Bilenkin540_Term_Project_All_5_Milestones

May 29, 2025

0.1 Milestone 1: Accessing dataset from WHO GHO OData API

[1065]:

```
import requests

# API URL
url = "https://ghoapi.azureedge.net/api/Indicator"
response = requests.get(url)

if response.status_code == 200:
    print("Success! API is accessible.")

    # Convert response to JSON
    data = response.json()

    # Extract all indicators
    indicators = data.get("value", [])  # 'value' contains the list of␣
↪indicators
    print(f"Found {len(indicators)} indicators.")  # Total count

    # Display only first 3 alcohol-related indicators
    alcohol_indicators = [ind for ind in indicators if "alcohol" in␣
↪ind["IndicatorName"].lower()]
    print(f"Found {len(alcohol_indicators)} alcohol-related indicators. Showing␣
↪first 3:")

    for ind in alcohol_indicators[:3]:  # Display only first 3
        print(f"ID: {ind['IndicatorCode']}, Name: {ind['IndicatorName']}")

else:
    print(f"Failed to access API. Status code: {response.status_code}")
```

```
Success! API is accessible.
Found 3004 indicators.
Found 275 alcohol-related indicators. Showing first 3:
ID: RSUD_720, Name: Open access interventions for alcohol
ID: RSUD_750, Name: Standards of care for professionals providing treatment for
alcohol and drug use disorders
ID: RSUD_890, Name: Treatment programmes for children and adolescents with
```

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alcohol use disorders
```

Fining Alcohol Consumption Indicator Code

[1066]:
```python
import requests

# Fetching list of available indicators
url = "https://ghoapi.azureedge.net/api/Indicator"
response = requests.get(url)

if response.status_code == 200:
    data = response.json()
    indicators = data['value']

    # Filtering indicators related to alcohol
    alcohol_indicators = [ind for ind in indicators if "alcohol" in␣
 ↪ind['IndicatorName'].lower()]

    # Printing results
    for ind in alcohol_indicators:
        print(ind['IndicatorCode'], ":", ind['IndicatorName'])

else:
    print(f"Failed to access API. Status code: {response.status_code}")
```

```
RSUD_720 : Open access interventions for alcohol
RSUD_750 : Standards of care for professionals providing treatment for alcohol
and drug use disorders
RSUD_890 : Treatment programmes for children and adolescents with alcohol use
disorders
SA_0000001398 : Alcohol, consumption of pure alcohol by type of beverage (%)
SA_0000001400_ARCHIVED : Alcohol, recorded per capita (15+) consumption (in
litres of pure alcohol)
SA_0000001401_ARCHIVED : Alcohol, recorded per capita (15+) consumption (in
litres of pure alcohol), three-year average
SA_0000001402 : Alcohol, estimate of five-year change in recorded per capita
(15+) consumption 2006-2010
RSUD_740 : Health professionals providing treatment for alcohol and drug use
disorders
RSUD_85 : NGOs for alcohol use disorders
RSUD_850 : System of monitoring alcohol involvement in forensic pathology
SA_0000001398_ARCHIVED : Alcohol, consumption of pure alcohol by type of
beverage (%)
SA_0000001400 : Alcohol, recorded per capita (15+) consumption (in litres of
pure alcohol), by beverage type
SA_0000001401 : Alcohol, recorded per capita (15+) consumption (in litres of
pure alcohol), three-year average
SA_0000001402_ARCHIVED : Alcohol, estimate of five-year change in recorded per
```

capita (15+) consumption 2006-2010
SA_0000001403 : Alcohol, total (recorded 3 year average + unrecorded) per capita (15+) consumption (in litres of pure alcohol)
SA_0000001403_ARCHIVED : Alcohol, total (recorded 3 year average + unrecorded) per capita (15+) consumption (in litres of pure alcohol)
SA_0000001404_ARCHIVED : Alcohol, drinkers only per capita (15+)consumption in litres of pure alcohol
SA_0000001409 : Alcohol, abstainers lifetime (%), age-standardized
SA_0000001411 : Alcohol, abstainers past 12 months (%), age-standardized
SA_0000001416 : Alcohol, heavy episodic drinking (15+), drinkers only, past 30 days (%), age-standardized
SA_0000001405 : Alcohol, tourist consumption (in litres of pure alcohol)
SA_0000001413_ARCHIVED : Alcohol, consumers past 12 months (%)
SA_0000001405_ARCHIVED : Alcohol, tourist consumption (in litres of pure alcohol)
SA_0000001406 : Alcohol, unrecorded per capita (15+) consumption (in litres of pure alcohol)
SA_0000001414 : Alcohol, former drinkers (%), age-standardized
SA_0000001415_ARCHIVED : Alcohol, heavy episodic drinking (population) past 30 days (%)
SA_0000001416_ARCHIVED : Alcohol, heavy episodic drinking (15+), drinkers only, past 30 days (%)
SA_0000001437 : Age-standardized death rates, alcohol use disorders, per 100,000
SA_0000001404 : Alcohol, drinkers only per capita (15+) consumption in litres of pure alcohol, three-year average
SA_0000001406_ARCHIVED : Alcohol, unrecorded per capita (15+) consumption (in litres of pure alcohol)
SA_0000001409_ARCHIVED : Alcohol, abstainers lifetime (%)
SA_0000001411_ARCHIVED : Alcohol, abstainers past 12 months (%)
SA_0000001413 : Alcohol, consumers past 12 months (%), age-standardized
SA_0000001414_ARCHIVED : Alcohol, former drinkers (%)
SA_0000001417 : Alcohol, patterns of drinking score
SA_0000001417_ARCHIVED : Alcohol, patterns of drinking score
SA_0000001461 : Alcohol dependence (15+), 12-month prevalence (%) with 95%CI
SA_0000001456 : Age-standardized death rates (15+ years), alcoholic liver disease, per 100,000
SA_0000001461_ARCHIVED : Alcohol dependence (15+), 12-month prevalence (%) with 95%CI
SA_0000001463 : Alcoholic psychosis, incidence, per 100,000
SA_0000001467 : Perceived trend in alcohol-related harm and consequences
SA_0000001470_ARCHIVED : Alcohol-related road traffic crashes, per 100,000 population
SA_0000001463_ARCHIVED : Alcoholic psychosis, incidence, per 100,000
SA_0000001465 : Hospital discharges, alcohol-related injuries and poisoning, per 100,000
SA_0000001472 : Alcohol-related injury mortality, per 1,000
SA_0000001418 : Age-standardized DALYs, alcohol use disorders, per 100,000
SA_0000001469 : Treatment admissions (inpatient), alcoholic psychosis, per

100,000
SA_0000001470 : Alcohol-related road traffic crashes, per 100,000 population
SA_0000001471 : Alcohol-related road traffic crashes (% of all traffic crashes)
SA_0000001476 : Alcohol expenditure as a per cent of total household expenditure
SA_0000001476_ARCHIVED : Alcohol expenditure as a per cent of total household expenditure
SA_0000001502 : Adopted written national policy on alcohol
SA_0000001504 : Alcohol use is banned
SA_0000001506 : National legislation to prevent illegal alcohol
SA_0000001502_ARCHIVED : Adopted written national policy on alcohol
SA_0000001503_ARCHIVED : Alcoholic beverage legally defined
SA_0000001506_ARCHIVED : National legislation to prevent illegal alcohol
SA_0000001471_ARCHIVED : Alcohol-related road traffic crashes (% of all traffic crashes)
SA_0000001473 : Alcohol-related disease mortality, per 100,000 (15+ years)
SA_0000001475 : Annual revenues from alcohol excise tax in millions US$
SA_0000001477 : Social costs of alcohol use in millions US$
SA_0000001503 : Alcoholic beverage legally defined
SA_0000001462 : Alcohol use disorders (15+), 12 month prevalence (%) with 95%
SA_0000001462_ARCHIVED : Alcohol use disorders (15+), 12 month prevalence (%) with 95%
SA_0000001504_ARCHIVED : Alcohol use is banned
SA_0000001523 : Prices for alcoholic beverages (average, US$)
SA_0000001725_ARCHIVED : National alcohol policy specifically involves young people activities
SA_0000001523_ARCHIVED : Prices for alcoholic beverages (average, US$)
SA_0000001466 : Hospital discharges, alcoholic liver disease, per 100,000
SA_0000001468 : Treatment admissions (inpatient), alcohol dependence, per 100,000
SA_0000001474 : Alcoholic excise tax revenue as a per cent of government revenue
SA_0000001474_ARCHIVED : Alcoholic excise tax revenue as a per cent of government revenue
SA_0000001475_ARCHIVED : Annual revenues from alcohol excise tax in millions US$
SA_0000001477_ARCHIVED : Social costs of alcohol use in millions US$
SA_0000001541_ARCHIVED : Restrictions on sales promotion from owners of pubs and bars (alcohol for free)
SA_0000001739 : Alcohol, heavy episodic drinking (15+) past 30 days (%), age-standardized
SA_0000001541 : Restrictions on sales promotion from owners of pubs and bars (alcohol for free)
SA_0000001546_ARCHIVED : Excise tax as a per cent of the retail price of alcoholic beverages
SA_0000001548 : Excise tax as a per cent of the total retail price for 1 litre of pure alcohol
SA_0000001725 : National alcohol policy specifically involves young people activities
SA_0000001732 : New types of alcoholic beverages emerging
SA_0000001735 : Alcohol content displayed on containers

SA_0000001735_ARCHIVED : Alcohol content displayed on containers
SA_0000001736_ARCHIVED : Action Plan for implementation of alcohol policy
SA_0000001732_ARCHIVED : New types of alcoholic beverages emerging
SA_0000001734_ARCHIVED : Number of standard alcoholic drinks displayed on containers
SA_0000001736 : Action Plan for implementation of alcohol policy
SA_0000001737_ARCHIVED : Alcohol, regional per capita (15+) consumption (in litres of pure alcohol)
SA_0000001740_ARCHIVED : Alcohol-attributable Years of Life Lost (YLL) score
SA_0000001743 : Alcohol-attributable fractions, all-cause deaths (%)
SA_0000001744_ARCHIVED : Alcohol, regional prevalence of alcohol dependence (%)
SA_0000001745 : Alcohol, regional prevalence of alcohol use disorders (%)
SA_0000001520 : Legal blood alcohol concentration (BAC) limits
SA_0000001520_ARCHIVED : Legal blood alcohol concentration (BAC) limits
SA_0000001737 : Alcohol, regional per capita (15+) consumption (in litres of pure alcohol)
SA_0000001741_ARCHIVED : Alcohol-attributable fractions (15+), liver cirrhosis deaths (%)
SA_0000001742 : Alcohol-attributable fractions (15+), road traffic crash deaths (%)
SA_0000001744 : Alcohol, regional prevalence of alcohol dependence (%)
SA_0000001745_ARCHIVED : Alcohol, regional prevalence of alcohol use disorders (%)
SA_0000001746 : Alcohol, total (recorded + unrecorded) per capita (15+) consumption with 95%CI, projections to 2025
SA_0000001746_ARCHIVED : Alcohol, total (recorded + unrecorded) per capita (15+) consumption with 95%CI, projections to 2025
SA_0000001747_ARCHIVED : Alcohol, recorded per capita (15+) consumption (in litres of pure alcohol), three-year average with 95%CI
SA_0000001748_ARCHIVED : Alcohol, unrecorded per capita (15+) consumption (in litres of pure alcohol) with 95%CI
SA_0000001749_ARCHIVED : Alcohol, total (recorded 3 year average + unrecorded) per capita (15+) consumption (in litres of pure alcohol) with 95%CI
SA_0000001751 : Alcohol, average daily intake in grams among drinkers, three-year average
SA_0000001751_ARCHIVED : Alcohol, average daily intake in grams among drinkers with 95%CI
SA_0000001752 : Alcohol, total (recorded + unrecorded) per capita (15+) consumption, projected estimates for 2016
SA_0000001739_ARCHIVED : Alcohol, heavy episodic drinking (15+) past 30 days (%), age-standardized with 95%CI
SA_0000001752_ARCHIVED : Alcohol, total (recorded + unrecorded) per capita (15+) consumption, projected estimates for 2016
SA_0000001754_ARCHIVED : Alcohol, harmful use (15+), 12 month prevalence (%) with 95%CI
SA_0000001748 : Alcohol, unrecorded per capita (15+) consumption (in litres of pure alcohol) with 95%CI
SA_0000001760_ARCHIVED : 15-19 years old total alcohol consumption in litres of

pure alcohol
SA_0000001761_ARCHIVED : National guidelines for the prevention and reduction of alcohol-related harm in schools
SA_0000001549_ARCHIVED : Duty paid or excise stamp on alcohol container
SA_0000001551 : Value-added tax (VAT) on alcohol (%)
SA_0000001550_ARCHIVED : Excise tax on alcoholic beverages
SA_0000001549 : Duty paid or excise stamp on alcohol container
SA_0000001550 : Excise tax on alcoholic beverages
SA_0000001553_ARCHIVED : Restrictions on alcohol use in public places
SA_0000001553 : Restrictions on alcohol use in public places
SA_0000001555_ARCHIVED : Health warning labels on alcohol containers
SA_0000001691 : Central coordinating entity for alcohol policy implementation
SA_0000001694 : Sectors represented in national alcohol policy
SA_0000001747 : Alcohol, recorded per capita (15+) consumption (in litres of pure alcohol), three-year average
SA_0000001753_ARCHIVED : Alcohol use disorders (15+), 12 month prevalence (%), age standardized, with 95%CI
SA_0000001760 : 15-19 years old total alcohol consumption in litres of pure alcohol
SA_0000001693 : Level of adoption of national alcohol policy
SA_0000001696 : Alcohol-related road traffic crashes with fatalities (% of all road traffic crashes with fatalities)
SA_0000001697 : Adopted written national policy on alcohol, year adopted
SA_0000001698 : Adopted written national policy on alcohol, year revised
SA_0000001698_ARCHIVED : Adopted written national policy on alcohol, year revised
SA_0000001700 : Consumer information on alcohol and health at points of sale
SA_0000001707 : Persons with alcohol use disorders receiving treatment (%)
SA_0000001763_ARCHIVED : Workplace representatives nationally involved to prevent and address alcohol-related harm
SA_0000001767_ARCHIVED : Legislation on alcohol testing at workplaces
SA_0000001769 : National systems for monitoring alcohol consumption and harms
SA_0000001769_ARCHIVED : National systems for monitoring alcohol consumption and harms
SA_0000001771_ARCHIVED : Comprehensive and regular reporting of alcohol situation
SA_0000001761 : National guidelines for the prevention and reduction of alcohol-related harm in schools
SA_0000001763 : Workplace representatives nationally involved to prevent and address alcohol-related harm
SA_0000001688_ARCHIVED : Total (recorded+unrecorded) alcohol per capita (15+) consumption
SA_0000001691_ARCHIVED : Central coordinating entity for alcohol policy implementation
SA_0000001767 : Legislation on alcohol testing at workplaces
SA_0000001692 : Framework of national alcohol policy
SA_0000001693_ARCHIVED : Level of adoption of national alcohol policy
SA_0000001694_ARCHIVED : Sectors represented in national alcohol policy

SA_0000001696_ARCHIVED : Alcohol-related road traffic crashes with fatalities (% of all road traffic crashes with fatalities)
SA_0000001697_ARCHIVED : Adopted written national policy on alcohol, year adopted
SA_0000001765 : Legal obligation for schools to include alcohol use prevention
SA_0000001773_ARCHIVED : National surveys on adult alcohol consumption
SA_0000001774 : National surveys on youth alcohol consumption
SA_0000001734 : Number of standard alcoholic drinks displayed on containers
SA_0000001740 : Alcohol-attributable Years of Life Lost (YLL) score
SA_0000001741 : Alcohol-attributable fractions (15+), liver cirrhosis deaths (%)
SA_0000001742_ARCHIVED : Alcohol-attributable fractions (15+), road traffic crash deaths (%)
SA_0000001743_ARCHIVED : Alcohol-attributable fractions, all-cause deaths (%)
SA_0000001546 : Excise tax as a per cent of the retail price of alcoholic beverages
SA_0000001548_ARCHIVED : Excise tax as a per cent of the total retail price for 1 litre of pure alcohol
SA_0000001551_ARCHIVED : Value-added tax (VAT) on alcohol (%)
SA_0000001771 : Comprehensive and regular reporting of alcohol situation
SA_0000001773 : National surveys on adult alcohol consumption
SA_0000001554 : Health warning labels on alcohol advertising
SA_0000001554_ARCHIVED : Health warning labels on alcohol advertising
SA_0000001555 : Health warning labels on alcohol containers
SA_0000001749 : Alcohol, total (recorded 3 year average + unrecorded) per capita (15+) consumption (in litres of pure alcohol) with 95%CI
SA_0000001754 : Alcohol, harmful use (15+), 12 month prevalence (%) with 95%CI
SA_0000001777 : Data collected on harm from alcohol at workplace
SA_0000001777_ARCHIVED : Data collected on harm from alcohol at workplace
SA_0000001781_ARCHIVED : 15-years old any alcoholic beverage consumed in past 12 months, (%)
SA_0000001784 : 15-years old, any alcoholic beverage consumed at least once a week, (%)
SA_0000001708 : Designation of alcohol tax revenues to health services
SA_0000001714 : Training in screening and brief interventions for alcohol problems
SA_0000001715 : Counselling to children in families with alcohol problems
SA_0000001716 : Counselling to pregnant women with alcohol problems
SA_0000001786 : 13-15-years old any alcoholic beverage consumed in past 30 days, (%)
RS_207 : Blood Alcohol Concentration (BAC) limit for drivers
RS_208 : Attribution of road traffic deaths to alcohol (%)
SA_0000001706 : National treatment policy for alcohol use disorders
SA_0000001717 : Prevention/counselling at workplaces for those with alcohol problems
SA_0000001781 : 15-years old any alcoholic beverage consumed in past 12 months, (%)
SA_0000001789 : Alcohol-related crimes (% of all crimes)
SA_0000001762 : National guidelines for alcohol problem prevention and

counselling at workplaces
SA_0000001762_ARCHIVED : National guidelines for alcohol problem prevention and counselling at workplaces
SA_0000001688 : Alcohol, total per capita (15+) consumption (in litres of pure alcohol) (SDG Indicator 3.5.2), three-year average
SA_0000001692_ARCHIVED : Framework of national alcohol policy
SA_0000001704 : Data collection on alcohol-related health indicators
SA_0000001765_ARCHIVED : Legal obligation for schools to include alcohol use prevention
SA_0000001774_ARCHIVED : National surveys on youth alcohol consumption
SA_0000001776 : Data collection on Foetal Alcohol Syndome
SA_0000001776_ARCHIVED : Data collection on Foetal Alcohol Syndome
RSUD_170 : Involvement of representatives of affected or targeted populations in the development and formulation of policies and strategies for prevention for alcohol and drugs
SA_0000001784_ARCHIVED : 15-years old, any alcoholic beverage consumed at least once a week, (%)
SA_0000001786_ARCHIVED : 13-15-years old any alcoholic beverage consumed in past 30 days, (%)
SA_0000001795 : Licensing required for imports of alcoholic beverages
SA_0000001802 : Monopoly on wholesale /distribution of alcoholic beverages
SA_0000001794 : Licensing required for exports of alcoholic beverages
SA_0000001800 : Monopoly on exports of alcoholic beverages
SA_0000001808 : Alcohol-attributable fractions (15+), cancer deaths
SA_0000001812 : Report with data from health services on alcohol use and AUDs
SA_0000001816 : Tax incentives for production low/no alcohol content beer
SA_0000001817 : Tax incentives for production of other alcoholic beverages
RSUD_230 : Compulsory treatment for people with alcohol use disorders in the criminal justice system
RSUD_29 : Sector for inpatient detoxification of alcohol use disorders
RSUD_27 : Government benefits for alcohol use disorders, subsidy or disability pension
SA_0000001809 : National system of epidemiological data collection for alcohol use
SA_0000001813 : National organization for monitoring alcohol
RSUD_3 : Age-standardized death rates, alcohol and drug use disorders, per 100 000
RSUD_32 : Sector for the treatment of alcohol-induced psychoses and other alcohol-induced psychiatric conditions
SA_0000001822 : Alcohol, total per capita (15+) consumption (in litres of pure alcohol) with 95%CI
RSUD_270 : Financing methods for treatment for alcohol use disorders
RSUD_33 : Sector for residential long-term rehabilitation of alcohol use disorders
RSUD_30 : Sector for inpatient treatment of alcohol dependence
RSUD_300 : Government benefits for people with alcohol use disorders
RSUD_31 : Sector for outpatient treatment of alcohol dependence
SA_0000001818 : Alcohol, total (recorded + unrecorded) per capita (15+)

consumption, projections
SA_0000001821_ARCHIVED : Alcohol, unrecorded per capita (15+) consumption (in litres of pure alcohol) with 95%CI
SA_0000001823_ARCHIVED : Alcohol, tourist consumption (in litres of pure alcohol)
SA_0000001824 : Alcohol, regional alcohol per capita (15+) consumption (in litres of pure alcohol)
RSUD_320 : Main sector for treatment for alcohol use disorders
RSUD_340 : Treatment programmes for children and adolescents with alcohol use disorders
SA_0000001705 : System for monitoring alcohol-related harm
SA_0000001710 : Public-funded alcohol research/monitoring programmes
SA_0000001711 : Public funds designated for alcohol research/monitoring programmes, in Euros
SA_0000001783 : 15-years old any alcoholic beverage consumed in past 30 days, (%)
SA_0000001783_ARCHIVED : 15-years old any alcoholic beverage consumed in past 30 days, (%)
SA_0000001788 : Alcohol-related road traffic crashes with fatalities, per 100,000 population
SA_0000001788_ARCHIVED : Alcohol-related road traffic crashes with fatalities, per 100,000 population
SA_0000001789_ARCHIVED : Alcohol-related crimes (% of all crimes)
SA_0000001792 : National legislation to prevent illegal alcohol sales
SA_0000001796 : Licensing required for wholesale/distribution of alcoholic beverages
SA_0000001801 : Monopoly on imports of alcoholic beverages
RSUD_1 : Point prevalence (%), alcohol use disorders, 15+ years
RSUD_44 : Treatment slots for alcohol and drug use disorders, outpatient, per 10 000
SA_0000001821 : Alcohol, unrecorded per capita (15+) consumption (in litres of pure alcohol), three-year average
SA_0000001823 : Alcohol, tourist consumption (in litres of pure alcohol), three-year average
RSUD_5 : Age-standardized DALYs, alcohol and drug use disorders, per 100 000
RSUD_590 : Prevention programmes for specific populations for alcohol
RSUD_180 : Involvement of representatives of affected or targeted populations in the development and implementation of national programmes for prevention for alcohol and drugs
RSUD_210 : Voluntary treatment for people with alcohol use disorders in the criminal justice system
SA_0000001822_ARCHIVED : Alcohol, total per capita (15+) consumption (in litres of pure alcohol) with 95%CI
RSUD_370 : Specialized treatment facilities for alcohol use disorders
RSUD_580 : Prevention programmes for alcohol
RSUD_700 : Employment services for alcohol use disorders
RSUD_660 : Treatment programmes for women with alcohol use disorders
RSUD_680 : Special housing services for alcohol use disorders

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RSUD_480 : Registration of medications for alcohol dependence and withdrawal
RSUD_68 : Pharmacotherapy used for the management of alcohol withdrawal
SA_0000001836 : Alcohol-related road traffic deaths (% of all road traffic
deaths)
NCD_CCS_ALC_TARGET : Existence of a national target on alcohol
SA_0000001845 : Average daily intake in grams of alcohol, population (15+)
SA_0000001832 : Alcohol-attributable all-cause deaths per 100,000, age
standardized
SA_0000001833 : Alcohol-attributable DALYs per 100,000 people (age standardized)
TAXBEV_EXCISE_UNIFORMTIERED_NONALCOHOLIC : Uniform or tiered excise tax system
applied on non-alcoholic beverage
TAXBEV_ABV : Alcohol content in beverage in percent of volume, (alcohol by
volume) (ABV %)
NCD_CCS_ALC_MGMT_GUIDE : Existence of evidence-based national
guidelines/protocols/standards for the management of alcohol use disorders
SA_0000001457_AA : Liver cirrhosis, alcohol-attributable, age-standardized death
rates, per 100,000 population
SA_0000001828_AA : Regional prevalence, alcohol-attributable DALYs, (%)
SA_0000001842 : Alcohol, 15-19 years heavy continuous drinkers, drinkers only,
past year (%)
SA_0000001839 : Alcohol, heavy continuous drinkers past year (%)
TAXBEV_ALCOHOLSALESTATUS : Status of alcohol sale
SA_0000001459_AA : Road traffic crash deaths, alcohol-attributable, age-
standardized death rates, per 100,000 population
SA_0000001844 : Alcohol-attributable all-cause deaths (all ages), (number)
PRISON_F1_ALCOHOL_TOT : In-prison people who drink/drank alcohol (number of
prisoners, in the last 12 months)
SA_0000001807_AA : Cancer, alcohol-attributable, age-standardized death rates,
per 100,000 population
TAXBEV_ALCOHOLBASEDTIERED : If tiered on the beverage, the tiers are alcohol-
based
SA_0000001840 : Alcohol, heavy continuous drinkers, drinkers only, past year (%)
NCD_CCS_AlcPlan : Existence of operational policy/strategy/action plan to reduce
the harmful use of alcohol
SA_0000001841 : Alcohol, 15-19 years heavy continuous drinkers past year (%)
SA_0000001843 : Alcohol-attributable DALYs lost from all causes (all ages),
(number)
SA_0000001837 : Alcohol poisoning deaths, per 100,000 population
SA_0000001838 : Alcohol-related cardiomyopathy deaths (% of all cardiomyopathy
deaths)
TAXBEV_EXCISE_UNIFORMTIERED_ALCOHOLIC : Uniform or tiered excise tax system
applied on alcoholic beverage
NCD_CCS_ALC_SVY : Has conducted a recent, national adult risk factor survey
covering harmful alcohol use
SA_0000001834 : Percent of all DALYs attributable to alcohol
SA_0000001835 : Alcohol-related road traffic deaths, per 100,000 population
```

Extracting data from the WHO GHO OData API and save it as CSV file.

[1067]:
```python
import requests
import pandas as pd

# Define the API endpoint
url = "https://ghoapi.azureedge.net/api/WHOSIS_000001"  # Replace with your␣
↪specific endpoint

# Fetch data from API
response = requests.get(url)
if response.status_code == 200:
    data = response.json()

    # Extract relevant data
    records = data.get('value', [])  # 'value' contains the dataset

    if records:
        df = pd.DataFrame(records)

        # Save to CSV
        df.to_csv("who_gho_data.csv", index=False)

        print("Data successfully extracted and saved as 'who_gho_data.csv'")

        # Display basic exploration
        print(df.info())
        print(df.head())
    else:
        print("No data found in API response.")
else:
    print(f"Failed to fetch data. Status Code: {response.status_code}")
```

```
Data successfully extracted and saved as 'who_gho_data.csv'
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12936 entries, 0 to 12935
Data columns (total 25 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Id                  12936 non-null  int64
 1   IndicatorCode       12936 non-null  object
 2   SpatialDimType      12936 non-null  object
 3   SpatialDim          12936 non-null  object
 4   TimeDimType         12936 non-null  object
 5   ParentLocationCode  12210 non-null  object
 6   ParentLocation      12210 non-null  object
 7   Dim1Type            12936 non-null  object
 8   Dim1                12936 non-null  object
 9   TimeDim             12936 non-null  int64
 10  Dim2Type            0 non-null      object
```

```
 11  Dim2                0 non-null      object
 12  Dim3Type            0 non-null      object
 13  Dim3                0 non-null      object
 14  DataSourceDimType   0 non-null      object
 15  DataSourceDim       0 non-null      object
 16  Value               12936 non-null  object
 17  NumericValue        12936 non-null  float64
 18  Low                 12916 non-null  float64
 19  High                12916 non-null  float64
 20  Comments            0 non-null      object
 21  Date                12936 non-null  object
 22  TimeDimensionValue  12936 non-null  object
 23  TimeDimensionBegin  12936 non-null  object
 24  TimeDimensionEnd    12936 non-null  object
dtypes: float64(3), int64(2), object(20)
memory usage: 2.5+ MB
None
        Id  IndicatorCode SpatialDimType SpatialDim TimeDimType  \
0  1325927  WHOSIS_000001        COUNTRY        EGY        YEAR
1  1326079  WHOSIS_000001        COUNTRY        AZE        YEAR
2  1326127  WHOSIS_000001        COUNTRY        NGA        YEAR
3  1327642  WHOSIS_000001        COUNTRY        BEN        YEAR
4  1328751  WHOSIS_000001        COUNTRY        SYR        YEAR

  ParentLocationCode         ParentLocation Dim1Type      Dim1  TimeDim  …  \
0                EMR  Eastern Mediterranean      SEX  SEX_FMLE     2011  …
1                EUR                 Europe      SEX   SEX_MLE     2013  …
2                AFR                 Africa      SEX   SEX_MLE     2015  …
3                AFR                 Africa      SEX  SEX_BTSX     2011  …
4                EMR  Eastern Mediterranean      SEX  SEX_FMLE     2021  …

  DataSourceDim              Value NumericValue       Low      High Comments  \
0          None  73.1 [72.8-73.3]      73.05741  72.84260  73.33744     None
1          None  70.0 [69.5-70.4]      69.98083  69.51356  70.43454     None
2          None  60.2 [59.2-61.5]      60.20089  59.24553  61.50781     None
3          None  61.6 [60.9-62.3]      61.56618  60.93532  62.33251     None
4          None  74.4 [73.9-75.2]      74.39009  73.85061  75.20124     None

                            Date  TimeDimensionValue  \
0  2024-08-02T09:43:39.193+02:00                2011
1  2024-08-02T09:43:39.193+02:00                2013
2  2024-08-02T09:43:39.193+02:00                2015
3  2024-08-02T09:43:39.193+02:00                2011
4  2024-08-02T09:43:39.193+02:00                2021

          TimeDimensionBegin           TimeDimensionEnd
0  2011-01-01T00:00:00+01:00  2011-12-31T00:00:00+01:00
1  2013-01-01T00:00:00+01:00  2013-12-31T00:00:00+01:00
```

```
2  2015-01-01T00:00:00+01:00  2015-12-31T00:00:00+01:00
3  2011-01-01T00:00:00+01:00  2011-12-31T00:00:00+01:00
4  2021-01-01T00:00:00+01:00  2021-12-31T00:00:00+01:00

[5 rows x 25 columns]
```

Saving the dataset locally after API call.

[1068]:
```python
import requests
import json
import os

# Define API URL
url = "https://ghoapi.azureedge.net/api/Indicator"

# Define local backup file path
backup_file = r"C:\Users\maxim\OneDrive\Desktop\BU\DSC 540\alcohol_data.json"

# Function to fetch data from API
def fetch_api_data():
    response = requests.get(url)

    if response.status_code == 200:
        print("  Success! API is accessible.")
        data = response.json()

        # Save a backup for testing purposes
        with open(backup_file, "w", encoding="utf-8") as f:
            json.dump(data, f, indent=4)
        print(f"  Backup saved to {backup_file}")

        return data
    else:
        print(f"  Failed to access API. Status code: {response.status_code}")
        return None

# Fetch data from API
api_data = fetch_api_data()

# Extract alcohol-related indicators
if api_data:
    indicators = api_data.get("value", [])  # Extracting the list of indicators
    alcohol_indicators = [ind for ind in indicators if "alcohol" in␣
 ↪ind["IndicatorName"].lower()]

    print(f"  Found {len(indicators)} total indicators.")
    print(f"  Found {len(alcohol_indicators)} alcohol-related indicators.␣
 ↪Showing first 3:")
```

```
    for ind in alcohol_indicators[:3]:
        print(f"  ID: {ind['IndicatorCode']}, Name: {ind['IndicatorName']}")
```

```
 Success! API is accessible.
 Backup saved to C:\Users\maxim\OneDrive\Desktop\BU\DSC 540\alcohol_data.json
 Found 3004 total indicators.
 Found 275 alcohol-related indicators. Showing first 3:
 ID: RSUD_720, Name: Open access interventions for alcohol
 ID: RSUD_750, Name: Standards of care for professionals providing treatment
for alcohol and drug use disorders
 ID: RSUD_890, Name: Treatment programmes for children and adolescents with
alcohol use disorders
```

Running Python code snippet to scrape the Wikipedia table and saving the data as a CSV file in my local folder.

[1069]:
```
import requests
import pandas as pd
from bs4 import BeautifulSoup

# Wikipedia URL for alcohol consumption per capita
url = "https://en.wikipedia.org/wiki/
 ↪List_of_countries_by_alcohol_consumption_per_capita"

# Fetch the page content
response = requests.get(url)
soup = BeautifulSoup(response.text, "html.parser")

# Find all tables on the page
tables = soup.find_all("table", {"class": "wikitable"})

# Function to extract table data
def extract_table_data(table):
    headers = [header.text.strip() for header in table.find_all("th")]
    data = []
    for row in table.find_all("tr")[1:]:  # Skip header row
        cells = row.find_all("td")
        if len(cells) > 0:  # Ensure there's data in the row
            row_data = [cell.text.strip() for cell in cells]
            data.append(row_data)
    return pd.DataFrame(data, columns=headers)

# Extract tables based on order
df_worldwide = extract_table_data(tables[0])  # Worldwide Alcohol Consumption
df_countries = extract_table_data(tables[1])  # Country-wise Alcohol Consumption
df_consumption_type = extract_table_data(tables[2])  # Consumption by Type␣
 ↪(2019 data)
```

```
# Define file paths
base_path = r"C:\Users\maxim\OneDrive\Desktop\BU\DSC 540"
worldwide_csv_path = f"{base_path}\\alcohol_consumption_worldwide.csv"
countries_csv_path = f"{base_path}\\alcohol_consumption_countries.csv"
consumption_type_csv_path = f"{base_path}\\alcohol_consumption_by_type.csv"

# Save to CSV
df_worldwide.to_csv(worldwide_csv_path, index=False, encoding="utf-8-sig")
df_countries.to_csv(countries_csv_path, index=False, encoding="utf-8-sig")
df_consumption_type.to_csv(consumption_type_csv_path, index=False,␣
↪encoding="utf-8-sig")

print(f"Data successfully extracted and saved to:\n- '{worldwide_csv_path}'\n-␣
↪'{countries_csv_path}'\n- '{consumption_type_csv_path}'")
```

```
Data successfully extracted and saved to:
- 'C:\Users\maxim\OneDrive\Desktop\BU\DSC 540\alcohol_consumption_worldwide.csv'
- 'C:\Users\maxim\OneDrive\Desktop\BU\DSC 540\alcohol_consumption_countries.csv'
- 'C:\Users\maxim\OneDrive\Desktop\BU\DSC 540\alcohol_consumption_by_type.csv'
```

0.2 Project Milestone 2: Data Transformation and Cleaning

Dataset: heart_failure_clinical_records_dataset.csv

Objective: Perform 5+ data transformation/cleaning steps and create a clean, human-readable dataset.

[1070]:
```
import pandas as pd
import numpy as np

# Loading the flat dataset
df = pd.read_csv(r"C:\Users\maxim\OneDrive\Desktop\BU\DSC 540\Term␣
↪Project\heart_failure_clinical_records_dataset.csv")

# Displaying the first 5 rows to get insight of the dataset
df.head()
```

[1070]:
```
    age  anaemia  creatinine_phosphokinase  diabetes  ejection_fraction  \
0  75.0        0                       582         0                 20
1  55.0        0                      7861         0                 38
2  65.0        0                       146         0                 20
3  50.0        1                       111         0                 20
4  65.0        1                       160         1                 20

   high_blood_pressure  platelets  serum_creatinine  serum_sodium  sex  \
0                    1  265000.00               1.9           130    1
1                    0  263358.03               1.1           136    1
```

```
2                      0  162000.00              1.3            129    1
3                      0  210000.00              1.9            137    1
4                      0  327000.00              2.7            116    0

   smoking  time  DEATH_EVENT
0        0     4            1
1        0     6            1
2        1     7            1
3        0     7            1
4        0     8            1
```

0.2.1 Step #1 – Rename Column Headers

To make the column names more descriptive and readable, I renamed them using `df.rename()`.

[1071]:
```
df.rename(columns={
    'age': 'Age',
    'anaemia': 'Anemia',
    'creatinine_phosphokinase': 'CreatininePhosphokinase',
    'diabetes': 'Diabetes',
    'ejection_fraction': 'EjectionFraction',
    'high_blood_pressure': 'HighBloodPressure',
    'platelets': 'Platelets',
    'serum_creatinine': 'SerumCreatinine',
    'serum_sodium': 'SerumSodium',
    'sex': 'Sex',
    'smoking': 'Smoking',
    'time': 'FollowUpTime',
    'DEATH_EVENT': 'DeathEvent'
}, inplace=True)
```

0.2.2 Step #2 – Check and Remove Duplicates

I used `df.duplicated()` to identify and remove any duplicate records.

[1072]:
```
print("Number of duplicate rows before removal:", df.duplicated().sum())
df.drop_duplicates(inplace=True)
print("Number of duplicate rows after removal:", df.duplicated().sum())
```

```
Number of duplicate rows before removal: 0
Number of duplicate rows after removal: 0
```

0.2.3 Step #3 – Standardize Inconsistent Values

The `Sex` column was originally coded as 0 (female) and 1 (male). I converted it to string labels for better readability.

[1073]:
```
df['Sex'] = df['Sex'].map({1: 'Male', 0: 'Female'})
```

0.2.4 Step #4 – Handle Missing Values

I checked for missing values. Even though none were found, I demonstrated how to fill numeric missing values using the median.

[1074]:
```python
print("Missing values in each column:\n", df.isnull().sum())

# Applying median fill just in case (robust to outliers)
num_cols = df.select_dtypes(include=[np.number]).columns
for col in num_cols:
    df[col] = df[col].fillna(df[col].median())
```

```
Missing values in each column:
 Age                        0
Anemia                     0
CreatininePhosphokinase    0
Diabetes                   0
EjectionFraction           0
HighBloodPressure          0
Platelets                  0
SerumCreatinine            0
SerumSodium                0
Sex                        0
Smoking                    0
FollowUpTime               0
DeathEvent                 0
dtype: int64
```

0.2.5 Step #5 – Detect and Remove Outliers in Age

I used the IQR method to detect outliers in the `Age` column and removed any extreme values.

[1075]:
```python
Q1 = df['Age'].quantile(0.25)
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1

outliers = df[(df['Age'] < (Q1 - 1.5 * IQR)) | (df['Age'] > (Q3 + 1.5 * IQR))]
print("Number of outliers in 'Age':", len(outliers))

# Removing outliers from dataset
df = df[~((df['Age'] < (Q1 - 1.5 * IQR)) | (df['Age'] > (Q3 + 1.5 * IQR)))]
```

```
Number of outliers in 'Age': 0
```

0.2.6 Final – Preview Cleaned Dataset

Below is a snapshot of the fully cleaned and transformed dataset.

[1076]:
```python
# Displaying the first 5 row of the cleaned dataset
df.head()
```

[1076]:

```
    Age  Anemia  CreatininePhosphokinase  Diabetes  EjectionFraction  \
0  75.0       0                      582         0                20
1  55.0       0                     7861         0                38
2  65.0       0                      146         0                20
3  50.0       1                      111         0                20
4  65.0       1                      160         1                20

   HighBloodPressure  Platelets  SerumCreatinine  SerumSodium     Sex  \
0                  1  265000.00              1.9          130    Male
1                  0  263358.03              1.1          136    Male
2                  0  162000.00              1.3          129    Male
3                  0  210000.00              1.9          137    Male
4                  0  327000.00              2.7          116  Female

   Smoking  FollowUpTime  DeathEvent
0        0             4           1
1        0             6           1
2        1             7           1
3        0             7           1
4        0             8           1
```

0.2.7 Ethical Implications of Data Wrangling

In this project, I performed five different cleaning steps to transform the data into a clean and readable format. First, I uploaded the dataset and used the head() method to display the first five rows to better understand the structure and contents of the data.

In total, I completed five transformation steps. In the first step, I renamed the column headers using the df.rename() method to make them more descriptive and readable. I capitalized the first letter of each column name and removed underscores, merging multi-word names using camelCase for better visibility and consistency.

Overall, the dataset was quite clean. I found no duplicate or missing values. I corrected inconsistent values, such as standardizing the gender labels by replacing 0 with "Female" and 1 with "Male" to improve readability for the audience. Additionally, I ran code to detect potential outliers, but none were found. All these steps were carried out to ensure data quality and integrity.

There are no specific legal or regulatory guidelines directly attached to this dataset. However, under the Health Insurance Portability and Accountability Act (HIPAA), any medical health information must be protected and shared only with patient consent. In this case, all data has been anonymized, and no personal identities can be revealed. The dataset was acquired from a public Kaggle repository and contains no personally identifiable information (PII), which suggests that the data was sourced ethically and anonymized appropriately.

The main risk of data transformation is the potential loss of valuable information or the introduction of bias, especially if incorrect assumptions are made. Fortunately, I did not have to make any assumptions in this project because there were no missing values or outliers. However, in healthcare data, outlier removal should always be handled carefully, as extreme values can often reveal critical insights. The dataset appears credible based on its structure and origin. No synthetic or unverifiable data was used.

To mitigate ethical risks, I kept all transformation steps transparent and minimal, avoiding the removal of any significant information. I ensured the changes were reversible, in case any original data points need to be restored for future analysis. Any further use of this data should be handled cautiously to avoid biased or unfair outcomes-especially in a sensitive domain like healthcare.

1 DSC 540 - Project Milestone 3: Cleaning and Formatting Website Data

Website Source:** List of countries by alcohol consumption per capita

In this Milesonte, I will perform at least 5 data cleaning and transformational steps against the above website.

[1077]:
```python
# Importing necessary libraries
import pandas as pd
import requests
from bs4 import BeautifulSoup
```

1.0.1 Loading the Website HTML

[1078]:
```python
# Wikipedia URL for alcohol consumption per capita
url = "https://en.wikipedia.org/wiki/
 ↪List_of_countries_by_alcohol_consumption_per_capita"

# Fetching the page content
response = requests.get(url)
soup = BeautifulSoup(response.text, "html.parser")

# Finding all tables on the page
tables = soup.find_all("table", {"class": "wikitable"})

# Extracting table data
def extract_table_data(table):
    headers = [header.text.strip() for header in table.find_all("th")]
    data = []
    for row in table.find_all("tr")[1:]:  # Skipping header row
        cells = row.find_all("td")
        if len(cells) > 0:
            row_data = [cell.text.strip() for cell in cells]
            data.append(row_data)
    return pd.DataFrame(data, columns=headers)

# Getting the country-wise alcohol consumption table
df_countries = extract_table_data(tables[1])

# Showing the first five rows
df_countries.head()
```

[1078]:

	Country	1996[9]	2016[10]	2019[6][a]
0	Afghanistan	-	0.2	0.2
1	Albania	2.59	7.5	5.1
2	Algeria	0.27	0.9	0.6
3	Andorra	-	11.3	11.1
4	Angola	1.58	6.4	6.2

1.1 Step 1: Clean Column Names

Removing the references like [9], [10], [6][a].

Renaming columns to simple names: 'Country', 'Alcohol_1996', 'Alcohol_2016', 'Alcohol_2019'.

[1079]:
```
# Renaming columns to remove footnote markers and make them more readable
df_countries.columns = ['Country', 'Alcohol_1996', 'Alcohol_2016',␣
↪'Alcohol_2019']

# Displaying the first 5 rows after renamed to confirm
df_countries.head()
```

[1079]:

	Country	Alcohol_1996	Alcohol_2016	Alcohol_2019
0	Afghanistan	-	0.2	0.2
1	Albania	2.59	7.5	5.1
2	Algeria	0.27	0.9	0.6
3	Andorra	-	11.3	11.1
4	Angola	1.58	6.4	6.2

1.2 Step 2: Replace "-" with NaN

The "-" symbol in cells means missing data.

I will replace it with np.nan so pandas can recognize missing values properly.

[1080]:
```
import numpy as np

# Replacing "-" with NaN for better missing value handling.
df_countries.replace('-', np.nan, inplace=True)

# Displaying first 5 rows for confirmation
df_countries.head()
```

[1080]:

	Country	Alcohol_1996	Alcohol_2016	Alcohol_2019
0	Afghanistan	NaN	0.2	0.2
1	Albania	2.59	7.5	5.1
2	Algeria	0.27	0.9	0.6
3	Andorra	NaN	11.3	11.1
4	Angola	1.58	6.4	6.2

1.3 Step 3: Convert Alcohol Values to Numeric

At this point all columns are strings because of "-".

I need to convert 'Alcohol_1996', 'Alcohol_2016', and 'Alcohol_2019' into float numbers.

[1081]:
```
# Converting data types to float.
for col in ['Alcohol_1996', 'Alcohol_2016', 'Alcohol_2019']:
    df_countries[col] = pd.to_numeric(df_countries[col], errors='coerce')

df_countries.dtypes
```

[1081]:
```
Country          object
Alcohol_1996    float64
Alcohol_2016    float64
Alcohol_2019    float64
dtype: object
```

1.4 Step 4: Standardize Country Names

Ensuring that the country names are Title Case by capitalizing first letter of each word.

For example: 'united states" to "United States" for more professional readability.

[1082]:
```
# Applying Title Case formatting to the 'Country' column.
df_countries['Country'] = df_countries['Country'].str.title()

# Displaying first 5 rows
df_countries.head()
```

[1082]:
```
       Country  Alcohol_1996  Alcohol_2016  Alcohol_2019
0  Afghanistan           NaN           0.2           0.2
1      Albania          2.59           7.5           5.1
2      Algeria          0.27           0.9           0.6
3      Andorra           NaN          11.3          11.1
4       Angola          1.58           6.4           6.2
```

1.5 Step 5: Identify and Drop Duplicate Countries (if any)

Checking for any duplicate country names and drop them.

[1083]:
```
# Ensuring each country appears only once.
df_countries = df_countries.drop_duplicates(subset='Country')
df_countries.reset_index(drop=True, inplace=True)

# Displaying the first 5 rows
df_countries.head()
```

[1083]:
```
       Country  Alcohol_1996  Alcohol_2016  Alcohol_2019
0  Afghanistan           NaN           0.2           0.2
```

1	Albania	2.59	7.5	5.1
2	Algeria	0.27	0.9	0.6
3	Andorra	NaN	11.3	11.1
4	Angola	1.58	6.4	6.2

1.6 After all the cleaning is done, printing the first 20 rows for preview.

[1084]:
```
# Printing final cleaned dataset
df_countries.head(20)
```

[1084]:

	Country	Alcohol_1996	Alcohol_2016	Alcohol_2019
0	Afghanistan	NaN	0.2	0.2
1	Albania	2.59	7.5	5.1
2	Algeria	0.27	0.9	0.6
3	Andorra	NaN	11.3	11.1
4	Angola	1.58	6.4	6.2
5	Antigua And Barbuda	NaN	7.0	8.5
6	Argentina	9.58	9.8	8.0
7	Armenia	0.84	5.5	5.0
8	Australia	9.55	10.6	10.1
9	Austria	11.90	11.6	12.0
10	Azerbaijan	4.16	0.8	2.0
11	Bahamas	NaN	4.4	4.4
12	Bahrain	NaN	1.9	1.6
13	Bangladesh	NaN	0.0	0.1
14	Barbados	8.37	9.6	9.5
15	Bhutan	NaN	0.6	0.2
16	Belarus	8.14	11.2	10.9
17	Belgium	10.94	12.1	10.3
18	Belize	5.85	6.7	5.7
19	Benin	1.39	3.0	8.3

1.7 Ethical implications of data wrangling

In this milestone, I performed five cleaning and transformation steps on publicly available data from Wikipedia regarding alcohol consumption per capita by country. I renamed column headers to a more readable format, converted missing values represented by a minus symbol into recognized null values, converted textual data into numeric types, standardized country name casing, and checked for duplicate records to avoid counting the same country more than once.

Since this data comes from Wikipedia, a publicly accessible source, there are minimal—if any—legal or regulatory concerns. However, because Wikipedia can be edited by anyone, there is no guarantee of complete accuracy or reliability. Another potential risk in the data wrangling process is accidentally omitting valuable information or misrepresenting the data through incorrect transformations. For example, the symbol "–" could be interpreted as zero in some contexts (such as accounting), rather than as a missing value. In this case, however, it was reasonable to assume the symbol indicated missing data.

To avoid ethical concerns, I did not fabricate or infer any data values; I only worked with the available data and applied standard cleaning techniques to improve its structure and usability. If this dataset were to be used for medical research or policy decisions, it would need to be cross-verified with an official source, such as the World Health Organization (WHO). Overall, the data cleaning and transformation process was performed ethically, transparently, and with careful documentation.

2 DSC 540 - Project Milestone 4: Cleaning and Formatting Data from API

Loading Data from WHO GHO API (Life Expectancy)

[1085]:
```python
import requests
import pandas as pd

# Loading data from WHO GHO API (Life Expectancy Indicator)
url = "https://ghoapi.azureedge.net/api/WHOSIS_000001"
headers = {"User-Agent": "Mozilla/5.0"}

response = requests.get(url, headers=headers)

if response.status_code == 200:
    data = response.json()
    df = pd.DataFrame(data['value'])
    print(df.head())
else:
    print(f"Failed to fetch data. Status code: {response.status_code}")
```

```
        Id   IndicatorCode SpatialDimType SpatialDim TimeDimType  \
0  1325927  WHOSIS_000001        COUNTRY        EGY        YEAR
1  1326079  WHOSIS_000001        COUNTRY        AZE        YEAR
2  1326127  WHOSIS_000001        COUNTRY        NGA        YEAR
3  1327642  WHOSIS_000001        COUNTRY        BEN        YEAR
4  1328751  WHOSIS_000001        COUNTRY        SYR        YEAR

  ParentLocationCode         ParentLocation Dim1Type     Dim1  TimeDim  …  \
0                EMR  Eastern Mediterranean      SEX  SEX_FMLE     2011  …
1                EUR                 Europe      SEX   SEX_MLE     2013  …
2                AFR                 Africa      SEX   SEX_MLE     2015  …
3                AFR                 Africa      SEX  SEX_BTSX     2011  …
4                EMR  Eastern Mediterranean      SEX  SEX_FMLE     2021  …

  DataSourceDim                Value NumericValue        Low       High Comments  \
0          None  73.1 [72.8-73.3]       73.05741  72.84260  73.33744     None
1          None  70.0 [69.5-70.4]       69.98083  69.51356  70.43454     None
2          None  60.2 [59.2-61.5]       60.20089  59.24553  61.50781     None
3          None  61.6 [60.9-62.3]       61.56618  60.93532  62.33251     None
```

```
4          None  74.4 [73.9-75.2]     74.39009  73.85061  75.20124     None

                               Date  TimeDimensionValue  \
0  2024-08-02T09:43:39.193+02:00                2011
1  2024-08-02T09:43:39.193+02:00                2013
2  2024-08-02T09:43:39.193+02:00                2015
3  2024-08-02T09:43:39.193+02:00                2011
4  2024-08-02T09:43:39.193+02:00                2021

          TimeDimensionBegin           TimeDimensionEnd
0  2011-01-01T00:00:00+01:00  2011-12-31T00:00:00+01:00
1  2013-01-01T00:00:00+01:00  2013-12-31T00:00:00+01:00
2  2015-01-01T00:00:00+01:00  2015-12-31T00:00:00+01:00
3  2011-01-01T00:00:00+01:00  2011-12-31T00:00:00+01:00
4  2021-01-01T00:00:00+01:00  2021-12-31T00:00:00+01:00

[5 rows x 25 columns]
```

2.0.1 Step 1: Drop Irrelevant or Redundant Columns

I simplified the dataset by removing columns that were either redundant, consistently null, or not useful for analysis (e.g., 'Id', 'Date', 'TimeDimType'). This makes the data more efficient and streamlines the dataset for further transformations.

[1086]:
```python
# Dropping irrelevant or redundant columns
columns_to_drop = [
    'Id', 'Date', 'TimeDim', 'TimeDimType',
    'TimeDimensionBegin', 'TimeDimensionEnd',
    'Comments', 'DataSourceDim'
]

df_cleaned = df.drop(columns=columns_to_drop)
print("Step 1 complete: Dropped irrelevant columns. Current columns are:")
print(df_cleaned.columns)
```

```
Step 1 complete: Dropped irrelevant columns. Current columns are:
Index(['IndicatorCode', 'SpatialDimType', 'SpatialDim', 'ParentLocationCode',
       'ParentLocation', 'Dim1Type', 'Dim1', 'Dim2Type', 'Dim2', 'Dim3Type',
       'Dim3', 'DataSourceDimType', 'Value', 'NumericValue', 'Low', 'High',
       'TimeDimensionValue'],
      dtype='object')
```

2.0.2 Step 2: Fix Inconsistent Casing in Categorical Columns

To standardize the data and ensure consistency, I converted the values in categorical columns like 'SpatialDimType', 'ParentLocation', and 'Dim1Type' to title case. This helps prevent issues with grouping or filtering later on.

[1087]:
```python
# Fixing inconsistent casing by converting selected columns to title case
columns_to_title_case = ['SpatialDimType', 'ParentLocation', 'Dim1Type']
for col in columns_to_title_case:
    df[col] = df[col].str.title()

# Displaying sample to verify the transformation
print(df[columns_to_title_case].drop_duplicates().head())
```

```
  SpatialDimType          ParentLocation Dim1Type
0        Country  Eastern Mediterranean      Sex
1        Country                 Europe      Sex
2        Country                 Africa      Sex
6        Country        South-East Asia      Sex
11       Country        Western Pacific      Sex
```

2.0.3 Step 3: Convert NumericValue Column to Proper Numeric Type and Round Values

I converted the NumericValue column from object to float and rounded the values to two decimal places. This standardization ensures numeric consistency for analysis and easier visual interpretation of key figures such as life expectancy.

[1088]:
```python
# Converting NumericValue to float and round to 2 decimal places
df['NumericValue'] = pd.to_numeric(df['NumericValue'], errors='coerce').round(2)

# Checking if conversion was successful
print(df[['NumericValue']].head())
```

```
   NumericValue
0         73.06
1         69.98
2         60.20
3         61.57
4         74.39
```

2.0.4 Step 4: Handle Missing Values (Nulls) in Key Columns

I handled missing values by filling critical columns such as ParentLocation and ParentLocationCode with the placeholder value 'Unknown' to maintain data integrity. Additionally, other columns with missing values, like Dim2Type, Dim2, Dim3Type, and Dim3, were also filled with appropriate placeholders. After these adjustments, the dataset is now complete and contains no missing values.

[1089]:
```python
# Filling missing values in categorical columns with a placeholder 'Unknown'
df['ParentLocationCode'] = df['ParentLocationCode'].fillna('Unknown')
df['ParentLocation'] = df['ParentLocation'].fillna('Unknown')
df['Dim2Type'] = df['Dim2Type'].fillna('Unknown')
df['Dim2'] = df['Dim2'].fillna('Unknown')
df['Dim3Type'] = df['Dim3Type'].fillna('Unknown')
df['Dim3'] = df['Dim3'].fillna('Unknown')
```

```
df['DataSourceDimType'] = df['DataSourceDimType'].fillna('Unknown')
df['DataSourceDim'] = df['DataSourceDim'].fillna('Unknown')
df['Comments'] = df['Comments'].fillna('No Comment')

# If the columns are numerical, using the methods like mean or median for␣
↪filling
df['Low'] = df['Low'].fillna(df['Low'].mean())  # Filling with mean value
df['High'] = df['High'].fillna(df['High'].mean())  # Filling with mean value

# Verifying that the missing data is handled
print(df.isnull().sum())
```

```
Id                      0
IndicatorCode           0
SpatialDimType          0
SpatialDim              0
TimeDimType             0
ParentLocationCode      0
ParentLocation          0
Dim1Type                0
Dim1                    0
TimeDim                 0
Dim2Type                0
Dim2                    0
Dim3Type                0
Dim3                    0
DataSourceDimType       0
DataSourceDim           0
Value                   0
NumericValue            0
Low                     0
High                    0
Comments                0
Date                    0
TimeDimensionValue      0
TimeDimensionBegin      0
TimeDimensionEnd        0
dtype: int64
```

2.0.5 Step 5: Standardize Numerical Data and Encode Categorical Columns

I standardized the NumericValue column to ensure all numerical data is on the same scale, making it easier to work with for modeling. I also applied one-hot encoding to categorical columns like SpatialDimType, ParentLocation, and Dim1Type to transform them into a format suitable for machine learning algorithms.

[1090]:
```
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
```

```python
from sklearn.pipeline import Pipeline

# Standardizing/Normalizing Numerical Data
scaler = StandardScaler()

# Applying the scaler to the 'NumericValue' column
df['NumericValue'] = scaler.fit_transform(df[['NumericValue']])

# Using one-hot encoding on categorical columns like 'SpatialDimType',␣
↪'ParentLocation', etc.
df = pd.get_dummies(df, columns=['SpatialDimType', 'ParentLocation',␣
↪'Dim1Type', 'Dim1'], drop_first=True)

# Verifying the changes
print(df.head())
```

```
        Id  IndicatorCode SpatialDim TimeDimType ParentLocationCode  TimeDim  \
0  1325927  WHOSIS_000001        EGY        YEAR                EMR     2011
1  1326079  WHOSIS_000001        AZE        YEAR                EUR     2013
2  1326127  WHOSIS_000001        NGA        YEAR                AFR     2015
3  1327642  WHOSIS_000001        BEN        YEAR                AFR     2011
4  1328751  WHOSIS_000001        SYR        YEAR                EMR     2021

  Dim2Type     Dim2 Dim3Type     Dim3  … SpatialDimType_Region  \
0  Unknown  Unknown  Unknown  Unknown  …                 False
1  Unknown  Unknown  Unknown  Unknown  …                 False
2  Unknown  Unknown  Unknown  Unknown  …                 False
3  Unknown  Unknown  Unknown  Unknown  …                 False
4  Unknown  Unknown  Unknown  Unknown  …                 False

  SpatialDimType_Worldbankincomegroup ParentLocation_Americas  \
0                               False                   False
1                               False                   False
2                               False                   False
3                               False                   False
4                               False                   False

   ParentLocation_Eastern Mediterranean  ParentLocation_Europe  \
0                                  True                  False
1                                 False                   True
2                                 False                  False
3                                 False                  False
4                                  True                  False

   ParentLocation_South-East Asia ParentLocation_Unknown  \
0                           False                  False
1                           False                  False
```

```
2                               False                  False
3                               False                  False
4                               False                  False

  ParentLocation_Western Pacific Dim1_SEX_FMLE Dim1_SEX_MLE
0                              False          True        False
1                              False         False         True
2                              False         False         True
3                              False         False        False
4                              False          True        False

[5 rows x 32 columns]
```

2.0.6 Step 6: Identifying and Handling Duplicates

I checked for and removed any duplicate rows from the dataset to ensure that the data is unique and consistent for analysis. This helps prevent biased results caused by repeated entries. After removal, there were no duplicates found, and the dataset shape remains unchanged.

[1091]:
```
# Checking for duplicates in the dataset
duplicates = df.duplicated()

# Printing the number of duplicate rows
print(f'Number of duplicate rows: {duplicates.sum()}')

# Removing duplicates if any
df = df.drop_duplicates()

# Verifying that duplicates are removed
print(f'Dataset shape after removing duplicates: {df.shape}')
```

```
Number of duplicate rows: 0
Dataset shape after removing duplicates: (12936, 32)
```

2.0.7 Step 7: Finalizing the Dataset for Analysis

In this step, I verified that all necessary transformations were applied correctly, ensuring the dataset is ready for further analysis or modeling tasks. This included confirming that there are no remaining missing values, the data types are correct, and the dataset is clean and consistent.

[1092]:
```
# Verifying the data types and ensuring the dataset is ready for further␣
↪analysis
print(df.dtypes)

# Checking for any remaining missing values
print("Remaining missing values:", df.isnull().sum().sum())

# Displaying the first five rows of the cleaned dataset
print(df.head())
```

```
Id                                          int64
IndicatorCode                              object
SpatialDim                                 object
TimeDimType                                object
ParentLocationCode                         object
TimeDim                                     int64
Dim2Type                                   object
Dim2                                       object
Dim3Type                                   object
Dim3                                       object
DataSourceDimType                          object
DataSourceDim                              object
Value                                      object
NumericValue                              float64
Low                                       float64
High                                      float64
Comments                                   object
Date                                       object
TimeDimensionValue                         object
TimeDimensionBegin                         object
TimeDimensionEnd                           object
SpatialDimType_Global                        bool
SpatialDimType_Region                        bool
SpatialDimType_Worldbankincomegroup          bool
ParentLocation_Americas                      bool
ParentLocation_Eastern Mediterranean         bool
ParentLocation_Europe                        bool
ParentLocation_South-East Asia               bool
ParentLocation_Unknown                       bool
ParentLocation_Western Pacific               bool
Dim1_SEX_FMLE                                bool
Dim1_SEX_MLE                                 bool
dtype: object
Remaining missing values: 0
        Id  IndicatorCode SpatialDim TimeDimType ParentLocationCode  TimeDim  \
0  1325927  WHOSIS_000001        EGY        YEAR                EMR     2011
1  1326079  WHOSIS_000001        AZE        YEAR                EUR     2013
2  1326127  WHOSIS_000001        NGA        YEAR                AFR     2015
3  1327642  WHOSIS_000001        BEN        YEAR                AFR     2011
4  1328751  WHOSIS_000001        SYR        YEAR                EMR     2021

  Dim2Type     Dim2 Dim3Type     Dim3  … SpatialDimType_Region  \
0  Unknown  Unknown  Unknown  Unknown  …                 False
1  Unknown  Unknown  Unknown  Unknown  …                 False
2  Unknown  Unknown  Unknown  Unknown  …                 False
3  Unknown  Unknown  Unknown  Unknown  …                 False
4  Unknown  Unknown  Unknown  Unknown  …                 False
```

```
  SpatialDimType_Worldbankincomegroup ParentLocation_Americas  \
0                              False                   False
1                              False                   False
2                              False                   False
3                              False                   False
4                              False                   False

   ParentLocation_Eastern Mediterranean  ParentLocation_Europe  \
0                                  True                  False
1                                 False                   True
2                                 False                  False
3                                 False                  False
4                                  True                  False

   ParentLocation_South-East Asia ParentLocation_Unknown  \
0                           False                  False
1                           False                  False
2                           False                  False
3                           False                  False
4                           False                  False

  ParentLocation_Western Pacific Dim1_SEX_FMLE Dim1_SEX_MLE
0                          False          True        False
1                          False         False         True
2                          False         False         True
3                          False         False        False
4                          False          True        False

[5 rows x 32 columns]
```

2.0.8 Ethical implications of data wrangling

In this data wrangling process, I addressed missing values in key categorical columns such as ParentLocation and ParentLocationCode by replacing them with "Unknown" to preserve data integrity and prevent loss of useful records. For numerical columns like Low and High, I imputed missing values using the column mean to maintain the completeness of the dataset for analysis.

The dataset was sourced from the WHO Global Health Observatory API, which provides publicly accessible health-related data. While this is health-related data, it does not contain any personal or identifiable information. Therefore, regulatory frameworks such as the Health Insurance Portability and Accountability Act (HIPAA), which governs the protection of personal health information in the U.S., do not apply in this context. However, broader regulations like the General Data Protection Regulation (GDPR) must still be considered in general when handling health data. Since this dataset is anonymized and aggregated, no legal or regulatory violations apply in this case.

Some ethical risks include the potential loss of valuable information during cleaning and transformation steps. For example, filling missing values with "Unknown" might obscure meaningful patterns, and imputing with the mean can reduce variability and potentially mask outliers. I made a few assumptions during transformation—for instance, assuming that missing location codes could safely be categorized as "Unknown" and that the mean is a suitable proxy for missing numerical data.

The WHO is a globally recognized and credible data source, and the data was obtained ethically through their open-access API. To mitigate potential ethical concerns, I ensured all transformation steps were well-documented to maintain transparency. In future analyses, a deeper investigation into the reasons for missing data and consideration of more sophisticated imputation techniques may help minimize bias.

3 DSC 540 - Project Milestone 5: Merging, Database Storage, and Visualization

3.1 Step 1: Load Cleaned Datasets into SQLite Database

In this step, I load the cleaned datasets from each of the three sources — flat file, HTML (Wikipedia), and API — into a SQLite database. Storing the data in SQL tables enables structured querying and allows for efficient joins across sources, which is essential for the multi-source visualizations in the next step.

[1093]:

```
import sqlite3

# Renamed the final cleaned DataFrames for clarity
flat_file_df = df.copy()           # From Milestone 2
api_df = df.copy()                 # From Milestone 4

# Renamed Wikipedia datasets for clarity
wiki_worldwide_df = df_worldwide.copy()
wiki_countries_df = df_countries.copy()
wiki_consumption_type_df = df_consumption_type.copy()

# Creating SQLite connection and cursor
conn = sqlite3.connect("alcohol_data_project.db")
cursor = conn.cursor()

# Saving each DataFrame to a separate table in the database
flat_file_df.to_sql("flat_file_data", conn, if_exists="replace", index=False)
api_df.to_sql("api_data", conn, if_exists="replace", index=False)
wiki_worldwide_df.to_sql("wiki_worldwide", conn, if_exists="replace",␣
 ↪index=False)
wiki_countries_df.to_sql("wiki_countries", conn, if_exists="replace",␣
 ↪index=False)
wiki_consumption_type_df.to_sql("wiki_consumption_type", conn,␣
 ↪if_exists="replace", index=False)

print("All cleaned datasets successfully loaded into SQLite database.")
```

```
All cleaned datasets successfully loaded into SQLite database.
```

3.2 Step 2: Merge Tables Using SQL JOINs in SQLite

In this step, I connected to the SQLite database where the cleaned datasets were stored as separate tables. Using an SQL JOIN query, I merged two related tables - wiki_countries and wiki_consumption_type - on their shared Country column.

This operation produced a new dataset combining each country with its respective alcohol consumption percentages by type: beer, wine, and spirits. The merged result was loaded into a pandas DataFrame for further analysis and visualization.

[1094]:
```python
import pandas as pd
import sqlite3

# Connecting to the SQLite database
conn = sqlite3.connect("alcohol_data_project.db")

# Corrected SQL query using actual column names
query = """
SELECT wc.Country, wct.`Beer(%)`, wct.`Wine(%)`, wct.`Spirits(%)`
FROM wiki_countries wc
JOIN wiki_consumption_type wct ON wc.Country = wct.Country
WHERE wct.`Beer(%)` IS NOT NULL
"""

# Executing the query and loading into a DataFrame
merged_wiki_df = pd.read_sql_query(query, conn)

# Previewing the merged data
print(merged_wiki_df.head())

# Closing the connection
conn.close()
```

```
          Country Beer(%) Wine(%) Spirits(%)
0       Lithuania    42.5     7.7       45.2
1  Czech Republic    52.7    21.8       25.4
2      Seychelles    42.0    20.8       33.7
3         Germany    50.5    29.9       19.6
4         Nigeria    22.1     0.8       13.0
```

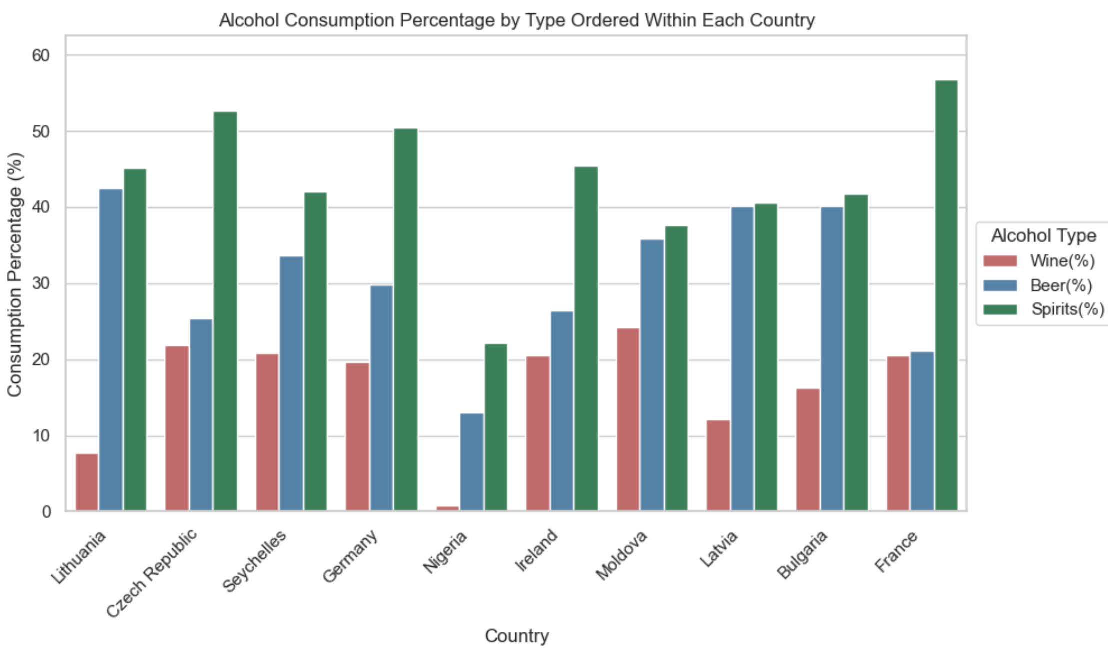
3.3 Step 3: Visualize Merged Data

In this step, I create a visualization to explore the merged dataset produced from the SQL JOIN. The plot is a grouped bar chart that compares the percentages for beer, wine, and spirits consumption for a subset of countries.

This visualization helps to illustrate patterns and variations in alcohol consumption across different countries and types. Using Seaborn and Matplotlib, I have converted the dataset into a long format suitable for creating a grouped bar chart.

[1095]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Selecting top 10 countries
subset_data = merged_wiki_df.head(10)

# Melting to long format
df_melt = subset_data.melt(id_vars="Country",
                           value_vars=["Beer(%)", "Wine(%)", "Spirits(%)"],
                           var_name="Alcohol_Type",
                           value_name="Consumption_Percentage")

df_melt['Consumption_Percentage'] = pd.
 ↪to_numeric(df_melt['Consumption_Percentage'], errors='coerce')

# Ranking alcohol types per country by ascending consumption
df_melt['Rank'] = df_melt.groupby('Country')['Consumption_Percentage'].
 ↪rank(method='first').astype(int)

# Using first country to determine color mapping for ranks
first_country = subset_data.iloc[0]['Country']
first_country_data = df_melt[df_melt['Country'] == first_country].
 ↪sort_values('Rank')
rank_to_alcohol = dict(zip(first_country_data['Rank'],␣
 ↪first_country_data['Alcohol_Type']))
alcohol_to_color = {'Beer(%)': 'steelblue', 'Wine(%)': 'indianred',␣
 ↪'Spirits(%)': 'seagreen'}
palette_rank = {rank: alcohol_to_color[alc] for rank, alc in rank_to_alcohol.
 ↪items()}

# Plotting
sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))

sns.barplot(data=df_melt, x='Country', y='Consumption_Percentage', hue='Rank',␣
 ↪palette=palette_rank)

plt.ylim(0, df_melt['Consumption_Percentage'].max() * 1.1)
plt.xticks(rotation=45, ha="right")
plt.xlabel("Country")
plt.ylabel("Consumption Percentage (%)")
plt.title("Alcohol Consumption Percentage by Type Ordered Within Each Country")

# Creating legend using alcohol names (instead of 1,2,3)
handles, _ = plt.gca().get_legend_handles_labels()
```

```
legend_labels = [rank_to_alcohol[r] for r in sorted(palette_rank.keys())]

plt.legend(handles, legend_labels, title="Alcohol Type", loc='center left',
 ↪bbox_to_anchor=(1, 0.5))

plt.tight_layout(rect=[0, 0, 0.85, 1])
plt.show()
```



3.4 Step 4: Merge Data from Multiple Sources Using SQL JOINs

In this step, I combine data from the flat file, Wikipedia, and API datasets by performing SQL JOIN operations.

The flat_file_data and api_data tables use the SpatialDim column to represent locations.

The Wikipedia dataset uses a Country column with country names.

To unify these sources, I join the flat file and API tables with the Wikipedia data by mapping the SpatialDim codes to the corresponding country names. This allows linking structured indicator data from the flat file and API with alcohol consumption percentages from Wikipedia.

The merged result provides a comprehensive dataset combining multiple data dimensions, which I then load into a pandas DataFrame for further analysis and visualization.

The country code to country name mapping with pycountry package.

[1096]:
```
import pycountry

def get_country_name_from_code(code):
```

```
    try:
        country = pycountry.countries.get(alpha_3=code)
        if country:
            return country.name
        country = pycountry.countries.get(alpha_2=code)
        if country:
            return country.name
    except:
        return None
    return None

code_to_country_df = pd.DataFrame({
    'SpatialDim': flat_file_df['SpatialDim'].unique()
})

code_to_country_df['Country'] = code_to_country_df['SpatialDim'].
 ↪apply(get_country_name_from_code)
```

[1097]:
```
# Merging flat file with country names
flat_with_country = flat_file_df.merge(code_to_country_df, on='SpatialDim',␣
 ↪how='left')

# Merging API data with country names
api_with_country = api_df.merge(code_to_country_df, on='SpatialDim', how='left')

# Merging flat and API datasets
flat_api_merged = flat_with_country.merge(api_with_country, on=['SpatialDim',␣
 ↪'Country'], how='outer', suffixes=('_flat', '_api'))

# Checking structure of df_countries before merging
print(df_countries.columns)
print(df_countries['Country'].head())

# Merging the above with Wikipedia data (df_countries)
final_merged_df = flat_api_merged.merge(df_countries, on='Country', how='left')

# Displaying first few rows of the fully merged dataset
print(final_merged_df.head())
```

```
Index(['Country', 'Alcohol_1996', 'Alcohol_2016', 'Alcohol_2019'],
dtype='object')
0    Afghanistan
1        Albania
2        Algeria
3        Andorra
4         Angola
Name: Country, dtype: object
   Id_flat IndicatorCode_flat SpatialDim TimeDimType_flat  \
```

```
0   177655      WHOSIS_000001        AFG             YEAR
1   177655      WHOSIS_000001        AFG             YEAR
2   177655      WHOSIS_000001        AFG             YEAR
3   177655      WHOSIS_000001        AFG             YEAR
4   177655      WHOSIS_000001        AFG             YEAR

  ParentLocationCode_flat  TimeDim_flat Dim2Type_flat Dim2_flat Dim3Type_flat  \
0                     EMR          2011       Unknown   Unknown       Unknown
1                     EMR          2011       Unknown   Unknown       Unknown
2                     EMR          2011       Unknown   Unknown       Unknown
3                     EMR          2011       Unknown   Unknown       Unknown
4                     EMR          2011       Unknown   Unknown       Unknown

  Dim3_flat  … ParentLocation_Eastern Mediterranean_api  \
0   Unknown  …                                      True
1   Unknown  …                                      True
2   Unknown  …                                      True
3   Unknown  …                                      True
4   Unknown  …                                      True

  ParentLocation_Europe_api ParentLocation_South-East Asia_api  \
0                     False                              False
1                     False                              False
2                     False                              False
3                     False                              False
4                     False                              False

   ParentLocation_Unknown_api  ParentLocation_Western Pacific_api  \
0                       False                               False
1                       False                               False
2                       False                               False
3                       False                               False
4                       False                               False

   Dim1_SEX_FMLE_api Dim1_SEX_MLE_api Alcohol_1996 Alcohol_2016 Alcohol_2019
0              False             True          NaN          0.2          0.2
1              False             True          NaN          0.2          0.2
2              False             True          NaN          0.2          0.2
3              False            False          NaN          0.2          0.2
4              False             True          NaN          0.2          0.2

[5 rows x 67 columns]
```

3.4.1 Step 5: Visualizing the Relationship Between Alcohol Consumption and Health Indicator

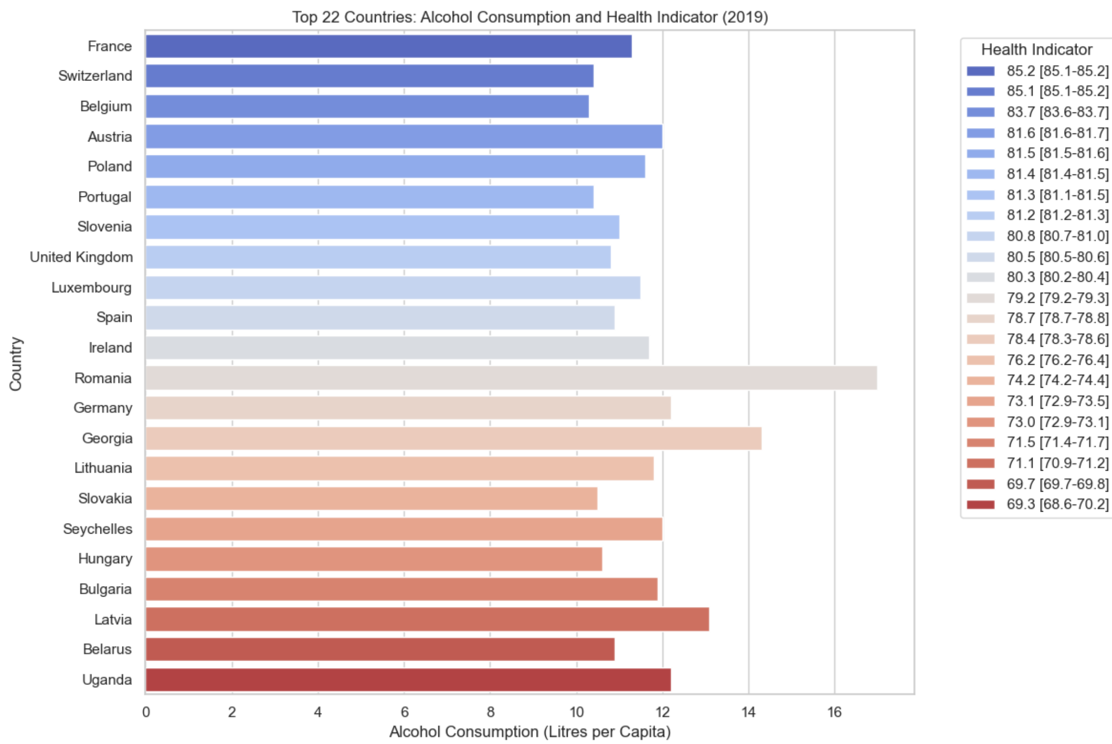
To explore potential relationships between alcohol consumption and health outcomes, I created a horizontal bar chart comparing average alcohol consumption per capita with a WHO health indicator, for the year 2019. This health indicator is constructed such that higher values reflect poorer health outcomes, including lower life expectancy or diminished well-being.

For this analysis, the dataset was filtered to include countries with available data for both alcohol consumption and the health indicator. The top 22 countries with the highest alcohol consumption were selected to highlight where heavier drinking may or may not align with worse health indicators.

This visualization helps evaluate whether greater alcohol use across countries correlates with worse health, or if other patterns and outliers emerge.

[1098]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Renaming columns for clarity
viz_df = viz_df.rename(columns={
    'Alcohol_2019': 'Alcohol_Consumption',
    'Value_api': 'Health_Indicator'
})

# Filtering for year 2019 records only
viz_df_2019 = viz_df[viz_df['TimeDim_api'] == 2019]

# Dropping duplicates to keep one record per country
viz_df_latest = viz_df_2019.drop_duplicates(subset='Country', keep='first')

# Sorting and select top 22 countries by alcohol consumption
viz_df_top = viz_df_latest.sort_values(by='Alcohol_Consumption',␣
 ↪ascending=False).head(22)

# Sorting these by Health Indicator in descending order
viz_df_top_sorted = viz_df_top.sort_values(by='Health_Indicator',␣
 ↪ascending=False)

# Plotting as horizontal bar chart
plt.figure(figsize=(12, 8))
sns.barplot(
    data=viz_df_top_sorted,
    x='Alcohol_Consumption',
    y='Country',
    hue='Health_Indicator',
    dodge=False,
    palette='coolwarm'
)

plt.title('Top 22 Countries: Alcohol Consumption and Health Indicator (2019)')
plt.xlabel('Alcohol Consumption (Litres per Capita)')
plt.ylabel('Country')
plt.legend(title='Health Indicator', bbox_to_anchor=(1.05, 1), loc='upper left')
```

```
plt.tight_layout()
plt.show()
```



3.4.2 Interpretation:

The visualization reveals that there is no clear or consistent relationship between alcohol consumption per capita and the health indicator, where higher values indicate worse health. For example, France does not have the highest alcohol consumption, yet it has the highest health indicator value (85.2), indicating worse health. On the other hand, Romania has the highest alcohol consumption among the countries analyzed, but its health indicator is lower (79.2), suggesting better health compared to France.

Additionally, countries like Austria and Seychelles both report alcohol consumption of 12 liters per capita, yet their health indicators differ significantly — 81.6 for Austria versus 73.1 for Seychelles. These inconsistencies suggest that alcohol consumption alone is not a reliable predictor of the selected health outcome, and that other variables such as healthcare access, socioeconomic factors, diet, and environment likely play a more influential role in determining a country's overall health.

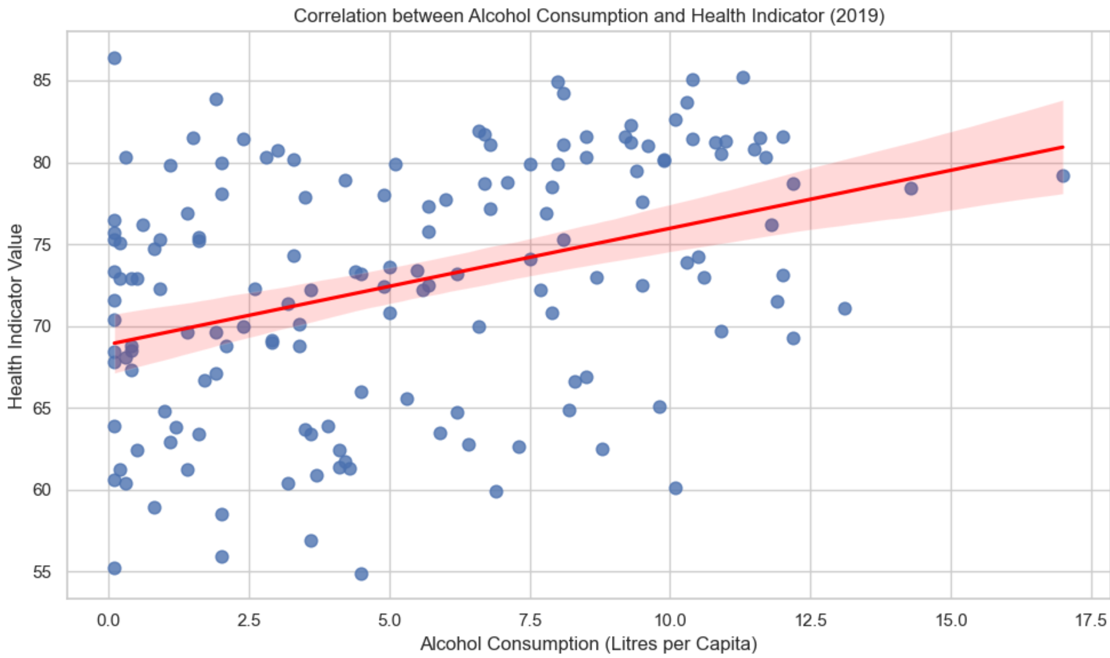
3.4.3 Step 6: Correlation Analysis

To evaluate the linear relationship between alcohol consumption and a selected health indicator, I calculated the Pearson correlation coefficient and created a regression plot for the year 2019. This approach helps quantify the strength and direction of the association between alcohol use (measured in liters per capita) and overall health outcomes (as indicated by the WHO metric used in this analysis).

Since higher values of the Health Indicator correspond to worse health outcomes, a positive correlation would suggest that increased alcohol consumption is associated with declining health at the population level. This step provides both statistical and visual insight into whether alcohol use might play a meaningful role in national health trends.

[1099]:
```
# Filtering for year 2019
viz_df_2019 = viz_df[viz_df['TimeDim_api'] == 2019]

# Dropping duplicates
viz_df_latest = viz_df_2019.drop_duplicates(subset='Country', keep='first')

# Removing rows where Health_Indicator is missing or empty
viz_df_latest = viz_df_latest[viz_df_latest['Health_Indicator'].notna() &␣
 ↪(viz_df_latest['Health_Indicator'] != '')]

# Extracting numeric part and convert to float
viz_df_latest['Health_Indicator'] = viz_df_latest['Health_Indicator'].
 ↪astype(str).str.extract(r'(\d+\.\d+)').astype(float)

# Preparing correlation DataFrame
corr_df = viz_df_latest[['Alcohol_Consumption', 'Health_Indicator']].dropna()

print(f"Number of rows after cleaning: {len(corr_df)}")

# Computing correlation
correlation = corr_df.corr().iloc[0, 1]
print(f"Correlation between Alcohol Consumption and Health Indicator:␣
 ↪{correlation:.2f}")

# Plotting regression
plt.figure(figsize=(10, 6))
sns.regplot(data=corr_df, x='Alcohol_Consumption', y='Health_Indicator',␣
 ↪scatter_kws={"s": 60}, line_kws={"color": "red"})
plt.title('Correlation between Alcohol Consumption and Health Indicator (2019)')
plt.xlabel('Alcohol Consumption (Litres per Capita)')
plt.ylabel('Health Indicator Value')
plt.tight_layout()
plt.show()
```

```
Number of rows after cleaning: 156
Correlation between Alcohol Consumption and Health Indicator: 0.38
```



3.4.4 Interpretation:

The calculated correlation coefficient is 0.38, or 38%, indicating a moderate positive relationship between alcohol consumption and the Health Indicator. Although not a strong correlation, this trend suggests that countries with higher alcohol consumption generally exhibit worse health outcomes (since higher indicator values correspond to poorer health).

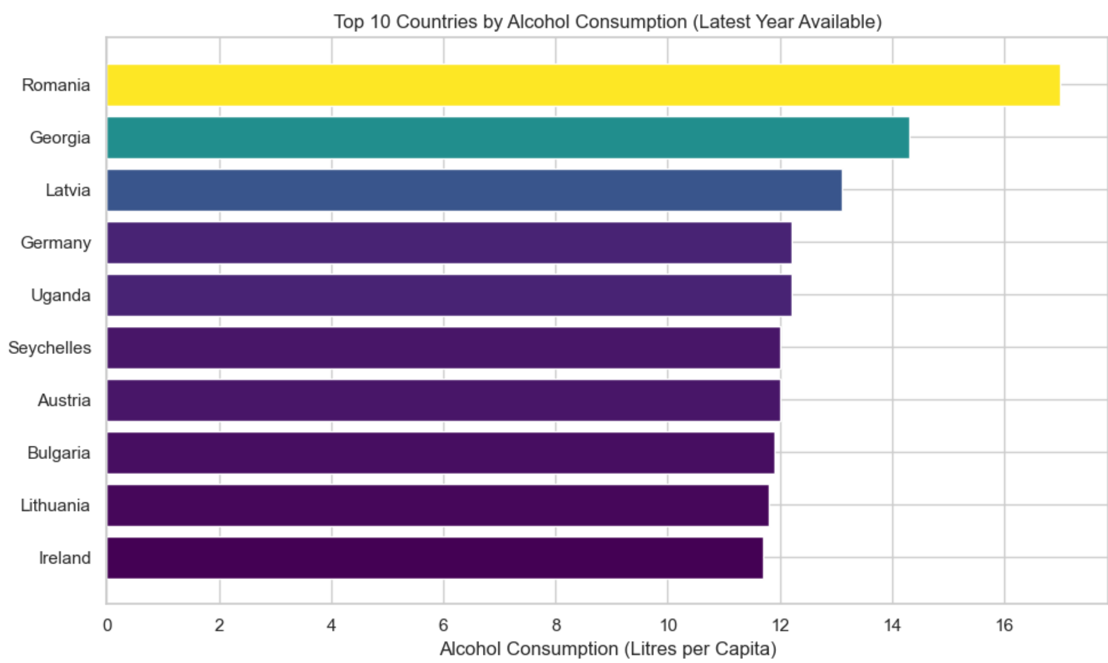
While this does not imply causation, it highlights a relationship worth monitoring. The upward-sloping regression line in the plot visually reinforces this trend. These findings suggest that excessive alcohol consumption may negatively impact public health and should be considered a relevant factor in health policy discussions.

3.4.5 Step 7: Top 10 Countries by Alcohol Consumption

Using visualization to show top 10 countries with the highest alcohol consumption, helping identify potential outliers or public health focus areas.

[1100]:
```python
# Getting the latest available year per country
alcohol_latest = viz_df.sort_values('TimeDim_api', ascending=False).
 ↪drop_duplicates(subset='Country', keep='first')

# Dropping rows where Alcohol_Consumption is NaN
alcohol_latest = alcohol_latest[alcohol_latest['Alcohol_Consumption'].notna()]

# Getting the top 10 countries by Alcohol Consumption
```

```python
top10_alcohol = alcohol_latest.sort_values('Alcohol_Consumption',␣
↪ascending=False).head(10)

# Sorting for clean plotting
top10_alcohol = top10_alcohol.sort_values('Alcohol_Consumption', ascending=True)

# Plotting
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import matplotlib.colors as mcolors

norm = mcolors.Normalize(vmin=top10_alcohol['Alcohol_Consumption'].min(),␣
↪vmax=top10_alcohol['Alcohol_Consumption'].max())
colors = cm.viridis(norm(top10_alcohol['Alcohol_Consumption']))

plt.figure(figsize=(10, 6))
plt.barh(top10_alcohol['Country'], top10_alcohol['Alcohol_Consumption'],␣
↪color=colors)
plt.xlabel('Alcohol Consumption (Litres per Capita)')
plt.title('Top 10 Countries by Alcohol Consumption (Latest Year Available)')
plt.tight_layout()
plt.show()
```



3.4.6 Interpretation from the result:

By plotting the top 10 countries by alcohol consumption, we can see that Romania has the highest consumption at 17 litres per capita annually. Georgia ranks second with approximately 14.3 litres, and Latvia comes in third with about 13 litres. On the lower end, Ireland has the lowest alcohol consumption among the top 10, at approximately 11.8 litres per capita per year.

To put this in perspective, Romania's 17 litres per year breaks down to roughly 1.42 litres per month, which is a significant amount and could be considered unhealthy for an individual's health.

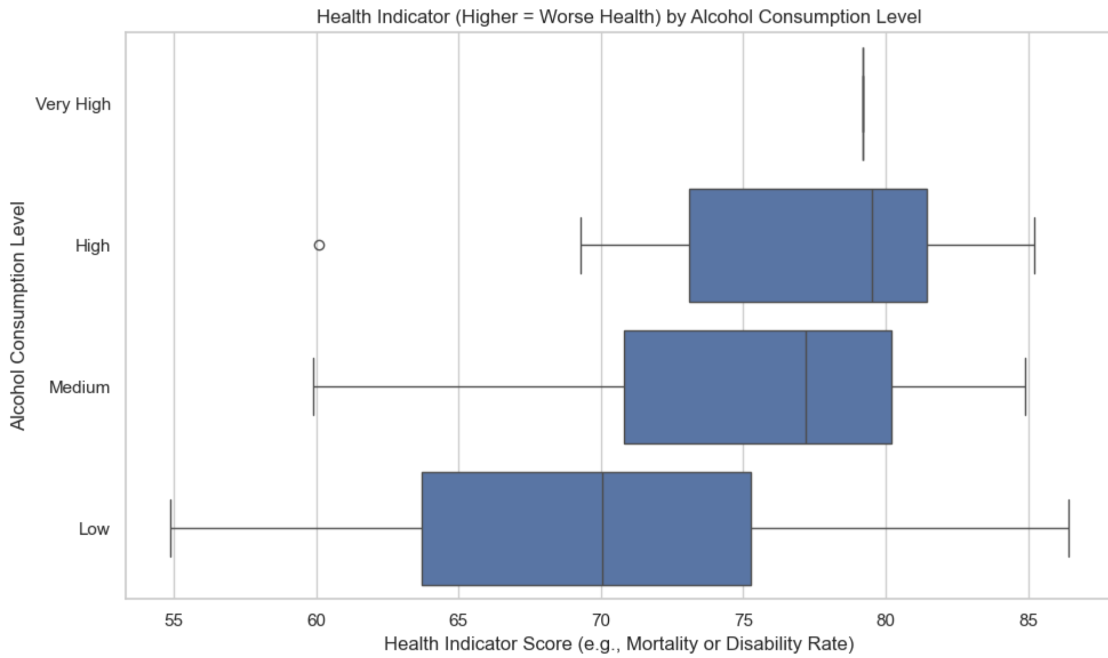
3.4.7 Step 8: Visualize the Relationship Between Alcohol Consumption and Health Indicator

In this step, I categorize countries into four alcohol consumption levels: Low, Medium, High, and Very High, based on their annual per capita alcohol intake. I then use a box plot to explore how the Health Indicator varies across these categories.

The goal is to determine whether countries with higher alcohol consumption levels tend to exhibit better or worse health outcomes, as reflected by the Health Indicator, where higher values indicate poorer health.

[1101]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Defining bins and labels for alcohol consumption levels
bins = [0, 5, 10, 15, 20]
labels = ['Low', 'Medium', 'High', 'Very High']
viz_df_latest['Alcohol_Level'] = pd.cut(
    viz_df_latest['Alcohol_Consumption'],
    bins=bins,
    labels=labels,
    include_lowest=True
)

# Ensuring the Alcohol_Level column is treated as an ordered categorical␣
 ↪variable
viz_df_latest['Alcohol_Level'] = pd.Categorical(
    viz_df_latest['Alcohol_Level'],
    categories=labels,
    ordered=True
)

# Creating a horizontal boxplot
plt.figure(figsize=(10,6))
sns.boxplot(data=viz_df_latest, y='Alcohol_Level', x='Health_Indicator',␣
 ↪orient='h')

# Flipping y-axis so Low consumption is at bottom, Very High at top
```

```
plt.gca().invert_yaxis()

# Updating labels and title for clarity
plt.title('Health Indicator (Higher = Worse Health) by Alcohol Consumption␣
↪Level')
plt.xlabel('Health Indicator Score (e.g., Mortality or Disability Rate)')
plt.ylabel('Alcohol Consumption Level')
plt.tight_layout()
plt.show()
```



3.4.8 Interpretation:

The boxplot reveals a noticeable trend: countries with higher alcohol consumption levels tend to have higher health indicator scores.

Since the Health Indicator in this dataset is defined such that higher values correspond to worse health outcomes (e.g., increased mortality or disability), this suggests that increased alcohol consumption is associated with poorer health.

This result aligns with general expectations and existing public health research, reinforcing the link between excessive alcohol intake and negative health effects at the population level.

3.4.9 Project Summary and Ethical Reflection

In this milestone, I merged data from three sources: a flat file, Wikipedia, and the WHO API. After transforming and cleaning each dataset, I used SQLite and pandas to join them using SQL-style operations. One of the main challenges was aligning country information across datasets. The flat file and API used ISO codes, while Wikipedia listed full country names. I used the `pycountry` package to map country codes to names, allowing me to merge on a consistent `Country` column.

Once merged, I explored and visualized trends across the datasets. For example, I examined how alcohol consumption (from Wikipedia) related to life expectancy and health indicators (from WHO). This helped confirm patterns and supported the data transformations I applied.

Ethically, transforming and merging data requires careful consideration. For instance, mapping codes to country names involved assumptions about accuracy and completeness. I also dropped rows with missing values in earlier steps, which might have introduced bias or excluded edge cases. These are small changes, but they can affect downstream analysis.

Since the data came from public sources like WHO and Wikipedia, there were no major legal concerns. However, if the data included personal health information, steps like anonymization and compliance with data protection laws (e.g., HIPAA, GDPR) would be essential.

One key risk is misinterpretation when combining data collected with different standards or methodologies. I assumed compatibility between WHO indicators and alcohol consumption data, which may not be exact. If this were for policy or research, I would document all assumptions clearly.

Overall, this project highlighted the importance of transparency and ethics in data processing, even with public datasets.