American University of Armenia

Zaven & Sonia Akian College of Science and Engineering

Capstone Project

Study of the impact of various socioeconomic factors on global mortality rates.

Robert Mirzoyan, Aram Harutyunyan

Supervised by Ashot Harutyunyan, PhD

Spring 2024

Table of Contents

Abstract

This study investigates the relationship between mortality rates and various socioeconomic factors in different countries and explores the behavior of death rates based on linear visualizations. We have analyzed data from multiple sources, including socioeconomic factors and demographic datasets of population and deaths, to discover patterns and relationships influencing mortality outcomes.

Our study focused on deaths per 1000 individuals as the primary mortality metric. Next, we also include several socioeconomic factors like gross domestic product (GDP), purchasing power parity (PPP), average level of education of the population, and many others. With the help of statistical techniques, simple data visualizations, and correlation heat maps, we examined the relationship between death rates and the socioeconomic indicators mentioned.

This study highlights the critical role of social and economic factors in shaping population health outcomes and relationships between mortality rates and socioeconomic factors. The findings promote the importance of targeted interventions and policies that will concentrate on issues in the socioeconomic sector and improve the overall well-being and health of the people.

Introduction

Over the last several decades, our planet has undergone many industrial, economic, and social changes. These transformations affected the lives of the nations in various ways, influencing not only economic growth or recession but also the population's health and well-being. How countries have responded to these shifts has both long-term and immediate impacts on the lives of their citizens.

Understanding the relationship between socioeconomic factors and mortality rates in each country is critical, and our study aims to unravel the connections between them across different states. By examining different datasets about gross domestic product (GDP), purchasing power parity (PPP), average years of education, percentage of unemployment, annual inflation, CO2 emissions, healthcare access and coverage of health services, and demographic information on population and deaths, we are seeking to identify patterns and correlations which will give us a chance to investigate mortality outcomes.

With the help of correlation assessments, statistical analyses, and data visualizations, we uncover how socioeconomic factors and death rates interact and develop hypotheses for further investigation. By this, we want to emphasize the importance of targeted interventions and developing proper policies to improve overall population well-being.

Related Work

The problem of investigating socioeconomic factors and their relation to mortality rates has become very topical in public health research. It was researched from various perspectives in the number of works, but the general total can supply valuable lessons for the present study.

Global Mortality and Socioeconomic Disparities The study conducted by Basu et al. The authors argue that globalization increases already-existing health inequalities, especially in low-income countries where reaching health facilities remains a pipe dream. There is a need to put in place policies that act on these disparities to reduce the levels of mortality (Basu et al., 2022).

National Academies of Sciences, Engineering, and Medicine (2021) The Role of Socioeconomic Status in Health and Mortality. Such risk factors that lower socioeconomic status also indicate are further associated with poor living conditions, limited access to health care, and high rates of chronic diseases, all of which ultimately translate into higher mortality rates for disadvantaged populations (National Academies of Sciences, Engineering, and Medicine, 2021).

Economic Factors and Mortality Rates in Ghana Boateng. According to the researchers, from their results, financial stability, based on GDP, employment rates, and related indices, greatly determines mortality rates. They argued that improved economic conditions result in better health conditions and reduced mortality rates, stressing the need for economic policies in health interventions. Mortality Trends Statistical Analysis The Ezzati et al. study (2023) employs advanced statistical methods, large datasets, and modeling techniques to show considerable disparities in mortality rates that are traceable to socioeconomic factors, further calling for directed public health techniques to offset the disproportions.

Socioeconomic Factors and Neonatal Mortality According to UNICEF (2021), newborn babies are very vulnerable in socioeconomically poor areas when it comes to the rates of neonatal mortality that have been witnessed recently. This report strongly links neonatal mortality, maternal education, access to health services, and household income. These findings suggest the importance of maternal and child health programs in a general sense to reduce newborn deaths.

Healthcare Access and Mortality The Institute for Health Metrics and Evaluation (2022) infers that healthcare access contributes to health outcomes and mortality. Better access to crucial health services will decrease mortality rates in middle- and low-income nations. More emphasis is also placed on improving health infrastructure and the equitable distribution of health assets to reduce mortality risks.

Conclusion: Current research supports the multifaceted relation of mortality rates with socioeconomic factors. Undoubtedly defined determinants of health outcomes are economic stability, healthcare access, and social policies. After these findings were integrated, we tried to explain the relationships further and how actionable insights for policymakers could help public health and mortality rates.

Datasets and Data Sources:

We explored different data sources to explore the relationship between mortality rates, socioeconomic factors, and overall changes in death rates over the years. We found the following datasets appropriate for our research. We divided datasets into two categories: Death-related and socioeconomic.

Death-related datasets:

The United Nations Department of Economic and Social Affairs provides mortality and population data from 1950 to 2022 (World et al., 2022). The data, in thousands, covers ages 0 to 99, with an additional column for ages 100+. Mortality data is available in three Excel files: Deaths by Single Age - Male, Deaths by Single Age - Female, and Deaths by Single Age - Both Sexes. Each file includes:

- Region, subregion, country, or area: Name of the location.
- Type: Indicates if the row represents a country, area, region, or subregion.
- Iso3 Alpha-code: Three-letter country code.
- Year: Year of the estimation.
- Columns 0, 1, 2 … 99, 100+: Number of deaths (in thousands) for each age.

The population data is organized the same way as mortality data, except the columns from 0 to 100 represent the population in the selected country and year in thousands.

For more precise visualization of the mortality rates, we found datasets for life expectancy (UN WPP, 2022; HMD, 2023; Zijdeman et al., 2015; Riley, 2005, as cited in Our World in Data) and median age (United et al., 2022, processed by Our World in Data) for each country starting for 1950 to 2022. Datasets contain country names, years, and corresponding values.

Socioeconomic datasets:

For socioeconomic data, we used several datasets:

- Purchasing power parity per capita (World Bank, n.d.)
- Gross domestic product per capita (World Bank, n.d.)
- Annual inflation on consumer prices (World Bank, n.d.)
- CO2 emissions metric tons per capita (World Bank, n.d.)
- Unemployment percentage of labor force (World Bank, n.d.)
- Coverage of essential health services (Institute of Health Metrics and Evaluation, 2022, processed by Our World in Data)

- Average years of education (Barro & Lee, 2015; Lee & Lee, 2016, processed by Our World in Data)
- Healthcare Access and Quality Index (Institute for Health Metrics and Evaluation, 2017, processed by Our World in Data)

The last two datasets include an "Entity" column containing country names, a "Code" column with short three-letter country codes, and a column with values. Other datasets have years as column names containing values for the corresponding year. All datasets are initially in CSV format. The datasets of socioeconomic factors are available for most countries; however, those are not present for all of them because of different reasons.

Data Management and Visualization Techniques

For the development and analysis of this project, from the wide range of programming languages and visualization tools, we chose SAS and R. SAS was mainly used as a data management and Standardization tool. R was largely used for data visualizations and some minor data changes. Having these two, we are sure that with the help of SAS as a data management and standardization tool, we got consistent and ready-for-analysis data, complementing it with R, which allows us to create good visualizations. Ultimately, we will get outputs that will make understanding patterns, trends, and relationships within data under investigation easy.

Data Management and Standardization Using SAS (Statistical Analysis System)

SAS (previously "Statistical Analysis System") is a statistical software developed by SAS Institute. It was developed at North Carolina State University (1966 -1976) when the SAS Institute was incorporated. In the 1980s and 1990s, SAS was enriched with new statistical procedures, the introduction of JMP, and other additional components. It is used for data management, advanced and multivariate analysis, business intelligence, predictive analytics, etc.

In this project, SAS handles essential processes such as importing and exporting, transforming, cleaning, and analyzing the data. Using "*PROC IMPORT*," SAS can import data from various sources like Excel, CSV, and databases to SAS datasets (.sas7bdat files) and export data by the same formats using proc '*PROC EXPORT*.' By "ODS" (Output Delivery System), SAS results can be exported in PDF, RTF, and HTML formats. A "DATA" step in SAS is a fundamental building block used to read, modify, and create data sets by processing data line-by-line. Data is cleaned using simple SAS functions, if-else statements, and SAS formats. For filtering, joining, aggregating, and subsetting data, we used *DATA* steps and "*PROC SQL*." We used macro programs, a set of instructions written using the SAS macro language, to automate repetitive tasks, make code more dynamic, and improve flexibility. We also used "*PROC TRANSPOSE*" to transpose data in case it is needed to maintain consistency between datasets. It is essential to mention that SAS programming language columns in datasets represent variables; each variable is a separate column in the .sas7bdat file.

Data Visualization with R

Data visualization is non-replaceable in data analytics since it lets us convert complicated datasets into easy-to-understand and clean visualizations. As a statistical programming language, R has compelling tools for producing attractive and practical graphics. It is armed with the necessary tools for powerful static and interactive data visualization, such as "*ggplot2*", "*Plotly*," and "*Shiny*" R packages and many others. The "*ggplot2*" is ahead by unique and practical functions to produce static pictures that can easily be customized, while "plotly" adds interactivity to plots. "*Shiny*" provides tools to develop interactive web apps where you can directly display data, which ultimately clarifies and strengthens the visual understanding of the user.

In addition to these packages, we used "*RColorBrewer*," which offers a range of color palettes to enhance the visual appeal of the plots. The "*dplyr*" package helped with data manipulation, making it easier to filter, select, and transform data. The "*magrittr*" package has the pipe operator (%>%), which combines multiple operations and makes code more readable and efficient. With the "*zoo*" package, one can do time series operations by having linear interpolation as one of its operations.

Methodology (Development Process)

Data Preparation

As mentioned in the previous section, we used SAS for Data management and Standardization. Still, before importing our files to SAS and converting them to the sas7bdat dataset type, we made some manual changes to the files. In some files, we have years as column names; in others, ages, based on the SAS variable naming rule, we cannot have numbers as column names, so we modified these names by adding text prefixes. For example, "1960" was changed to "Yr1960," and "18" was changed to "Age18." After modifications, we imported all datasets using the import procedure.

Economic Factors Dataset

As mentioned, "Average Years of Education" and "Healthcare Access and Quality Index" already need structure so we will get back to them later. As for other datasets, we combined them by setting in one data step and giving indicator names for each economic factor. In the same block, since datasets came from different sources, country names were modified to keep consistency between observations. For example, "Syrian Arab Republic" was changed to "Syria," so we will not have two different groups for the same country. After that, to have the needed structure, i.e., years, as separate columns, we use "*proc transpose*." In the Transpose procedure, we group by countries, and for each group, transpose the Yr1960-Yr2022 variables(columns), using the values in the "indicator name" variable to create new column names in the output dataset. After transposing, we merge outputted data with the remaining two datasets by country name and year using SQL procedure and export the resulting dataset as a CSV file using "proc export."

Mortality Datasets

For further analyses, we need to preserve values in a single column, but in the initial dataset, values are kept for every age separately in different columns. We begin by loading deaths data, focusing on key variables (columns) such as year, country, sex, and age. This data is transposed and grouped by country, year, and sex for all age variables. Next, we combine male and female population data, ensuring it only includes relevant entries. We calculate the total population by summing age-related variables. After sorting, this population data is also transposed. Using SQL, we create a summary table to get the total population per country and year and join it with the transposed deaths data. This allows us to calculate deaths per 1000 individuals for each age and the total population. Finally, we sort the data and split it into four different CSV files as the data is too big to be supported by just one. The reason is that the CSV file limit is one million raws

(1,048,576). The same was done by excluding sex in grouping variables to get data without gender separation, so we got two additional CSV files.

For the research, we decided also to combine ages into four groups:

- Children: From age 0 to 7.
- Young Adults: From age 8 to 17.
- Adults: From age 18 to 59.
- Geriatric: Age 60 and more.

For this purpose, we created macro "%grouping," which processes data by category (deaths or population) and sex (male, female, both sexes). It creates datasets for each category and sex by summing deaths or population numbers into age groups. Then, we apply the macro for deaths and population data for each sex.

```
%macro grouping (category=,sex =);
        data &category._&sex._groups;
                set capstone.&category._&sex.;
                if Type = "Country/Area" or Type = "World";
                country = 'Region, subregion, country or ar'n;
                Country_Code = "ISO3 Alpha-code"n;
                children = input(age0, best.);
                array childrenarr {7} age1-age7;
                do i=1 to 7;
                children = sum(children , input(childrenarr[i], best.));
                end;
                youngadults = input(age8, best.);
                array youngadultsarr {9} age9-age17;
                do i=1 to 9;
                youngadults = sum(youngadults , input(youngadultsarr[i], best.));
                end;
                adults = input(age18, best.);
                array adultsarr {41} age19-age59;
                do i=1 to 41;
                        adults = sum(adults , input(adultsarr[i], best.));
                end;
                geriatric = input('age100+'n, best.);
                array geriatricarr {40} age60-age99;
                do i=1 to 40;
                        geriatric = sum(geriatric , input(geriatricarr[i], best.));
                end;
                keep year country Country_Code children youngadults adults geriatric;
        run;
%mend;
```

After creating grouped datasets, we calculate deaths per 1000 individuals for each age group by joining deaths and population datasets. This step is repeated for both male and female datasets. We sort and transpose the data to get a long-format dataset. The same steps are performed for male and female datasets. Next, we combine and export all the datasets as a CSV file. Finally, we create a test table to validate the dataset by checking for consistency in country names and codes. This completes the grouping, transforming, and exporting the deaths per 1000 population data categorized by sex and age groups.

Moving to R

We converted the CSV files to Rdata format to enhance performance during visualizations and saved the results for further analysis. This optimization reduces the processing time, as R works more efficiently with Rdata-type datasets compared to CSV files, eliminating the need for repeated conversions.

We also used R to fill in some datasets using linear interpolation. Two economic factors are '*Average years of education*' and '*Healthcare Access and Quality Index*'; the data starts from 1990 and is available only every five years. For example, in the case of Armenia in 1990, the Healthcare Access and Quality Index value was 56.8, and the next available value was 55.6 in 1995. We used the "zoo" library to do a linear interpolation by the 'na.aprox()' function to fill this four-year gap.

Correlations, Visualizations, and Shiny Application

We designed an interactive data visualization tool to analyze existing data. We can separate the process into several vital stages: data preparation, subset data selection based on user input, dynamic and interactive plot design using *'ggplot2'*, and the *'plotly'* packages in R.

The data could be subsets for specific analysis based on the user's country of choice. Because some social and economic factors may be absent from the particular data, we are validating the country for each social and economic factor. For example, we display GDP data only if the country has more than nine non-missing observations (GDP data available for at least ten years). If a country is validated and provided, then the function' *req(input$inflation_country)*' shall be performed in the '*subset()*' function to extract the data of the selected country.

Economic Plots

Using the package '*ggplot2*', we first create a '*ggplot*' object, which initializes a plot with some specified aesthetics: the x-axis, which represents the years, and the y-axis, which means the socioeconomic factors value at that year. The color and line-type aesthetics were also defined to differentiate the country selected.

Some essential parts of the '*ggplot*' object created for socioeconomic data visualizations:

- *geom_point(size = 2)*: This adds points to the plot with size 2.

- *geom_smooth(method="loess" se=FALSE, color = "blue" line type = "dashed")*: The smoothed line LOESS gives a local trend of the data, the same as the blue dashed line.
- *geom_smooth(method="lm",se=FALSE,color="green",linetype = "solid")* : Adds a linear regression trend line but removes the confidence interval. It will be solid and green in this case.
- *theme_minimal()*: Set the plot to a minimal theme for a nice and clean look.
- *labs()*: Sets the labels and title for the y-axis and the plot, respectively, according to the selected country.
- *scale_x_continuous(breaks = seq(min(df_country$year), max(df_country$year), by = 5))*: Configures the x-axis to show breaks every five years.

Mortality Plots

We also used the ggplot2 package to create a line plot for the number of deaths per 1000 people in each age group and sex group. We also carefully defined the plot aesthetics to ensure a clear presentation of the underlying trends. The x-axis represents the years, and the y-axis represents the number of deaths per 1000 people.

Some essential parts of the '*ggplot*' object created for deaths per age group visualization:

- *geom_line(linewidth = 1.2)*: We plot the lines in the plots with a thicker line to make the trends more visible.
- *scale_color_manual(values = c("Male" = "blue", "Female" = "red"), labels = c("Male", "Female"))*: We assign different colors to the two values and define the colors in the legend.
- *scale_linetype_manual(values = c("children (0-7)" = "dotted", "youngadults (8-17)" = "dashed", "adults (18-59)" = "dotdash", "geriatric (60+)" = "solid")*: We differentiate the line types in the four age groups to make them distinguishable.
- *theme_minimal()*: We apply the minimal theme to the plot.t for a clean look.
- *scale_x_continuous(breaks = seq(min(df_country$Year), max(df_country$Year), by = 5))*: Configures the x-axis to show breaks every five years.
- *scale_y_continuous(breaks = seq(0, max(df_country$deaths), by = round((max(df_country$deaths) - min(df_country$deaths)) / 8)))*: We adjust the y-axis breaks to the varying ranges of death counts.

Another '*ggplot*' object was created, setting the year as the x-axis and the number of deaths per 1000 as the y-axis, with sex differentiating the data points by color. As described above, this one is customized for clarity and visual appeal, employing a minimal theme, specific color settings for male and female data points, and enlarged axis texts and titles for better readability. The x and y axes are set with particular breaks to facilitate easy interpretation of the data over time.

One more '*ggplot*' object was created, setting the year as the x-axis and the number of deaths per 1000 as the y-axis. The data points are differentiated by sex using colors (blue for male and red for female) and are animated over all ages.

The last '*ggplot*' object for Death data visualizations was created again, setting the year as the x-axis and the number of deaths per 1000 as the y-axis. Similar to the previous plot, data points are differentiated by sex using colors, but in this case, they have been animated over the years. Also, this graph includes Median Age and Life Expectancy for each year as two separate segments.

Correlation Heatmaps

First, this data of a total correlation visualization is cleaned. This way, the country the user desires will come up purely based on the variability in its data. Columns showing more consistency than others are often filtered out of the dataset, so more variable, and hence more informative, columns can come up, giving prominence to the data. Secondly, we created a correlation matrix of the filtered data, describing the strength and direction between the variables. To avoid redundancy in visualization, the upper triangle of the matrix will be set to NA.

Next, we create a 'ggplot' object to visualize the correlation matrix using a heatmap, a graphical display of data used to show data values in a matrix. In our case, colors will range from blue, representing a negative correlation, to red, representing a positive correlation, and white for no correlation. After that, we used text annotations to display the exact correlation values.

The first correlation heatmap represents the deaths per 1000 people in correlation with the obtained socioeconomic factors. The second heatmap does the same for each gender. The third heatmap represents the correlation between mortality rates grouped by age and socioeconomic factors.

Interactivity With Plotly

The 'ggplot' object was converted into a 'plotly' object to make the visualization more interactive and user-friendly. It uses the 'ggplotly()' function call, which puts the '*ggplot*' object into it. This way, the visualization can include interactive features such as dynamic tooltips, functions like zoom, hover, playing with the axis, and making a group of points visible or non-visible. Hover labels were adjusted with a light blue background using the '*layout()*' function for better readability.

Shiny Application

The Shiny app's work starts from a functional definition generateTab, which dynamically creates tab panels. It has a title, country input, plot output, and a list of valid countries as parameters, and it returns a tab panel with the title as mentioned above, a country selector, and a main panel containing plots.

```
generateTab <- function(title, country_input, plot_output, valid_countries) {
  tabPanel(
    title,
    fluidPage(
      titlePanel(paste(title)),
      absolutePanel(
        top = 10, right = 10, width = "200px",
        selectInput(country_input, "Select Country", choices = valid_countries)
      ),
      tags$head(
        tags$style(HTML("
          .plot-container {
            height: calc(100vh - 150px) !important;
          }
          .plot-legend text {
            font-size: 14px;
          }
          .navbar {
            min-width: 500px; /* Adjust height as needed */
            max-width: 515px; /* Adjust height as needed */
          }
        "))
      ),
      mainPanel(
        div(
          plotlyOutput(plot_output, height = "90%", width = "155%"),
          class = "plot-container"
        )
      )
    )
  )
}
```

We define the app's structure using 'fluidPage' in the UI; the app's title is "Country Data Analysis." We also use *'navbarPage'* to divide the content into three main menus, "Economic Factors," "Deaths," and "Correlations." Each of them has several tabs created using the generateTab function. For instance, the "Economic Factors" menu has tabs for inflation, unemployment, GDP per capita, etc.

In turn, the server part of the Shiny app provides the logic and data processing to make the interactivity of the plots and correlations map possible. It takes input fields, which the users fill out, processes these values to make calculations using predefined functions, and then visually shows them. It was created considering that the Shiny app has to handle multiple user choices, such as the country for plotting and the indicator of the economic factor or the death statistic. It is modified to be more readable and interactive.

Findings

General Observations

Looking at the scatterplot of the number of deaths per 1,000 people by country over time, broken down by gender (male and female), we can make several general observations.

Therefore, there are general observations to make with these different trends in death rates over time, specific to a country: what one would expect—up, down, or the same over time. Developed countries with advancing health systems and improved disease management often depict decreased death rates over decades. This will not be the story for countries that are ailing with healthcare infrastructure or going through prolonged conflicts.

Over the observed time of 1960 to 2020, this death rate per 1,000 people seems to be stable or increasing for many other countries. This may correspond to changes in population demography, such as aging populations, or may be associated with healthcare developments, economic conditions, and periods of conflict.

Another noticeable trend is that the death rates differ for the two genders, where most of the time, males have slightly higher death rates than females. The gender disparity in mortality rates is a common feature around the world and likely occurs due to a majority of biological, social, and behavioral factors. It is also from the plots that it can be seen that some years have very high tides or shallow tides in terms of death rates. Such may be associated with some historical events, such as wars, famines, economic crises, or disease outbreaks, for example, the epidemics of HIV/AIDS and COVID-19. There is also an apparent disparity in mortality rates between countries from different regions. For instance, more developing countries may have much higher or more volatile death rates because of worse health conditions or the effects of conflict. In developed countries, on the other hand, death rates are steadier and sometimes lower, maybe due to more functional health systems and living standards.

Long Period Changes

Correlation heat maps are an attractive visual tool to assess long-term changes in mortality. They are effective in showing and revealing patterns among variables over time. Such heat maps use color coding to represent the strength and direction of relationships among variables over time. This matrix format of the correlation coefficients facilitates a very simple way for a researcher to detect very rapidly which variables are positively or negatively correlated or not correlated at all, hence getting deeper into the understanding of the factors that may affect mortality trends. It would show potential areas worthy of further statistical analysis and aid in communicating complicated relationships in an intuitive and user-friendly manner.

Heatmaps and Correlation: Countries

This correlation heatmap seeks to find the main relationships between the death rate per 1,000 people and various socioeconomic indicators in several countries. There is a general negative relationship between death rates and major economic indicators, such as GDP per capita and PPP per capita; they indicate that higher economic prosperity is related to lower mortality among the likely linked factors—better access to healthcare and living conditions. Clearly, on the other hand, the death rate commonly has a negative correlation with inflation and the unemployment rate, which suggests that higher economic instability and joblessness can be linked to a rise in mortality, probably because of decreased access to key services and increased socioeconomic stress.

Moreover, environmental factors such as the number of CO2 emissions per capita display mixed correlations with death rates, hence the nuanced impact of industrialization on health outcomes. Powerful positive relations between healthcare access and average years of education with low death rates further underline the role of social infrastructure in creating and improving health conditions among the population. These interrelations identify economic development together with social conditions and health outcomes and the role that has to be played by multifaceted policy intervention in this regard to improve life expectancy and decrease mortality rates globally.

However, some countries have slightly different trends. One of the exceptional cases is Japan, which has a high GDP but high death rates. This can be mainly related to its aging population since Japan has a significant population of elderly individuals, who naturally have a higher mortality rate. Another example is Greece, which has had an economic crisis recently. Due to different social measures and the informal economy, Greece maintained relatively low unemployment rates, but the death rate remained high. This could be because of economic instability, reduced public health spending, etc.

Heatmaps and Correlation: Genders

It is clear from the comparison of the effect of socioeconomic factors on the level of mortality between males and females that both genders experience almost similar influences from GDP per Capita and Healthcare Access, whereby strong negative correlation coefficients indicate that higher economic output and better healthcare access lead to low mortality rates in either gender. Inflation indicates a minor difference in the mortality rate between the gender sets; therefore, a fluctuation in inflation does not form a critical determinant of the mortality differences. In many cases, data does not lead to a difference in how such economic-related aspects will affect the mortality rate for the two groups of males and females. This means that both economic improvement and accessibility to healthcare represent universally good things, regardless of gender. Therefore, the importance of such factors in public health and economic policy must be emphasized.

Heatmaps and Correlation: Age Groups

The correlations between different ages, such as children, young adults, adults, and geriatrics, and socioeconomic factors have a propensity by which the distinct trends reflect the needs and vulnerabilities of the group.

For children, this strongly correlates with environmental factors that impact development, which will be GDP per capita and access to healthcare. This means that the interpretation infers a tendency for high GDP to go along with a good correlation, indicating better grounds for growth and development, while high inflation goes together with a bad correlation, showing higher challenges in these places.

The indicators for young adults and adults are usually economic activities and stability, which are based on GDP per capita, unemployment rates, and educational attainment. Young adults benefit from a positive correlation regarding access to increased education levels in higher learning institutions and healthcare. They will have more chances of employment and better living conditions due to improved health conditions while dealing with a much stronger economy. Economic stability in relation to high GDP per capita and low levels of unemployment appears to correlate with the enhancement of living conditions and well-being in adult ages.

The necessity of health care and economic stability is particularly highlighted for the geriatric group. Thus, old populations suffer from this inflation because their purchasing power erodes and their quality of life falls. On the other hand, good access to care was related to positive well-being among geriatric people. In this way, further reasoning is needed for a good healthcare service system for an aging population. The results reflect a much larger complex interplay across socioeconomic variables on well-being over different life stages, suggesting broader societal trends and priorities.

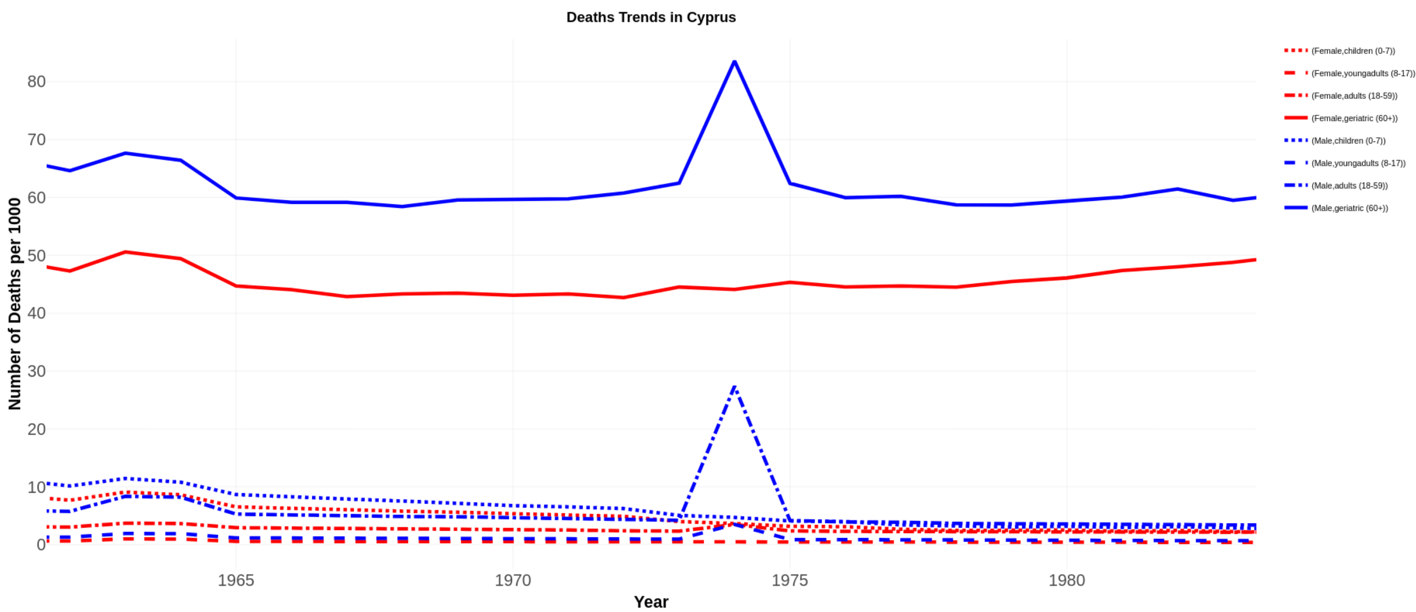
Short Period Changes

Different categories of events have been associated with short-term changes in mortality, which act randomly on the population. Events can be classified in terms of the groups they affect and the duration of their impact.

- Events That Tend to Affect Selected Groups

    Mortality changes in a short period are bound to affect selected demographic sections mainly because of the nature of the event occurring.

Wars: Wars and battles typically tend to affect the mortality rate of adult males to a greater extent, as this group is the main group of combatants in wars. For instance, the Turkish invasion of Cyprus(1974) has considerably ramped up the mortality rates of young adult males and geriatric males.



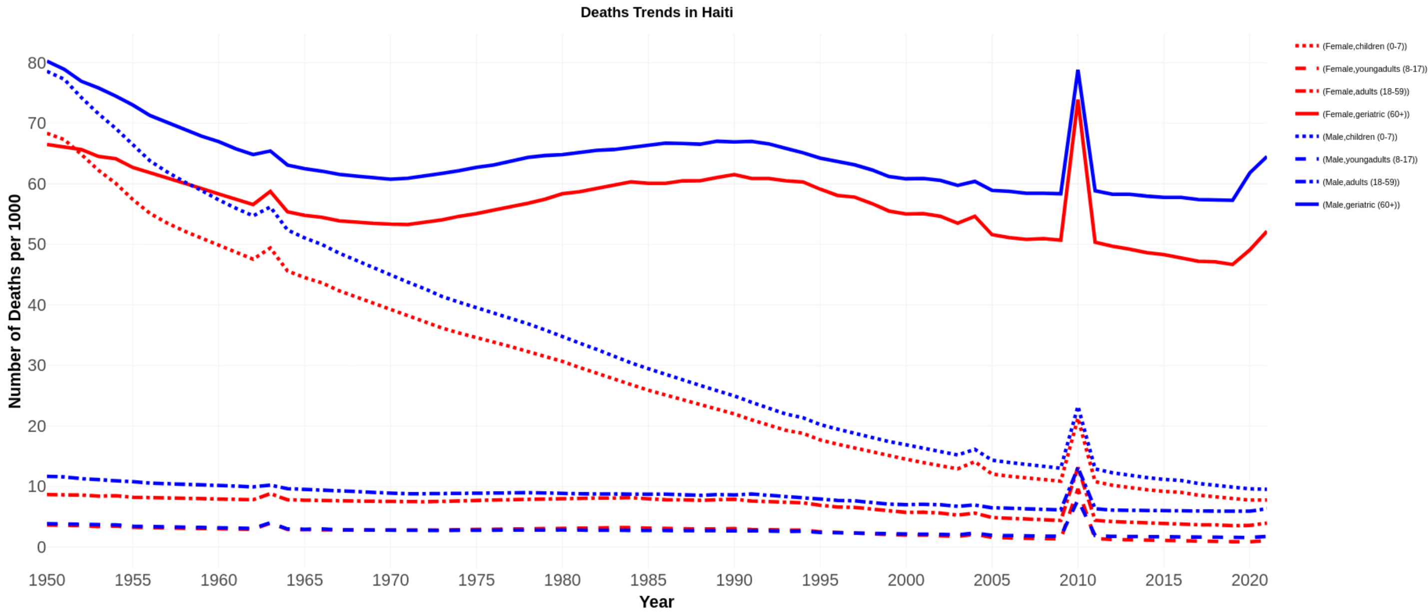
Pandemics: These often affect the mortality rates of selective age groups, dependent on the nature of the disease in terms of its characteristics. For instance, the COVID-19 pandemic is more severe in older people and those with existing conditions, increasing the mortality in these communities in most countries.

- Events Resulting in Mortality Increase for all Demographic Groups

Some other kinds of events result in increased mortality but affect all the demographic groups in a population. They are in general terms, and one can classify them further in terms of the following:

  - One-Year Span: Sudden and disastrous events can result in a mortality increase, but their force will be felt fully for just one year, for example, natural disasters.

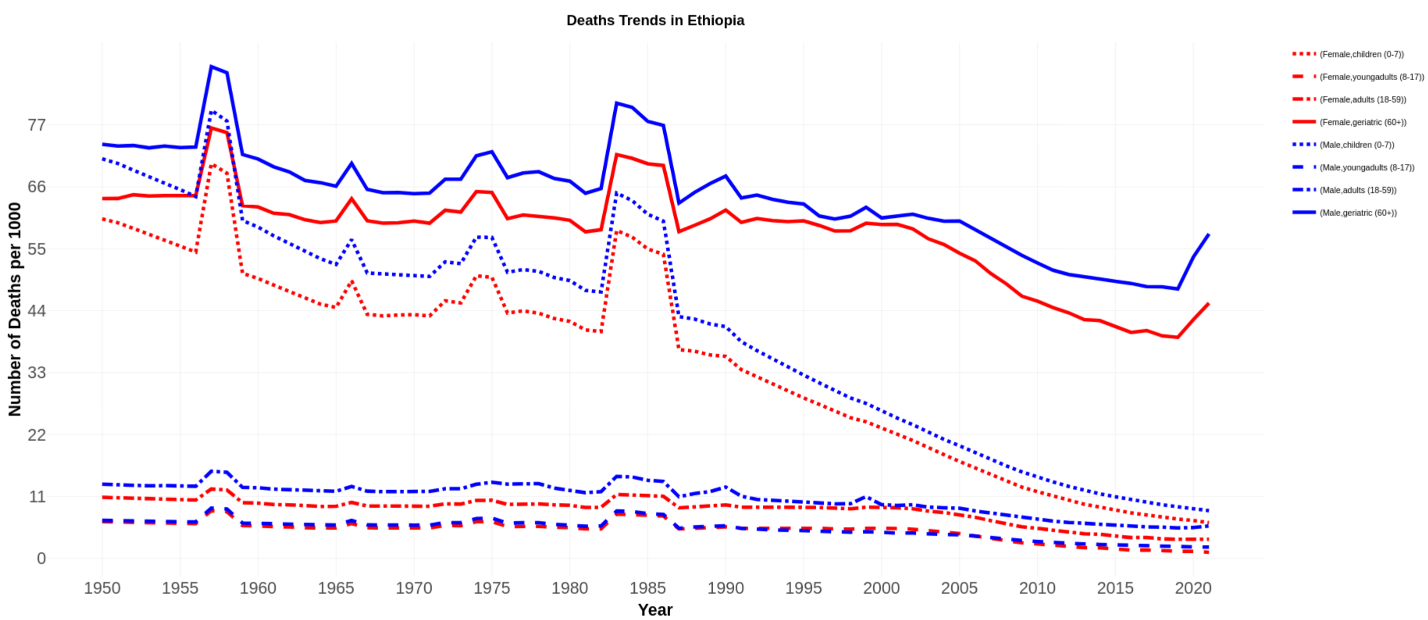
    These include earthquakes, tsunamis, hurricanes, and floods. For instance, in the year 2010, the earthquake in Haiti saw a marked increase in the number of deaths.



- Several Year Range Events lead to prolonged increases in mortality rates over some years, often because of sustained hardship and instability.

The range of man-made events

This involves civil wars, wars of independence, occupations, and famines. For instance, the First Sudanese Civil War (1955-1972) has been noted to be responsible for the rise in mortality as a result of conflict. Ethiopian Famine (1983-1985) affected all age groups and sexes.



This classification framework helps classify different events and systematically categorizes them according to their nature and impact on mortality rates, further facilitating more appropriate responses and interventions.

References

- Basu, S., McKee, M., & Stuckler, D. (2022). Globalization and health. *Globalization and Health*, *18*(1), 55. https://globalizationandhealth.biomedcentral.com/articles/10.1186/s12992-022-00855-z
- National Academies of Sciences, Engineering, and Medicine. (2021). *The impact of socioeconomic status on health outcomes*. https://www.ncbi.nlm.nih.gov/books/NBK571926/#:~:text=Research%20has%20shown%20that%20exposure,%2C%20suicide%2C%20and%20violent%20crime
- Boateng, K. P., & Awunyo-Vitor, D. (2020). Economic factors that influence mortality rate: An evidence from Ghana. *Journal of Public Health*, *28*(2), 213-225. https://www.researchgate.net/publication/339629549_Economic_Factors_That_Influence_Mortality_Rate_An_Evidence_From_Ghana
- Ezzati, M., & Galea, S. (2023). Statistical analysis of mortality trends. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *130*(1), 137-156. https://academic.oup.com/jrsssa/article-abstract/130/1/137/7103066?redirectedFrom=PDF
- UNICEF. (2021). Neonatal mortality. https://data.unicef.org/topic/child-survival/neonatal-mortality/#:~:text=The%20neonatal%20period%20is%20the%20most%20vulnerable%20time%20for%20a%20child&text=In%20comparison%2C%20the%20probability%20of,deaths%20per%201%2C000%20in%202021
- Robert-MI. (n.d.). Capstone Files [Python scripts and datasets]. GitHub. Retrieved May 18, 2024, from https://github.com/Robert-MI/Capstone-Files.git
- Institute for Health Metrics and Evaluation. (2022). *Healthcare access and quality index*. https://www.healthdata.org/results/country-profiles
- United Nations. (2024). Mortality. Retrieved from https://population.un.org/wpp/Download/Standard/Mortality/
- United Nations. (2024). Population. Retrieved from https://population.un.org/wpp/Download/Standard/Population/
- World Bank. (2024). GDP per capita by country. Retrieved from https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
- World Bank. (2024). PPP per capita by country. Retrieved from https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD
- World Bank. (2024). CO2 emissions (metric tons per capita). Retrieved from https://data.worldbank.org/indicator/EN.ATM.CO2E.PC
- World Bank. (2024). Inflation, consumer prices (annual %). Retrieved from https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG
- World Bank. (2024). Unemployment, total (% of total labor force) (modeled ILO estimate). Retrieved from https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS

- Our World in Data. (2024). Mean years of schooling long run. In Barro and Lee (2015); Lee and Lee (2016) – with major processing by Our World in Data. Retrieved from https://ourworldindata.org/grapher/mean-years-of-schooling-long-run?tab=table
- Our World in Data. (2024). Healthcare access and quality index. In Institute for Health Metrics and Evaluation (2017) – processed by Our World in Data. "HAQ Index (IHME (2017))" [dataset]. Institute for Health Metrics and Evaluation (2017) [original data]. Retrieved from https://ourworldindata.org/grapher/healthcare-access-and-quality-index?tab=table
- Our World in Data. (2024). Healthcare access quality IHME. In Institute of Health Metrics and Evaluation (2022) – processed by Our World in Data. "Coverage of essential health services, as defined by the UHC service coverage index - Both Sexes - Estimate" [dataset]. Institute of Health Metrics and Evaluation (2022) [original data]. Retrieved from https://ourworldindata.org/grapher/healthcare-access-quality-ihme?tab=table