

# B518 | Week 4 | Group Project | Submission 1

Group 4 - Alex Toon | Nicholas Carlson | Divya Reddy Konda

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## 1 Project Idea One - Covid 19 (2021 ONLY - USA, UK, China, Belgium)

## 2 Selection Criteria:

The data (see above) does meet the criteria of the assignment. In that it is relevant to health, publically accessible, sizable (61 columns and 530,292 rows), includes both categorical (e.g. country) and continuous variables (e.g. new\_cases\_per\_million, total\_deaths\_per\_million) and finally has been ethically sourced and de-identified.

## 3 Introduction

This project uses Covid 19 data from 'Our world in data'. We use this to primarily compare how daily new cases per million varied across four countries in 2021. We focus on 2021 to keep our comparisons on a common phase of the pandemic. The dataset itself does cover many more countries and years and also includes data on total cases and total deaths. We used the fields that have the suffix 'per\_million' as any comparisons scale by population size.

## 4 Dataset justification

**Relevance:** Directly biomedical/public-health, reflecting real-world cases and death metrics during COVID-19.

**Size/structure:** The file far exceeds the minimum requirements (61 columns and 530k rows) and includes both categorical (e.g. Country) and continuous fields (total\_deaths\_per\_million, new\_cases\_per\_million)

**Accessibility/ethics:** Publicly accessible aggregated, de-identified counts suitable for academic use.

**Analytical potential:** Feasible for tables, histograms, boxplots, time trends. Using the fields with the suffix "per\_million" allows better scaling for cross country comparisons and summaries.

**Ethical use.** The dataset consists of aggregated, de-identified counts without PII; no patient-level identifiers are present, aligning with course requirements for ethical, public data.

## 5 Variables and structure

This analysis focuses on a few key variables from the dataset. The primary categorical variable is ‘country’, which we have filtered to four specific nations. The main continuous variable is ‘new\_cases\_per\_million’, which allows for a fair comparison of infection rates by account for population differences. Finally, the ‘date’ variable was used to filter the data to the 2021 calendar year.

A list of all the fields: - “country” - “date” - “total\_cases”, “total\_cases\_per\_million” - “new\_cases”, “new\_cases\_smoothed”, “new\_cases\_per\_million”, “new\_cases\_smoothed\_per\_million” - “total\_deaths”, “new\_deaths”, “new\_deaths\_smoothed”, “total\_deaths\_per\_million”

## 6 Research questions

- 1. What share of days exceed a threshold (to simulated a government policy threshold to “flatten the curve”) e.g 50 cases per million in each country
- 2. Which of the selected countries had the highest typical daily new cases per million in 2021
- 3. How did the monthly mean of new cases per million over 2021 for each country

## 7 Data clean up & Processing plan

We parsed the date field and derived a ‘year’ variable, then restricted the dataset to 2021 to keep figures more legible and comparable. We fixed our analysis to a small set of countries (United States, United Kingdom, China, Belgium) and then verified each has sufficient non missing values for ‘new\_cases\_per\_million’ in 2021. this processing prepares the data for descriptive statistics and many visualisations.

## 8 Descriptive statistics (figures in Appendix)

We summarise categories (counts/proportions), report center & spread for one numeric variable and add simple plots to visualise patterns

## 9 Planned statistical methods

To formally test for differences in the median daily new cases between the four countries, we plan to use a non-parametric test such as the Kruskal-Wallis test, given the skewed nature of the data. Further analysis could involve using correlation to explore the relationship between vaccination rates and new cases over time for each country.

## 10 Limitations

- Measurement differences - countries have different reporting rules, testing cadence & breadth.
- Scope - Only 2021 was analysed. Other years or waves of the disease may show other patterns.
- per million rates do not adjust for demographics of each country, which may show other patterns.
- China has several near zero analysis - This may reflect reporting practices of this specific country

## 11 Appendix - Project One

### 11.1 One-Way frequency table (categorical)

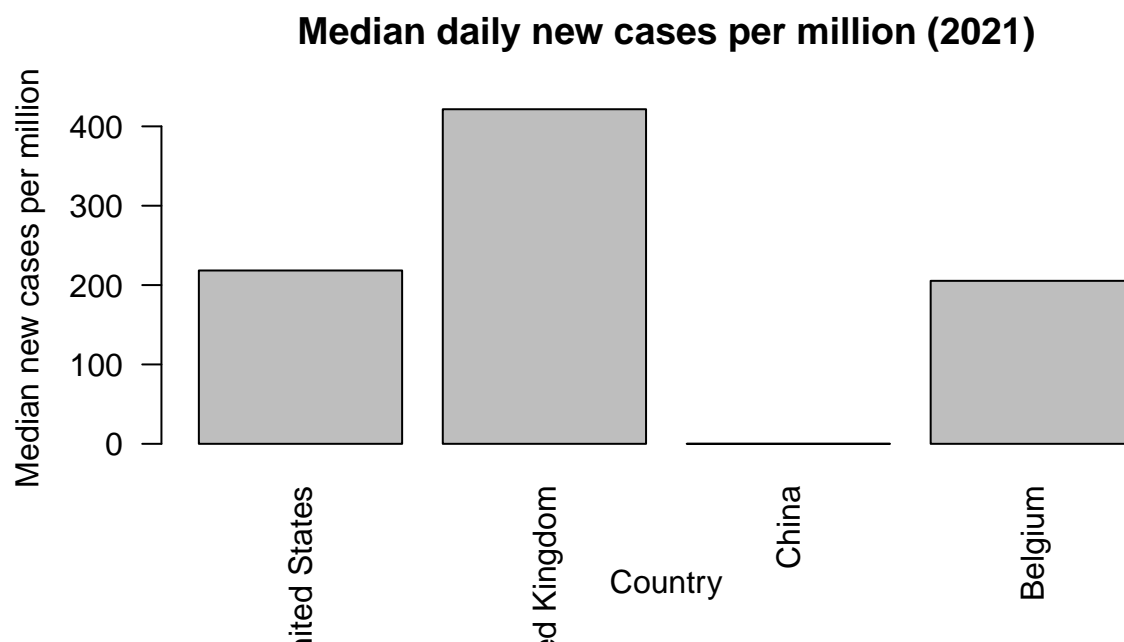
Counts and proportions for a categorical variable

```
##
## United States United Kingdom China Belgium
##          365          365          365          365

##
## United States United Kingdom China Belgium
##          0.25          0.25          0.25          0.25
```

### 11.2 Bar Chart of Disease.Category (counts)

Bar chart / Bar plot of disease category by count



### 11.3 Two way table (category by category)

```
##
##                FALSE TRUE
## United States      37  328
## United Kingdom     55  310
## China              365    0
## Belgium            20  345
```

```
##
##                FALSE  TRUE
## United States  0.101 0.899
## United Kingdom 0.151 0.849
## China          1.000 0.000
## Belgium        0.055 0.945
```

```
##
##                FALSE  TRUE
## United States  0.078 0.334
## United Kingdom 0.115 0.315
## China          0.765 0.000
## Belgium        0.042 0.351
```

```
##
##                FALSE TRUE  Sum
## United States      37  328  365
## United Kingdom     55  310  365
## China              365    0  365
## Belgium            20  345  365
## Sum                477  983 1460
```

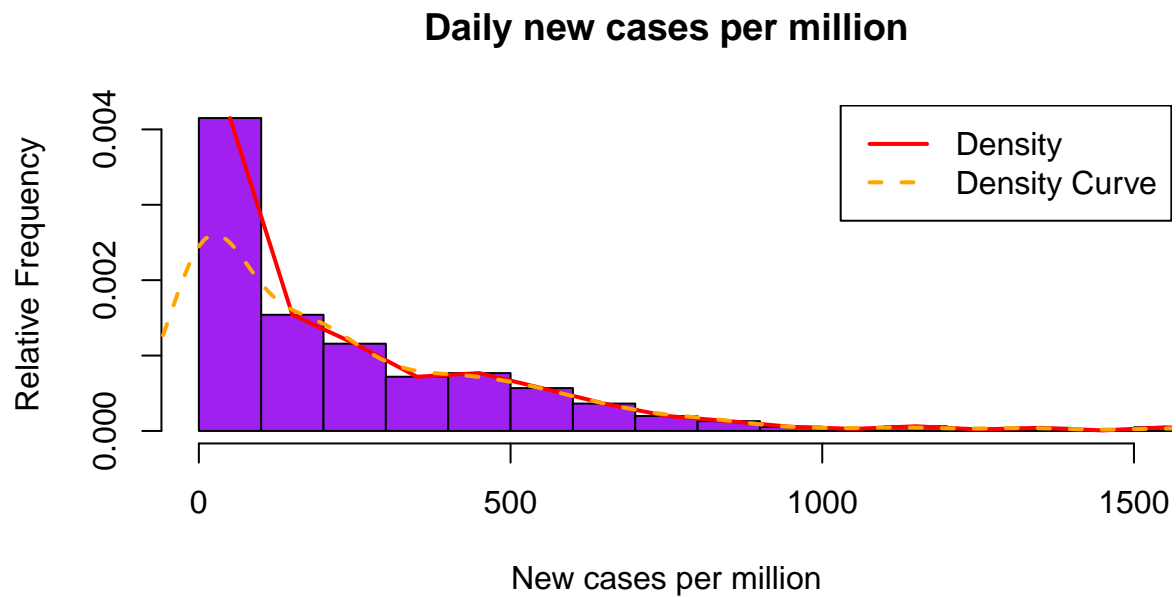
```
## United States United Kingdom      China      Belgium
##          0.899          0.849      0.000          0.945
```

### 11.4 Center & Spread (overall, selected countries, 2021)

```
## median    IQR    sd
## 162.9  379.7 357.4
```

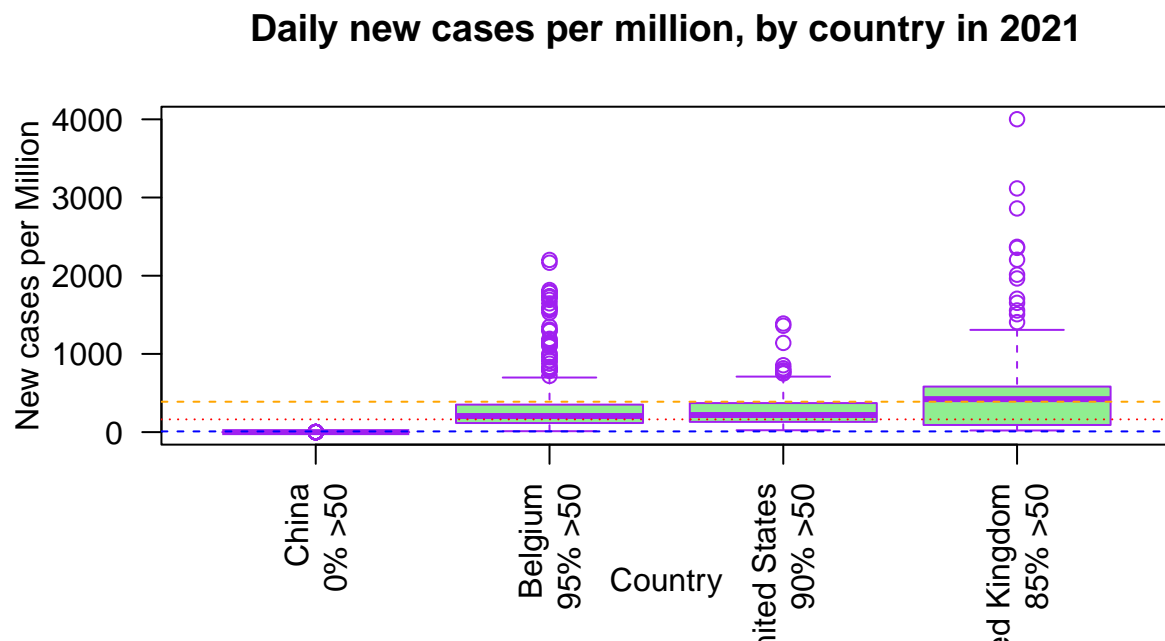
```
##          country median    IQR    sd
## 1 United States  218.4 240.7 201.6
## 2 United Kingdom 421.6 491.1 456.4
## 3      China      0.0   0.1   0.1
## 4      Belgium  205.4 235.4 396.2
```

## 11.5 Histogram (shape of the distribution)

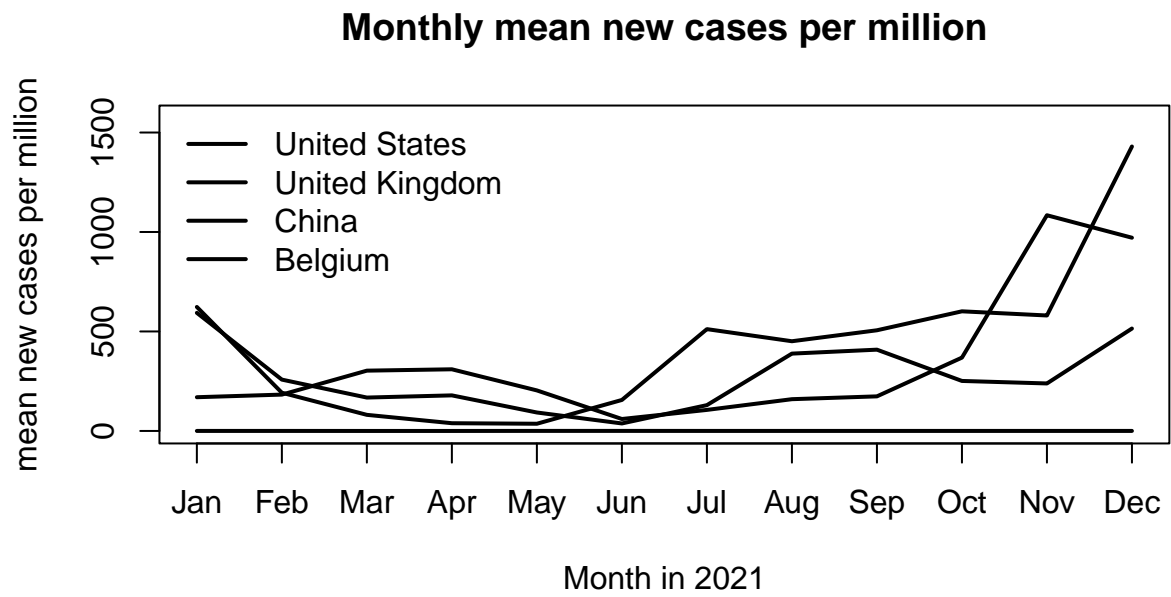


## 11.6 Boxplot (numeric by category)

Boxplot (Mortality rate by category)



### 11.7 Simple time trend (average by year)



## 12 Project Idea Two - Covid 19 Hospitalizations in France

### 13 Link to the dataset

Kaggle - Coronavirusdataset France (file: `chiffres-cles.csv`)

Actual URL: <https://www.kaggle.com/datasets/mclikmb4/coronavirusdataset-france?select=chiffres-cles.csv> Google drive URL: [https://drive.google.com/file/d/1rXHdGEDWFAMaitmkNSgehAt\\_e2FaC\\_PZ/view?usp=sharing](https://drive.google.com/file/d/1rXHdGEDWFAMaitmkNSgehAt_e2FaC_PZ/view?usp=sharing)

### 14 Introduction to the dataset

This dataset provides daily COVID-19 surveillance indicators for France at multiple geographic granularities (country, region, department, overseas collectivities). Each record includes a calendar date, a location code, and a location name, enabling comparisons across space and time. Indicators cover hospitalized patients, ICU occupancy, cumulative deaths, cumulative recoveries, and daily flows of new admissions (hospital and ICU). Source/provenance fields support auditability. The structure suits descriptive analyses and visualizations, with optional regional comparisons to highlight spatial heterogeneity. These indicators and their definitions are documented on the Kaggle dataset page (mclikmb4, 2020-2021).

### 15 Dataset justification

**Relevance:** Directly biomedical/public-health, reflecting real-world hospital and ICU loads during COVID-19.

**Size/structure:** The file far exceeds the minimum requirements (well over 100 rows and more than 20 columns) and includes both categorical (granularity, location IDs, sources) and continuous (counts) variables.

**Accessibility/ethics:** Publicly accessible aggregated, de-identified counts suitable for academic use.

**Analytical potential:** Enables trend estimation, wave identification, geographic comparison, and lead-lag analysis between admissions (“flow”) and occupancy (“stock”).

**Ethical use.** The dataset consists of aggregated, de-identified counts without PII; no patient-level identifiers are present, aligning with course requirements for ethical, public data.

### 16 Variables description

**Key columns:**

`date` (daily), `granularity` (country, region, department), `location_code` (location code), `location_name` (location name).

**Indicators:**

- `hospitalized` - current hospitalized patients

- `icu_patients` - current ICU patients
- `deaths` - cumulative deaths
- `recovered` - cumulative recoveries
- `new_hospitalizations` - new daily hospital admissions
- `new_icu_admissions` - new daily ICU admissions

#### Additional fields:

`confirmed_cases` and `tested` may be present with different levels of completeness.

**Note:** Due to several missing/invalid values (NaN/Inf), the `tested` column is largely unusable for analysis and is excluded from primary summaries and plots.

#### Source metadata:

`source_name`, `source_url`, `source_archive`, `source_type`.

Table 1: Row counts by geographic granularity

granularity	n
department	40715
region	7708
country	817
overseas_collectivity	131
world	83

Table 2: Summary statistics for key numeric indicators

variable	n	mean	sd	median	min	max
<code>confirmed_cases</code>	3081	121010.685	508142.429	27.0	0	3560764
<code>deaths</code>	47928	920.086	4150.452	135.0	0	70574
<code>hospitalized</code>	46826	578.225	2597.057	91.0	0	33497
<code>icu_patients</code>	46743	80.489	387.667	10.0	0	7148
<code>new_hospitalizations</code>	46095	32.664	166.648	4.0	0	4281
<code>new_icu_admissions</code>	46095	5.421	28.033	0.0	0	771
<code>recovered</code>	46712	3949.800	17835.138	645.5	0	299624
<code>tested</code>	0	NaN	NA	NA	Inf	-Inf

## 17 Research question(s)

1. **National waves:** How did France’s national hospitalization and ICU occupancy evolve across early pandemic waves (2020-2021)?
2. **Flow-stock timing:** Do peaks in new hospital admissions precede peaks in current hospitalizations, and by roughly how many days?



## 18 Data cleanup and processing plan

- **Parsing and types:** Ensure the `date` field is properly parsed as a date variable and convert indicator fields into numeric types for consistency.
- **Subsetting:** For national trends, include only rows classified as country with `location_code` = “FRA”. For geographic comparisons, restrict the dataset to rows where `granularity` is region.
- **Missingness:** Quantify missing values for each column and handle them transparently by applying listwise deletion for plotted series (no imputation).
- **Duplicates:** Identify and remove duplicate entries defined by the combination of `date` and `location_code`.
- **Provenance:** Retain all source metadata fields, and include them in the appendix when relevant for transparency.

## 19 Descriptive statistics (figures in Appendix)

France’s national indicators exhibit multi-wave patterns during 2020-2021. Hospital occupancy and ICU burden rise and fall in tandem with case surges, while cumulative deaths increase monotonically. The timing relationship between new admissions (flow) and current occupancy (stock) suggests admissions lead occupancy by several days. For visuals supporting these statements, see Appendix Figures A1-A3. Tables above summarize structure and central tendencies.

Across all rows, the median current hospitalizations was 91, with an IQR of 25-285; ICU occupancy had a much lower median, which is expected since ICU is a subset of the total hospital (median 10), consistent with ICU being a subset of total hospital burden.

## 20 Planned statistical methods

- **Lagged cross-correlation** between `new_hospitalizations` (flow) and `hospitalized` (stock) to estimate lead time from admissions to occupancy.
- **Regional comparison** of ICU vs hospital burden by wave period (medians, IQRs).
- **Simple time-series decomposition** on national hospitalizations to separate trend/seasonal/residual components (if applicable).

## 21 Limitations

Several fields like `tested` and early `confirmed_cases` have bad coverage over time, and indicators are hospital-centric rather than community-representative. Counts are aggregated and de-identified, so patient-level cannot be controlled. Because the dataset mixes granularities (national, regional, departmental), comparing across levels requires careful subsetting (`granularity == "country"`

for national trends). These constraints limit causal interpretation, so we have to focus more on descriptive trends and clearly labeled comparisons.

## 22 Appendix - Project Two

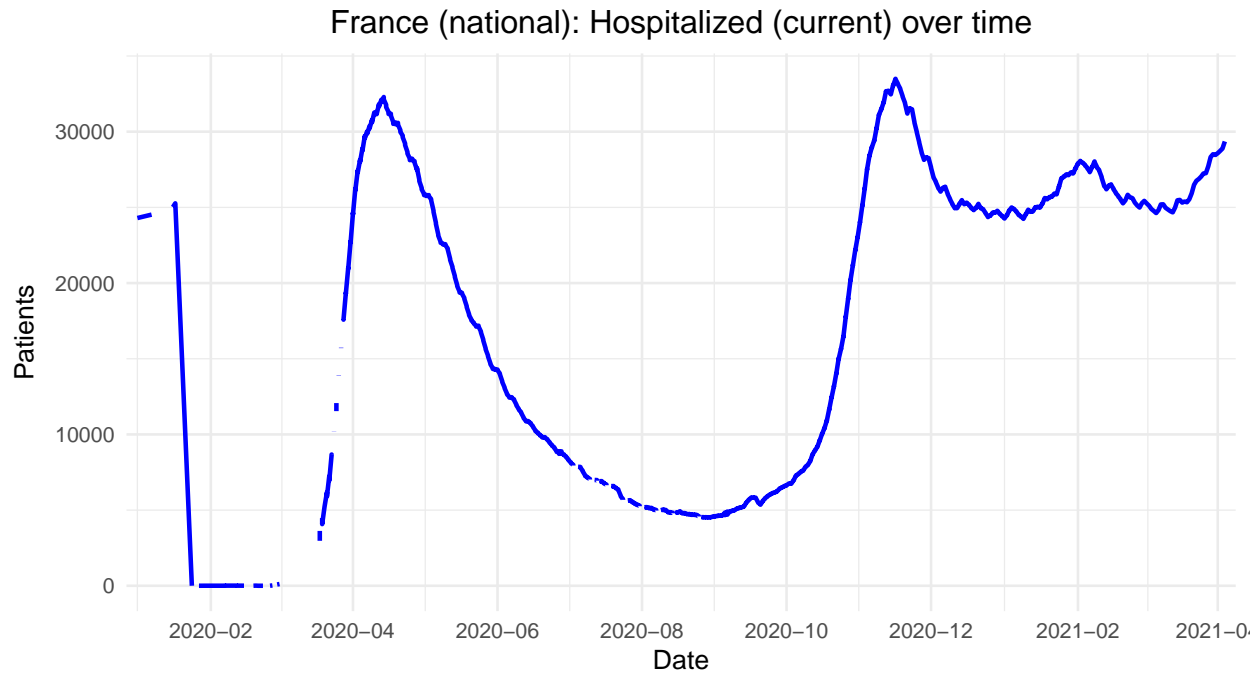


Figure 1: France (national): Hospitalized (current) over time.

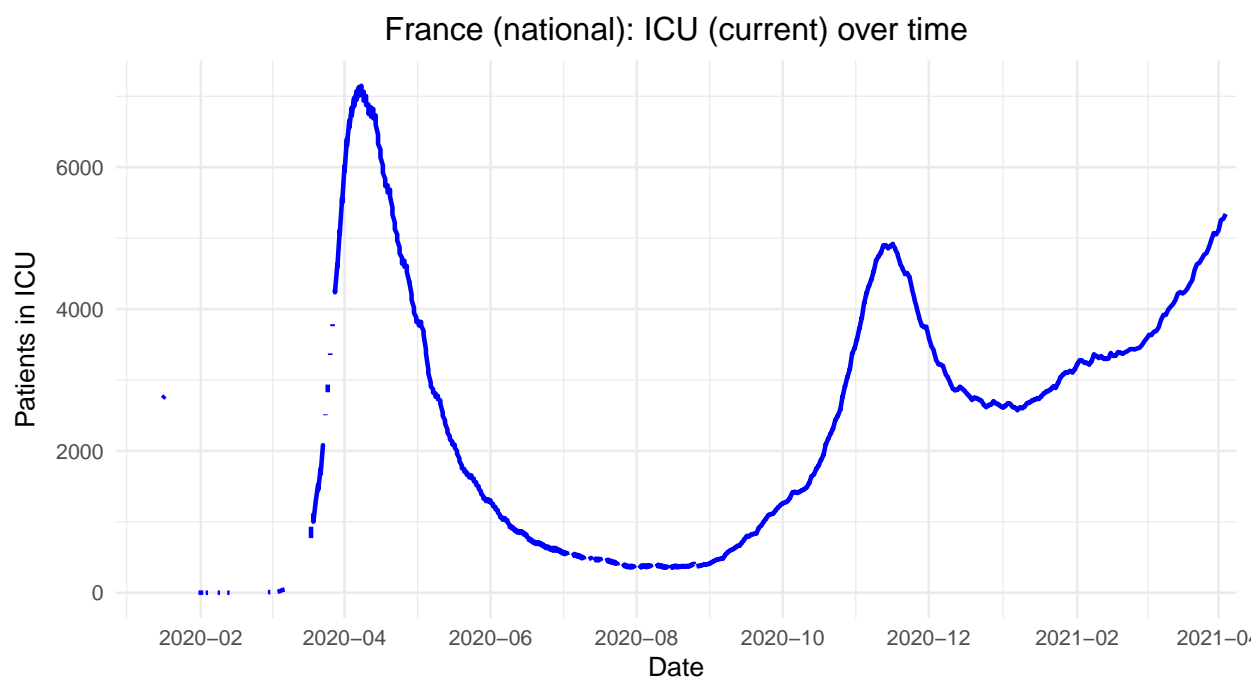


Figure 2: France (national): ICU (current) over time.

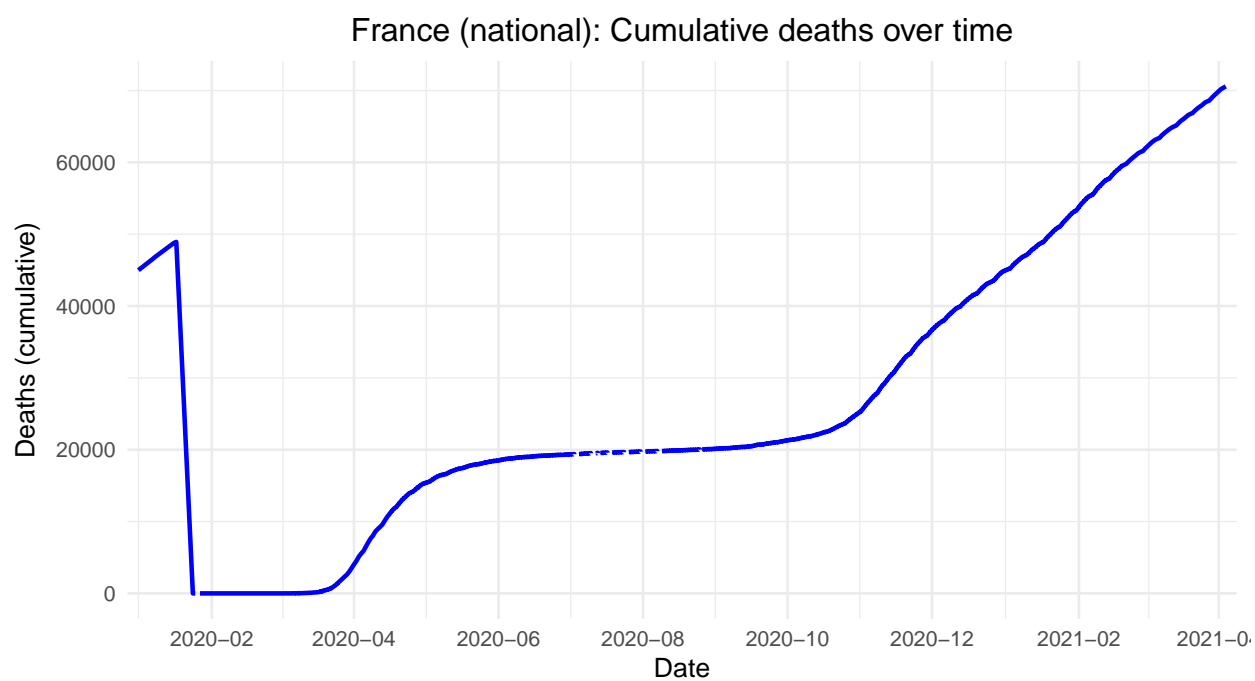


Figure 3: France (national): Cumulative deaths over time.

## 23 Project Idea Three - Heart attack

## 24 Link to the dataset

<https://www.kaggle.com/datasets/iamsouravbanerjee/heart-attack-prediction-dataset>

## 25 Introduction to dataset

The Heart Attack Prediction Dataset, available on Kaggle, is a comprehensive resource for studying the clinical, lifestyle, and demographic factors associated with cardiovascular risk. It consists of 8,763 de-identified patient records, including continuous variables such as age, cholesterol, blood pressure, and heart rate, as well as categorical features like sex, chest pain type, smoking habits, diabetes status, and dietary patterns. Socioeconomic and geographic attributes, including income and region, further enrich the dataset by adding broader context to heart health predictors. The primary outcome variable indicates whether a patient is at risk of a heart attack, making the dataset well-suited for statistical analysis, visualization, and classification tasks. Its diverse mix of variables supports exploration of correlations, risk factors, and group comparisons, while also providing an ethical and accessible foundation for predictive modeling in cardiovascular health research.

## 26 Dataset justification

I chose the Heart Attack Prediction Dataset because it directly addresses a critical biomedical challenge cardiovascular disease which remains one of the leading causes of mortality worldwide. The dataset integrates clinical, lifestyle, and demographic variables, making it highly relevant for exploring the multifactorial nature of heart health. With its balanced mix of categorical and continuous features, it offers strong potential for applying a variety of statistical methods, visualizations, and predictive modeling techniques. Its size and diversity of attributes make it complex enough to yield meaningful insights, yet still manageable for academic analysis. Overall, this dataset provides both real-world relevance and analytical richness, making it an excellent candidate for this project.

## 27 Variables description

Key columns include Patient ID (unique identifier for each record), Age (in years), Sex (male or female), Cholesterol (cholesterol levels in mg/dL), Blood Pressure (systolic/diastolic in mmHg), Heart Rate (beats per minute), and BMI (body mass index, kg/m<sup>2</sup>). Clinical indicators capture Diabetes status (Yes/No), Family History of heart problems (1 = Yes, 0 = No), Previous Heart Problems (1 = Yes, 0 = No), Medication Use (1 = Yes, 0 = No), and Triglyceride levels (mg/dL).

Lifestyle-related attributes include Smoking (1 = Smoker, 0 = Non-smoker), Obesity (1 = Obese, 0 = Not obese), Alcohol Consumption (None, Light, Moderate, Heavy), Diet (Healthy, Average, Unhealthy), Exercise Hours Per Week, Physical Activity Days Per Week, Stress Level (1–10 scale), Sedentary Hours Per Day, and Sleep Hours Per Day. Socioeconomic and demographic fields consist of Income, Country, Continent, and Hemisphere.

The target variable, Heart Attack Risk, is a binary indicator (1 = Yes, 0 = No) denoting whether the patient is at risk of a heart attack.

```
## 'data.frame':    8763 obs. of  26 variables:
## $ Patient.ID      : chr  "BMW7812" "CZE1114" "BNI9906" "JLN3497" ...
## $ Age             : int   67 21 21 84 66 54 90 84 20 43 ...
## $ Sex             : chr   "Male" "Male" "Female" "Male" ...
## $ Cholesterol      : int  208 389 324 383 318 297 358 220 145 248 ...
## $ Blood.Pressure   : chr   "158/88" "165/93" "174/99" "163/100" ...
## $ Heart.Rate       : int   72 98 72 73 93 48 84 107 68 55 ...
## $ Diabetes         : int    0 1 1 1 1 1 0 0 1 0 ...
## $ Family.History   : int    0 1 0 1 1 1 0 0 0 1 ...
## $ Smoking          : int    1 1 0 1 1 1 1 1 1 1 ...
## $ Obesity          : int    0 1 0 0 1 0 0 1 1 1 ...
## $ Alcohol.Consumption : int    0 1 0 1 0 1 1 1 0 1 ...
## $ Exercise.Hours.Per.Week : num  4.17 1.81 2.08 9.83 5.8 ...
## $ Diet             : chr   "Average" "Unhealthy" "Healthy" "Average" ...
## $ Previous.Heart.Problems : int    0 1 1 1 1 1 0 0 0 0 ...
## $ Medication.Use    : int    0 0 1 0 0 1 0 1 0 0 ...
## $ Stress.Level      : int    9 1 9 9 6 2 7 4 5 4 ...
## $ Sedentary.Hours.Per.Day : num  6.62 4.96 9.46 7.65 1.51 ...
## $ Income           : int  261404 285768 235282 125640 160555 241339 190450 1...
## $ BMI              : num   31.3 27.2 28.2 36.5 21.8 ...
## $ Triglycerides     : int   286 235 587 378 231 795 284 370 790 232 ...
## $ Physical.Activity.Days.Per.Week : int    0 1 4 3 1 5 4 6 7 7 ...
## $ Sleep.Hours.Per.Day : int    6 7 4 4 5 10 10 7 4 7 ...
## $ Country           : chr   "Argentina" "Canada" "France" "Canada" ...
## $ Continent         : chr   "South America" "North America" "Europe" "North Am...
## $ Hemisphere        : chr   "Southern Hemisphere" "Northern Hemisphere" "North...
## $ Heart.Attack.Risk : int    0 0 0 0 0 1 1 1 0 0 ...

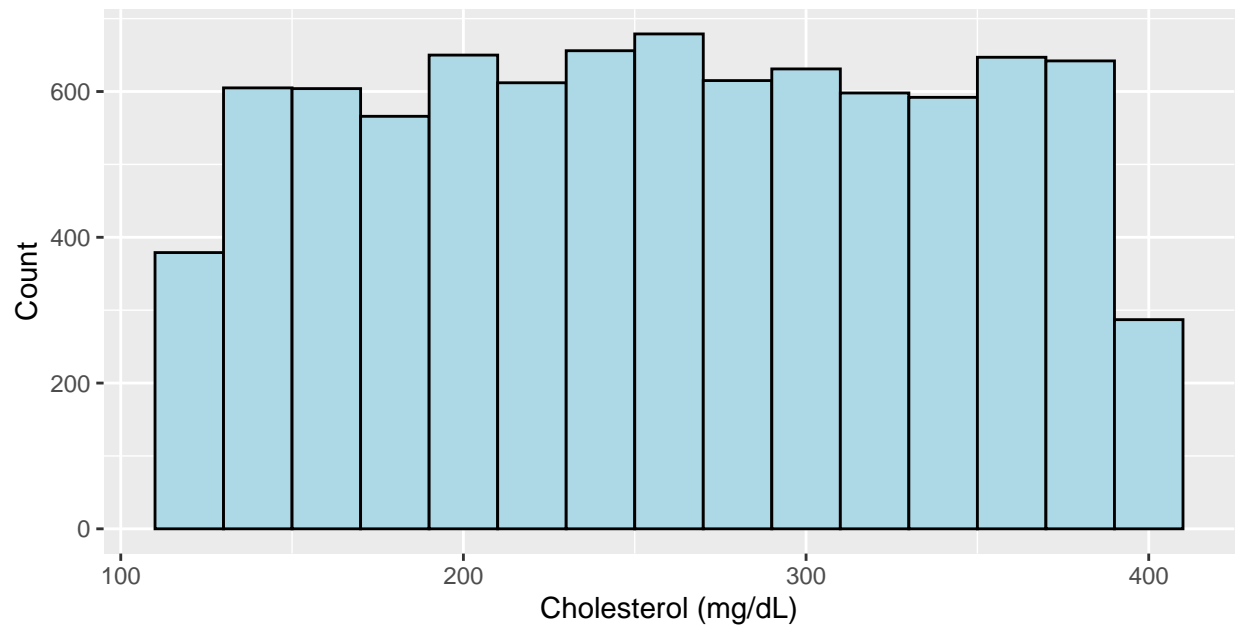
## Patient.ID      Age      Sex      Cholesterol
## Length:8763      Min.    :18.00 Length:8763      Min.    :120.0
## Class :character  1st Qu.:35.00 Class :character  1st Qu.:192.0
## Mode  :character  Median :54.00 Mode  :character  Median :259.0
##                      Mean    :53.71                      Mean    :259.9
##                      3rd Qu.:72.00                      3rd Qu.:330.0
##                      Max.    :90.00                      Max.    :400.0
## Blood.Pressure    Heart.Rate    Diabetes    Family.History
## Length:8763      Min.    : 40.00 Min.    :0.0000 Min.    :0.000
## Class :character  1st Qu.: 57.00 1st Qu.:0.0000 1st Qu.:0.000
## Mode  :character  Median : 75.00 Median :1.0000 Median :0.000
##                      Mean    : 75.02 Mean    :0.6523 Mean    :0.493
##                      3rd Qu.: 93.00 3rd Qu.:1.0000 3rd Qu.:1.000
##                      Max.    :110.00 Max.    :1.0000 Max.    :1.000
## Smoking           Obesity       Alcohol.Consumption Exercise.Hours.Per.Week
## Min.    :0.0000 Min.    :0.0000 Min.    :0.0000 Min.    : 0.002442
```

```

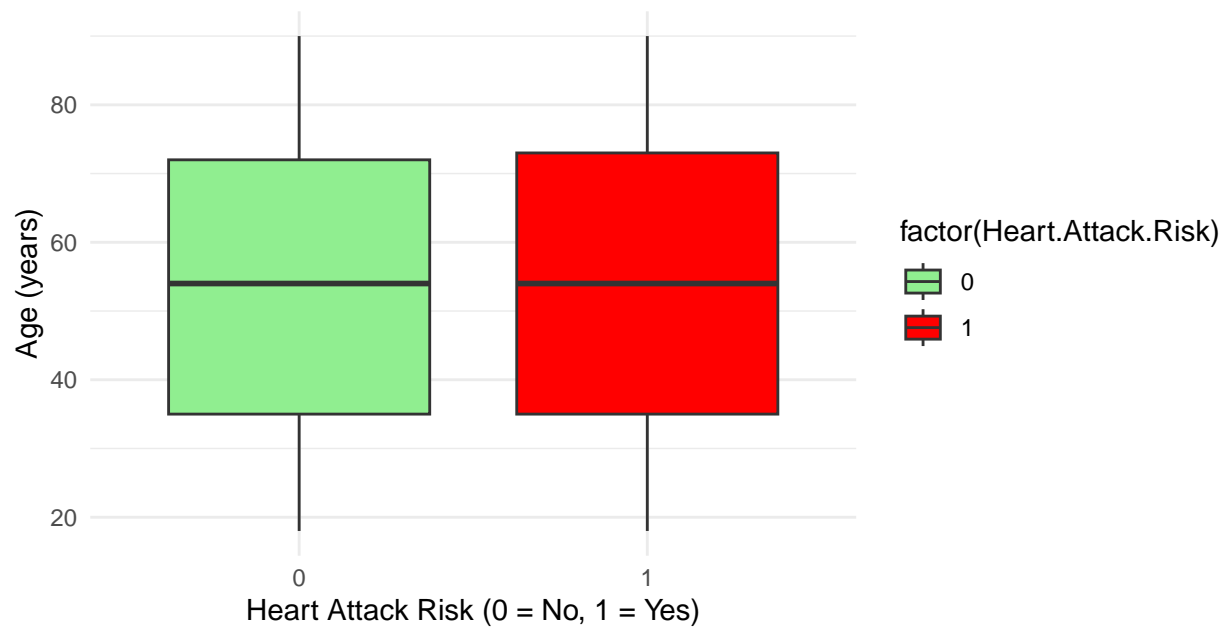
## 1st Qu.:1.0000 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.: 4.981579
## Median :1.0000 Median :1.0000 Median :1.0000 Median :10.069559
## Mean :0.8968 Mean :0.5014 Mean :0.5981 Mean :10.014284
## 3rd Qu.:1.0000 3rd Qu.:1.0000 3rd Qu.:1.0000 3rd Qu.:15.050018
## Max. :1.0000 Max. :1.0000 Max. :1.0000 Max. :19.998709
## Diet Previous.Heart.Problems Medication.Use Stress.Level
## Length:8763 Min. :0.0000 Min. :0.0000 Min. : 1.00
## Class :character 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.: 3.00
## Mode :character Median :0.0000 Median :0.0000 Median : 5.00
## Mean :0.4958 Mean :0.4983 Mean : 5.47
## 3rd Qu.:1.0000 3rd Qu.:1.0000 3rd Qu.: 8.00
## Max. :1.0000 Max. :1.0000 Max. :10.00
## Sedentary.Hours.Per.Day Income BMI Triglycerides
## Min. : 0.001263 Min. : 20062 Min. :18.00 Min. : 30.0
## 1st Qu.: 2.998794 1st Qu.: 88310 1st Qu.:23.42 1st Qu.:225.5
## Median : 5.933622 Median :157866 Median :28.77 Median :417.0
## Mean : 5.993690 Mean :158263 Mean :28.89 Mean :417.7
## 3rd Qu.: 9.019125 3rd Qu.:227749 3rd Qu.:34.32 3rd Qu.:612.0
## Max. :11.999313 Max. :299954 Max. :40.00 Max. :800.0
## Physical.Activity.Days.Per.Week Sleep.Hours.Per.Day Country
## Min. :0.00 Min. : 4.000 Length:8763
## 1st Qu.:2.00 1st Qu.: 5.000 Class :character
## Median :3.00 Median : 7.000 Mode :character
## Mean :3.49 Mean : 7.024
## 3rd Qu.:5.00 3rd Qu.: 9.000
## Max. :7.00 Max. :10.000
## Continent Hemisphere Heart.Attack.Risk
## Length:8763 Length:8763 Min. :0.0000
## Class :character Class :character 1st Qu.:0.0000
## Mode :character Mode :character Median :0.0000
## Mean :0.3582
## 3rd Qu.:1.0000
## Max. :1.0000

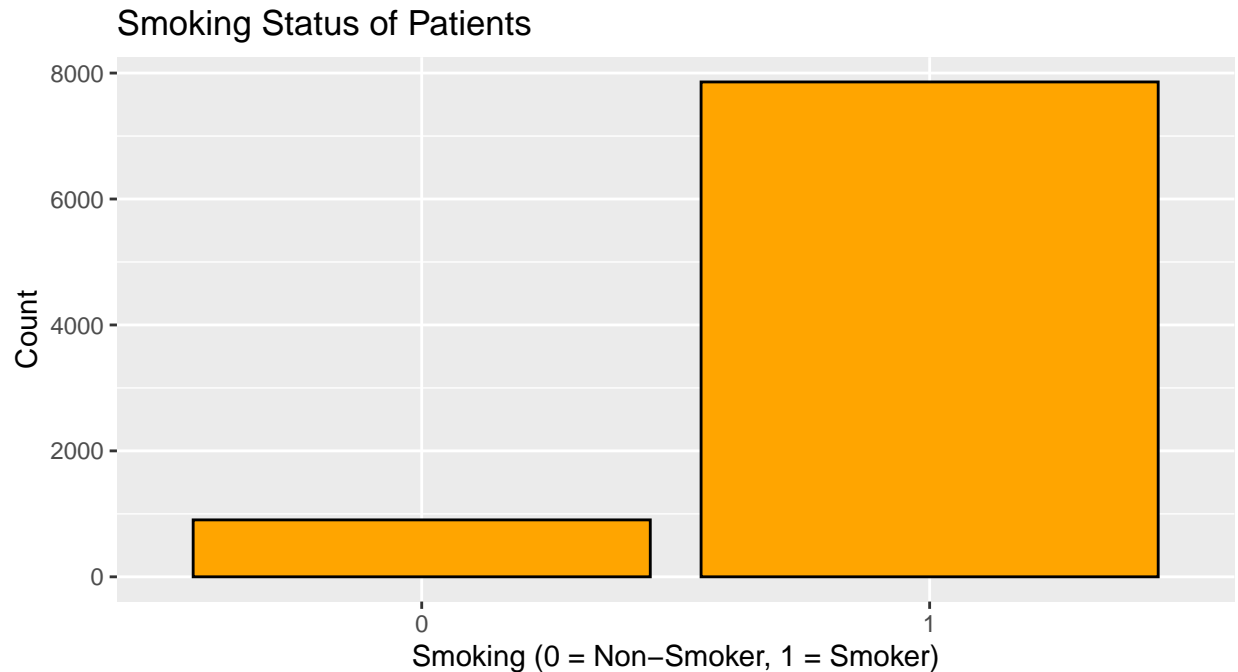
```

Distribution of Cholesterol Levels



Age Distribution by Heart Attack Risk





## 28 Research questions

1. Which clinical, lifestyle, and demographic factors are most strongly associated with the risk of heart attack in patients?
2. Which features contribute most to a machine learning model's decision boundary for predicting heart attack risk?

## 29 Data cleanup and processing plan

- Check for missing values: Identify NAs using `colSums(is.na(hd))`; if very few, remove those rows; if moderate, impute using mean/median for continuous variables (e.g., Cholesterol, BMI) and mode for categorical variables (e.g., Diet, Alcohol Consumption).
- Remove duplicate entries: Drop exact duplicates or repeated Patient IDs to avoid over-representation using `hd <- hd[!duplicated(hd), ]`.
- Fix inconsistent formats: Split Blood Pressure into two numeric columns (Systolic and Diastolic) and convert binary indicators (0/1) like Diabetes, Smoking, and Heart Attack Risk into categorical factors.
- Validate ranges & handle outliers: Review continuous variables (e.g., Cholesterol, Triglycerides, BMI, Sleep Hours) for biologically implausible values; correct, cap, or remove extreme outliers as appropriate.
- Standardize categorical variables: Ensure consistent levels for Sex (Male/Female), Diet (Healthy/Average/Unhealthy), and Alcohol Consumption (None/Light/Moderate/Heavy).



- Create derived variables: Add new groupings such as Age Groups (e.g., 18–30, 31–50, 51–70, 71–90) and BMI Categories (Underweight, Normal, Overweight, Obese) to facilitate group comparisons in descriptive statistics and visualization.

## 30 Descriptive statistics (figures in Appendix)

## 31 Planned statistical methods

As the project progresses, I plan to use chi-square tests to assess associations between categorical factors (e.g., smoking, diabetes) and heart attack risk, and t-tests/ANOVA to compare continuous measures (e.g., cholesterol, BMI) across groups. To build predictive insight, I will apply logistic regression and may explore machine learning models such as decision trees or random forests. These methods will help identify key risk factors and evaluate their predictive power.

## 32 Limitations

## 33 Appendix - Project Three

```
##
## Variable: Age
## Mean: 53.70798
## Median: 54
## Range: 72
## Standard Deviation: 21.24951
##
## Variable: Cholesterol
## Mean: 259.8772
## Median: 259
## Range: 280
## Standard Deviation: 80.86328
##
## Variable: Heart.Rate
## Mean: 75.02168
## Median: 75
## Range: 70
## Standard Deviation: 20.55095
##
## Variable: BMI
## Mean: 28.89145
## Median: 28.769
## Range: 21.99487
## Standard Deviation: 6.319181
##
## Variable: Triglycerides
```

```

## Mean: 417.6771
## Median: 417
## Range: 770
## Standard Deviation: 223.7481
##
## Variable: Exercise.Hours.Per.Week
## Mean: 10.01428
## Median: 10.06956
## Range: 19.99627
## Standard Deviation: 5.783745
##
## Variable: Stress.Level
## Mean: 5.469702
## Median: 5
## Range: 9
## Standard Deviation: 2.859622
##
## Variable: Sedentary.Hours.Per.Day
## Mean: 5.99369
## Median: 5.933622
## Range: 11.99805
## Standard Deviation: 3.466359
##
## Variable: Income
## Mean: 158263.2
## Median: 157866
## Range: 279892
## Standard Deviation: 80575.19
##
## Variable: Physical.Activity.Days.Per.Week
## Mean: 3.489672
## Median: 3
## Range: 7
## Standard Deviation: 2.282687
##
## Variable: Sleep.Hours.Per.Day
## Mean: 7.023508
## Median: 7
## Range: 6
## Standard Deviation: 1.988473
##
##
## Variable: Sex
##
## Female    Male
##    2652    6111
##
## Variable: Diabetes

```

```

##
##      0      1
## 3047 5716
##
## Variable: Family.History
##
##      0      1
## 4443 4320
##
## Variable: Smoking
##
##      0      1
##  904 7859
##
## Variable: Obesity
##
##      0      1
## 4369 4394
##
## Variable: Alcohol.Consumption
##
##      0      1
## 3522 5241
##
## Variable: Diet
##
##      Average      Healthy Unhealthy
##          2912          2960          2891
##
## Variable: Previous.Heart.Problems
##
##      0      1
## 4418 4345
##
## Variable: Medication.Use
##
##      0      1
## 4396 4367
##
## Variable: Country
##
##      Argentina      Australia      Brazil      Canada      China
##          471          449          462          440          436
##      Colombia      France      Germany      India      Italy
##          429          446          477          412          431
##          Japan      New Zealand      Nigeria      South Africa      South Korea
##          433          435          448          425          409
##          Spain      Thailand United Kingdom      United States      Vietnam

```

```

##          430          428          457          420          425
##
## Variable: Continent
##
##          Africa          Asia          Australia          Europe North America
##          873          2543          884          2241          860
## South America
##          1362
##
## Variable: Hemisphere
##
## Northern Hemisphere Southern Hemisphere
##          5660          3103
##
## Variable: Heart.Attack.Risk
##
##      0      1
## 5624 3139

```

```
## Categorical Columns:
```

```

## [1] "Patient.ID"      "Sex"              "Blood.Pressure"  "Diet"
## [5] "Country"         "Continent"        "Hemisphere"

```

```
##
```

```
## Numerical Columns:
```

```

## [1] "Age"              "Cholesterol"
## [3] "Heart.Rate"       "Diabetes"
## [5] "Family.History"   "Smoking"
## [7] "Obesity"          "Alcohol.Consumption"
## [9] "Exercise.Hours.Per.Week" "Previous.Heart.Problems"
## [11] "Medication.Use"   "Stress.Level"
## [13] "Sedentary.Hours.Per.Day" "Income"
## [15] "BMI"              "Triglycerides"
## [17] "Physical.Activity.Days.Per.Week" "Sleep.Hours.Per.Day"
## [19] "Heart.Attack.Risk"

```

```

##          variable      n      mean
## Age                Age 8763    53.71
## Cholesterol        Cholesterol 8763    259.88
## Heart.Rate         Heart.Rate 8763    75.02
## Diabetes           Diabetes 8763     0.65
## Family.History     Family.History 8763    0.49
## Smoking            Smoking 8763     0.90
## Obesity            Obesity 8763     0.50
## Alcohol.Consumption Alcohol.Consumption 8763    0.60

```

## Exercise.Hours.Per.Week	Exercise.Hours.Per.Week	8763	10.01
## Previous.Heart.Problems	Previous.Heart.Problems	8763	0.50
## Medication.Use	Medication.Use	8763	0.50
## Stress.Level	Stress.Level	8763	5.47
## Sedentary.Hours.Per.Day	Sedentary.Hours.Per.Day	8763	5.99
## Income	Income	8763	158263.18
## BMI	BMI	8763	28.89
## Triglycerides	Triglycerides	8763	417.68
## Physical.Activity.Days.Per.Week	Physical.Activity.Days.Per.Week	8763	3.49
## Sleep.Hours.Per.Day	Sleep.Hours.Per.Day	8763	7.02
## Heart.Attack.Risk	Heart.Attack.Risk	8763	0.36
##	median	range	
## Age	54.00	72.00	
## Cholesterol	259.00	280.00	
## Heart.Rate	75.00	70.00	
## Diabetes	1.00	1.00	
## Family.History	0.00	1.00	
## Smoking	1.00	1.00	
## Obesity	1.00	1.00	
## Alcohol.Consumption	1.00	1.00	
## Exercise.Hours.Per.Week	10.07	20.00	
## Previous.Heart.Problems	0.00	1.00	
## Medication.Use	0.00	1.00	
## Stress.Level	5.00	9.00	
## Sedentary.Hours.Per.Day	5.93	12.00	
## Income	157866.00	279892.00	
## BMI	28.77	21.99	
## Triglycerides	417.00	770.00	
## Physical.Activity.Days.Per.Week	3.00	7.00	
## Sleep.Hours.Per.Day	7.00	6.00	
## Heart.Attack.Risk	0.00	1.00	

## 34 ) JOINT PROJECTS - References

- Project 1 - Our World in Data. (2024). Coronavirus Pandemic (COVID-19) dataset. <https://docs.owid.io/projects/covid/en/latest/dataset.html>
- Project 2 - mclikmb4, (2021, April 4), Coronavirus-dataset France, Kaggle, <https://www.kaggle.com/datasets/mclikmb4/coronavirusdataset-france?select=chiffres-cles.csv>
- Project 3 - Banerjee, S. (2021). Heart Attack Prediction Dataset. Kaggle. <https://www.kaggle.com/datasets/iamsouravbanerjee/heart-attack-prediction-dataset>