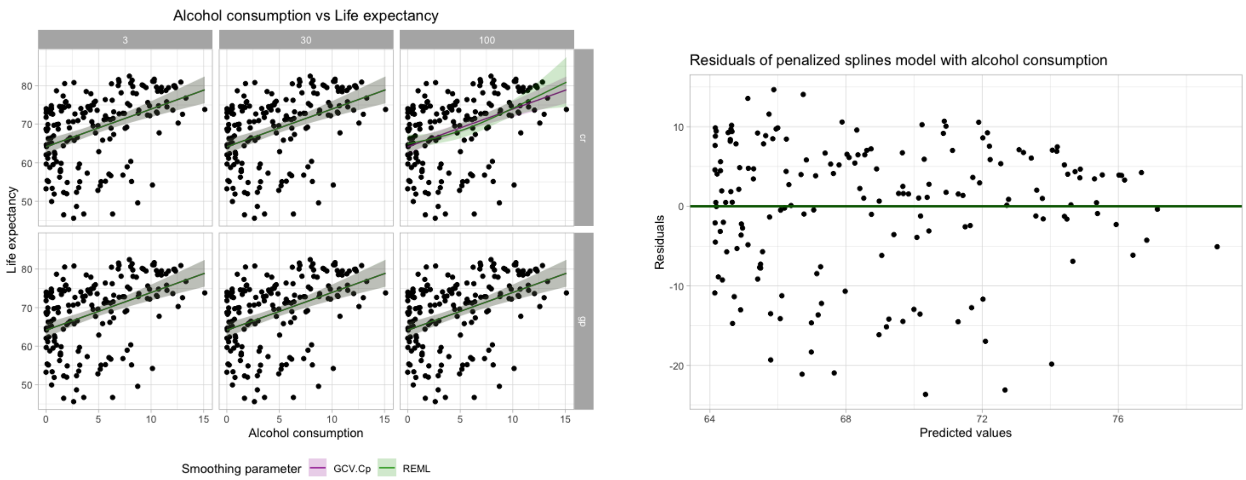

Figure 4: Data plots with fitted curves and a plot of residuals against fitted values based on the most optimal model involving alcohol consumption.

Once again, we focus on the residual plot for the most optimal penalized splines model visible in Table 2, i.e. the one with 3 knots, smoothing parameter estimated with GCV and cubic regression as the basis functions.

Although there are still more residuals at lower predicted values, their spread in this model appears fairly random, especially compared to the second plot in Figure 1. However, they are still not evenly distributed around 0, and their variance does not appear constant. In general, these residuals exhibit more desirable statistical properties than those of the quadratic regression model.

Models with different specifications do not exhibit visible differences, except for the one with 100 knots, cubic regression basis functions, and the REML estimator, which shows greater curvature and most closely resembles the previously obtained quadratic regression fit. In other scenarios, the relationship between the dependent and explanatory variables appears almost linear.

The overall trend suggests that higher alcohol consumption in a country is associated with higher life expectancy. The wider 95% confidence intervals for very low and very high levels of alcohol consumption around the smoothing lines indicate greater uncertainty.

4.3 Simple semiparametric regression

Using simple semiparametric regression, we can model the simultaneous impact of average BMI and alcohol consumption on life expectancy in a country. Once again, we construct various models using different specifications:

- 3, 10 and 30 knots,

- cubic regression and Gaussian process basis functions,
- Generalized Cross Validation and REML as smoothing parameter estimators.

Figure 5 presents the result plots, analogous to those for the previous models.

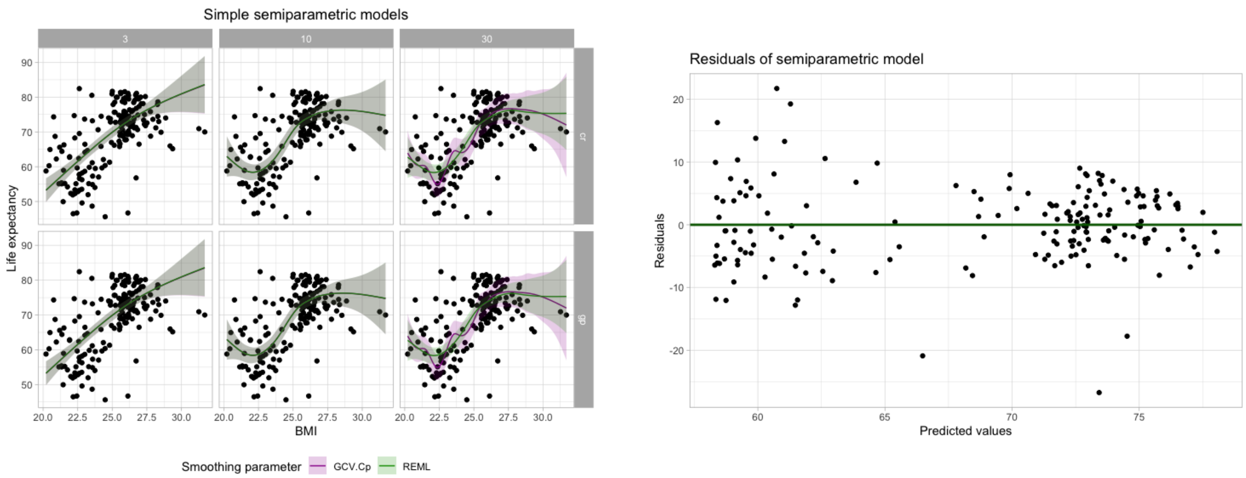

Figure 5: Data plots with fitted curves and a plot of residuals against fitted values based on the most optimal simple semiparametric model.

The most optimal semiparametric model, presented in Table 2, is the one with 10 knots, the GCV estimator and cubic regression basis functions. Its residuals exhibit moderate clustering and are evenly dispersed around 0, except for a few outliers. Moreover, their variance appears fairly constant. Overall, we can assume that these residuals exhibit desirable properties.

The obtained curves are displayed on the plot of life expectancy versus BMI. They do not vary with respect to the type of basis functions. However, the fit changes with the number of knots, adapting more closely to the data as the number increases. Although the difference between 10 and 30 knots for the REML smoothing parameter estimator is small, the model using the GCV estimator is visibly overfitted in the latter case.

The average trend based on the models with 10 and 30 knots shows that life expectancy tends to be highest for individuals with BMI around 27.5 and is the lowest when BMI is approximately 22, taking into consideration the alcohol consumption. However, when there are 3 knots, the life expectancy increases with the BMI. This pattern is consistent across different levels of alcohol consumption.

The confidence intervals around the smoothing lines highlight the uncertainty in the predictions. Notably, the intervals are wider at the extremes of the range, indicating greater uncertainty for these values. This suggests that the model's predictions are less reliable for very low or very high BMI values given the alcohol consumption.

4.4 Bivariate smoothing

In the model under consideration, we assumed the number of wicks 3, 5 and 8. A larger number of nodes results in an error in R, which informs us that the model has more coefficients than available data. Again, we use GCV and REML estimators.

Figure 6 shows predictions heatmaps and a plot of residuals against predicted values based on the model with 5 knots and GCV estimator.

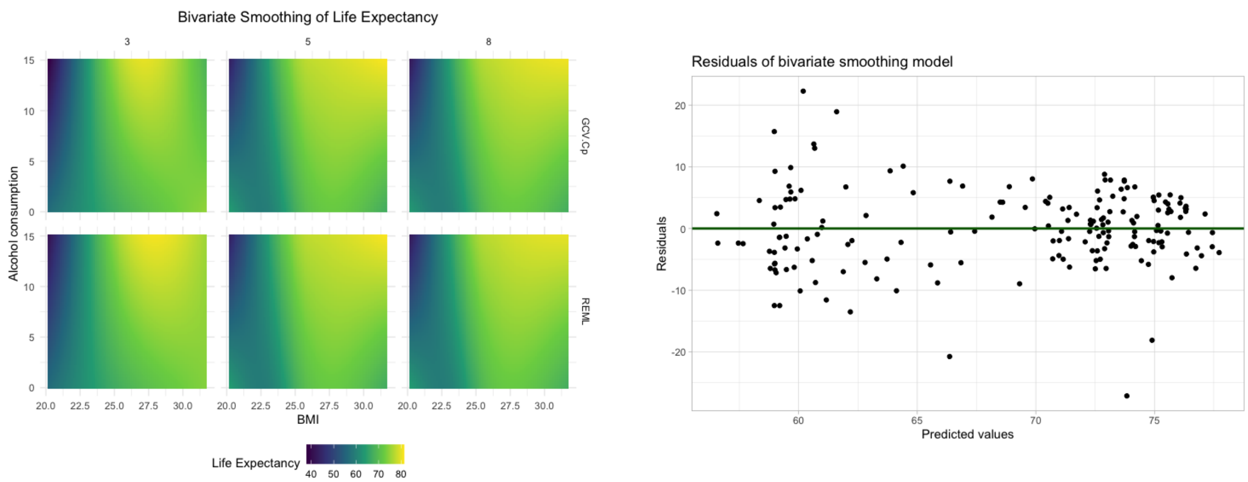

Figure 6: Bivariate smoothing predictions heatmaps and residual plot for the most optimal model.

The residual plot resembles the one for the semiparametric model in Figure 5. Although there are a few outliers and moderate clustering, the residuals appear to exhibit reasonable statistical properties.

Heatmaps provide a visual representation of life expectancy depending on both BMI and alcohol consumption, with yellow areas representing higher life expectancy and purple areas indicating lower life expectancy.

Moderate differences between all scenarios can be observed. The models with 3 knots do not predict the highest life expectancies for the highest values of BMI and alcohol consumption, unlike the models with 5 and 8 knots. However, the latter ones predict lower life expectancy for the highest BMI and the lowest alcohol consumption compared to the predictions based on the models with 3 knots.

Overall, regions indicating the highest life expectancy are consistently found at higher BMI values and high alcohol consumption. The darker areas, representing lower life expectancy, are more prevalent at extremely low BMI and become more intensely purple with increasing alcohol consumption.

Tabel 7 presents the values of model selection criteria for different bivariate smoothing models.

Model	R^2	AIC	BIC	Smoothing parameter	Knots number
Bivariate smoothing	0.4487839	1203.450	1225.121	GCV.Cp	3
Bivariate smoothing	0.4475590	1204.202	1226.104	REML	3
Bivariate smoothing	0.5012667	1187.449	1215.452	GCV.Cp	5
Bivariate smoothing	0.5015225	1189.224	1220.363	REML	5
Bivariate smoothing	0.4995845	1188.462	1217.837	GCV.Cp	8
Bivariate smoothing	0.5002295	1191.094	1225.458	REML	8

Figure 7: Bivariate smoothing - measures

The model with 5 knots using the GCV estimator seems to provide the best fit, as indicated by the high R^2 value and the lowest AIC and BIC values. The differences between GCV and REML are minor, with Generalized Cross Validation estimation performing slightly better only for the model with 3 knots.

5 Models with the best indicator values

We will look only at those models that had the best indicator values. The entire table would be suboptimal to present here.

Here are the models with the best values of each indicator:

Model	R^2	AIC	BIC	Estimator	Knots	Basis function
Spline BMI	0.488	1190.579	1213.240	GCV	30	Gaussian process
Spline alcohol	0.168	1273.338	1282.900	GCV	3	Cubic regression
Semiparametric	0.506	1185.465	1212.720	GCV	10	Cubic regression
Bivariate smoothing	0.501	1187.449	1215.452	GCV	5	-

Table 2: The most optimal models

- **Best R^2 Value**: The Simple Semiparametric model with 10 knots and cubic regression basis function has the highest R^2 value of 0.5061470, indicating the best fit to the data.
- **Lowest AIC Value**: The Simple Semiparametric model also has the lowest AIC value of 1185.465, suggesting it is the most parsimonious model with the best balance of fit and complexity.
- **Lowest BIC Value**: The Spline Regression BMI model has a slightly higher BIC value (1213.240) compared to the Simple Semiparametric model (1212.720), indicating it might be slightly less preferred when considering model complexity.
- **Smoothing Parameter and Knots Number**: The GCV smoothing parameter is consistently used across the models, and the number of knots varies, with 10 knots providing the best overall results in the Simple Semiparametric model.

The Simple Semiparametric model, with 10 knots and cubic regression basis function, emerges as the optimal model with the best R^2, AIC, and BIC values, confirming its superiority in fitting the data while maintaining a balance between model complexity and goodness of fit.

6 Applications

Starting with the quadratic model, we drew some key conclusions: The quadratic model for BMI shows a better fit compared to the quadratic model for alcohol consumption, suggesting that BMI is a better predictor of life expectancy than alcohol consumption levels. The quadratic model for alcohol intake shows a poorer fit to the data, which may suggest that alcohol intake is a less significant predictor of life expectancy.

When analyzing successive models, we observed curve fitting as a function of the number of nodes, basis functions and smoothing parameters. In the case of alcohol consumption, we noticed a straight line rather than a curve, while with BMI we could observe a significant undulation of the curve.

In the semiparametric model, we noted that the fits were not significantly different from BMI alone, only for 30 nodes was an even better model fit apparent. This model also had the best values for the indices. The last model analyzed was bivariate smoothing. Its indicator values were as good as those of the semiparametric model. However, it presented a curio result, indicating that higher body weight and higher alcohol consumption correlate with longer life expectancy.

This is puzzling, but can be explained given that obese people tend to live in highly developed countries, where they have easy access to alcohol, drugs and medical care. In our data, examples of countries who have a high BMI and alcohol consumptiom are: Australia, Austria, Czechia, Portugal.

In general, it is important to keep in mind that we have little data on people with high BMI and high alcohol consumption, which may affect the large range of error in fitting models for such parameters.

Availability of data and materials

The dataset used in the project study is available under the link `https://www.kaggle.com/datasets/shreyasg23/life-expectancy-averaged-dataset?`.

References

[1] Benjamin O. Anderson et al. "Health and cancer risks associated with low levels of alcohol consumption". In: *The Lancet Public Health* 8 (Jan. 1, 2023). Publisher: Elsevier. DOI: 10.1016/S2468-2667(22)00317-6. URL: https://www.thelancet.com/journals/lanpub/article/PIIS2468-2667(22)00317-6/fulltext.

[2] Gunilla Ringbäck Weitoft, Mats Eliasson, and Måns Rosén. "Underweight, overweight and obesity as risk factors for mortality and hospitalization". In: *Scandinavian Journal of Public Health* 36.2 (Mar. 1, 2008). Publisher: SAGE Publications Ltd STM, pp. 169–176. DOI: 10.1177/1403494807085080.

[3] World Health Organisation. *A healthy lifestyle - WHO recommendations*. Accessed: 2025-01-17. URL: https://www.who.int/europe/news-room/fact-sheets/item/a-healthy-lifestyle---who-recommendations.

[4] Sarah H Wild and Christopher D Byrne. "Body mass index and mortality: understanding the patterns and paradoxes". In: *BMJ* (2016). DOI: 10.1136/bmj.i2433.