F78DS - Data Science Life Cycle

Coursework 1

Arthur Grossmann Le Mauguen

H00494101

27/02/2025

Part 1

Importing libraries required to open csv, xls and json files

In [1]:
```
import pandas as pd
import json
```

Importing the files and storing them in DataFrames

The following code processes data from three different sources and formats. The data are stored as CSV, Excel (XLS), and JSON files, sourced from the United Nations, The World Bank, and a file on Canvas. These files are downloaded and saved in a directory named "data," located in the same folder as my notebook. The dataset "WPP2024_ByAge.csv" is read using pd.read_csv(), "GDP.xls" is loaded as a dictionary of DataFrames with pd.read_excel(sheet_name=None), and "vehicule.json" is imported using pd.read_json()

In [2]:
```
# There seems to be an issue with the file stored on the Canvas.
# I need to connect to my account so that I can download the file.

# Import the required libraries
import requests
import os
import gzip
import shutil
"""
# URL of the file
url_vehicle = 'https://canvas.hw.ac.uk/files/3969360/'
# Define the filename to save the file as
filename = 'vehicle.json'
# Create a folder named 'data' if it doesn't exist
folder = 'data'
if not os.path.exists(folder):
    os.makedirs(folder)
# Define the path to save the file in the 'data' folder
file_path = os.path.join(folder, filename)
# Send a GET request to the URL
response = requests.get(url_vehicle, allow_redirects=True)
# Check if the request was successful
if response.status_code == 200:
    # Write the content to the file inside the 'data' folder
    with open(file_path, 'wb') as file:
        file.write(response.content)
```

```
    print(f'File downloaded and saved as {file_path}')
else:
    print(f'Failed to download file. Status code: {response.status_code}')
"""
# URL for the GDP file
url_gdp = 'https://api.worldbank.org/v2/en/indicator/NY.GDP.MKTP.CD?downloadformat=
# Define the filename to save the file as
filename_gdp = 'GDP.xls'
# Create a folder named 'data' if it doesn't exist
folder = 'data'
if not os.path.exists(folder):
    os.makedirs(folder)
# Define the path to save the GDP file in the 'data' folder
file_path_gdp = os.path.join(folder, filename_gdp)
# Send a GET request to the URL for GDP file
response_gdp = requests.get(url_gdp, allow_redirects=True)
# Check if the request was successful
if response_gdp.status_code == 200:
    # Write the content to the file inside the 'data' folder
    with open(file_path_gdp, 'wb') as file:
        file.write(response_gdp.content)
    print(f'GDP file downloaded and saved as {file_path_gdp}')
else:
    print(f'Failed to download GDP file. Status code: {response_gdp.status_code}')


# URL for the Population file
url_population = 'https://population.un.org/wpp/assets/Excel%20Files/1_Indicator%20
# Define the filename to save the original .gz file as
filename_population_gz = 'WPP2024_Population.csv.gz'
# Define the filename to save the decompressed .csv file as
filename_population_csv = 'WPP2024_ByAge.csv'
# Define the path to save the .gz file and the decompressed .csv file in the 'data'
file_path_population_gz = os.path.join(folder, filename_population_gz)
file_path_population_csv = os.path.join(folder, filename_population_csv)
# Send a GET request to the URL for the Population file
response_population = requests.get(url_population, allow_redirects=True)
# Check if the request was successful
if response_population.status_code == 200:
    # Save the .gz file to the 'data' folder
    with open(file_path_population_gz, 'wb') as file:
        file.write(response_population.content)
    print(f'Population .gz file downloaded and saved as {file_path_population_gz}')
    # Decompress the .gz file and save as a .csv file
    with gzip.open(file_path_population_gz, 'rb') as f_in:
        with open(file_path_population_csv, 'wb') as f_out:
            shutil.copyfileobj(f_in, f_out) # Copy the content of the .gz file to t
    print(f'File decompressed and saved as {file_path_population_csv}')
else:
    print(f'Failed to download Population file. Status code: {response_population.s
```

```
GDP file downloaded and saved as data\GDP.xls
Population .gz file downloaded and saved as data\WPP2024_Population.csv.gz
File decompressed and saved as data\WPP2024_ByAge.csv
```

Load the data into pandas dataframes

In [3]:
```
df_WPP2024_ByAge = pd.read_csv('data/WPP2024_ByAge.csv', low_memory=False)
df_GDP = pd.read_excel('data/GDP.xls', sheet_name=None)
df_vehicle = pd.read_json('data/vehicle.json')
```

Inspecting/ reading the data in the DataFrames

describe(): Summarizes statistics (count, mean, min, max, quartiles) for numeric columns.

head(): Displays the first 5 rows of the DataFrame

dtypes: Displays the data type of each column in the Dataframe

columns: Lists the column names of the Dataframe

shape: Displays the dimensions of the Dataframe (rows, columns)

WPP2024_ByAge.csv:

This file comes from the World Population Prospects (WPP) 2024 dataset and contains population data broken down by age group from 1950 to 2023.

In [4]:
```
df_WPP2024_ByAge.describe()
```

Out[4]:

	SortOrder	LocID	SDMX_code	LocTypeID	ParentID	VarID	
count	2.399154e+06	4.148070e+06	2.130090e+06	2.399154e+06	2.399154e+06	4148070.0	4.14807
mean	1.656137e+02	1.413716e+04	4.117684e+02	5.292835e+00	1.569710e+03	2.0	1.98650
std	9.325424e+01	3.277972e+04	2.709341e+02	3.395285e+00	1.496598e+03	0.0	2.13600
min	1.000000e+00	4.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00	2.0	1.95000
25%	8.600000e+01	5.120000e+02	1.580000e+02	4.000000e+00	9.140000e+02	2.0	1.96800
50%	1.660000e+02	1.207000e+03	4.170000e+02	4.000000e+00	9.230000e+02	2.0	1.98650
75%	2.460000e+02	2.079000e+03	6.460000e+02	4.000000e+00	9.570000e+02	2.0	2.00500
max	3.260000e+02	9.850900e+04	9.140000e+02	1.400000e+01	5.560000e+03	2.0	2.02300

In [5]:
```
df_WPP2024_ByAge.head()
```

Out[5]:

	SortOrder	LocID	Notes	ISO3_code	ISO2_code	SDMX_code	LocTypeID	LocTypeName	Paren
0	NaN	5507	NaN	NaN	NaN	NaN	NaN	NaN	N
1	NaN	5507	NaN	NaN	NaN	NaN	NaN	NaN	N
2	NaN	5507	NaN	NaN	NaN	NaN	NaN	NaN	N
3	NaN	5507	NaN	NaN	NaN	NaN	NaN	NaN	N
4	NaN	5507	NaN	NaN	NaN	NaN	NaN	NaN	N

In [6]:

```
df_WPP2024_ByAge.dtypes
```

Out[6]:

```
SortOrder       float64
LocID             int64
Notes            object
ISO3_code        object
ISO2_code        object
SDMX_code       float64
LocTypeID       float64
LocTypeName      object
ParentID        float64
Location         object
VarID             int64
Variant          object
Time              int64
MidPeriod         int64
AgeGrp           object
AgeGrpStart       int64
AgeGrpSpan        int64
PopMale         float64
PopFemale       float64
PopTotal        float64
dtype: object
```

In [7]:

```
df_WPP2024_ByAge.columns
```

Out[7]:
```
Index(['SortOrder', 'LocID', 'Notes', 'ISO3_code', 'ISO2_code', 'SDMX_code',
       'LocTypeID', 'LocTypeName', 'ParentID', 'Location', 'VarID', 'Variant',
       'Time', 'MidPeriod', 'AgeGrp', 'AgeGrpStart', 'AgeGrpSpan', 'PopMale',
       'PopFemale', 'PopTotal'],
      dtype='object')
```

In [8]:
```
df_WPP2024_ByAge.shape
```

Out[8]:
```
(4148070, 20)
```

GDP.xls:

This file contains data related to Gross Domestic Product (GDP) of various countries or regions. The first sheet has the following kinf of data: country name, country code, currency (US dollar), and GDP value from 1960 to 2023 (some of them are missing).

In [9]:
```
# Loop through the sheet names and perform the analysis for each sheet in the Excel
for sheet in df_GDP.keys():
    print(f"Analysis for sheet: {sheet}")
    # There is a header in the sheet named "Data", so we need to skip 3 rows for th
    if sheet == "Data":
        df_GDP[sheet] = pd.read_excel('data/GDP.xls', sheet_name=sheet, skiprows=3)
    print(df_GDP[sheet].describe())
    print(df_GDP[sheet].head())
    print(df_GDP[sheet].dtypes)
    print(df_GDP[sheet].columns)
    print(df_GDP[sheet].shape)
    print("--------------------------------------------------")  # Separator betwee
```

```
Analysis for sheet: Data
               1960          1961          1962          1963          1964  \
count  1.510000e+02  1.540000e+02  1.570000e+02  1.570000e+02  1.570000e+02
mean   6.786171e+10  6.982251e+10  7.327492e+10  7.908218e+10  8.680328e+10
std    2.019254e+11  2.116016e+11  2.257269e+11  2.427310e+11  2.657976e+11
min    1.201202e+07  1.159202e+07  1.254164e+07  1.283330e+07  1.341663e+07
25%    5.079241e+08  5.007338e+08  5.740911e+08  5.862949e+08  5.828164e+08
50%    3.359404e+09  3.330233e+09  3.308913e+09  3.988462e+09  4.016794e+09
75%    3.325071e+10  3.282977e+10  3.184162e+10  3.657288e+10  3.319881e+10
max    1.371947e+12  1.445951e+12  1.550598e+12  1.669570e+12  1.830168e+12

               1965          1966          1967          1968          1969  \
count  1.630000e+02  1.640000e+02  1.670000e+02  1.680000e+02  1.680000e+02
mean   9.133482e+10  9.793328e+10  1.014971e+11  1.086794e+11  1.203480e+11
std    2.844773e+11  3.088386e+11  3.257876e+11  3.515860e+11  3.876032e+11
min    1.359393e+07  1.446908e+07  1.583511e+07  1.460000e+07  1.585000e+07
25%    5.956572e+08  6.450667e+08  6.311234e+08  6.211906e+08  6.574670e+08
50%    3.817227e+09  4.153527e+09  3.532700e+09  4.529031e+09  5.087251e+09
75%    3.464910e+10  3.720117e+10  3.658090e+10  3.851340e+10  4.334334e+10
max    1.994298e+12  2.161754e+12  2.293944e+12  2.478900e+12  2.738144e+12

       ...          2014          2015          2016          2017  \
count  ...  2.610000e+02  2.590000e+02  2.580000e+02  2.580000e+02
mean   ...  2.512526e+12  2.382043e+12  2.424134e+12  2.597268e+12
std    ...  8.609254e+12  8.174322e+12  8.328694e+12  8.865044e+12
min    ...  3.876098e+07  3.681194e+07  4.162906e+07  4.527660e+07
25%    ...  9.112605e+09  8.766202e+09  8.620784e+09  9.193745e+09
50%    ...  5.027181e+10  4.871750e+10  4.806565e+10  5.277001e+10
75%    ...  5.421342e+11  4.973625e+11  5.042315e+11  5.341521e+11
max    ...  8.002034e+13  7.547247e+13  7.670255e+13  8.171204e+13

               2018          2019          2020          2021          2022  \
count  2.580000e+02  2.580000e+02  2.570000e+02  2.570000e+02  2.540000e+02
mean   2.765285e+12  2.807353e+12  2.736278e+12  3.141029e+12  3.307885e+12
std    9.440413e+12  9.580867e+12  9.368340e+12  1.069643e+13  1.114471e+13
min    4.801526e+07  5.412320e+07  5.174659e+07  6.019641e+07  5.906598e+07
25%    9.928840e+09  1.011166e+10  9.516738e+09  1.007135e+10  1.246361e+10
50%    5.609719e+10  5.775248e+10  5.366864e+10  6.152928e+10  6.970415e+10
75%    5.491441e+11  5.421641e+11  5.451476e+11  6.371869e+11  6.799031e+11
max    8.688484e+13  8.814985e+13  8.576301e+13  9.784830e+13  1.017709e+14

               2023
count  2.420000e+02
mean   3.618640e+12
std    1.190401e+13
min    6.228031e+07
25%    1.543170e+10
50%    8.383752e+10
75%    1.021922e+12
max    1.061717e+14

[8 rows x 64 columns]
                  Country Name Country Code     Indicator Name  \
0                        Aruba          ABW  GDP (current US$)
1  Africa Eastern and Southern          AFE  GDP (current US$)
2                  Afghanistan          AFG  GDP (current US$)
3   Africa Western and Central          AFW  GDP (current US$)
4                       Angola          AGO  GDP (current US$)

   Indicator Code          1960          1961          1962          1963  \
0  NY.GDP.MKTP.CD           NaN           NaN           NaN           NaN
1  NY.GDP.MKTP.CD  2.421063e+10  2.496398e+10  2.707880e+10  3.177575e+10
2  NY.GDP.MKTP.CD           NaN           NaN           NaN           NaN
3  NY.GDP.MKTP.CD  1.190495e+10  1.270788e+10  1.363076e+10  1.446909e+10
```

```
4  NY.GDP.MKTP.CD           NaN           NaN           NaN           NaN

           1964          1965  ...          2014          2015          2016  \
0           NaN           NaN  ...  2.790850e+09  2.962907e+09  2.983635e+09
1  3.028579e+10  3.381317e+10  ...  9.787083e+11  8.982778e+11  8.289428e+11
2           NaN           NaN  ...  2.049713e+10  1.913422e+10  1.811657e+10
3  1.580376e+10  1.692109e+10  ...  8.974157e+11  7.717669e+11  6.943610e+11
4           NaN           NaN  ...  1.359668e+11  9.049642e+10  5.276162e+10

           2017          2018          2019          2020          2021  \
0  3.092429e+09  3.276184e+09  3.395799e+09  2.481857e+09  2.929447e+09
1  9.729989e+11  1.012306e+12  1.009721e+12  9.333918e+11  1.085745e+12
2  1.875346e+10  1.805322e+10  1.879944e+10  1.995593e+10  1.426000e+10
3  6.878492e+11  7.704950e+11  8.264838e+11  7.898017e+11  8.493124e+11
4  7.369015e+10  7.945069e+10  7.089796e+10  4.850156e+10  6.650513e+10

           2022          2023
0  3.279344e+09  3.648573e+09
1  1.191423e+12  1.245472e+12
2  1.449724e+10  1.723305e+10
3  8.839739e+11  7.991060e+11
4  1.043997e+11  8.482465e+10

[5 rows x 68 columns]
Country Name       object
Country Code       object
Indicator Name     object
Indicator Code     object
1960              float64
                   ...
2019              float64
2020              float64
2021              float64
2022              float64
2023              float64
Length: 68, dtype: object
Index(['Country Name', 'Country Code', 'Indicator Name', 'Indicator Code',
       '1960', '1961', '1962', '1963', '1964', '1965', '1966', '1967', '1968',
       '1969', '1970', '1971', '1972', '1973', '1974', '1975', '1976', '1977',
       '1978', '1979', '1980', '1981', '1982', '1983', '1984', '1985', '1986',
       '1987', '1988', '1989', '1990', '1991', '1992', '1993', '1994', '1995',
       '1996', '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004',
       '2005', '2006', '2007', '2008', '2009', '2010', '2011', '2012', '2013',
       '2014', '2015', '2016', '2017', '2018', '2019', '2020', '2021', '2022',
       '2023'],
      dtype='object')
(266, 68)
--------------------------------------------------
Analysis for sheet: Metadata - Countries
       Country Code                 Region  IncomeGroup  \
count           265                    217          216
unique          265                      7            4
top             ABW  Europe & Central Asia  High income
freq              1                     58           85

                                              SpecialNotes TableName
count                                                  127       265
unique                                                 113       265
top     Fiscal year end: March 31; reporting period fo...     Aruba
freq                                                     7         1
  Country Code                     Region          IncomeGroup  \
0          ABW  Latin America & Caribbean          High income
1          AFE                        NaN                  NaN
2          AFG                 South Asia           Low income
```

```
3          AFW                        NaN                  NaN
4          AGO         Sub-Saharan Africa  Lower middle income

                                        SpecialNotes  \
0                                                NaN
1  26 countries, stretching from the Red Sea in t...
2  The reporting period for national accounts dat...
3  22 countries, stretching from the westernmost ...
4  The World Bank systematically assesses the app...

                     TableName
0                        Aruba
1  Africa Eastern and Southern
2                  Afghanistan
3   Africa Western and Central
4                       Angola
Country Code    object
Region          object
IncomeGroup     object
SpecialNotes    object
TableName       object
dtype: object
Index(['Country Code', 'Region', 'IncomeGroup', 'SpecialNotes', 'TableName'], dtyp
e='object')
(265, 5)
--------------------------------------------------
Analysis for sheet: Metadata - Indicators
        INDICATOR_CODE     INDICATOR_NAME  \
count                1                  1
unique               1                  1
top     NY.GDP.MKTP.CD  GDP (current US$)
freq                 1                  1

                                              SOURCE_NOTE  \
count                                                   1
unique                                                  1
top     GDP at purchaser's prices is the sum of gross ...
freq                                                    1

                                      SOURCE_ORGANIZATION
count                                                   1
unique                                                  1
top     World Bank national accounts data, and OECD Na...
freq                                                    1
   INDICATOR_CODE     INDICATOR_NAME  \
0  NY.GDP.MKTP.CD  GDP (current US$)

                                         SOURCE_NOTE  \
0  GDP at purchaser's prices is the sum of gross ...

                                 SOURCE_ORGANIZATION
0  World Bank national accounts data, and OECD Na...
INDICATOR_CODE         object
INDICATOR_NAME         object
SOURCE_NOTE            object
SOURCE_ORGANIZATION    object
dtype: object
Index(['INDICATOR_CODE', 'INDICATOR_NAME', 'SOURCE_NOTE',
       'SOURCE_ORGANIZATION'],
      dtype='object')
(1, 4)
--------------------------------------------------
```

vehicule.json:

The data consists of records for three nations (UK, UAE, and Malaysia) with values for the years 2013 to 2022. Each record includes the following structure: "Nation": The country name and 2013 to 2022: Values for each year, representing the number of vehicule sold.

United Kingdom (UK): The data shows vehicle sales in the UK peaking in 2016 at 2,692,786 units, with a decline in the following years. Sales dropped significantly in 2020 to 1,631,064, likely due to the impact of the pandemic. By 2022, sales stabilized at 1,614,063 units.

United Arab Emirates (UAE): Vehicle sales in the UAE were relatively stable between 2013 and 2015, peaking at 214,000 units in 2015. However, sales dropped to zero in 2017 and 2018 which might be an error, likely due to external factors or data reporting gaps. Sales began recovering in 2019 and reached 171,414 units in 2022.

Malaysia: In Malaysia, vehicle sales fluctuated within the range of approximately 500,000 units from 2013 to 2022, with a slight drop in 2021 to 452,663 units. Sales rebounded in 2022, reaching 544,838 units.

In [10]:
```
df_vehicle.describe()
```

Out[10]:

	2013	2014	2015	2016	2017	2018	
count	3.000000e+00	3.000000e+00	3.000000e+00	3.000000e+00	3.000000e+00	3.000000e+00	3.00
mean	1.016037e+06	1.090494e+06	1.146259e+06	1.124577e+06	1.018432e+06	9.667827e+05	1.01
std	1.097114e+06	1.215334e+06	1.301731e+06	1.369219e+06	1.343134e+06	1.241709e+06	1.13
min	2.067000e+05	2.067000e+05	2.140000e+05	1.664000e+05	0.000000e+00	0.000000e+00	1.98
25%	3.916875e+05	3.975240e+05	4.026375e+05	3.404725e+05	2.573400e+05	2.666005e+05	3.74
50%	5.766750e+05	5.883480e+05	5.912750e+05	5.145450e+05	5.146800e+05	5.332010e+05	5.50
75%	1.420706e+06	1.532392e+06	1.612389e+06	1.603666e+06	1.527648e+06	1.450174e+06	1.43
max	2.264737e+06	2.476435e+06	2.633503e+06	2.692786e+06	2.540617e+06	2.367147e+06	2.31

In [11]:
```
df_vehicle.head()
```

Out[11]:

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
0	2264737	2476435	2633503	2692786	2540617	2367147	2311140	1631064	1647181	1614063
1	206700	206700	214000	166400	0	0	198520	129901	156780	171414
2	576675	588348	591275	514545	514680	533201	550182	480965	452663	544838

In [12]:
```
df_vehicle.dtypes
```

Out[12]:
```
2013       int64
2014       int64
2015       int64
2016       int64
2017       int64
2018       int64
2019       int64
2020       int64
2021       int64
2022       int64
Nation    object
dtype: object
```

In [13]:
```
df_vehicle.columns
```

Out[13]:
```
Index(['2013', '2014', '2015', '2016', '2017', '2018', '2019', '2020', '2021',
       '2022', 'Nation'],
      dtype='object')
```

In [14]:
```
df_vehicle.shape
```

Out[14]:
```
(3, 11)
```

Wrangle the data

This coursework only needs data for **UK, UAE and Malaysia** and I choosed to only keep the data from **2013 to 2022** because I only got number of car sold of those years

First I print the number of different locations containted in the file.

In [15]:
```
location_number = df_WPP2024_ByAge['Location'].nunique() # Count the number of unic
print(f"Number of unique locations in the WPP2024_ByAge dataset: {location_number}'
```

```
Number of unique locations in the WPP2024_ByAge dataset: 553
```

There is 553 different locations, that's a lot so I found the name they used and made a filter using them.

In [16]:
```
location = ['United Kingdom (and dependencies)', 'Malaysia', 'United Arab Emirates'

# Filter the dataset by checking the Location column and keeping only the rows that
filtered_df = df_WPP2024_ByAge[df_WPP2024_ByAge['Location'].isin(location)]

# Further filter the dataset for the years 2013 to 2022
filtered_df = filtered_df[(filtered_df['Time'] >= 2013) & (filtered_df['Time'] <= 2

# Save the filtered data to a new CSV file for further analysis
filtered_df.to_csv('data/Wrangled_WPP2024_ByAge.csv', index=False)

# Print a sample of the filtered dataset to check the results manually
print(filtered_df.head())

# PS: We could have used a another way to filter the data without using the isin()
"""
filter_country=((df_WPP2024_ByAge['Location']=='United Kingdom (and dependencies)')
filter_year=((df_WPP2024_ByAge['Time']>=2013) & (df_WPP2024_ByAge['Time']<=2022))
filtered_df = df_WPP2024_ByAge[filter_country & filter_year]
print(filtered_df.head())
"""
```

```
          SortOrder  LocID Notes ISO3_code ISO2_code  SDMX_code  LocTypeID  \
1605799         NaN   1110   NaN       NaN       NaN        NaN        NaN   
1605800         NaN   1110   NaN       NaN       NaN        NaN        NaN   
1605801         NaN   1110   NaN       NaN       NaN        NaN        NaN   
1605802         NaN   1110   NaN       NaN       NaN        NaN        NaN   
1605803         NaN   1110   NaN       NaN       NaN        NaN        NaN   

        LocTypeName  ParentID                            Location  VarID  \
1605799         NaN       NaN  United Kingdom (and dependencies)      2   
1605800         NaN       NaN  United Kingdom (and dependencies)      2   
1605801         NaN       NaN  United Kingdom (and dependencies)      2   
1605802         NaN       NaN  United Kingdom (and dependencies)      2   
1605803         NaN       NaN  United Kingdom (and dependencies)      2   

        Variant  Time  MidPeriod AgeGrp  AgeGrpStart  AgeGrpSpan  PopMale  \
1605799  Medium  2013       2013      0            0           1  419.888   
1605800  Medium  2013       2013      1            1           1  424.854   
1605801  Medium  2013       2013      2            2           1  418.939   
1605802  Medium  2013       2013      3            3           1  413.518   
1605803  Medium  2013       2013      4            4           1  414.283   

          PopFemale  PopTotal  
1605799    399.109   818.997  
1605800    404.618   829.472  
1605801    399.889   818.828  
1605802    395.076   808.594  
1605803    395.307   809.590  
```

Out[16]:

```
"\nfilter_country=((df_WPP2024_ByAge['Location']=='United Kingdom (and dependencie
s)') | (df_WPP2024_ByAge['Location']=='Malaysia') | (df_WPP2024_ByAge['Location']=
='United Arab Emirates'))\nfilter_year=((df_WPP2024_ByAge['Time']>=2013) & (df_WPP
2024_ByAge['Time']<=2022))\nfiltered_df = df_WPP2024_ByAge[filter_country & filter
_year]\nprint(filtered_df.head())\n"
```

In [17]:

```python
 # Read the data starting from row 4 to skip the data source information and the da
df_GDP_Data = pd.read_excel('data/GDP.xls', "Data", skiprows=3)
df_GDP_Metadata = pd.read_excel('data/GDP.xls', "Metadata - Countries") # Read the 
# we don't need to read the third sheet, because it doesn't contain any useful info

# Filter for the countries we want to keep, UAE, UK, and Malaysia
# list of strings, the names of the countries we want to keep
countries_to_keep = ["United Arab Emirates", "United Kingdom", "Malaysia"]
filtered_df_GDP_Data = df_GDP_Data[df_GDP_Data['Country Name'].isin(countries_to_ke
filtered_df_GDP_Metadata = df_GDP_Metadata[df_GDP_Metadata['TableName'].isin(countr

# Keep only columns from 2013 to 2022, and the first 4 text columns
text_columns = ['Country Name', 'Country Code', 'Indicator Name', 'Indicator Code']
# I convert the years to strings to match the column names in the DataFrame
columns_to_keep = text_columns + [str(year) for year in range(2013, 2023)]
# Filter the DataFrame to keep only the necessary columns
filtered_df_GDP_Data = filtered_df_GDP_Data[columns_to_keep]

# Save both dataframes to the same Excel file with separate sheets
with pd.ExcelWriter("data/Wrangled_GDP.xlsx") as writer:
    filtered_df_GDP_Data.to_excel(writer, sheet_name="Data", index=False)
    filtered_df_GDP_Metadata.to_excel(writer, sheet_name="Metadata - Countries", in

# Display the filtered data for manual verification
print(filtered_df_GDP_Data)
print(filtered_df_GDP_Metadata)

# PS: We could have used a another way to filter the data without using the isin()
"""
filter_country=((df_GDP_Data['Country Name']=='United Arab Emirates') | (df_GDP_Dat
filter_year=((df_GDP_Data.columns>='2013') & (df_GDP_Data.columns<='2022'))
```

```
filtered_df_GDP_Data = df_GDP_Data[filter_country & filter_year]
print(filtered_df_GDP_Data.head())
"""
```

```
              Country Name Country Code     Indicator Name  Indicator Code  \
8     United Arab Emirates          ARE  GDP (current US$)  NY.GDP.MKTP.CD
81          United Kingdom          GBR  GDP (current US$)  NY.GDP.MKTP.CD
169               Malaysia          MYS  GDP (current US$)  NY.GDP.MKTP.CD

              2013          2014          2015          2016          2017  \
8     4.002185e+11  4.141054e+11  3.702755e+11  3.692553e+11  3.905168e+11
81    2.784854e+12  3.064708e+12  2.927911e+12  2.689107e+12  2.680148e+12
169   3.232762e+11  3.380661e+11  3.013553e+11  3.012560e+11  3.191091e+11

              2018          2019          2020          2021          2022
8     4.270494e+11  4.179897e+11  3.494730e+11  4.151788e+11  5.027319e+11
81    2.871340e+12  2.851407e+12  2.696778e+12  3.143323e+12  3.114042e+12
169   3.587888e+11  3.651777e+11  3.374562e+11  3.737848e+11  4.076058e+11
    Country Code                      Region          IncomeGroup  \
8            ARE  Middle East & North Africa          High income
81           GBR       Europe & Central Asia          High income
168          MYS         East Asia & Pacific  Upper middle income

    SpecialNotes             TableName
8            NaN  United Arab Emirates
81           NaN        United Kingdom
168          NaN              Malaysia
```

Out[17]:

```
"\nfilter_country=((df_GDP_Data['Country Name']=='United Arab Emirates') | (df_GDP
_Data['Country Name']=='United Kingdom') | (df_GDP_Data['Country Name']=='Malaysi
a'))\nfilter_year=((df_GDP_Data.columns>='2013') & (df_GDP_Data.columns<='2022'))
\nfiltered_df_GDP_Data = df_GDP_Data[filter_country & filter_year]\nprint(filtered
_df_GDP_Data.head())\n"
```

Fix the missing datas

The vehicule data sets show a **zero car sold during a few years** (2017 and 2018 in the UAE), it likely indicates missing or incorrect values rather than an actual car sold count.

In [18]:

```
# Print the data contained in the JSON file without any modifications
with open('data/vehicle.json') as f:
    data = json.load(f)
    print (data)

# Option 1: Replace with the mean of the other years with non-zero values for the s
# Note: This option uses the mean of the non-zero values for the same country to re
# but it is not perfect because of the fluctuation of the data especially in 2020 a
for record in data:
    nation_data = [record[str(year)] for year in range(2013, 2023)] # Extract the d
    non_zero_data = [value for value in nation_data if value != 0] # Find the non-z
    mean_value = sum(non_zero_data) / len(non_zero_data) if non_zero_data else 0
    # Calculate the mean of the non-zero values or set to 0 if no non-zero values
    rounded_mean_value = round(mean_value)
    # Round the mean value to the closest integer because the data is a number of c
    for year in range(2013, 2023): # Replace zero values with the rounded mean
        if record[str(year)] == 0:
            record[str(year)] = rounded_mean_value
# Print the updated data after applying the first option
print(data)

# We need to read the data again because the previous code modified the data in mem
with open('data/vehicle.json') as f:
    data = json.load(f)
# Option 2: Replace with the previous year's value or the next year's value if the
```

```
def replace_with_previous_or_next(data):
    for entry in data:
        for year in range(2013, 2023):
            if entry[str(year)] == 0:
                if entry[str(year - 1)] != 0 and entry[str(year + 1)] == 0: # Try t
                    entry[str(year)] = entry[str(year - 1)]
                    entry[str(year + 1)] = entry[str(year + 2)]
    return data
# Apply the modified option
data_with_previous_or_next = replace_with_previous_or_next(data.copy())
print (data_with_previous_or_next)

# We need to read the data again because the previous code modified the data in mem
with open('data/vehicle.json') as f:
    data = json.load(f)
# Option 3: replace with linear interpolation
def replace_with_interpolation(data):
    for entry in data:
        non_zero_years = [year for year in range(2013, 2023) if entry[str(year)] !=
        # Create a list of years with non-zero values
        for year in range(2013, 2023):
            if entry[str(year)] == 0:
                previous_year = max([y for y in non_zero_years if y < year]) # Find
                next_year = min([y for y in non_zero_years if y > year])
                # Perform linear interpolation
                entry[str(year)] = round(entry[str(previous_year)] + (entry[str(nex
    return data
data_with_interpolation = replace_with_interpolation(data.copy())
print(data_with_interpolation)

# In my opinion, the linear interpolation is the best option for this dataset becau
# of the missing values compared to the other methods.
# Store the data in a new json file
with open('data/Wrangled_vehicle.json', 'w') as f:
    json.dump(data_with_interpolation, f, indent=2)

# PS: We could have used a numpy function to perform the linear interpolation
"""
import numpy as np

# Load data from the JSON file
with open('data/vehicle.json') as f:
    data = json.load(f)

# Option 3: replace with linear interpolation using NumPy
def replace_with_interpolation(data):
    for entry in data:
        years = np.array(range(2013, 2023))
        values = np.array([entry[str(year)] for year in years])
        non_zero_indices = np.where(values != 0)[0] # Find indices of zero and non-
        zero_indices = np.where(values == 0)[0]
        if len(non_zero_indices) > 1:
            interpolated_values = np.interp(zero_indices, non_zero_indices, values[
            values[zero_indices] = np.round(interpolated_values)  # Round to neares
            # Update entry with interpolated values
            for i, year in enumerate(years):
                entry[str(year)] = int(values[i])
    return data

data_with_interpolation = replace_with_interpolation(data.copy())

print(data_with_interpolation)

# Store the data in a new json file
```

```
with open('data/vehicle_interpolation.json', 'w') as f:
    json.dump(data_with_interpolation, f, indent=2)
"""
# PS 2: We could have used a pandas function to perform the linear interpolation
"""
import numpy as np

def replace_with_interpolation(data):
    # Iterate through each nation in the dataset
    nations = data["Nation"].unique()
    for nation in nations:
        # Filter data for the current nation
        nation_data = data[data["Nation"] == nation].copy()
        # Specify the years to interpolate (2013 to 2022)
        years_to_interpolate = [str(year) for year in range(2013, 2023)]
        # Replace 0 with NaN for interpolation and interpolate the missing values
        # Round and convert interpolated data to integer
        nation_data.loc[:, years_to_interpolate] = nation_data.loc[:, years_to_inte
        # Update the original data with the interpolated nation data
        data.loc[data["Nation"] == nation, years_to_interpolate] = nation_data.loc[
    # Return the updated dataset
    return data

# Load the vehicle data
vehicle_data = pd.read_json("data/vehicle.json")
# Call the function to replace missing values with interpolation
vehicle_data = replace_with_interpolation(vehicle_data)
# Store the final vehicle data to a new JSON file
vehicle_data.to_json("data/data_with_interpolation.json", orient="records", lines=T
# Print the final vehicle data
print(vehicle_data)
"""
```

```
[{'2013': 2264737, '2014': 2476435, '2015': 2633503, '2016': 2692786, '2017': 2540
617, '2018': 2367147, '2019': 2311140, '2020': 1631064, '2021': 1647181, '2022': 1
614063, 'Nation': 'UK'}, {'2013': 206700, '2014': 206700, '2015': 214000, '2016':
166400, '2017': 0, '2018': 0, '2019': 198520, '2020': 129901, '2021': 156780, '202
2': 171414, 'Nation': 'UAE'}, {'2013': 576675, '2014': 588348, '2015': 591275, '20
16': 514545, '2017': 514680, '2018': 533201, '2019': 550182, '2020': 480965, '202
1': 452663, '2022': 544838, 'Nation': 'Malaysia'}]
[{'2013': 2264737, '2014': 2476435, '2015': 2633503, '2016': 2692786, '2017': 2540
617, '2018': 2367147, '2019': 2311140, '2020': 1631064, '2021': 1647181, '2022': 1
614063, 'Nation': 'UK'}, {'2013': 206700, '2014': 206700, '2015': 214000, '2016':
166400, '2017': 181302, '2018': 181302, '2019': 198520, '2020': 129901, '2021': 15
6780, '2022': 171414, 'Nation': 'UAE'}, {'2013': 576675, '2014': 588348, '2015': 5
91275, '2016': 514545, '2017': 514680, '2018': 533201, '2019': 550182, '2020': 480
965, '2021': 452663, '2022': 544838, 'Nation': 'Malaysia'}]
[{'2013': 2264737, '2014': 2476435, '2015': 2633503, '2016': 2692786, '2017': 2540
617, '2018': 2367147, '2019': 2311140, '2020': 1631064, '2021': 1647181, '2022': 1
614063, 'Nation': 'UK'}, {'2013': 206700, '2014': 206700, '2015': 214000, '2016':
166400, '2017': 166400, '2018': 198520, '2019': 198520, '2020': 129901, '2021': 15
6780, '2022': 171414, 'Nation': 'UAE'}, {'2013': 576675, '2014': 588348, '2015': 5
91275, '2016': 514545, '2017': 514680, '2018': 533201, '2019': 550182, '2020': 480
965, '2021': 452663, '2022': 544838, 'Nation': 'Malaysia'}]
[{'2013': 2264737, '2014': 2476435, '2015': 2633503, '2016': 2692786, '2017': 2540
617, '2018': 2367147, '2019': 2311140, '2020': 1631064, '2021': 1647181, '2022': 1
614063, 'Nation': 'UK'}, {'2013': 206700, '2014': 206700, '2015': 214000, '2016':
166400, '2017': 177107, '2018': 187813, '2019': 198520, '2020': 129901, '2021': 15
6780, '2022': 171414, 'Nation': 'UAE'}, {'2013': 576675, '2014': 588348, '2015': 5
91275, '2016': 514545, '2017': 514680, '2018': 533201, '2019': 550182, '2020': 480
965, '2021': 452663, '2022': 544838, 'Nation': 'Malaysia'}]
```

Out[18]:
```
'\nimport numpy as np\n\ndef replace_with_interpolation(data):\n    # Iterate through each nation in the dataset\n    nations = data["Nation"].unique()\n    for nation in nations:\n        # Filter data for the current nation\n        nation_data = data[data["Nation"] == nation].copy()\n        # Specify the years to interpolate (2013 to 2022)\n        years_to_interpolate = [str(year) for year in range(2013, 2023)]\n        # Replace 0 with NaN for interpolation and interpolate the missing values\n        # Round and convert interpolated data to integer\n        nation_data.loc[:, years_to_interpolate] = nation_data.loc[:, years_to_interpolate].replace(0, np.nan).interpolate(method="linear", axis=1).round().astype(int)\n        # Update the original data with the interpolated nation data\n        data.loc[data["Nation"] == nation, years_to_interpolate] = nation_data.loc[:, years_to_interpolate]\n    # Return the updated dataset\n    return data\n\n# Load the vehicle data\nvehicle_data = pd.read_json("data/vehicle.json")\n# Call the function to replace missing values with interpolation\nvehicle_data = replace_with_interpolation(vehicle_data)\n# Store the final vehicle data to a new JSON file\nvehicle_data.to_json("data/data_with_interpolation.json", orient="records", lines=True)\n# Print the final vehicle data\nprint(vehicle_data)\n'
```

The countries are not referred by the same name in all the files, some are using abreviation like UK or UAE, we need to use the same name in each file.

In [20]:
```python
# Dictionary mapping country names to their abbreviations or standardized names
name_mapping = {
    "United Kingdom": "UK",
    "United Kingdom (and dependencies)": "UK",
    "United Arab Emirates": "UAE",
    "Malaysia": "Malaysia"}

# Load the JSON file
with open("data/Wrangled_vehicle.json", "r", encoding="utf-8") as file:
    data = json.load(file)
# Replace country names based on the mapping dictionary
for entry in data:
    if entry["Nation"] in name_mapping:  # Check if the country name exists in the
        entry["Nation"] = name_mapping[entry["Nation"]]  # Replace with the mapped
# Save the modified data back to the JSON file
with open("data/Wrangled_vehicle.json", "w", encoding="utf-8") as file:
    json.dump(data, file, indent=2)  # Write the updated data with indentation for
# Load the GDP data
wrangled_gdp = pd.read_excel('data/Wrangled_GDP.xlsx')
# Load the population data
wrangled_wpp2024_byage = pd.read_csv('data/Wrangled_WPP2024_ByAge.csv')
# Apply the name mapping to the country columns in both datasets
wrangled_gdp['Country Name'] = wrangled_gdp['Country Name'].replace(name_mapping)
wrangled_wpp2024_byage['Location'] = wrangled_wpp2024_byage['Location'].replace(nam
# Save the modified datasets
wrangled_gdp.to_excel('data/Wrangled_GDP.xlsx', index=False)
wrangled_wpp2024_byage.to_csv('data/Wrangled_WPP2024_ByAge.csv', index=False)
```

Fix the wrong values

The outliers (detected using the 3 STD rule, Standard Deviations) are replaced by a regression values

The 3 Standard Deviations (STD) Rule is used to identify outliers by considering values beyond three times the standard deviation from the mean as anomalies. In the code, for each country, the mean and standard deviation of the population (PopTotal) are computed, and values outside the defined range are flagged as outliers. Instead of removing them, a linear regression model is trained using the non-outlier data, predicting and replacing the outlier values with estimated trends. This ensures a smooth and realistic population evolution over time. The cleaned data is then merged with GDP information to calculate GDP per capita (perPopGDP) before being saved as a JSON file for further analysis.

The cleaned population data is then merged with GDP information to calculate GDP per capita (perPopGDP). The GDP data is first reshaped into a long format, making it easier to merge with the population data. After merging, rows where PopTotal is zero or missing are filtered out to ensure meaningful calculations. Finally, the processed dataset is saved as a JSON file for further analysis, ensuring a structured and accessible format for subsequent analyses.

In [21]:

```
# Import necessary libraries
import numpy as np
from sklearn.linear_model import LinearRegression

# Load the GDP data
gdp_data = pd.read_excel('data/Wrangled_GDP.xlsx')
# Load the population data
pop_data = pd.read_csv('data/Wrangled_WPP2024_ByAge.csv')

# Reshape GDP data to long format for easier merging
gdp_data_long=pd.melt(gdp_data, id_vars=['Country Name'], var_name='Year', value_na
# Filter out rows where 'Year' is not numeric
gdp_data_long = gdp_data_long[gdp_data_long['Year'].apply(lambda x: str(x).isdigit(
# Ensure 'Year' column is in integer format
gdp_data_long['Year'] = gdp_data_long['Year'].astype(int)
# Select relevant columns from population data
pop_data_relevant = pop_data[['Location', 'Time', 'PopTotal']]
pop_data_relevant.rename(columns={'Location': 'Country Name', 'Time': 'Year'}, inpl
# Convert 'PopTotal' to numeric and fix formatting issues
pop_data_relevant['PopTotal'] = pop_data_relevant['PopTotal'].astype(str).str.repla
# Group population data by country and year, summing the population
pop_data_grouped = pop_data_relevant.groupby(['Country Name', 'Year'])['PopTotal'].

# Function to replace outliers using linear regression
def replace_outliers_with_regression(group):
    pop_mean = group['PopTotal'].mean()
    pop_std = group['PopTotal'].std()
    lower_bound = pop_mean - 3 * pop_std # 3 standard deviations away from the mear
    upper_bound = pop_mean + 3 * pop_std
    # Identify outliers using the lower and upper bounds (3 standard deviations fro
    mask_outliers = (group['PopTotal'] < lower_bound) | (group['PopTotal'] > upper_
    if mask_outliers.any():
        # Prepare data for regression
        X = group.loc[~mask_outliers, 'Year'].values.reshape(-1, 1) # Years without
        y = group.loc[~mask_outliers, 'PopTotal'].values # Population values withou
        model = LinearRegression() # Create a linear regression model
        model.fit(X, y) # Fit the model to the data
        # Predict values for outliers and replace them
        group.loc[mask_outliers, 'PopTotal'] = model.predict(group.loc[mask_outlier
    return group
# Apply the function to each country group
pop_data_grouped = pop_data_grouped.groupby('Country Name').apply(replace_outliers_

# Merge GDP and population data
merged_data = pd.merge(gdp_data_long, pop_data_grouped, on=['Country Name', 'Year']
# Filter out rows where 'PopTotal' is zero or missing (shoudn't happen after outlie
merged_data = merged_data[merged_data['PopTotal'] > 0]
# Calculate perWorkerGDP: GDP / PopTotal
merged_data['perPopGDP'] = merged_data['GDP'] / merged_data['PopTotal']
```

```
# Remove rows with missing perWorkerGDP (shouldn't happen)
merged_data = merged_data.dropna(subset=['perPopGDP'])
# Save the merged data to a JSON file
merged_data.to_json('data/Merged_data.json', orient='records', lines=False, indent=
print(merged_data)
```

```
   Country Name  Year                   GDP  PopTotal     perPopGDP
0           UAE  2013   400218529747.596985   7291555  54887.953221
1            UK  2013  2784853502534.291992  56400556  49376.348392
2      Malaysia  2013   323276235524.415283  26392079  12248.987112
3           UAE  2014   414105366758.910889   7201500  57502.654552
4            UK  2014  3064708247921.428223  59152397  51810.381377
5      Malaysia  2014   338066095097.254395  27547235  12272.233315
6           UAE  2015   370275469560.166077   7824509    47322.5182
7            UK  2015  2927911140916.730957  59231099  49431.990801
8      Malaysia  2015   301355266964.947327  27580633  10926.336135
9           UAE  2016   369255326235.771301   7510116  49167.726069
10           UK  2016   2689106566899.61084  54678695  49180.152652
11     Malaysia  2016   301256033870.333618  29632094  10166.545566
12          UAE  2017   390516804016.500977   8770935  44523.965121
13           UK  2017  2680148052335.298828  62104802  43155.246712
14     Malaysia  2017   319109094160.343079  28704813  11116.919457
15          UAE  2018   427049432149.345215   8350842  51138.487849
16           UK  2018  2871340347581.786133  59219791  48486.161452
17     Malaysia  2018   358788845712.529724  31189631   11503.46555
18          UAE  2019   417989721734.494202   8455193  49435.858145
19           UK  2019  2851407164907.808105  59978753  47540.287557
20     Malaysia  2019   365177721021.516113  30204879  12090.024298
21          UAE  2020   349473015336.939392   8825816   39596.68039
22           UK  2020  2696778386607.651855  61611027  43771.034471
23     Malaysia  2020   337456163961.211182  30277033  11145.615357
24          UAE  2021   415178792769.884277   8877040  46769.958541
25           UK  2021  3143323050707.257812  61751140  50903.077266
26     Malaysia  2021   373784823672.946289  31548017    11848.1242
27          UAE  2022   502731935197.486816   9822341  51182.496637
28           UK  2022  3114042471144.388184  65761443  47353.621348
29     Malaysia  2022   407605841348.234802  31263962  13037.561949
```

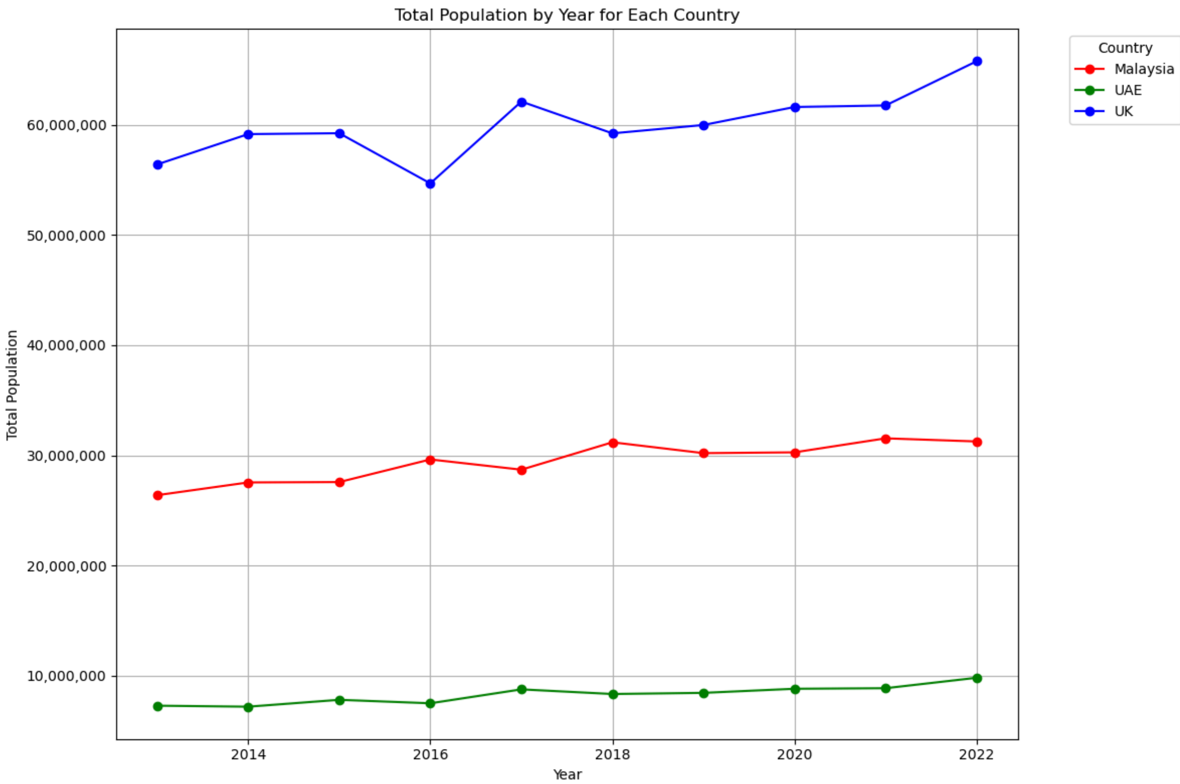
```
C:\Users\ag4016\AppData\Local\Temp\ipykernel_4924\262722827.py:18: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  pop_data_relevant.rename(columns={'Location': 'Country Name', 'Time': 'Year'}, i
nplace=True)
C:\Users\ag4016\AppData\Local\Temp\ipykernel_4924\262722827.py:20: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  pop_data_relevant['PopTotal'] = pop_data_relevant['PopTotal'].astype(str).str.re
place('.', '', regex=False).astype(int)
```

Part 2

1) Plot an appropriate graph for the population growth by year for the 3 different nations (UK, UAE, Malaysia).

In [22]:
```
# Import necessary libraries
import matplotlib.pyplot as plt
```

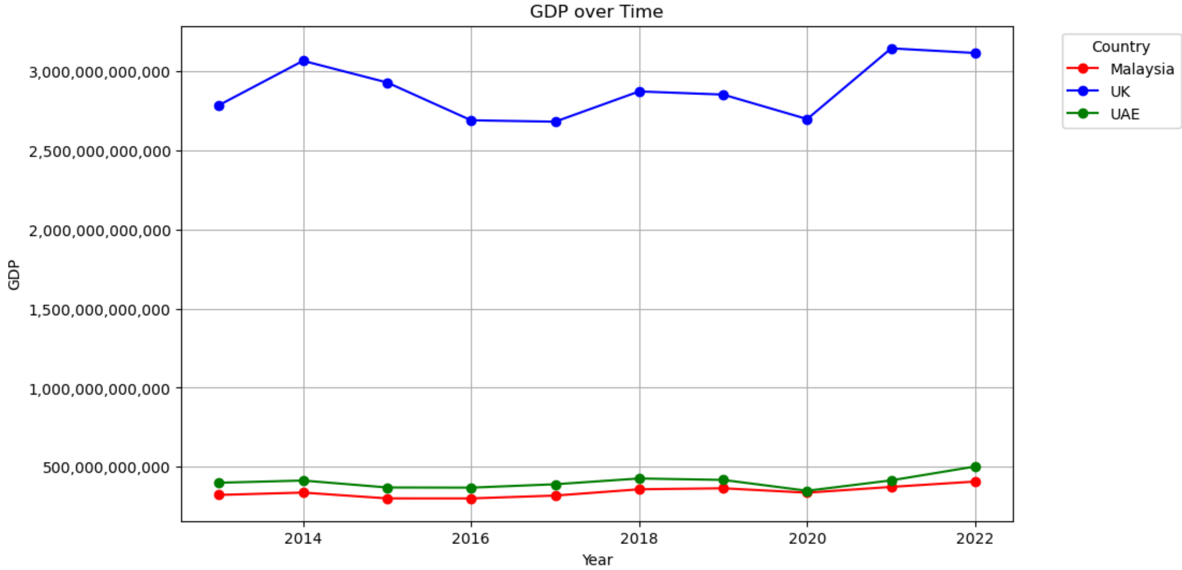
```python
from matplotlib.ticker import FuncFormatter

# Load the data from the JSON file
with open('data/Merged_data.json', 'r') as f:
    df = json.load(f)
# Convert JSON data to pandas DataFrame
df = pd.DataFrame(df)
# Group by 'Country Name' and 'Year', then sum the population for each country each
population_by_country_year = df.groupby(['Country Name', 'Year'])['PopTotal'].sum()

# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
def get_color(country):
    return country_colors.get(country, 'gray')  # Default to gray if country is not

# Create a formatter function to format y-axis values
def currency_formatter(x, pos):
    return f'{int(x):,}'  # Use commas as thousands separator

# Plotting the total population for each country across years
plt.figure(figsize=(12, 8))
# Plot each country's population over the years
for country in population_by_country_year.index:
    plt.plot(population_by_country_year.columns, population_by_country_year.loc[cou
plt.title('Total Population by Year for Each Country')
plt.xlabel('Year')
plt.ylabel('Total Population')
plt.legend(title='Country', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
# Apply the custom y-axis formatter
plt.gca().yaxis.set_major_formatter(FuncFormatter(currency_formatter))
# Adjust layout and show plot
plt.tight_layout()
plt.show()
```



This script plots the population growth over the years for three countries: United Kingdom (UK), United Arab Emirates (UAE), and Malaysia. I have checked that this data is consistent with the available online sources. We observe a slow overall population growth in all three countries, despite a slight decline in 2016 in the United Kingdom, which could possibly be linked to Brexit.

Plot of GDP in each country over time

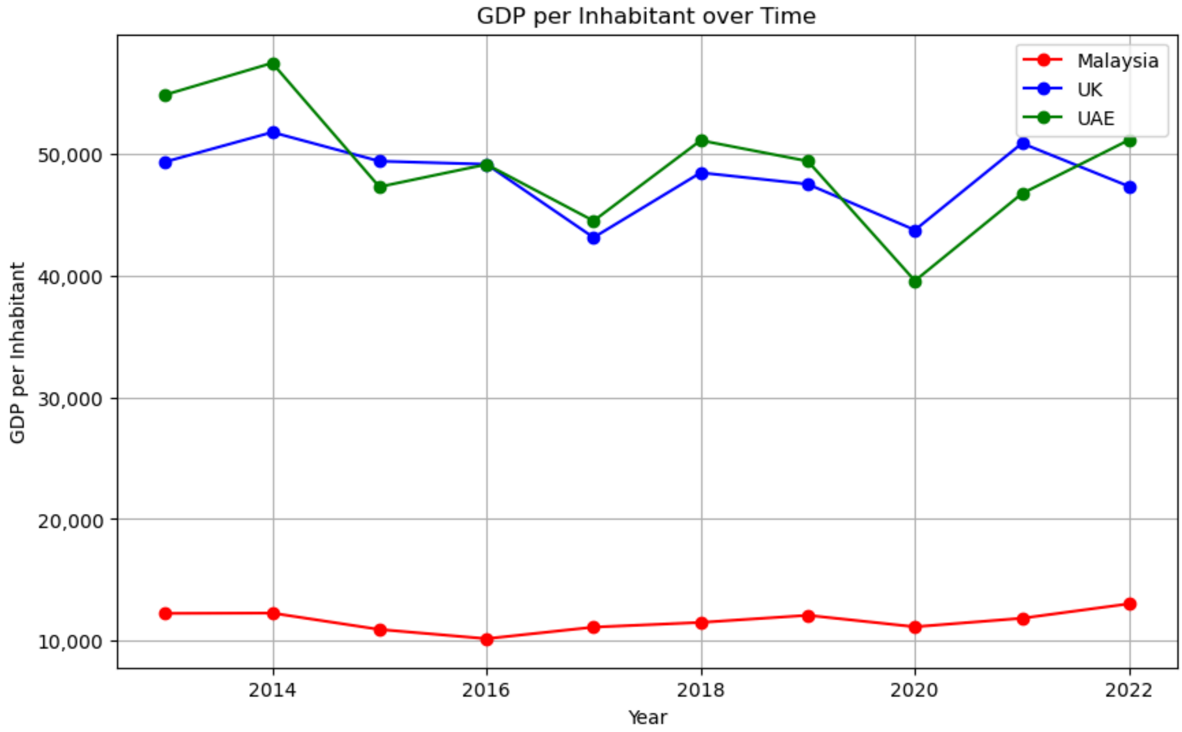
In [23]:
```
# Load the data from the JSON file
with open('data/Merged_data.json', 'r') as file:
    data = json.load(file)
# Extract country names, years, and GDP
countries = set(entry['Country Name'] for entry in data)
years = sorted(set(entry['Year'] for entry in data))
# Create a dictionary to store GDP by country and year
gdp_data = {country: {year: None for year in years} for country in countries}
for entry in data:
    gdp_data[entry['Country Name']][entry['Year']] = entry['GDP']

# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
def get_color(country):
    return country_colors.get(country, 'gray')  # Default to gray if country is not

# Plotting the GDP data over time
plt.figure(figsize=(10, 6))
for country, gdp_by_year in gdp_data.items():
    plt.plot(years, [gdp_by_year[year] for year in years], label=country, color=get
# Adding the title and labels
plt.title('GDP over Time')
plt.xlabel('Year')
plt.ylabel('GDP')
# Adding the legend to differentiate countries
plt.legend(title='Country', bbox_to_anchor=(1.05, 1), loc='upper left')
# Adding a grid for better readability
plt.grid(True)
# Formatter function to add ',' as thousand separator
formatter = FuncFormatter(lambda x, pos: f'{int(x):,}')
plt.gca().yaxis.set_major_formatter(formatter)
# Show the plot
plt.show()
```



The GDP remains relatively stable with a slow upward trend, but the UK experienced a decline starting in 2016, possibly due to Brexit related incertainties. Additionally, all three countries saw a drop in GDP in 2020, likely caused by the COVID-19 pandemic and lockdown measures. This highlights the economic impact of major geopolitical and global health events on national economies.

Plot of GDP per Inhabitant in each country over time

In [24]:
```
# Load the data from the JSON file
with open('data/Merged_data.json', 'r') as file:
    data = json.load(file)

# Extract country names, years, and perWorkerGDP
countries = set(entry['Country Name'] for entry in data)
years = sorted(set(entry['Year'] for entry in data))
# Create a dictionary to store perWorkerGDP by country and year
gdp_data = {country: {year: None for year in years} for country in countries}
for entry in data:
    gdp_data[entry['Country Name']][entry['Year']] = entry['perPopGDP']
# Define colors for seach country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
def get_color(country):
    return country_colors.get(country, 'gray')  # Default to gray if country is not
# Plotting the data
plt.figure(figsize=(10, 6))
for country, gdp_by_year in gdp_data.items():
    plt.plot(years, [gdp_by_year[year] for year in years], label=country, color=get
plt.title('GDP per Inhabitant over Time')
plt.xlabel('Year')
plt.ylabel('GDP per Inhabitant')
plt.legend()
plt.grid(True)
# Formatter function to add ',' as thousand separator
formatter = FuncFormatter(lambda x, pos: f'{int(x):,}')
plt.gca().yaxis.set_major_formatter(formatter)
# Formatter function to add space as thousand separator (alternative)
#formatter = FuncFormatter(lambda x, pos: f'{int(x):,}'.replace(',', ' '))
#plt.gca().yaxis.set_major_formatter(formatter)
plt.show()
```



The GDP per inhabitant has been steadily decreasing in both the UK and the UAE, while showing a slow but consistent increase in Malaysia. The impact of Brexit is still visible in the UK's decline starting in 2016, and all three countries experienced a noticeable drop in 2020 due to the economic consequences of the COVID-19 pandemic.

1. Compute the number of potential working population for each of the 3 different nations (UK, UAE, Malaysia) by year.

   Hint: generally this is from 15 or 16 to retirement age. State your source of information on the legal age to work and on the retirement age, as well as assumptions that you may make. (Note: retirement age may change over time).

The minimum age for employment and the standard retirement age vary across the UK, UAE, and Malaysia.

United Kingdom (UK):

Minimum Age to Work: In the UK, the minimum age for employment is 13. However, there are restrictions on the types of work and the hours that individuals under **16** can perform.

(source [gov.uk]: https://www.gov.uk/child-employment)

Retirement Age: The UK does not have a mandatory retirement age. Individuals can choose to retire at any age, but the age at which they can access their state pension is subject to change. As of February 2025, the minimum age to access full state pension us **66** years old.

(source [Wikipédia]: https://en.wikipedia.org/wiki/Retirement_age)

(Note: Between 2010 and 2018 the state pension age for women rose from 60 to 65, so that it became the same as that for men. Between 2018 and 2020 it then rose from age 65 to 66 for both men and women.

(source [Institute for Fiscal Studies]: https://ifs.org.uk/articles/planned-increase-state-pension-age-67-68#:~:text=Between%202010%20and%202018%20the,due%20to%20rise%20to%2067.

[commonslibrary]: https://commonslibrary.parliament.uk/research-briefings/cbp-9967/#:~:text=The%20Pensions%20Act%201995%20legislated,to%2065%20to%20November%2
))

United Arab Emirates (UAE):

Minimum Age to Work: The minimum age for employment in the UAE is **18**. However, individuals aged 15 to 18 can work under specific conditions with a juvenile work permit.

(source [U.AE]: https://u.ae/en/information-and-services/jobs/employment-and-training-of-minors)

Retirement Age: The standard retirement age in the UAE is **60** years. However, employees aged 60 to 65 can continue working if their employer successfully applies for a work permit renewal. Beyond 65, permits are granted on a case-by-case basis, often at a higher cost.

(source [Wikipédia]: https://en.wikipedia.org/wiki/Retirement_age)

Malaysia:

Minimum Age to Work: In Malaysia, the minimum age for employment is 13. However, there are restrictions on the types of work and the hours that individuals under **15** can perform.

(source [unicef]: https://www.unicef.cn/sites/unicef.org.china/files/2020-12/Malaysia-summary-ENG.pdf)

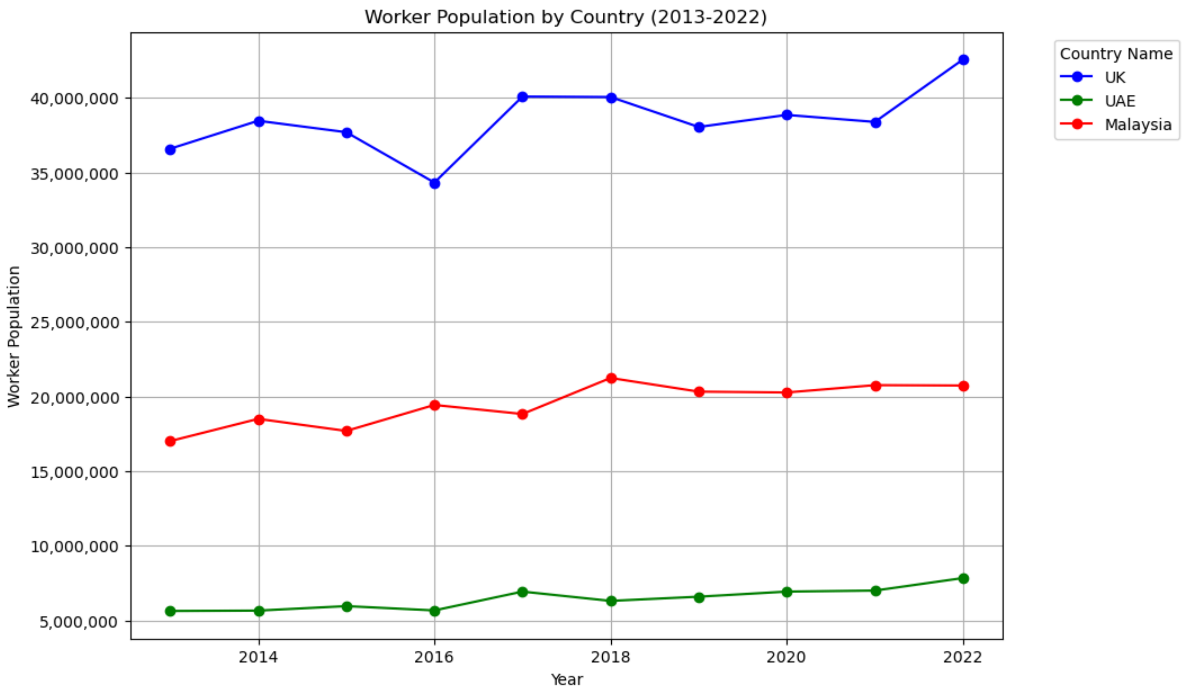
Retirement Age: The minimum retirement age in Malaysia is **60** years for private-sector employees, as stipulated by the Minimum Retirement Age Act 2012.

(source [Wikipédia]: https://en.wikipedia.org/wiki/Retirement_age)

Without taking into account the retirement age change in the UK between 2010 and 2020

In [25]:
```
# Load the GDP data
gdp_data = pd.read_excel('data/Wrangled_GDP.xlsx')
# Load the population data
pop_data = pd.read_csv('data/Wrangled_WPP2024_ByAge.csv')

# Clean the "AgeGrp" column
pop_data["AgeGrp"] = pop_data["AgeGrp"].replace("100+", "100").astype(int)
# Clean the 'PopTotal' column to ensure it's numeric (removes any periods, if prese
pop_data['PopTotal'] = pop_data['PopTotal'].astype(str).str.replace('.', '', regex=

# Define age filters for the countries
age_filters = {
    'UK': (16, 66),
    'UAE': (18, 60),
    'Malaysia': (15, 60)}
# Apply the age filter dynamically based on the country
filtered_population = []
```

```
for country, (min_age, max_age) in age_filters.items():
    country_filter = (pop_data["Location"] == country) & (pop_data["AgeGrp"] >= mir
    filtered_population.append(pop_data[country_filter])
# Combine the filtered data for all countries
worker_population = pd.concat(filtered_population)
# Group by country and year, summing the population
worker_population_regrouped = worker_population.groupby(["Location", "Time"])["PopT
# Add a new column "WorkerPopulation" with the sum of the filtered population
worker_population_regrouped["WorkerPopulation"] = worker_population.groupby(["Locat

# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
def get_color(country):
    return country_colors.get(country, 'gray')  # Default to gray if country is not
# Plot the graph
plt.figure(figsize=(10, 7))
# Define countries and their corresponding colors
countries = ["UK", "UAE", "Malaysia"]
# Plot data for each country
for country in countries:
    worker_data = worker_population_regrouped.loc[worker_population_regrouped["Loca
    plt.plot(worker_data["Time"], worker_data["WorkerPopulation"], label=country, m
# Add labels, title, and grid
plt.xlabel("Year")
plt.ylabel("Worker Population")
plt.title("Worker Population by Country (2013-2022)")
plt.legend(title='Country Name', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
formatter = FuncFormatter(lambda x, pos: f'{int(x):,}')
plt.gca().yaxis.set_major_formatter(formatter)
# Show the plot
plt.show()

print(worker_population_regrouped)
```



```
    Location  Time  PopTotal  WorkerPopulation
0   Malaysia  2013  17012674          17012674
1   Malaysia  2014  18501481          18501481
2   Malaysia  2015  17694041          17694041
3   Malaysia  2016  19433770          19433770
4   Malaysia  2017  18827370          18827370
5   Malaysia  2018  21240300          21240300
6   Malaysia  2019  20325554          20325554
7   Malaysia  2020  20269028          20269028
8   Malaysia  2021  20758824          20758824
9   Malaysia  2022  20734982          20734982
10       UAE  2013   5638824           5638824
11       UAE  2014   5663133           5663133
12       UAE  2015   5963275           5963275
13       UAE  2016   5675126           5675126
14       UAE  2017   6936951           6936951
15       UAE  2018   6313510           6313510
16       UAE  2019   6594853           6594853
17       UAE  2020   6936493           6936493
18       UAE  2021   7003931           7003931
19       UAE  2022   7842568           7842568
20        UK  2013  36585591          36585591
21        UK  2014  38461588          38461588
22        UK  2015  37695444          37695444
23        UK  2016  34324382          34324382
24        UK  2017  40081586          40081586
25        UK  2018  40052421          40052421
26        UK  2019  38047627          38047627
27        UK  2020  38854393          38854393
28        UK  2021  38383867          38383867
29        UK  2022  42562631          42562631
```

The worker population appears to follow the same trend as the total population. In the UK, there is a decline starting in 2016, followed by a slow recovery. Meanwhile, the UAE and Malaysia show a steady but slow growth in their worker populations over time.

In [26]:

```
#code to reorder the data based on the desired order of countries and years

# Load the JSON data from a file
with open("data/Merged_data.json", "r") as file:
    data = json.load(file)
# Define the desired order of countries
order = ["Malaysia", "UAE", "UK"]
# Sort data based on the country order and year
sorted_data = sorted(data, key=lambda x: (order.index(x["Country Name"]), x["Year"]
# Save the reordered data back to a new JSON file
with open("data/Merged_data.json", "w") as file:
    json.dump(sorted_data, file, indent=2)

# code to add the 'WorkerPopulation' column to the merged data and save it back to

with open('data/Merged_data.json', 'r') as file:
    data = json.load(file)
# Convert the data to a DataFrame
df = pd.DataFrame(data)
df['WorkerPopulation'] = worker_population_regrouped['WorkerPopulation']
# Save the updated DataFrame to a new JSON file
df.to_json('data/Merged_data.json', orient='records', lines=False, indent=1)
print (df)
```

```
   Country Name  Year           GDP  PopTotal     perPopGDP  WorkerPopulation
0      Malaysia  2013  3.232762e+11  26392079  12248.987112          17012674
1      Malaysia  2014  3.380661e+11  27547235  12272.233315          18501481
2      Malaysia  2015  3.013553e+11  27580633  10926.336135          17694041
3      Malaysia  2016  3.012560e+11  29632094  10166.545566          19433770
4      Malaysia  2017  3.191091e+11  28704813  11116.919457          18827370
5      Malaysia  2018  3.587888e+11  31189631  11503.465550          21240300
6      Malaysia  2019  3.651777e+11  30204879  12090.024298          20325554
7      Malaysia  2020  3.374562e+11  30277033  11145.615357          20269028
8      Malaysia  2021  3.737848e+11  31548017  11848.124200          20758824
9      Malaysia  2022  4.076058e+11  31263962  13037.561949          20734982
10          UAE  2013  4.002185e+11   7291555  54887.953221           5638824
11          UAE  2014  4.141054e+11   7201500  57502.654552           5663133
12          UAE  2015  3.702755e+11   7824509  47322.518200           5963275
13          UAE  2016  3.692553e+11   7510116  49167.726069           5675126
14          UAE  2017  3.905168e+11   8770935  44523.965121           6936951
15          UAE  2018  4.270494e+11   8350842  51138.487849           6313510
16          UAE  2019  4.179897e+11   8455193  49435.858145           6594853
17          UAE  2020  3.494730e+11   8825816  39596.680390           6936493
18          UAE  2021  4.151788e+11   8877040  46769.958541           7003931
19          UAE  2022  5.027319e+11   9822341  51182.496637           7842568
20           UK  2013  2.784854e+12  56400556  49376.348392          36585591
21           UK  2014  3.064708e+12  59152397  51810.381377          38461588
22           UK  2015  2.927911e+12  59231099  49431.990801          37695444
23           UK  2016  2.689107e+12  54678695  49180.152652          34324382
24           UK  2017  2.680148e+12  62104802  43155.246712          40081586
25           UK  2018  2.871340e+12  59219791  48486.161452          40052421
26           UK  2019  2.851407e+12  59978753  47540.287557          38047627
27           UK  2020  2.696778e+12  61611027  43771.034471          38854393
28           UK  2021  3.143323e+12  61751140  50903.077266          38383867
29           UK  2022  3.114042e+12  65761443  47353.621348          42562631
```

Taking into account the retirement age change in the UK between 2010 and 2020

(Does't work at the moment)

In [ ]:

```
"""
# Load the GDP data
gdp_data = pd.read_excel('data/Wrangled_GDP.xlsx')
# Load the population data
pop_data = pd.read_csv('data/Wrangled_WPP2024_ByAge.csv')

wpp_reduced = pop_data

# Clean the "AgeGrp" column to ensure it's numeric (100+ to 100)
wpp_reduced["AgeGrp"] = wpp_reduced["AgeGrp"].replace("100+", "100").astype(int)
# Clean the 'PopTotal' column to ensure it's numeric (removes any periods, if prese
wpp_reduced['PopTotal'] = wpp_reduced['PopTotal'].astype(str).str.replace('.', '',

# Define age filters for the countries with UK pension age considerations
def get_uk_age_filter(year):
    #Returns the maximum age for the UK based on the pension age policy for that ye
    #The pension age gradually rises from 60 in 2010 to 65 by 2018, and then to 66
    if 2010 <= year <= 2018:
        # Gradually rising from 60 to 65 for women
        age_increase = (year - 2010) * (65 - 60) / (2018 - 2010)  # Linear increase
        max_age = 60 + age_increase  # Start at 60.5 and increase over time
        return round(max_age)  # Round to the nearest whole number because age is i
    elif 2018 < year <= 2020:
        # Gradually rising from 65 to 66 for women and men
        age_increase = (year - 2018) * (66 - 65) / (2020 - 2018)  # Linear increase
        max_age = 65 + age_increase  # Start at 65 and increase to 66
        return round(max_age)  # Round to the nearest whole number (e.g., 65.5 -> 6
```

```
    else:
        return 66  # After 2020, the pension age is 66 for both


# Apply the age filter dynamically based on the country and year
filtered_population = []

for country, (min_age, max_age) in age_filters.items():
    if country == 'UK':
        # Apply the dynamic age filter based on year
        for year in wpp_reduced['Time'].unique():
            max_age = get_uk_age_filter(year)
            country_filter = (wpp_reduced["Location"] == country) & (wpp_reduced["A
            filtered_population.append(wpp_reduced[country_filter])
    else:
        country_filter = (wpp_reduced["Location"] == country) & (wpp_reduced["AgeGr
        filtered_population.append(wpp_reduced[country_filter])


# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
def get_color(country):
    return country_colors.get(country, 'gray')  # Default to gray if country is not

# Plot the graph
plt.figure(figsize=(10, 7))
# Define countries and their corresponding colors
countries = ["UK", "UAE", "Malaysia"]
# Plot data for each country
for country in countries:
    worker_data = worker_population_regrouped.loc[worker_population_regrouped["Loca
    plt.plot(worker_data["Time"], worker_data["WorkerPopulation"], label=country, m
# Add labels, title, and grid
plt.xlabel("Year")
plt.ylabel("Worker Population")
plt.title("Worker Population by Country (2013-2022)")
plt.legend(title='Country Name', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
formatter = FuncFormatter(lambda x, pos: f'{int(x):,}')
plt.gca().yaxis.set_major_formatter(formatter)
# Show the plot
plt.show()
# Print the regrouped worker population data for verification
print(worker_population_regrouped)
"""
```

If this code worked, we would have observed no change in the number of workers in the UAE and Malaysia. However, for the UK, we would have seen a significant drop starting in 2013, with the gap closing by 2020, and then no difference from 2020 to 2023.

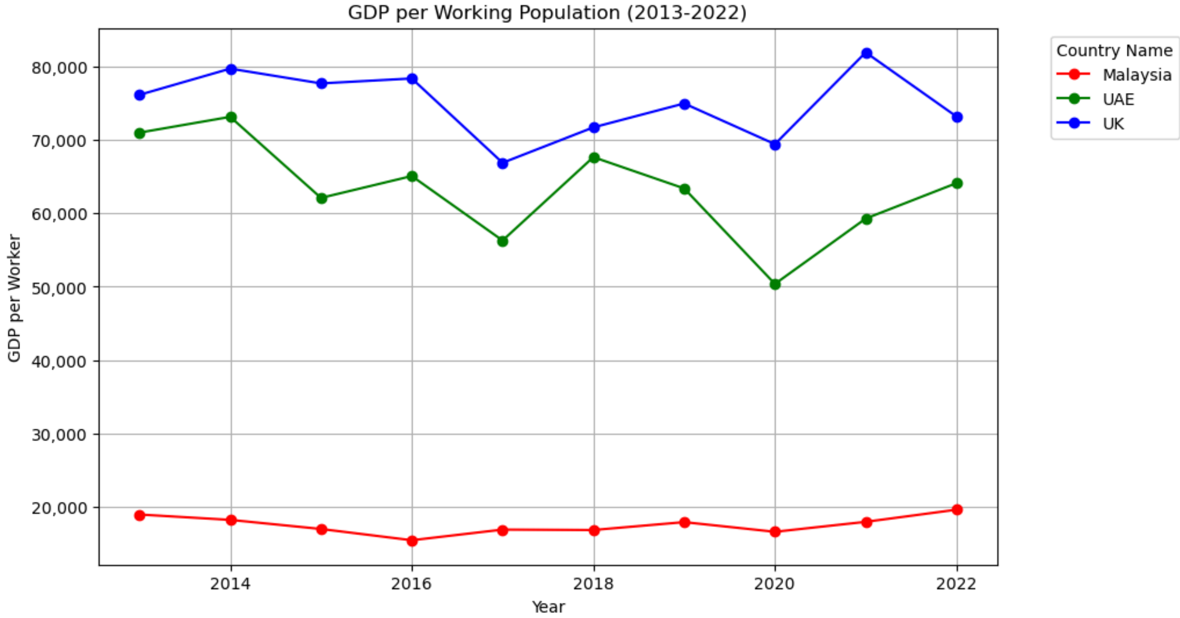
1. Instead of GDP per population (GDPpercapita), what about GDP per working population? What are your assumptions and opinions on using this (GDP per working population) measure?

GDP per working population might be a better indicator than GDP per inhabitant but ignores those of working age without jobs. A better metric might be GDP per licensed driver, as it captures both workers and retirees who participate in the economy. The retired population remains economically active, often wealthier than the median worker, allowing them to buy cars and contribute to the market.

In [27]:

```
# Load JSON data
with open('data/Merged_data.json', 'r') as file:
    data = json.load(file)
# Convert to DataFrame
df = pd.DataFrame(data)

# Compute GDP per working population
df['GDP_per_Worker'] = df['GDP'] / df['WorkerPopulation']
print(df)

# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
def get_color(country):
    return country_colors.get(country, 'gray')  # Default to gray if country is not

# Plot
plt.figure(figsize=(10, 6))
for country in df['Country Name'].unique():
    country_data = df[df['Country Name'] == country]
    plt.plot(country_data['Year'], country_data['GDP_per_Worker'], marker='o', labe

plt.xlabel('Year')
plt.ylabel('GDP per Worker')
plt.title('GDP per Working Population (2013-2022)')
plt.legend(title='Country Name', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid()
plt.grid(True)
formatter = FuncFormatter(lambda x, pos: f'{int(x):,}')
plt.gca().yaxis.set_major_formatter(formatter)
plt.show()
```

```
   Country Name  Year           GDP  PopTotal     perPopGDP  WorkerPopulation  \
0      Malaysia  2013  3.232762e+11  26392079  12248.987112          17012674
1      Malaysia  2014  3.380661e+11  27547235  12272.233315          18501481
2      Malaysia  2015  3.013553e+11  27580633  10926.336135          17694041
3      Malaysia  2016  3.012560e+11  29632094  10166.545566          19433770
4      Malaysia  2017  3.191091e+11  28704813  11116.919457          18827370
5      Malaysia  2018  3.587888e+11  31189631  11503.465550          21240300
6      Malaysia  2019  3.651777e+11  30204879  12090.024298          20325554
7      Malaysia  2020  3.374562e+11  30277033  11145.615357          20269028
8      Malaysia  2021  3.737848e+11  31548017  11848.124200          20758824
9      Malaysia  2022  4.076058e+11  31263962  13037.561949          20734982
10          UAE  2013  4.002185e+11   7291555  54887.953221           5638824
11          UAE  2014  4.141054e+11   7201500  57502.654552           5663133
12          UAE  2015  3.702755e+11   7824509  47322.518200           5963275
13          UAE  2016  3.692553e+11   7510116  49167.726069           5675126
14          UAE  2017  3.905168e+11   8770935  44523.965121           6936951
15          UAE  2018  4.270494e+11   8350842  51138.487849           6313510
16          UAE  2019  4.179897e+11   8455193  49435.858145           6594853
17          UAE  2020  3.494730e+11   8825816  39596.680390           6936493
18          UAE  2021  4.151788e+11   8877040  46769.958541           7003931
19          UAE  2022  5.027319e+11   9822341  51182.496637           7842568
20           UK  2013  2.784854e+12  56400556  49376.348392          36585591
21           UK  2014  3.064708e+12  59152397  51810.381377          38461588
22           UK  2015  2.927911e+12  59231099  49431.990801          37695444
23           UK  2016  2.689107e+12  54678695  49180.152652          34324382
24           UK  2017  2.680148e+12  62104802  43155.246712          40081586
25           UK  2018  2.871340e+12  59219791  48486.161452          40052421
26           UK  2019  2.851407e+12  59978753  47540.287557          38047627
27           UK  2020  2.696778e+12  61611027  43771.034471          38854393
28           UK  2021  3.143323e+12  61751140  50903.077266          38383867
29           UK  2022  3.114042e+12  65761443  47353.621348          42562631

    GDP_per_Worker
0     19002.082537
1     18272.380200
2     17031.455221
3     15501.677434
4     16949.212458
5     16891.891626
6     17966.433831
7     16648.857753
8     18006.069307
9     19657.882575
10    70975.531378
11    73123.016316
12    62092.636942
13    65065.573211
14    56295.165414
15    67640.572700
16    63381.203756
17    50381.801775
18    59277.967297
19    64102.974332
20    76118.860634
21    79682.311815
22    77672.812155
23    78343.917944
24    66867.315389
25    71689.557732
26    74943.101311
27    69407.296792
28    81891.776321
29    73163.768263
```



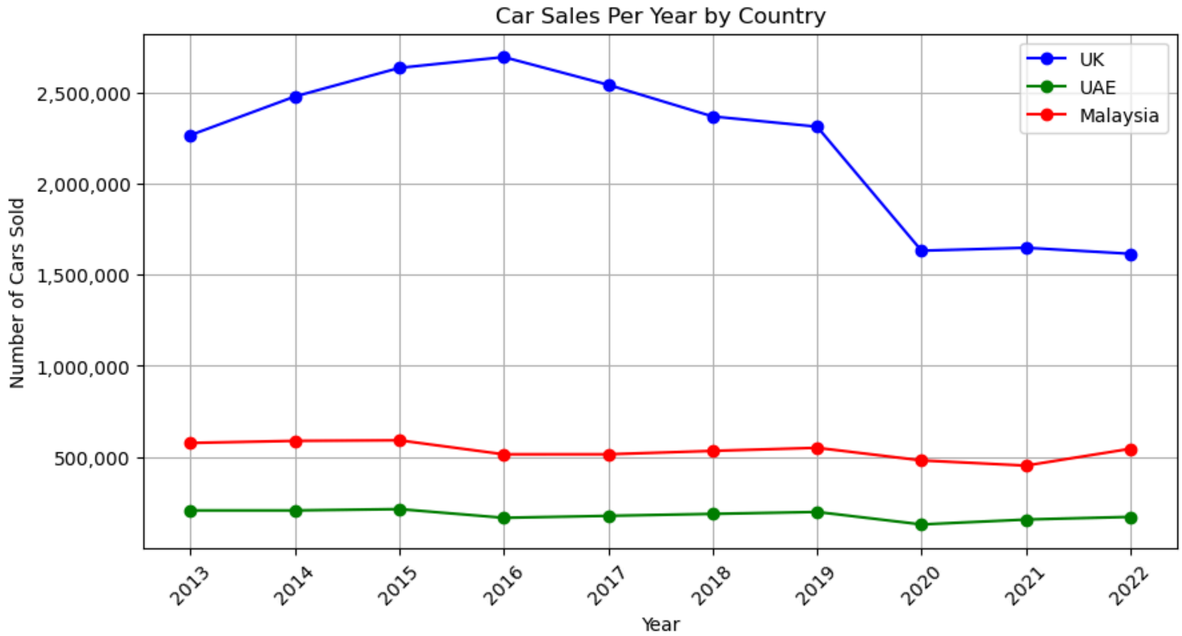
Obviously, GDP per worker is higher than GDP per inhabitant. We can observe that the UK and UAE, which were close in terms of GDP per inhabitant, are now more separated, suggesting that the UK has a higher proportion of workers relative to its total population. However, the best ratio seems to be Malaysia, where the GDP per worker is nearly double the GDP per inhabitant.

1. Compare GDP, GDP per population, GDP per working population against that of the number of vehicles sold. Choose the appropriate visualisation and provide insights with substantiated references. For example, you may want to justify the insights based on cultural influence, better public transport, vehicle cost of ownership, and/or any other reasons. This is the story telling part, but you do need to substantiate it with factual references,

In [28]:

```
# Load the JSON data from the file
with open('data/Wrangled_vehicle.json', 'r') as file:
    json_data = json.load(file)
# Extract years dynamically from the first entry (excluding "Nation")
years = sorted([int(year) for year in json_data[0] if year.isdigit()])

# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
# Plot data
plt.figure(figsize=(10, 5))
for country_data in json_data:
    country = country_data["Nation"]
    sales = [country_data[str(year)] for year in years]  # Convert year to string f
    plt.plot(years, sales, marker='o', label=country, color=country_colors.get(cour
# Customize plot
plt.xlabel("Year")
plt.ylabel("Number of Cars Sold")
plt.title("Car Sales Per Year by Country")
plt.xticks(years, rotation=45)
plt.legend()
plt.grid(True)
# Format the y-axis
```

```
formatter = FuncFormatter(lambda x, pos: f'{int(x):,}')
plt.gca().yaxis.set_major_formatter(formatter)
# Show the plot
plt.show()
```



The number of cars sold in the UAE and Malaysia appears to be fairly stable over time. However, in the UK, there is a gradual decline in sales starting from 2016, followed by a sharp drop in 2020 during the COVID lockdown. Sales have never fully recovered to pre-COVID levels, likely due to factors such as the rise in remote work, increased bike usage, and greater reliance on public transport.

This code merges the vehicle data into Merged_data.json, adding the number of vehicles for each country and year, and saves the updated dataset.

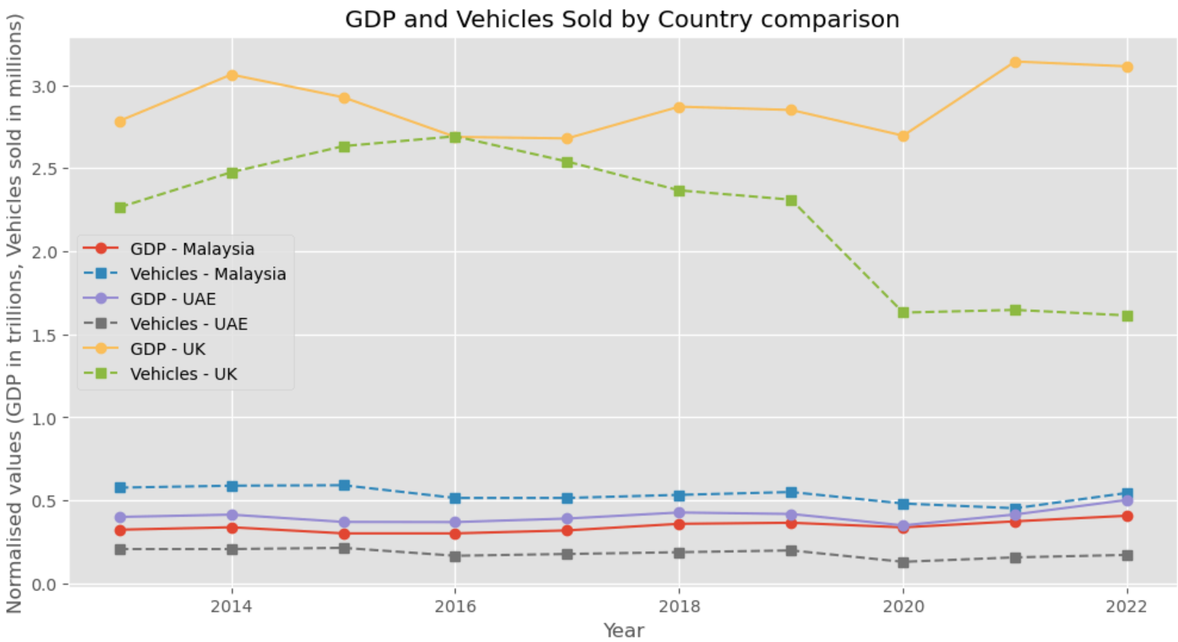
In [29]:

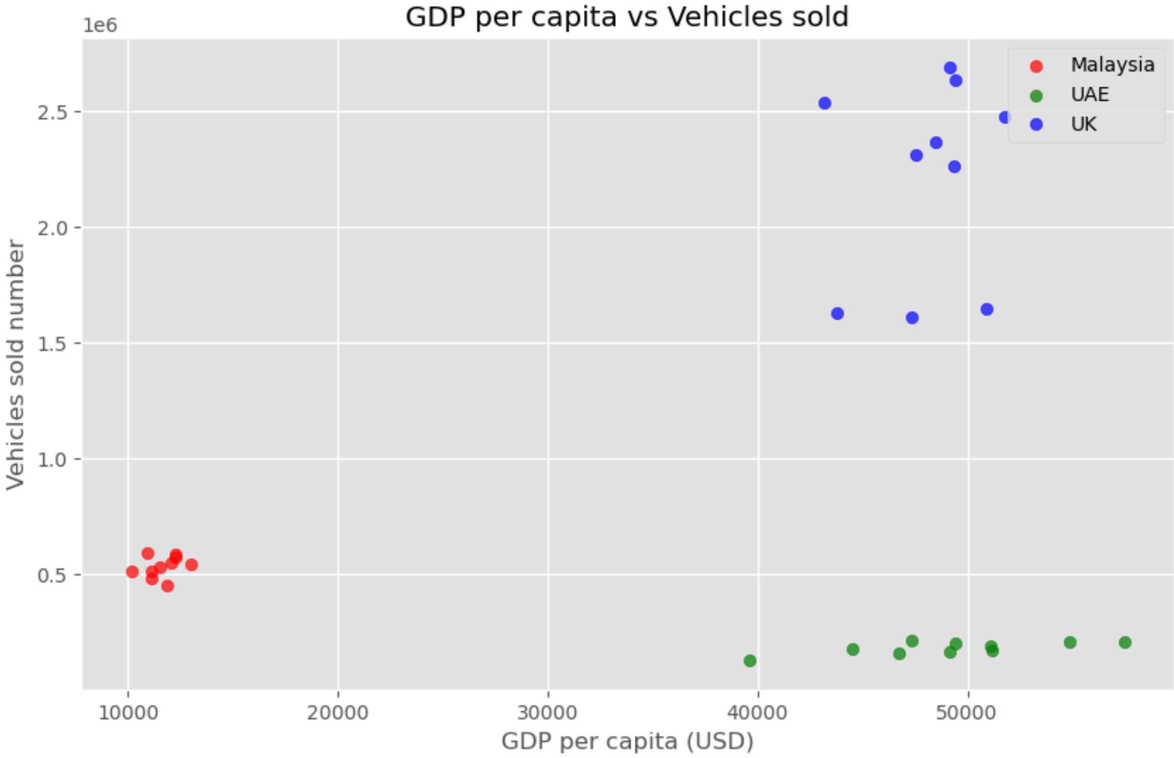
```
# Load Merged_data.json
with open("data/Merged_data.json", "r") as f:
    merged_data = json.load(f)
# Load Wrangled_vehicule.json
with open("data/Wrangled_vehicle.json", "r") as f:
    vehicle_data = json.load(f)

# Create a lookup dictionary for vehicle data
vehicle_dict = {entry["Nation"]: {str(year): entry[str(year)] for year in range(201
# Merge data
for entry in merged_data:
    country = entry["Country Name"]
    year = str(entry["Year"])  # Convert year to string for dictionary lookup
    if country in vehicle_dict and year in vehicle_dict[country]:
        entry["Vehicles"] = vehicle_dict[country][year]
    else:
        entry["Vehicles"] = None  # If no data is found, set to None

# Save the merged JSON
with open("data/Merged_data.json", "w") as f:
    json.dump(merged_data, f, indent=4)
```

In [30]:

```
# Load the merged data
with open("data/Merged_data.json", "r") as file:
    data = json.load(file)
df = pd.DataFrame(data)
```

```
# Select the columns of interest
countries = df["Country Name"].unique()

plt.style.use("ggplot")
plt.figure(figsize=(12, 6))
# Comapre GDP and Vehicles sold for each country
for country in countries:
    subset = df[df["Country Name"] == country]
    plt.plot(subset["Year"], subset["GDP"] / 1e12, marker="o", linestyle="-", label
    plt.plot(subset["Year"], subset["Vehicles"] / 1e6, marker="s", linestyle="--",
plt.xlabel("Year")
plt.ylabel("Normalised values (GDP in trillions, Vehicles sold in millions)")
plt.title("GDP and Vehicles Sold by Country comparison")
plt.legend()
plt.show()

# Scatter plot GDP per capita vs Vehicles sold
plt.figure(figsize=(10, 6))
colors = plt.cm.tab10.colors
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}
for country in countries:
    subset = df[df["Country Name"] == country]
    plt.scatter(subset["perPopGDP"], subset["Vehicles"], color=country_colors[count
plt.xlabel("GDP per capita (USD)")
plt.ylabel("Vehicles sold number")
plt.title("GDP per capita vs Vehicles sold")
plt.legend()
plt.show()
```





Interpretation

- Malaysia has a high volume of vehicle sales despite a relatively low GDP per capita, a phenomenon that can be attributed to several factors. A strong car culture plays a significant role, with personal vehicle ownership being widely regarded as a symbol of status and convenience. Additionally, Malaysia's automotive industry is supported by national car manufacturers such as Proton and Perodua, which produce affordable vehicles tailored to local consumers. Limited public transportation infrastructure in certain regions further incentivizes car ownership, as many Malaysians rely on personal vehicles for daily commuting. Government policies, including tax incentives and protectionist measures favoring domestic car brands, also contribute to the high rate of car ownership in the country.

(source [Quora]: https://www.quora.com/Why-does-Malaysia-have-the-highest-passenger-car-ownership-rate-in-SE-Asia

[Wikipédia]: https://en.wikipedia.org/wiki/Automotive_industry_in_Malaysia)

- The United Kingdom has a higher GDP but a mature automotive market, where car sales have been declining in recent years. This decline can be attributed to several factors, including improvements in public transportation infrastructure, a growing preference for alternative mobility solutions such as ride-sharing and cycling, and an increase in remote working, which has reduced the need for personal vehicles. Additionally, economic uncertainty and rising costs of car ownership, including insurance and fuel prices, have contributed to weaker demand.

(source [sky]: https://news.sky.com/story/new-car-sales-fall-in-uk-as-europes-manufacturers-feel-strain-from-weak-demand-13209442#:~:text=News%20%7C%20Sky%20News-,New%20car%20sales%20fall%20in%20UK%2 [lease fetcher]: https://www.leasefetcher.co.uk/content/remote-working-and-car-ownership)

- The United Arab Emirates exhibits a more fluctuating relationship in vehicle sales, which can likely be attributed to several key factors. The country's demographics play a major role, as a significant portion of the population consists of expatriates, whose presence and purchasing power are influenced by economic conditions, visa policies, and job market stability. Additionally, the high cost of living, particularly in cities like Dubai and Abu Dhabi, affects consumer spending patterns, including car ownership. Fluctuations in oil prices and government policies, such as fuel subsidies or taxation changes, also contribute to variations in vehicle demand. Furthermore, the UAE's well-developed public transportation infrastructure, including metro systems and ride-sharing services, provides alternatives to car ownership, influencing overall market trends.

(source [dubizzle]: https://www.dubizzle.com/blog/cars/impact-fuel-prices-uae-auto-market/

[faster capital]: https://fastercapital.com/content/UAE-Local-Market-Dynamics--Automotive-Market-Trends---Desert-Drives--Automotive-Market-Trends-in-the-UAE.html)

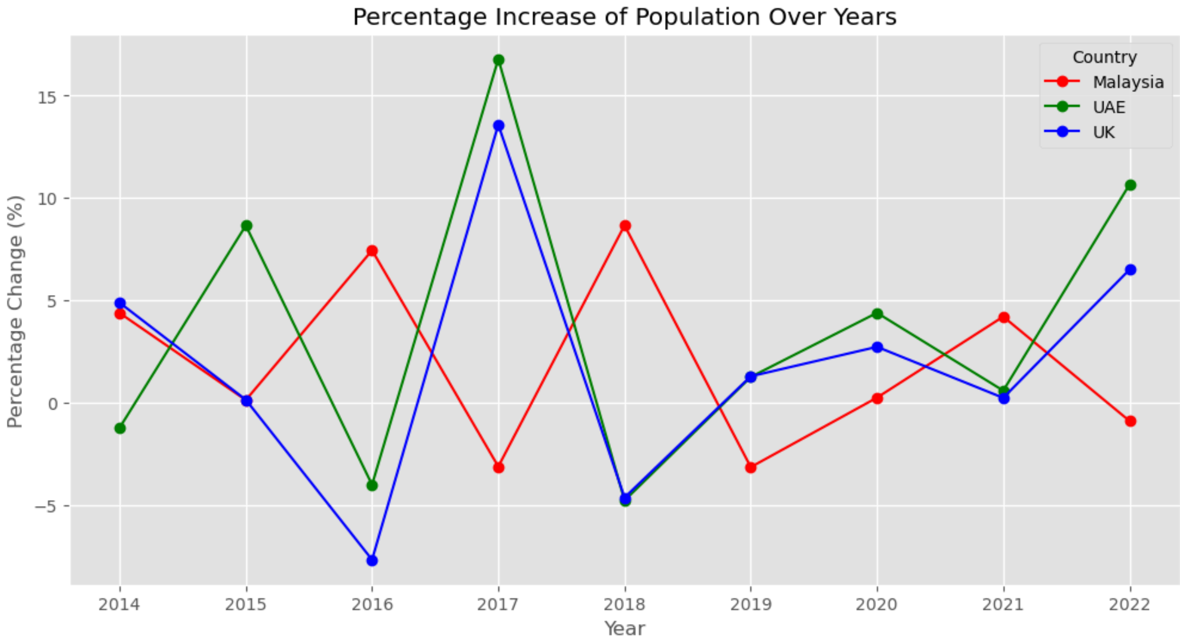
The output consists of four line plots, each illustrating the percentage change over the years for different metrics across the selected countries: Malaysia, UAE, and the UK.

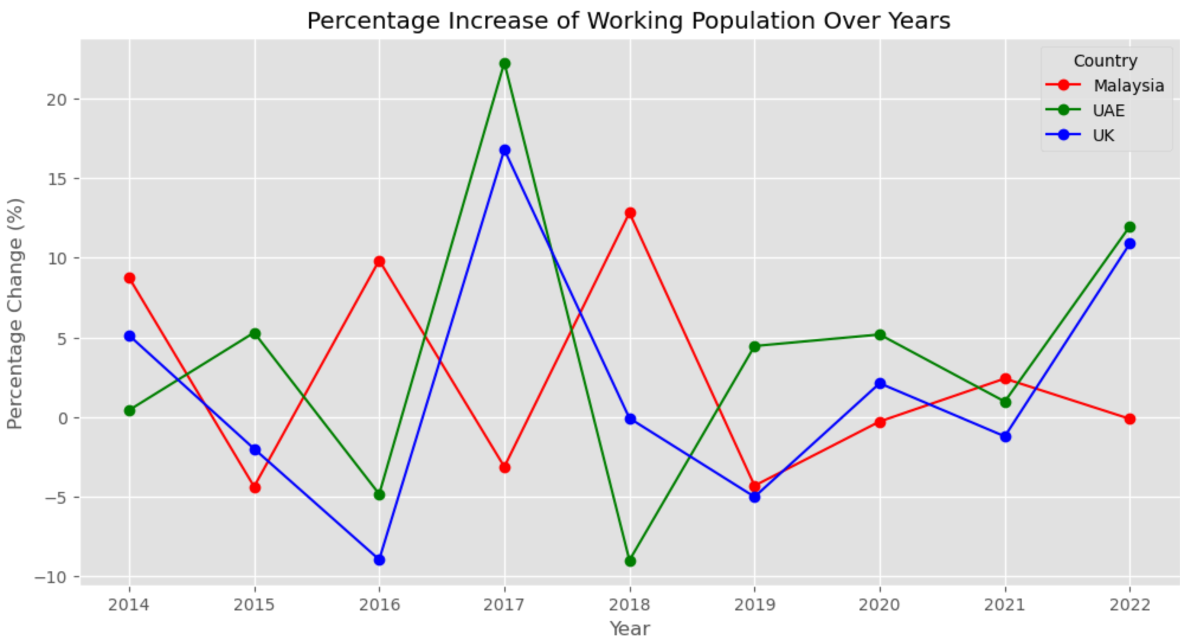
1. The first plot shows the percentage increase in the total population for each country, revealing trends in population growth over the years.
2. The second plot focuses on the working population, highlighting how the labor force has evolved in each country.
3. The third plot depicts the percentage change in GDP, showing the economic growth or decline in the selected countries.
4. The final plot illustrates the percentage change in vehicle sales, which provides insight into the automotive market trends in these countries.

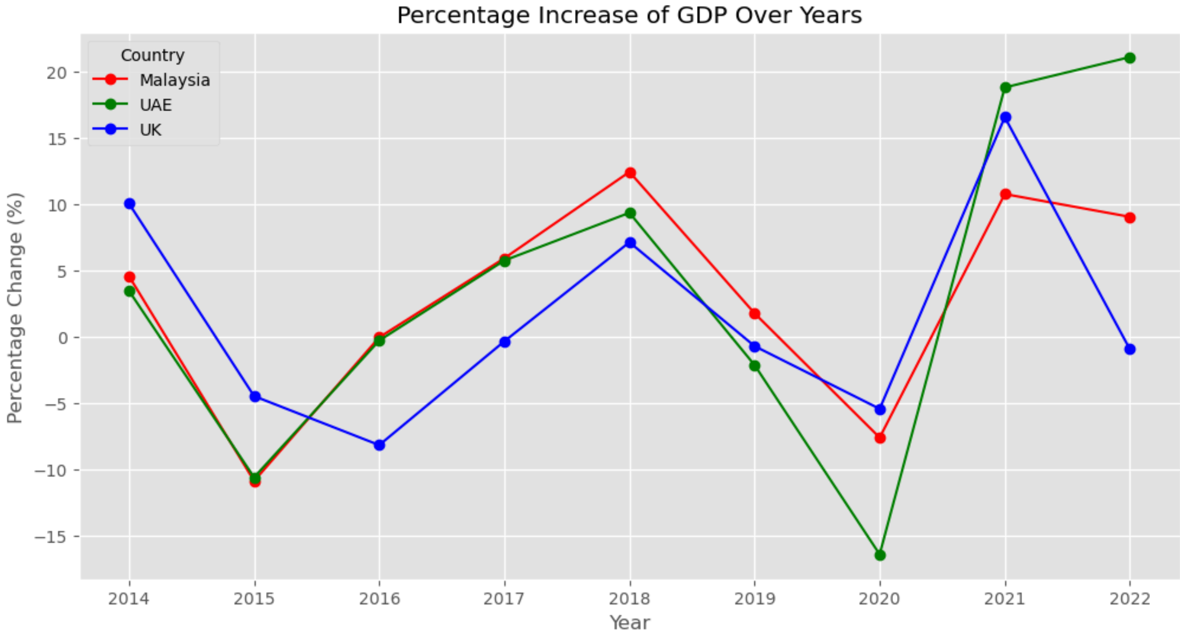
Each plot will display clear trends, with the countries represented by distinct colors for easy comparison.

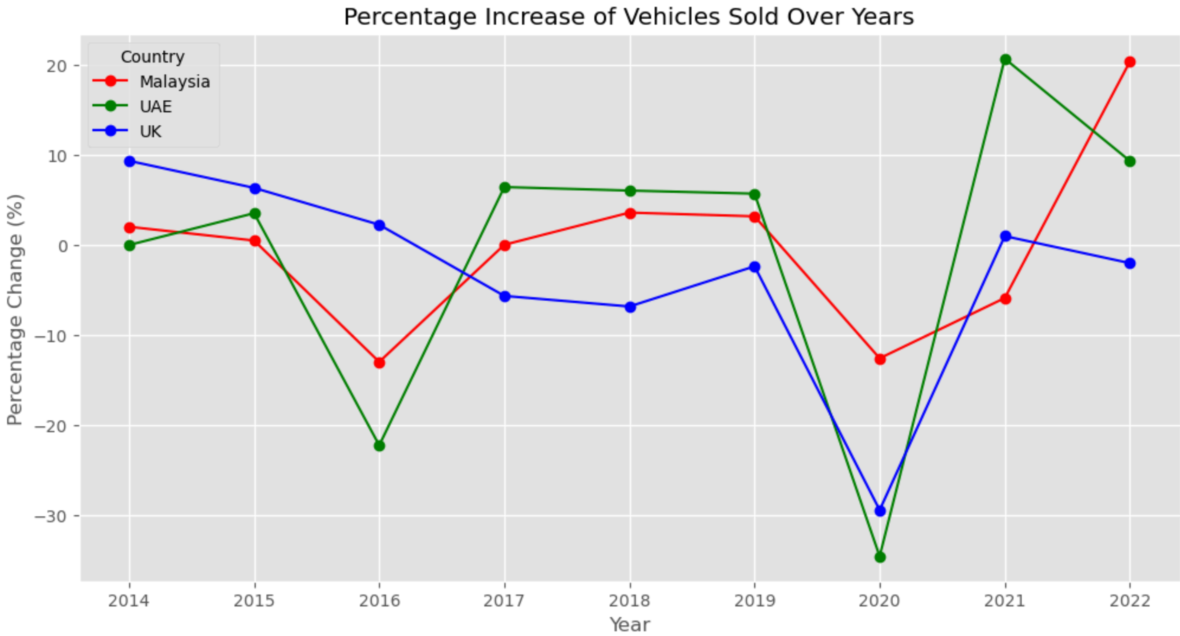
In [31]:
```
# Load the JSON data
with open('data/Merged_data.json', 'r') as file:
    data = json.load(file)
# Convert JSON data to a Pandas DataFrame
df = pd.DataFrame(data)
# Filter data for selected countries
selected_countries = ['Malaysia', 'UAE', 'UK']
df = df[df['Country Name'].isin(selected_countries)]

# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}

# Compute Percentage Increase for Population, Working Population, GDP, and Vehicle
df_sorted = df.sort_values(by=['Country Name', 'Year'])
```

```
df_sorted['Population_Perc_Change'] = df_sorted.groupby('Country Name')['PopTotal']
df_sorted['WorkerPopulation_Perc_Change'] = df_sorted.groupby('Country Name')['Work
df_sorted['GDP_Perc_Change'] = df_sorted.groupby('Country Name')['GDP'].pct_change(
df_sorted['Vehicles_Perc_Change'] = df_sorted.groupby('Country Name')['Vehicles'].p

# Function to plot data
def plot_data(y_column, title, ylabel):
    plt.figure(figsize=(12, 6))
    for country in selected_countries:
        country_data = df_sorted[df_sorted['Country Name'] == country]
        plt.plot(country_data['Year'], country_data[y_column], marker='o', label=co
    plt.title(title)
    plt.ylabel(ylabel)
    plt.xlabel('Year')
    plt.legend(title='Country')
    plt.grid(True)
    plt.show()
# Plot each metric
plot_data('Population_Perc_Change', 'Percentage Increase of Population Over Years',
plot_data('WorkerPopulation_Perc_Change', 'Percentage Increase of Working Populatic
plot_data('GDP_Perc_Change', 'Percentage Increase of GDP Over Years', 'Percentage C
plot_data('Vehicles_Perc_Change', 'Percentage Increase of Vehicles Sold Over Years'
```









The output consists of three plots, each comparing the percentage change in car sales (vehicles sold) with the percentage change in GDP per worker for Malaysia, UAE, and the UK.

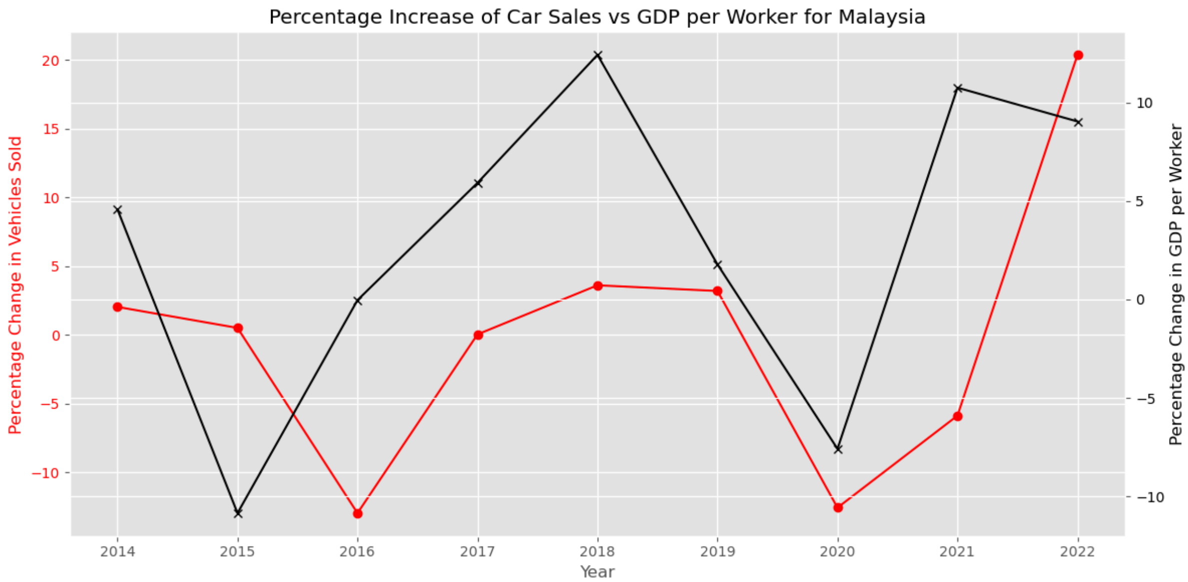
For each country, the plot displays two trends: the first is the percentage change in vehicle sales (represented by a line with circles), and the second is the percentage change in GDP per worker (represented by a line with crosses).

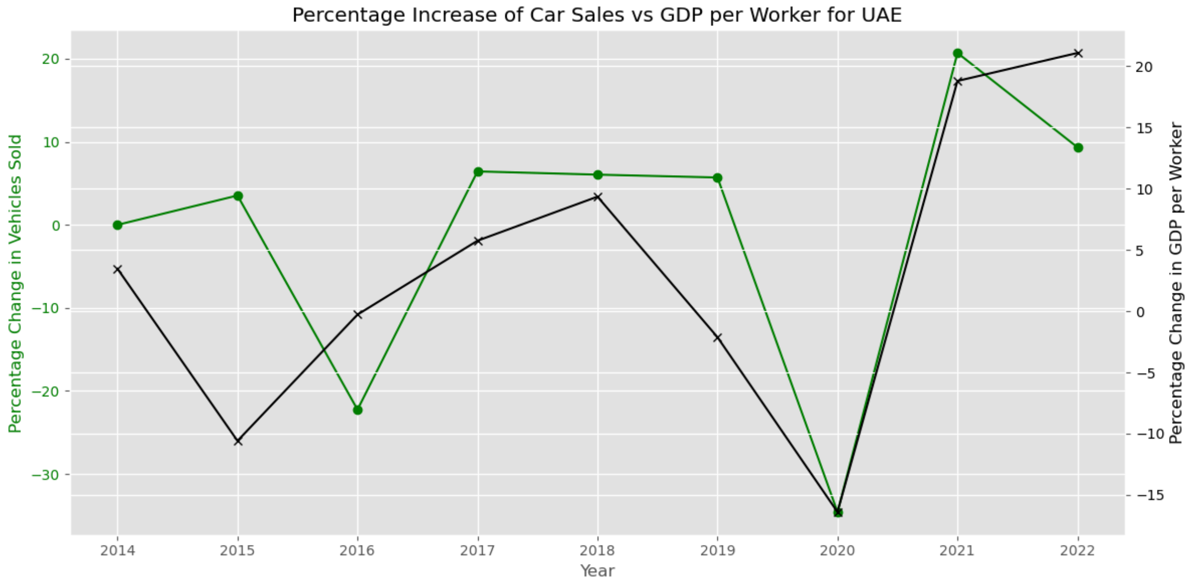
The plot for each country has dual y-axes. The left y-axis shows the percentage change in vehicle sales, with a color corresponding to the country's color, while the right y-axis displays the percentage change in GDP per worker in black.

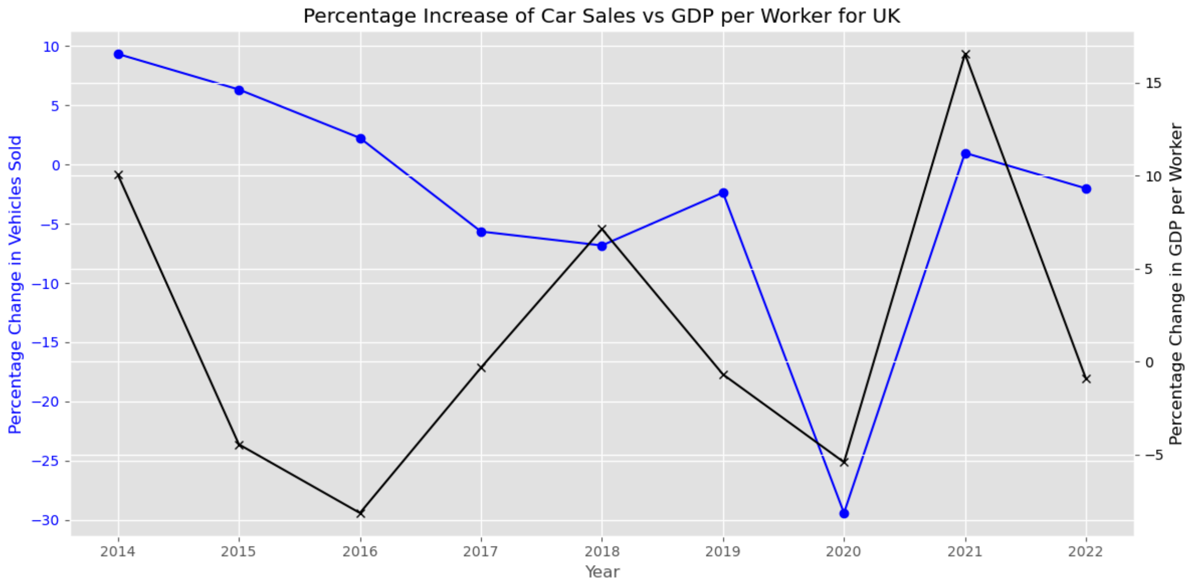
These plots offer insights into the relationship between vehicle sales and economic productivity (GDP per worker) across the countries over the years.

In [32]:
```
# Load the JSON data
with open('data/Merged_data.json', 'r') as file:
    data = json.load(file)
# Convert JSON data to a Pandas DataFrame
df = pd.DataFrame(data)
```

```
# Filter data for selected countries
selected_countries = ['Malaysia', 'UAE', 'UK']
df = df[df['Country Name'].isin(selected_countries)]

# Define colors for each country
country_colors = {
    'UK': 'blue',
    'UAE': 'green',
    'Malaysia': 'red'}

# Compute Percentage Increase for Population, Working Population, GDP, and Vehicle
df_sorted = df.sort_values(by=['Country Name', 'Year'])
df_sorted['Population_Perc_Change'] = df_sorted.groupby('Country Name')['PopTotal']
df_sorted['WorkerPopulation_Perc_Change'] = df_sorted.groupby('Country Name')['Work
df_sorted['GDP_Perc_Change'] = df_sorted.groupby('Country Name')['GDP'].pct_change(
df_sorted['Vehicles_Perc_Change'] = df_sorted.groupby('Country Name')['Vehicles'].p

# Function to plot car sales vs GDP per worker for each country
def plot_car_sales_vs_gdp(country):
    country_data = df_sorted[df_sorted['Country Name'] == country]
    fig, ax1 = plt.subplots(figsize=(12, 6))
    # Plot percentage change in vehicles (car sales)
    ax1.set_xlabel('Year')
    ax1.set_ylabel('Percentage Change in Vehicles Sold', color=country_colors[count
    ax1.plot(country_data['Year'], country_data['Vehicles_Perc_Change'], marker='o'
    ax1.tick_params(axis='y', labelcolor=country_colors[country])
    # Create a second y-axis for GDP per worker percentage change
    ax2 = ax1.twinx()
    ax2.set_ylabel('Percentage Change in GDP per Worker', color='black')
    ax2.plot(country_data['Year'], country_data['GDP_Perc_Change'], marker='x', lab
    ax2.tick_params(axis='y', labelcolor='black')
    # Add title and legend
    plt.title(f'Percentage Increase of Car Sales vs GDP per Worker for {country}')
    fig.tight_layout()
    plt.show()
# Plot for each selected country
for country in selected_countries:
    plot_car_sales_vs_gdp(country)
```







In Malaysia and the UAE, there appears to be a correlation between the percentage increase in car sales and the percentage increase in GDP per worker. As car sales grow, there is a noticeable increase in GDP per worker, suggesting a potential link between the two variables. However, this trend does not seem to hold in the UK. Although the trends in car sales and GDP per worker appear relatively similar, the correlation is not as evident, and the two variables do not align as closely as they do in Malaysia and the UAE. This divergence could indicate different economic dynamics at play in the UK, where other factors may influence GDP per worker and vehicle sales more independently.