Project Proposal

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Project Team: PaRaF Team

Title: HEALTH STATUS AND EXPENDITURES

Problem Definition:

Due to the varying nature of healthcare expenditures, it is essential to understand their intricate relationships with crucial health indicators, including the number of hospitals per province, overall obesity rates, hospital bed capacities, social assistance programs, and the general health status of individuals. The analysis will provide insights into the effectiveness of healthcare spending, regional variations in health indicators, and the overall health and well-being of the population.

Dataset(s) Sources:

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import geopandas as gp
from sklearn.preprocessing import PolynomialFeatures
import matplotlib.pyplot as plt
```

Our first dataset:

In [2]:
```
expenditures = pd.read_excel('saglik harcamalari ile ilgili gostergeler.xls'
expenditures.head()
```

Out[2]:

	Sağlık harcamaları ile ilgili göstergeler, 1999-2022	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unna
0	Indicators on health expenditures, 1999-2022	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	NaN	1999.0	2000.0	2001	2002.00	2003.00	2004.000000	2005
3	Toplam sağlık harcaması (Milyon TL)	NaN	NaN	NaN	NaN	NaN	NaN	
4	Total health expenditure (Million TRY)	4985.0	8248.0	12395.88	18773.94	24278.91	30020.845725	35358

5 rows × 25 columns

In [3]:
```
# Define the `years_index` variable to determine columns
target_row_index = 2
expenditures.columns = expenditures.iloc[target_row_index]

# Retrieve rows after the `target_row_index` and drop any missing values
expenditures = expenditures.iloc[target_row_index + 1:]
expenditures = expenditures.dropna()

# Obtain the updated `expenditures` DataFrame after the operations
expenditures
```

Out[3]:

2	NaN	1999.0	2000.0	2001.0	2002.0	2003.0	2004.0	2005.0	
4	Total health expenditure (Million TRY)	4985.0	8248.0	12395.88	18773.94	24278.91	30020.845725	35358.90747	4406ٍ
7	Health expenditure per capita (TRY)	79.0	128.0	190	284.00	363.00	444.000000	517.00000	63

2 rows × 25 columns

Our first dataset includes Health Expenditures between 1999 – 2022 years. This dataset is our main dataset to investigate the relation between others. The column headers are set based on the third row (row including years) of the dataset, and rows preceding this target row are dropped to eliminate unnecessary information. The DataFrame is then filtered to

In [4]:
```
columns = [int(col) if pd.notna(col) else col for col in expenditures.column
expenditures.columns = ['Expenditures'] + columns[1:]
expenditures = expenditures[expenditures["Expenditures"] == "Total health ex

expenditures
```

Out[4]:

	Expenditures	1999	2000	2001	2002	2003	2004	2005	
4	Total health expenditure (Million TRY)	4985.0	8248.0	12395.88	18773.94	24278.91	30020.845725	35358.90747	44(

1 rows × 25 columns

Additionally, the code applies a transformation to convert numerical values with decimals to integers for consistency. The column names are modified to ensure clarity and consistency, with the first column renamed as 'Expenditures.

Our second dataset:

In [5]:
```
healthcare = pd.read_excel('sosyal_yardm.xls')
healthcare
```

Out[5]:

	Ayni ve nakdi sosyal koruma yardımlarının risk/ihtiyaç gruplarına göre dağılımı, 2000-2021	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5
0	Distribution of cash and in kind social protec...	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	Nakdi yardımlar\nCash benefits	NaN	NaN	NaN
3	NaN	NaN	2000	2001.000000	2002.000000	2003.000000
4	Sosyal koruma yardımları toplamı	NaN	NaN	NaN	NaN	NaN
5	Total social protection benefits	NaN	7558.409299	11763.398537	18350.796838	28118.596365
6	NaN	Hastalık/sağlık bakımı	NaN	NaN	NaN	NaN
7	NaN	Sickness/health care	74.44108	115.190728	168.978380	233.433253
8	NaN	Engelli/malul	NaN	NaN	NaN	NaN
9	NaN	Disability	346.570101	501.634844	752.849231	970.658708
10	NaN	Emekli/yaşlı	NaN	NaN	NaN	NaN
11	NaN	Old age	5292.245455	8396.505002	13203.516775	20465.604076
12	NaN	Dul/yetim	NaN	NaN	NaN	NaN
13	NaN	Survivors	1377.869619	2247.474215	3427.228303	5435.027646
14	NaN	Aile/çocuk	NaN	NaN	NaN	NaN
15	NaN	Family/children	202.170309	321.030006	540.368905	664.120792
16	NaN	İşsizlik	NaN	NaN	NaN	NaN
17	NaN	Unemployment	9.900239	11.455664	67.866021	143.844073
18	NaN	Sosyal dışlanma b.y.s	NaN	NaN	NaN	NaN
19	NaN	Social exclusion n.e.c.	255.212495	170.108078	189.989224	205.907816
20	TÜİK, Sosyal Koruma İstatistikleri	NaN	NaN	NaN	NaN	NaN
21	TurkStat, Social Protection Statistics	NaN	NaN	NaN	NaN	NaN

	Ayni ve nakdi sosyal koruma yardımlarının risk/ihtiyaç gruplarına göre dağılımı, 2000-2021	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5
22	Tablodaki rakamlar, yuvarlamadan dolayı toplam...	NaN	NaN	NaN	NaN	NaN
23	Figures in table may not add up to totals due ...	NaN	NaN	NaN	NaN	NaN
24	(r) İlgili yılı verileri idari kayıtların günc...	NaN	NaN	NaN	NaN	NaN
25	(r) Data have been revised due to the update o...	NaN	NaN	NaN	NaN	NaN

26 rows × 47 columns

In [6]:

```
# Selecting the first 24 columns of the healthcare DataFrame
healthcare_show = healthcare.iloc[:, :24]

# Selecting specific rows (index 3 and index 7) from the subset of columns (
healthcare_show = healthcare_show.iloc[[3, 7]]

# Displaying the resulting subset of the DataFrame
healthcare_show
```

Out[6]:

	Ayni ve nakdi sosyal koruma yardımlarının risk/ihtiyaç gruplarına göre dağılımı, 2000-2021	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: (
3	NaN	NaN	2000	2001.000000	2002.00000	2003.000000	2004.00000(
7	NaN	Sickness/health care	74.44108	115.190728	168.97838	233.433253	303.61811(

2 rows × 24 columns

In [7]:

```
# Define the index for the year
target_row_index = 3

# Set DataFrame columns to the values in the row at 'year_index'
healthcare.columns = healthcare.iloc[target_row_index]

# Select rows after 'target_row_index' and retain only the first 24 columns
healthcare = healthcare.iloc[target_row_index + 1:]
selected_rows_and_columns = healthcare.iloc[:, :24]

# Select the 4th row after filtering and drop any columns with NaN values
healthcare_last = selected_rows_and_columns.iloc[[3]]
healthcare_last = healthcare_last.dropna(axis=1)

# Display the resulting DataFrame with the last operations applied
healthcare_last
```

Out[7]:

3	NaN	2000	2001.0	2002.0	2003.0	2004.0	2005.0	2
7	Sickness/health care	74.44108	115.190728	168.97838	233.433253	303.618116	340.075046	323.2

1 rows × 23 columns

In [8]:

```
# Rename the '2020(r)' column to '2020'
healthcare_last.rename(columns={'2020(r)': '2020'}, inplace=True)

# Convert column names to integers where possible, preserving NaN values
columns = [int(col) if pd.notna(col) else col for col in healthcare_last.col

# Assign the modified column names back to the DataFrame, preserving the fir
healthcare_last.columns = ['Health\Years'] + columns[1:]
healthcare_last
```

Out[8]:

	Health\Years	2000	2001	2002	2003	2004	2005	
7	Sickness/health care	74.44108	115.190728	168.97838	233.433253	303.618116	340.075046	323.2

1 rows × 23 columns

The dataset above includes Social Health for Sickness/Healthcare between 2000 – 2021 years. We only used this row in this dataset. Rows preceding this target row are dropped to eliminate unnecessary information. Any columns with NaN values are removed, and the column names are modified for clarity and consistency.

In [9]:
```
# Drop the 'Health\\Years' column
healthcare_last = healthcare_last.drop("Health\Years", axis=1)

# Transpose the DataFrame
healthcare_last = healthcare_last.T

# Create a new 'Years' column with values from 2000 to 2021
healthcare_last["Years"] = np.array(range(2000,2022))

# Rename a specific column (column index 7) to 'Status'
healthcare_last.rename(columns={7: 'Status'}, inplace=True)

# Reset the index of the DataFrame
healthcare_last = healthcare_last.reset_index(drop=True)
```

Our third dataset:

In [10]:
```
body_mass = pd.read_excel('obezite verisi.xls')
body_mass
```

Out[10]:

	Yıl ve cinsiyet\nYear and sex	Unnamed: 1	Toplam\nTotal	Düşük kilolu\nUnderweight	Normal kilolu\nNormal weight	Obez öncesi\nPre-obese
0	2008.0	Toplam-Total	100,0	4.200000	48.200000	32.400000
1	NaN	Erkek-Male	100,0	2.700000	48.100000	36.900000
2	NaN	Kadın-Female	100,0	5.900000	48.200000	27.400000
3	2010.0	Toplam-Total	99.99	4.650000	45.450000	32.980000
4	NaN	Erkek-Male	100	3.460000	46.120000	37.260000
5	NaN	Kadın-Female	100	5.930000	44.730000	28.390000
6	2012.0	Toplam-Total	99.99	3.860000	44.150000	34.760000
7	NaN	Erkek-Male	100	2.650000	44.650000	38.980000
8	NaN	Kadın-Female	100	5.130000	43.620000	30.350000
9	2014.0	Toplam-Total	100	4.190000	42.180000	33.710000
10	NaN	Erkek-Male	100.01	2.820000	43.730000	38.210000
11	NaN	Kadın-Female	100	5.530000	40.670000	29.320000
12	2016.0	Toplam-Total	100	4.030065	42.095703	34.260058
13	NaN	Erkek-Male	100.01	2.471060	43.786032	38.553524
14	NaN	Kadın-Female	100	5.554548	40.442803	30.061666
15	2019.0	Toplam-Total	100	3.797784	40.111766	34.981619
16	NaN	Erkek-Male	100.01	2.711452	40.255777	39.704092
17	NaN	Kadın-Female	100	4.858696	39.971125	30.369646
18	2022.0	Toplam-Total	100	3.626760	40.552985	35.581430
19	NaN	Erkek-Male	100.01	2.303913	40.553743	40.362008
20	NaN	Kadın-Female	100	4.923053	40.552242	30.896814

In [11]:
```
body_mass = body_mass.dropna()
body_mass = body_mass.round(1)
body_mass
```

Out[11]:

	Yıl ve cinsiyet\nYear and sex	Unnamed: 1	Toplam\nTotal	Düşük kilolu\nUnderweight	Normal kilolu\nNormal weight	Obez öncesi\nPre-obese
0	2008.0	Toplam-Total	100,0	4.2	48.2	32.4
3	2010.0	Toplam-Total	99.99	4.6	45.4	33.0
6	2012.0	Toplam-Total	99.99	3.9	44.2	34.8
9	2014.0	Toplam-Total	100	4.2	42.2	33.7
12	2016.0	Toplam-Total	100	4.0	42.1	34.3
15	2019.0	Toplam-Total	100	3.8	40.1	35.0
18	2022.0	Toplam-Total	100	3.6	40.6	35.6

In [12]:
```
# Define the target header and columns to be removed
target_header = 'Toplam\nTotal'
columns_to_remove = ['Unnamed: 1', 'Toplam\nTotal']

# Get the column indexes of columns to be removed
indexes_to_remove = [body_mass.columns.get_loc(col) for col in columns_to_re

# Drop columns from the DataFrame based on their indexes
body_mass = body_mass.drop(body_mass.columns[indexes_to_remove], axis=1)

body_mass
```

Out[12]:

	Yıl ve cinsiyet\nYear and sex	Düşük kilolu\nUnderweight	Normal kilolu\nNormal weight	Obez öncesi\nPre-obese	Obez\nObese
0	2008.0	4.2	48.2	32.4	15.2
3	2010.0	4.6	45.4	33.0	16.9
6	2012.0	3.9	44.2	34.8	17.2
9	2014.0	4.2	42.2	33.7	19.9
12	2016.0	4.0	42.1	34.3	19.6
15	2019.0	3.8	40.1	35.0	21.1
18	2022.0	3.6	40.6	35.6	20.2

The dataset above includes Obesity Data between 2008 – 2022 years. We used this data to check if the health expenditures affect the health status in terms of body mass index. Although male and female data were given separately, we looked at the total result.

In [13]:
```
body_mass['Yıl ve cinsiyet\nYear and sex'] = body_mass['Yıl ve cinsiyet\nYea
body_mass.rename(columns={'Yıl ve cinsiyet\nYear and sex': 'Years'}, inplace
body_mass.rename(columns={'Düşük kilolu\nUnderweight': 'Underweight'}, inpla
body_mass.rename(columns={'Normal kilolu\nNormal weight': 'Normal weight'},
body_mass.rename(columns={'Obez öncesi\nPre-obese': 'Pre-obese'}, inplace=Tr
body_mass.rename(columns={'Obez\nObese': 'Obese'}, inplace=True)
body_mass = body_mass.set_index('Years').transpose()

body_mass
```

Out[13]:

Years	2008	2010	2012	2014	2016	2019	2022
Underweight	4.2	4.6	3.9	4.2	4.0	3.8	3.6
Normal weight	48.2	45.4	44.2	42.2	42.1	40.1	40.6
Pre-obese	32.4	33.0	34.8	33.7	34.3	35.0	35.6
Obese	15.2	16.9	17.2	19.9	19.6	21.1	20.2

We translated column names from Turkish to English, converted the 'Years' column to integers, and transposed the DataFrame for better analysis, resulting in a more structured and readable dataset.

Our fourth dataset:

In [14]:
```
# Read the Excel file into a DataFrame
df1 = pd.read_excel('hastane_yatak_says.xls')

# Concatenate specific row ranges to create a new DataFrame
concatenated_df = pd.concat([df1.iloc[5:7, :], df1.iloc[7:62, :]], ignore_in

# Drop columns with NaN values
df = concatenated_df.dropna(axis=1)

# Combine two rows to create a new row
combined_row = df.iloc[0].astype(str) + '' + df.iloc[1].astype(str)

# Clean up sentences in the combined row
corrected_sentences = []
for index, sentence in combined_row.items():
    corrected_sentence = ' '.join(sentence.split())
    corrected_sentences.append(corrected_sentence)

# Create a DataFrame with corrected sentences
combined_row = pd.concat([combined_row, pd.DataFrame(corrected_sentences, co
combined_row.columns = ["0", "1"]
combined_row = combined_row.drop("0", axis=1)
combined_row = combined_row.dropna(axis=0)

# Remove two rows from the DataFrame
# df = df.drop([1, 2])

# Add the newly created row to the DataFrame
df.columns = combined_row["1"]
df = df.drop([0, 1])
df = df.reset_index()
df = df.drop("index", axis=1)
df = df.rename(columns={'Yıllar Years': 'Years'})

# Define a function to convert values to integers
def convert_to_int(value):
    try:
        return int(value)
    except:
        print(value)
        return value

# Convert "Years" column to integers
df["Years"] = df["Years"].apply(convert_to_int)
df['Years'] = df['Years'].replace('2017(r)', 2017)
df['Number of outpatient medical institutions(1)'] = df['Number of outpatien

#This is extra dataframe we use it later.
hospitalnumber = df[["Years", "Total number of medical institutions"]]
df
```

```
2017(r)
```

Out[14]:

1	Years	Total number of medical institutions	Number of inpatient medical institutions	Number of outpatient medical institutions(1)	Total number of hospital beds	Number of hospital beds per 1000 population
0	1967	664	664	0	59173	1.81
1	1968	681	681	0	64966	1.93
2	1969	725	725	0	69224	2.01
3	1970	743	743	0	71486	2.02
4	1971	759	759	0	74556	2.06
5	1972	778	778	0	77372	2.08
6	1973	790	790	0	81075	2.13
7	1974	796	796	0	83458	2.14
8	1975	798	798	0	81264	2.03
9	1976	790	790	0	82945	2.03
10	1977	772	772	0	83036	1.99
11	1978	776	776	0	86526	2.03
12	1979	822	822	0	96752	2.22
13	1980	827	827	0	99117	2.23
14	1981	831	831	0	97765	2.15
15	1982	648	648	0	96138	2.06
16	1983	646	646	0	99396	2.08
17	1984	687	687	0	100496	2.05
18	1985	722	722	0	103918	2.07
19	1986	736	736	0	107152	2.08
20	1987	756	756	0	111135	2.12
21	1988	777	777	0	112248	2.11
22	1989	812	812	0	116061	2.14
23	1990	857	857	0	120738	2.19
24	1991	899	899	0	123706	2.21
25	1992	928	928	0	126611	2.22
26	1993	962	962	0	131874	2.28
27	1994	982	982	0	134665	2.29
28	1995	1009	1009	0	136072	2.28
29	1996	1034	1034	0	139919	2.31
30	1997	1078	1078	0	144984	2.35
31	1998	1138	1138	0	148987	2.39
32	1999	1171	1171	0	153465	2.42
33	2000	10747	1183	9564	134950	2.08
34	2001	10581	1199	9382	140710	2.14
35	2002	9685	1156	8529	164471	2.48
36	2003	9183	1174	8009	165465	2.46

1	Years	Total number of medical institutions	Number of inpatient medical institutions	Number of outpatient medical institutions(1)	Total number of hospital beds	Number of hospital beds per 1000 population
37	2004	9038	1217	7821	166707	2.45
38	2005	8772	1196	7576	170972	2.48
39	2006	8891	1203	7688	174342	2.5
40	2007	11837	1317	10520	178000	2.52
41	2008	13818	1350	12468	183183	2.56
42	2009	15205	1389	13816	188638	2.6
43	2010	26993	1439	25554	200239	2.72
44	2011	27997	1453	26544	194504	2.6
45	2012	29960	1483	28477	200072	2.65
46	2013	30116	1517	28599	202031	2.64
47	2014	30176	1528	28648	206836	2.66
48	2015	30449	1533	28916	209648	2.66
49	2016	32981	1510	31471	217771	2.73
50	2017	33585	1518	32067	225863	2.79
51	2018	34559	1534	33025	231913	2.83
52	2019	34595	1538	33057	237504	2.86
53	2020	34621	1534	33087	251182	3
54	2021	34941	1547	33394	254497	3.01

The dataset above includes The Number of Beds in Hospitals, Total number of medical institutions (headers that we use) between 1967 – 2021 years. The DataFrame is cleaned by dropping unnecessary columns with NaN values, combining two rows into a single row to have proper column headers, and removing the original rows Redundant rows are removed to create a more organized and structured dataset.

Our fifth dataset:

In [15]:
```
df = pd.read_excel('bireylerin genel saglik durumunun cinsiyet ve yas grubun

# Select the column "Yaş grubu/"
features = df["Yaş grubu/"]

# Drop rows not containing "Total"
dropValues = []
temp = df[:].T.values
count = 0
for i in temp:
    if "Total" not in i:
        dropValues.append(count)
    count += 1

# Reset column names to start from index 0
df.columns = range(len(df.columns))

# Drop identified rows
df = df.drop(dropValues, axis=1)

df
```

Out[15]:

	2	6	10	14	18	22	26
0	2008	2010	2012	2014	2016	2019	2022
1	Toplam	Toplam	Toplam	Toplam	Toplam	Toplam	Toplam
2	Total	Total	Total	Total	Total	Total	Total
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	63.558859	64.944515	70.695846	61.209135	63.545131	60.894945	63.426429
5	10.139912	9.957522	7.224874	11.480119	10.690481	10.425135	8.087863
6	NaN	NaN	NaN	NaN	NaN	NaN	NaN
7	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
8	2.268091	2.490049	1.35741	2.232231	2.284011	1.452639	1.809318
9	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10	NaN	NaN	NaN	NaN	NaN	NaN	NaN
11	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
12	4.004234	3.641029	2.140142	3.717021	3.278658	2.88645	2.425228
13	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14	NaN	NaN	NaN	NaN	NaN	NaN	NaN
15	NaN	NaN	NaN	NaN	NaN	NaN	NaN
16	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
17	8.170229	7.780288	4.216576	7.893857	6.609468	5.721206	4.594693
18	NaN	NaN	NaN	NaN	NaN	NaN	NaN
19	NaN	NaN	NaN	NaN	NaN	NaN	NaN
20	NaN	NaN	NaN	NaN	NaN	NaN	NaN
21	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
22	13.433625	9.984121	7.92397	13.90374	13.400577	12.727024	7.971515
23	NaN	NaN	NaN	NaN	NaN	NaN	NaN
24	NaN	NaN	NaN	NaN	NaN	NaN	NaN
25	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
26	20.37369	19.871192	14.989148	21.996697	18.736494	16.857929	12.683897
27	NaN	NaN	NaN	NaN	NaN	NaN	NaN
28	25.877803	28.562561	31.912311	26.876753	26.131565	25.777905	28.538399
29	29.159589	31.937874	23.079654	32.362497	30.521885	28.780771	20.584595
30	NaN	NaN	NaN	NaN	NaN	NaN	NaN
31	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585
32	38.274452	44.336026	37.635196	45.333257	42.551386	45.339869	36.786384

In [16]:
```
# Merge "Yaş grubu/" column with other columns
df = pd.concat([features, df], axis=1)

# Drop all rows with NaN values
df = df.dropna(how="all")
df
```

Out[16]:

	Yaş grubu/	2	6	10	14	18	22	2
0	Sağlık durumu	2008	2010	2012	2014	2016	2019	202
1	Age group/	Toplam	Toplam	Toplam	Toplam	Toplam	Toplam	Topla
2	Health status	Total	Total	Total	Total	Total	Total	Tot
3	Toplam - Total	NaN	NaN	NaN	NaN	NaN	NaN	Na
4	Çok iyi/ İyi\nVery good/Good	63.558859	64.944515	70.695846	61.209135	63.545131	60.894945	63.4264
5	Kötü/Çok kötü\nBad/Very bad	10.139912	9.957522	7.224874	11.480119	10.690481	10.425135	8.0878
6	15-24	NaN	NaN	NaN	NaN	NaN	NaN	Na
7	Çok iyi/ İyi\nVery good/Good	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.2016
8	Kötü/Çok kötü\nBad/Very bad	2.268091	2.490049	1.35741	2.232231	2.284011	1.452639	1.8093
9	25-34	NaN	NaN	NaN	NaN	NaN	NaN	Na
11	Çok iyi/ İyi\nVery good/Good	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.1264
12	Kötü/Çok kötü\nBad/Very bad	4.004234	3.641029	2.140142	3.717021	3.278658	2.88645	2.4252
14	35-44	NaN	NaN	NaN	NaN	NaN	NaN	Na
16	Çok iyi/ İyi\nVery good/Good	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.6764
17	Kötü/Çok kötü\nBad/Very bad	8.170229	7.780288	4.216576	7.893857	6.609468	5.721206	4.5946
19	45-54	NaN	NaN	NaN	NaN	NaN	NaN	Na
21	Çok iyi/ İyi\nVery good/Good	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.4025
22	Kötü/Çok kötü\nBad/Very bad	13.433625	9.984121	7.92397	13.90374	13.400577	12.727024	7.9715
23	55-64	NaN	NaN	NaN	NaN	NaN	NaN	Na
25	Çok iyi/ İyi\nVery good/Good	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.8798
26	Kötü/Çok kötü\nBad/Very bad	20.37369	19.871192	14.989148	21.996697	18.736494	16.857929	12.6838
27	65-74	NaN	NaN	NaN	NaN	NaN	NaN	Na
28	Çok iyi/ İyi\nVery good/Good	25.877803	28.562561	31.912311	26.876753	26.131565	25.777905	28.5383

	Yaş grubu/	2	6	10	14	18	22	2
29	Kötü/Çok kötü\nBad/Very bad	29.159589	31.937874	23.079654	32.362497	30.521885	28.780771	20.5845
30	75+	NaN	NaN	NaN	NaN	NaN	NaN	Na
31	Çok iyi/ İyi\nVery good/Good	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.2025
32	Kötü/Çok kötü\nBad/Very bad	38.274452	44.336026	37.635196	45.333257	42.551386	45.339869	36.7863

In [17]:
```
# Drop rows containing "Kötü/Çok"
df = df[~df['Yaş grubu/'].str.contains('Kötü/Çok')]

# Fill NaN values with the next available value
df = df.fillna(method="bfill")
df
```

Out[17]:

	Yaş grubu/	2	6	10	14	18	22	26
0	Sağlık durumu	2008	2010	2012	2014	2016	2019	2022
1	Age group/	Toplam	Toplam	Toplam	Toplam	Toplam	Toplam	Toplam
2	Health status	Total	Total	Total	Total	Total	Total	Total
3	Toplam - Total	63.558859	64.944515	70.695846	61.209135	63.545131	60.894945	63.426429
4	Çok iyi/ İyi\nVery good/Good	63.558859	64.944515	70.695846	61.209135	63.545131	60.894945	63.426429
6	15-24	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
7	Çok iyi/ İyi\nVery good/Good	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
9	25-34	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
11	Çok iyi/ İyi\nVery good/Good	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
14	35-44	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
16	Çok iyi/ İyi\nVery good/Good	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
19	45-54	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
21	Çok iyi/ İyi\nVery good/Good	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
23	55-64	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
25	Çok iyi/ İyi\nVery good/Good	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
27	65-74	25.877803	28.562561	31.912311	26.876753	26.131565	25.777905	28.538399
28	Çok iyi/ İyi\nVery good/Good	25.877803	28.562561	31.912311	26.876753	26.131565	25.777905	28.538399
30	75+	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585
31	Çok iyi/ İyi\nVery good/Good	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585

In [18]:
```
# Assign the first row as column names
df.columns = df.iloc[0]

# Drop the first row and the row below it
df = df.iloc[2:]
df
```

Out[18]:

	Sağlık durumu	2008	2010	2012	2014	2016	2019	2022
2	Health status	Total	Total	Total	Total	Total	Total	Total
3	Toplam - Total	63.558859	64.944515	70.695846	61.209135	63.545131	60.894945	63.426429
4	Çok iyi/ İyi\nVery good/Good	63.558859	64.944515	70.695846	61.209135	63.545131	60.894945	63.426429
6	15-24	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
7	Çok iyi/ İyi\nVery good/Good	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
9	25-34	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
11	Çok iyi/ İyi\nVery good/Good	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
14	35-44	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
16	Çok iyi/ İyi\nVery good/Good	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
19	45-54	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
21	Çok iyi/ İyi\nVery good/Good	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
23	55-64	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
25	Çok iyi/ İyi\nVery good/Good	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
27	65-74	25.877803	28.562561	31.912311	26.876753	26.131565	25.777905	28.538399
28	Çok iyi/ İyi\nVery good/Good	25.877803	28.562561	31.912311	26.876753	26.131565	25.777905	28.538399
30	75+	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585
31	Çok iyi/ İyi\nVery good/Good	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585

In [19]:
```
# Get the name of the first column
title = df.columns[0]

# Create a list of specified age groups
age_groups = ['15-24', '25-34', '35-44', '45-54', '55-64', '75+']

# Select rows with specified age groups
df = df[df[title].isin(age_groups)]
df
```

Out[19]:

	Sağlık durumu	2008	2010	2012	2014	2016	2019	2022
6	15-24	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
9	25-34	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
14	35-44	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
19	45-54	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
23	55-64	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
30	75+	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585

In [ ]:

In [20]:
```
# Rename the first column to "Ages"
df = df.rename(columns={title: "Ages"})

# Convert columns except the first one to float
columns_to_convert = df.columns[1:]
df[columns_to_convert] = df[columns_to_convert].astype(float)
df=df.reset_index(drop=True)
health_with_ages = df
health_with_ages
```

Out[20]:

	Ages	2008	2010	2012	2014	2016	2019	2022
0	15-24	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
1	25-34	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
2	35-44	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
3	45-54	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
4	55-64	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
5	75+	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585

We edited the column names. We took only ages and health levels without making gender distinctions. We cropped the dataframe by taking the degree of "Very Good" levels in each year. Finally, we converted the data in the Dataframe to float type, thus obtaining a more structured and readable data set.

Our sixth dataset:

In [21]:
```
# Read data from Excel file
hospital_cities = pd.read_excel('ili_l_hasatane.xls')
df
```

Out[21]:

	Ages	2008	2010	2012	2014	2016	2019	2022
0	15-24	85.882503	84.925497	92.478169	85.751447	89.533237	86.082044	87.201652
1	25-34	75.901548	80.545748	85.296996	76.667881	81.075248	79.774367	81.126461
2	35-44	63.265173	65.212058	73.682511	62.534223	66.958897	65.985747	69.676422
3	45-54	51.782979	53.840895	60.473288	47.833804	49.201874	48.850269	55.402543
4	55-64	38.294831	40.113756	45.408718	38.229355	40.725837	38.388261	42.879847
5	75+	21.837342	17.457172	17.911589	17.899089	14.025103	14.824537	17.202585

In [22]:
```
# Select rows where the column "Hastane sayılarının illere göre dağılımı, 20
years = hospital_cities[hospital_cities["Hastane sayılarının illere göre dağ

# Drop NaN values along columns and the specified column
years = years.dropna(axis=1)
years = years.drop("Hastane sayılarının illere göre dağılımı, 2002-2021", ax
# Convert the data to numpy array and then to a list for years
years = np.array(years)
years = list(years[0])
years
```

Out[22]:
```
[2002,
 2003,
 2004,
 2005,
 2006,
 2007,
 2008,
 2009,
 2010,
 2011,
 2012,
 2013,
 2014,
 2015,
 2016,
 2017,
 2018,
 2019,
 2020,
 2021]
```

In [23]:
```
# Fill NaN values in the specified column with the forward-fill method
hospital_cities["Hastane sayılarının illere göre dağılımı, 2002-2021"] = hos

# Assign new column names to the DataFrame
hospital_cities.columns = ["Cities"] + ["Ministry"] + years

hospital_cities
```

Out[23]:

	Cities	Ministry	2002	2003	2004	2005	2006	2007	2008	2009	...	2012	2013	2
0	Distribution of number of hospitals by provinc...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
1	Distribution of number of hospitals by provinc...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
2	İller - Provinces	NaN	2002	2003	2004	2005	2006	2007	2008	2009	...	2012	2013	2
3	İller - Provinces	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
4	Türkiye - Turkey	NaN	1156	1174	1217	1196	1203	1317	1350	1389	...	1483	1517	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
499	2016 yılında MSB'ye bağlı hastaneler Sağlık Ba...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
500	(1) 2002-2015 periods, "Other" is defined as t...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
501	Hospitals affiliated to MoND were transferred ...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
502	- Bilgi yoktur.	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
503	- Denotes magnitude null.	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N

504 rows × 22 columns

In [24]:
```
# Drop rows with NaN values
hospital_cities = hospital_cities.dropna()

# Replace '-' with 0
hospital_cities = hospital_cities.replace("-", 0)
hospital_cities
```

Out[24]:

	Cities	Ministry	2002	2003	2004	2005	2006	2007	2008	2009	...	2012	2013	2
5	Türkiye - Turkey	Sağlık Bakanlığı - Ministry of Health	774	789	829	793	767	848	847	834	...	832	854	
6	Türkiye - Turkey	Üniversite - University	50	50	52	53	56	56	57	59	...	65	69	
7	Türkiye - Turkey	Özel - Private	271	274	278	293	331	365	400	450	...	541	550	
8	Türkiye - Turkey	Diğer (1) - Other (1)	61	61	58	57	49	48	46	46	...	45	44	
11	Adana	Sağlık Bakanlığı - Ministry of Health	11	14	14	15	14	13	12	12	...	11	11	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
488	Osmaniye	Diğer (1) - Other (1)	0	0	0	0	0	0	0	0	...	0	0	
491	Düzce	Sağlık Bakanlığı - Ministry of Health	3	3	4	3	2	2	2	2	...	2	3	
492	Düzce	Üniversite - University	1	1	1	1	1	1	1	1	...	1	1	
493	Düzce	Özel - Private	1	0	0	0	1	1	1	1	...	1	1	
494	Düzce	Diğer (1) - Other (1)	0	0	0	0	0	0	0	0	...	0	0	

328 rows × 22 columns

In [25]:
```
# Select rows where the "Ministry" column is "Sağlık Bakanlığı - Ministry of
hospital_cities = hospital_cities[hospital_cities["Ministry"] == "Sağlık Bak
# Exclude the row with "Türkiye - Turkey" from the DataFrame
hospital_cities = hospital_cities[hospital_cities["Cities"] != "Türkiye - Tu

# Sort values by 'Cities' column
hospital_cities = hospital_cities.sort_values(by='Cities')

# Reset the index
hospital_cities = hospital_cities.reset_index(drop=True)
hospital_cities
```

Out[25]:

	Cities	Ministry	2002	2003	2004	2005	2006	2007	2008	2009	...	2012	2013
0	Adana	Sağlık Bakanlığı - Ministry of Health	11	14	14	15	14	13	12	12	...	11	11
1	Adıyaman	Sağlık Bakanlığı - Ministry of Health	7	7	7	7	7	8	8	8	...	8	8
2	Afyonkarahisar	Sağlık Bakanlığı - Ministry of Health	17	16	16	16	16	16	15	15	...	17	17
3	Aksaray	Sağlık Bakanlığı - Ministry of Health	8	9	10	10	10	10	9	9	...	7	7
4	Amasya	Sağlık Bakanlığı - Ministry of Health	7	7	7	6	6	6	6	5	...	6	6
...	...	...	...	...	...	...	...	...	...	...	...	...	...
76	Çorum	Sağlık Bakanlığı - Ministry of Health	14	15	15	15	15	15	13	14	...	14	14
77	İstanbul	Sağlık Bakanlığı - Ministry of Health	44	45	48	50	51	52	53	52	...	52	55
78	İzmir	Sağlık Bakanlığı - Ministry of Health	25	25	29	26	26	26	26	29	...	27	29
79	Şanlıurfa	Sağlık Bakanlığı - Ministry of Health	11	11	12	12	12	13	13	14	...	14	14
80	Şırnak	Sağlık Bakanlığı - Ministry of Health	4	5	5	5	5	5	5	5	...	7	7

81 rows × 22 columns

In [26]:

```
#Change the data type of the columns with names in the 'years' list to int
for col in years:
    if col in hospital_cities.columns:
        hospital_cities[col] = hospital_cities[col].astype(int)

hospital_cities
```

Out[26]:

	Cities	Ministry	2002	2003	2004	2005	2006	2007	2008	2009	...	2012	2013
0	Adana	Sağlık Bakanlığı - Ministry of Health	11	14	14	15	14	13	12	12	...	11	11
1	Adıyaman	Sağlık Bakanlığı - Ministry of Health	7	7	7	7	7	8	8	8	...	8	8
2	Afyonkarahisar	Sağlık Bakanlığı - Ministry of Health	17	16	16	16	16	16	15	15	...	17	17
3	Aksaray	Sağlık Bakanlığı - Ministry of Health	8	9	10	10	10	10	9	9	...	7	7
4	Amasya	Sağlık Bakanlığı - Ministry of Health	7	7	7	6	6	6	6	5	...	6	6
...	...	...	...	...	...	...	...	...	...	...	...	...	...
76	Çorum	Sağlık Bakanlığı - Ministry of Health	14	15	15	15	15	15	13	14	...	14	14
77	İstanbul	Sağlık Bakanlığı - Ministry of Health	44	45	48	50	51	52	53	52	...	52	55
78	İzmir	Sağlık Bakanlığı - Ministry of Health	25	25	29	26	26	26	26	29	...	27	29
79	Şanlıurfa	Sağlık Bakanlığı - Ministry of Health	11	11	12	12	12	13	13	14	...	14	14
80	Şırnak	Sağlık Bakanlığı - Ministry of Health	4	5	5	5	5	5	5	5	...	7	7

81 rows × 22 columns

In [27]:
```
# Calculate the difference between 2021 and 2002 hospital numbers
result_hospital = hospital_cities.loc[:, 2021] - hospital_cities.loc[:, 2002
result_hospital
```

Out[27]:
```
0      3
1      3
2      1
3     -1
4      0
      ..
76     0
77    10
78     4
79     2
80     3
Length: 81, dtype: int32
```

In [28]:
```
# Create a new DataFrame with cities and hospital number differences
result_cities = hospital_cities["Cities"]
result_changes = pd.concat([result_cities, result_hospital], axis=1)
result_changes.reset_index(drop=True)
hospital_difference = result_changes
hospital_difference = hospital_difference.rename(columns={0: "Difference"})


# Sort the DataFrame by the 'Difference' column in descending order
hospital_difference = hospital_difference.sort_values(by='Difference', ascen

# Get the top 5 rows with the highest 'Difference'
top5 = hospital_difference.head(5)

# Get the bottom 5 rows with the lowest 'Difference'
lowest5 = hospital_difference.tail(5)

hospital_difference
```

Out[28]:

	Cities	Difference
22	Diyarbakır	10
77	İstanbul	10
27	Erzurum	9
9	Aydın	6
29	Gaziantep	5
...	...	...
48	Kırşehir	-2
50	Manisa	-2
46	Kırklareli	-2
47	Kırıkkale	-2
34	Isparta	-3

81 rows × 2 columns

We edited the column names. We only took data from the Ministry of Health because we accepted that expenditures in the field of health are made by the state. We assigned this difference as the change in the number of hospitals as the difference between the number of hospitals in the provinces in 2021 and the number of hospitals in 2002. Then, using this data, we will obtain the change in the number of hospitals between these years from city to city. Finally, we converted the data in the Dataframe to int type, thus obtaining a more structured and readable data set.

In [29]:
```
import geopandas as gp

# Read the countries data from the geojson file
countries = gp.read_file("countries.geojson")

# Read the shapefile data for Turkey
turkey_geo = gp.read_file('TUR_adm\TUR_adm1.shp')

countries
```

Out[29]:

	ADMIN	ISO_A3	geometry
0	Aruba	ABW	POLYGON ((-69.99694 12.57758, -69.93639 12.531...
1	Afghanistan	AFG	POLYGON ((71.04980 38.40866, 71.05714 38.40903...
2	Angola	AGO	MULTIPOLYGON (((11.73752 -16.69258, 11.73851 -...
3	Anguilla	AIA	MULTIPOLYGON (((-63.03767 18.21296, -63.09952 ...
4	Albania	ALB	POLYGON ((19.74777 42.57890, 19.74601 42.57993...
...	...	...	...
250	Samoa	WSM	MULTIPOLYGON (((-171.57002 -13.93816, -171.564...
251	Yemen	YEM	MULTIPOLYGON (((53.30824 12.11839, 53.31027 12...
252	South Africa	ZAF	MULTIPOLYGON (((37.86378 -46.94085, 37.83644 -...
253	Zambia	ZMB	POLYGON ((31.11984 -8.61663, 31.14102 -8.60619...
254	Zimbabwe	ZWE	POLYGON ((30.01065 -15.64623, 30.05024 -15.640...

255 rows × 3 columns

In [30]:
```
turkey_geo
```

Out[30]:

	ID_0	ISO	NAME_0	ID_1	NAME_1	TYPE_1	ENGTYPE_1	NL_NAME_1	VARNAME_1
0	235	TUR	Turkey	1	Çanakkale	Il	Province	None	None
1	235	TUR	Turkey	2	Çankiri	Il	Province	None	Çankırı|Changra
2	235	TUR	Turkey	3	Çorum	Il	Province	None	None
3	235	TUR	Turkey	4	Adana	Il	Province	None	Seyhan
4	235	TUR	Turkey	5	Adiyaman	Il	Province	None	Adıyaman
...	...	...	...	...	...	...	...	...	...
76	235	TUR	Turkey	77	Usak	Il	Province	None	Uşak
77	235	TUR	Turkey	78	Van	Il	Province	None	None
78	235	TUR	Turkey	79	Yalova	Il	Province	None	None
79	235	TUR	Turkey	80	Yozgat	Il	Province	None	None
80	235	TUR	Turkey	81	Zinguldak	Il	Province	None	Zonguldak

81 rows × 10 columns

In [31]:
```
# Select specific columns and rename one of them
turkey = turkey_geo[["NAME_1", "geometry"]]
turkey.rename(columns={"NAME_1": "Province"}, inplace=True)

# Rename columns in the resultdegisim DataFrame
hospital_difference.columns = ["Province", "Difference"]

# Check for provinces in Turkey that do not exist in the resultdegisim DataF
for index, row in turkey["Province"].items():
    if row in hospital_difference["Province"].tolist():
        pass
    else:
        print(row + " does not exist")
```

```
Çankiri does not exist
Adiyaman does not exist
Afyon does not exist
Agri does not exist
Aydin does not exist
Balikesir does not exist
Diyarbakir does not exist
Eskisehir does not exist
Gümüshane does not exist
Istanbul does not exist
Izmir does not exist
K. Maras does not exist
Kinkkale does not exist
Kirklareli does not exist
Kirsehir does not exist
Mugla does not exist
Mus does not exist
Nevsehir does not exist
Nigde does not exist
Sanliurfa does not exist
Sirnak does not exist
Tekirdag does not exist
Usak does not exist
Zinguldak does not exist

C:\Users\furkngoksu\AppData\Local\Temp\ipykernel_32016\123275968.py:3: Sett
ingWithCopyWarning:
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-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://p
andas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-vi
ew-versus-a-copy)
  turkey.rename(columns={"NAME_1": "Province"}, inplace=True)
```

In [32]:
```
# Replace province names in the 'turkey' DataFrame with correct spellings
turkey.replace('Çankiri', 'Çankırı', inplace=True)
turkey.replace('Adiyaman', 'Adıyaman', inplace=True)
turkey.replace('Afyon', 'Afyonkarahisar', inplace=True)
turkey.replace('Agri', 'Ağrı', inplace=True)
turkey.replace('Aydin', 'Aydın', inplace=True)
turkey.replace('Balikesir', 'Balıkesir', inplace=True)
turkey.replace('Diyarbakir', 'Diyarbakır', inplace=True)
turkey.replace('Eskisehir', 'Eskişehir', inplace=True)
turkey.replace('Gümüshane', 'Gümüşhane', inplace=True)
turkey.replace('Istanbul', 'İstanbul', inplace=True)
turkey.replace('Izmir', 'İzmir', inplace=True)
turkey.replace('K. Maras', 'Kahramanmaraş', inplace=True)
turkey.replace('Kinkkale', 'Kırıkkale', inplace=True)
turkey.replace('Kirklareli', 'Kırklareli', inplace=True)
turkey.replace('Kirsehir', 'Kırşehir', inplace=True)
turkey.replace('Mugla', 'Muğla', inplace=True)
turkey.replace('Mus', 'Muş', inplace=True)
turkey.replace('Nevsehir', 'Nevşehir', inplace=True)
turkey.replace('Nigde', 'Niğde', inplace=True)
turkey.replace('Sanliurfa', 'Şanlıurfa', inplace=True)
turkey.replace('Sirnak', 'Şırnak', inplace=True)
turkey.replace('Tekirdag', 'Tekirdağ', inplace=True)
turkey.replace('Usak', 'Uşak', inplace=True)
turkey.replace('Zinguldak', 'Zonguldak', inplace=True)

turkey
```

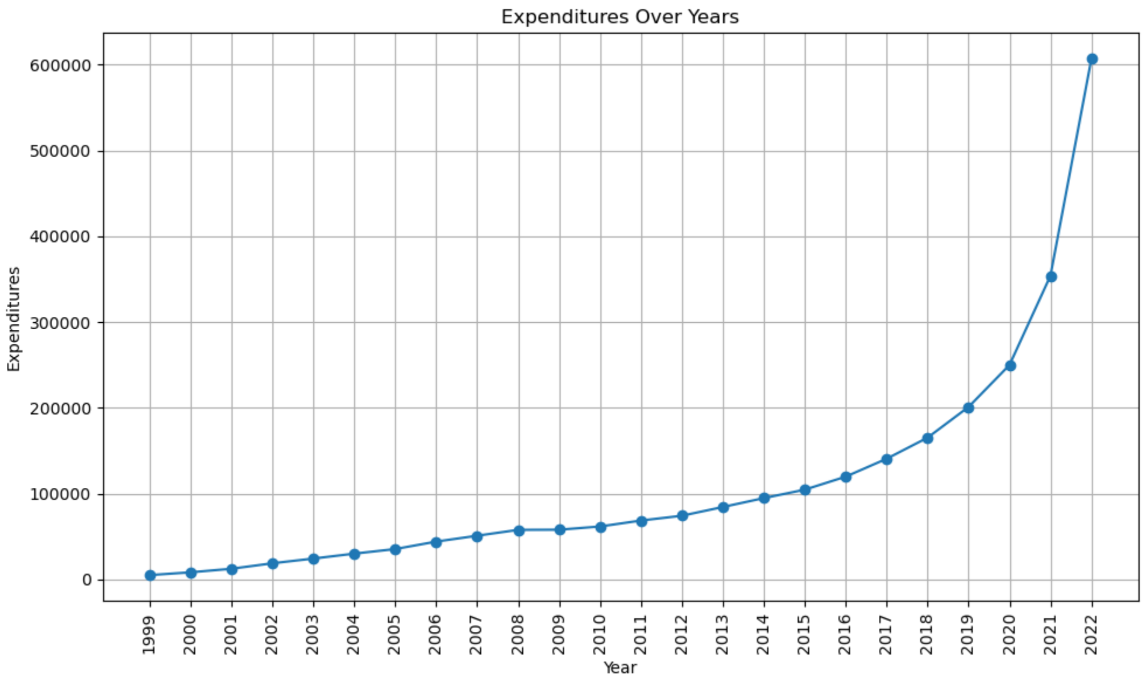
```
C:\Users\furkngoksu\AppData\Local\Temp\ipykernel_32016\3067283171.py:18:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  turkey.replace('Mus', 'Muş', inplace=True)
C:\Users\furkngoksu\AppData\Local\Temp\ipykernel_32016\3067283171.py:19:
SettingWithCopyWarning:
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-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (http
s://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returni
ng-a-view-versus-a-copy)
  turkey.replace('Nevsehir', 'Nevşehir', inplace=True)
C:\Users\furkngoksu\AppData\Local\Temp\ipykernel_32016\3067283171.py:20:
SettingWithCopyWarning:
```

EDA

Data example, some visualizations from your data.

Expeenditures Graph Over Years

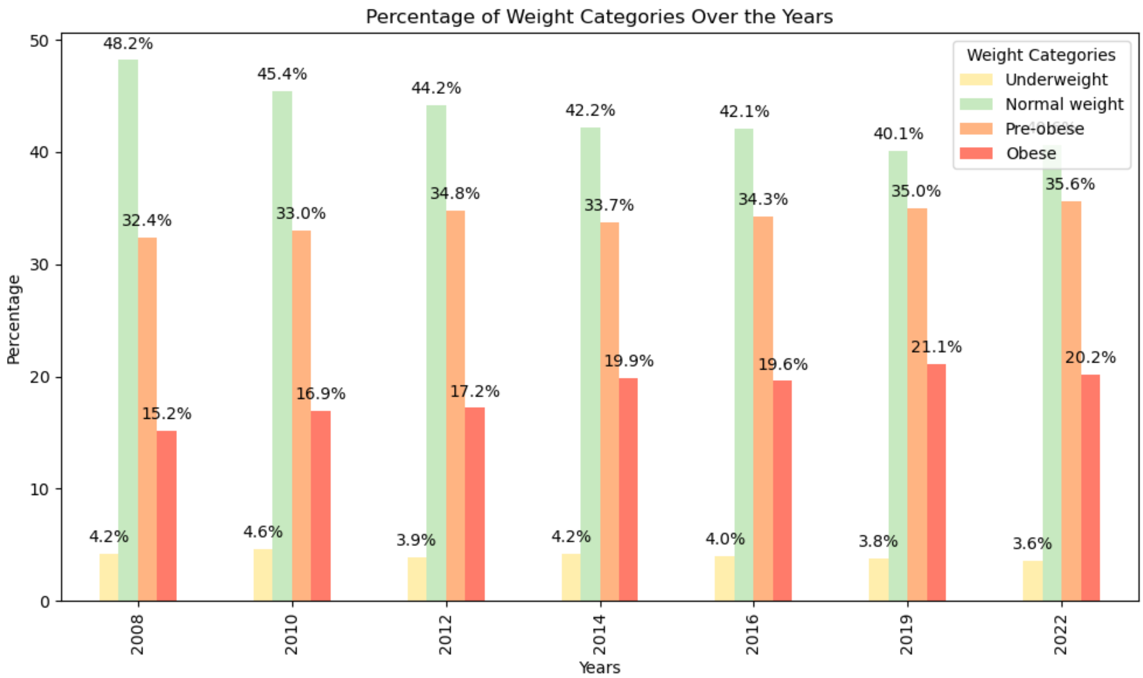
In [33]:
```
#Get the year and cost data
years = expenditures.columns[1:]
expenditure_data = expenditures.iloc[0,1:]
years_int = [int(year) for year in years]

plt.figure(figsize=(10, 6))
plt.plot(years_int, expenditure_data, marker='o', linestyle='-')
plt.title('Expenditures Over Years')
plt.xlabel('Year')
plt.ylabel('Expenditures')
plt.xticks(years_int, rotation=90)
plt.grid(True)
plt.tight_layout()
plt.show()
```



This graph shows that health expenditures increased slowly for a while, but have recently been increasing at a very high pace. With the results obtained from this graph, the impact of the Covid19 Pandemic is clearly visible. In the year of this pandemic and after this year, health expenditures have increased at a very high level, which shows that the importance given to health has increased.

Obese Distribution

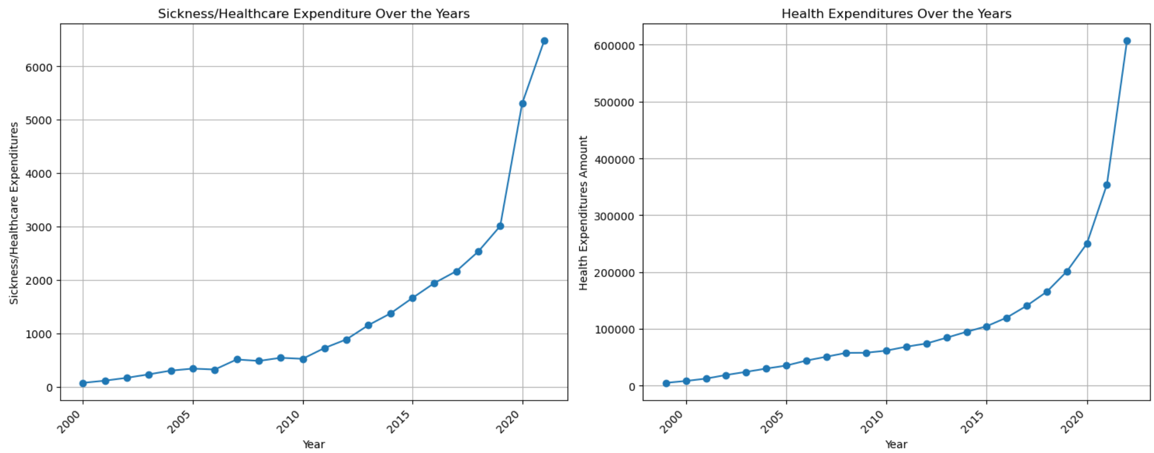
In [34]:
```
colors = {'Underweight': '#ffeead', 'Normal weight': '#c7e9c0', 'Pre-obese':
# Plotting the bar chart
ax = body_mass.transpose().plot(kind='bar', color=[colors[col] for col in bc

plt.title('Percentage of Weight Categories Over the Years')
plt.xlabel('Years')
plt.ylabel('Percentage')
plt.legend(title='Weight Categories')

for p in ax.patches:
    ax.annotate(f'{p.get_height():.1f}%', (p.get_x() + p.get_width() / 2., p
                ha='center', va='center', xytext=(0, 10), textcoords='offset

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



Obesity is a health problem caused by an excessive body mass index. Contrary to efforts in raising awareness within the society, we observe an increase in healthcare expenditures related to obesity over the years. There is a general decrease in the percentage of individuals with normal weight, a tendency of overall decline in underweight individuals, and a fluctuating graph for pre-obese individuals, independent of expenditures.

Sickness/Healthcare Expenditure Over the Years

In [35]:
```
expenditures = pd.read_excel('saglik harcamalari ile ilgili gostergeler.xls'

target_row_index_health = 2

expenditures.columns = expenditures.iloc[target_row_index_health]

expenditures = expenditures.iloc[target_row_index_health + 1:]

expenditures = expenditures.dropna()

expenditures = expenditures.applymap(lambda x: int(x) if pd.notnull(x) and i

columns_health = [int(col) if pd.notna(col) else col for col in expenditures
expenditures.columns = ['Expenditures'] + columns_health[1:]

# Plotting both graphs side by side
plt.figure(figsize=(15, 6))

# Plot for Social Assistance
plt.subplot(1, 2, 1)
plt.plot(healthcare_last.iloc[:,1], healthcare_last.iloc[:, 0], marker='o',
plt.title('Sickness/Healthcare Expenditure Over the Years')
plt.xlabel('Year')
plt.ylabel('Sickness/Healthcare Expenditures')
plt.grid(True)
plt.xticks(rotation=45, ha='right')


# Plot for Health Expenditures
plt.subplot(1, 2, 2)
plt.plot(expenditures.columns[1:], expenditures.iloc[0, 1:], marker='o', lin
plt.title('Health Expenditures Over the Years')
plt.xlabel('Year')
plt.ylabel('Health Expenditures Amount')
plt.grid(True)
plt.xticks(rotation=45, ha='right')

# Adjust layout and display the subplots
plt.tight_layout()
plt.show()
```



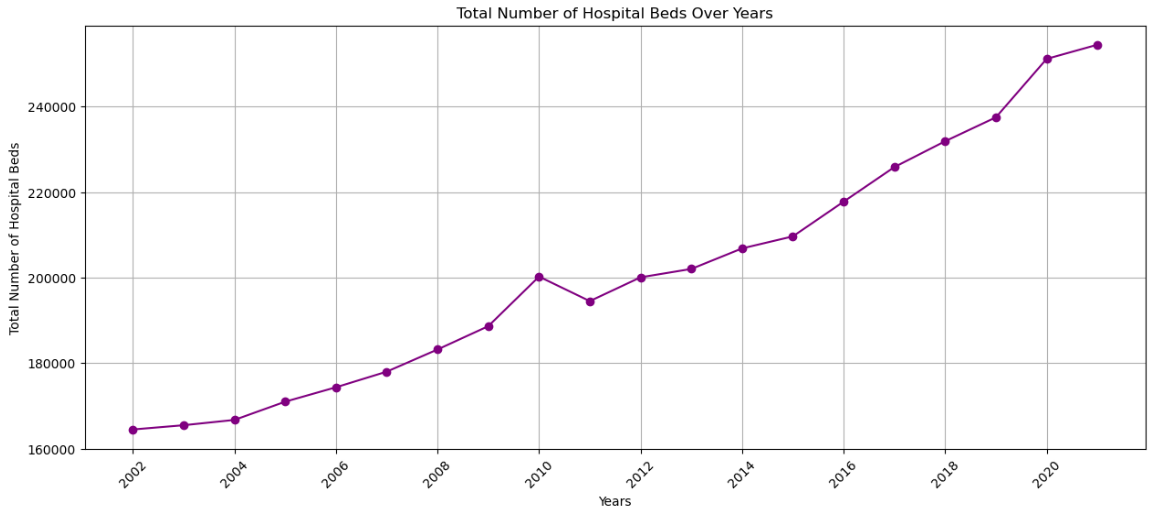
The inference has been made that a portion of healthcare expenditures falls under the category of social assistance. As observed, over the years, expenditures in the healthcare sector and health services under the umbrella of social assistance have shown a coordinated increase.

Total Number of Hospital Beds Over Years

In [36]:
```
df1 = pd.read_excel('hastane_yatak_says.xls')

concatenated_df = pd.concat([df1.iloc[5:7, :], df1.iloc[41:62, :]], ignore_i

concatenated_df= concatenated_df.dropna(axis=1)
combined_row = concatenated_df.iloc[0].astype(str) + ' ' + concatenated_df.i
concatenated_df = concatenated_df.drop([1, 2])
concatenated_df.loc[-1] = combined_row
concatenated_df.index = concatenated_df.index + 1
concatenated_df = concatenated_df.sort_index()
concatenated_df = concatenated_df.drop(1)

target_row_index = 0
concatenated_df.columns = concatenated_df.iloc[target_row_index]
concatenated_df = concatenated_df.iloc[target_row_index + 1:]
```

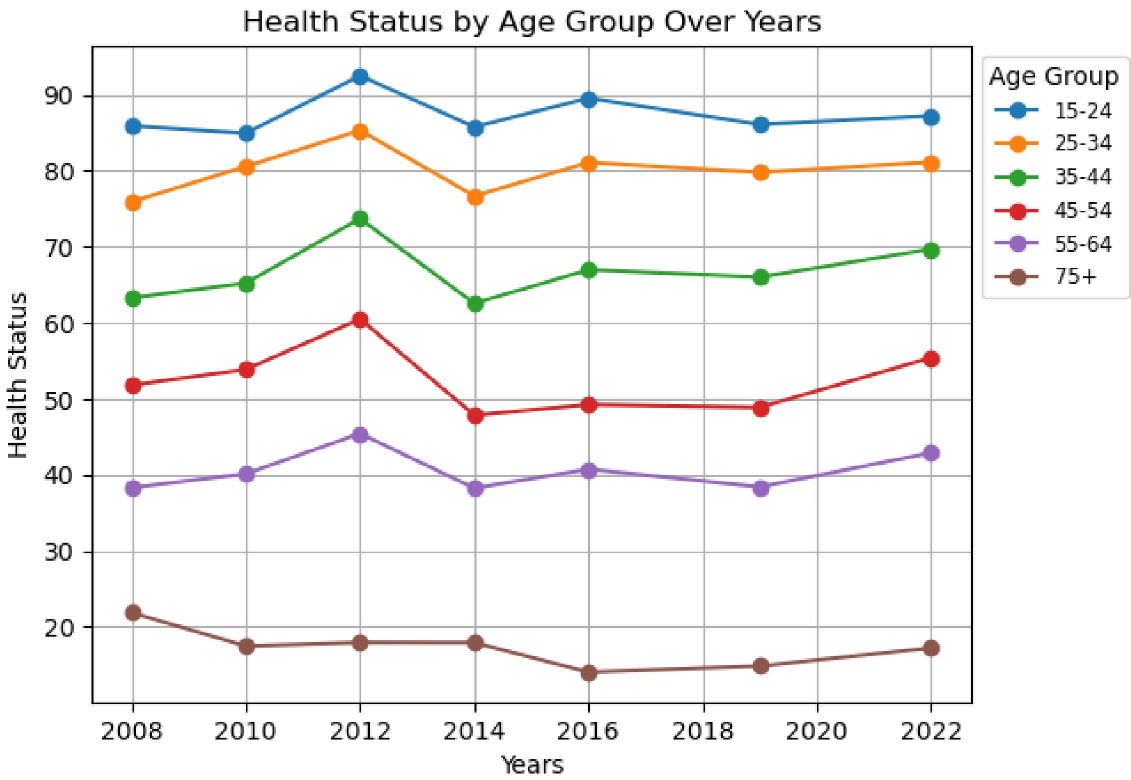
In [37]:
```
years_df = concatenated_df[concatenated_df.columns[0]].values

int_years = [int(year[:4]) if type(year) == str else int(year) for year in y

print(int_years)

beds_df = concatenated_df[['Total number of  hospital beds']].copy()

# Plot the graph
plt.figure(figsize=(15, 6))
plt.plot(int_years, beds_df, marker='o', linestyle='-', color='purple')
plt.title('Total Number of Hospital Beds Over Years')
plt.xlabel('Years')
plt.ylabel('Total Number of Hospital Beds')
plt.xticks(range(min(int_years), max(int_years)+1, 2), rotation=45)
plt.grid(True)
plt.show()
```

```
[2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 20
14, 2015, 2016, 2017, 2018, 2019, 2020, 2021]
```



Health Status by Age Group Over Years

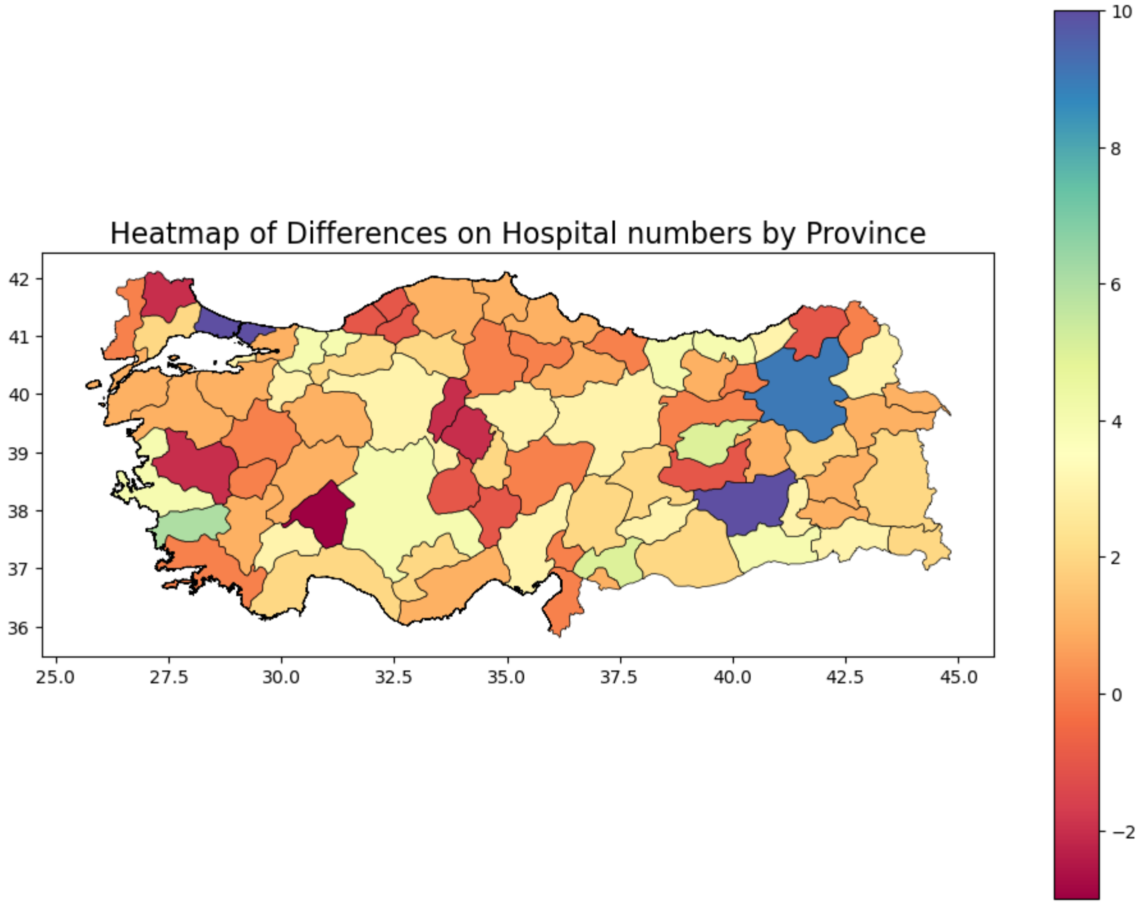
In [38]:
```
# Loop through each row and plot
for index, row in health_with_ages.iterrows():
    plt.plot(health_with_ages.columns[1:], row[1:], label=row['Ages'], marke

# Add labels and title
plt.xlabel('Years')
plt.ylabel('Health Status')
plt.title('Health Status by Age Group Over Years')

plt.rcParams.update({'legend.fontsize': 'small'})

# Add legend to differentiate lines and change its position
plt.legend(title='Age Group', loc='upper left', bbox_to_anchor=(1, 1))
plt.grid()

# Show the plot
plt.show()
```



The dataset above displays the overall health status of individuals across different age groups from 2008 to 2022. This data enables us to observe how health conditions have evolved over the years. Simultaneously, it illustrates how this change varies across different age brackets, showcasing the alteration in health status among age groups over the years.

Hospital Difference Turkey Map

In [39]:
```
geoturkey = pd.merge(turkey,hospital_difference,on="Province")

fig, ax = plt.subplots(1, 1, figsize=(12, 9))
geoturkey.plot(column="Difference", legend=True, cmap="Spectral", ax=ax,edge
plt.title('Heatmap of Differences on Hospital numbers by Province', fontsize

top_cities = geoturkey.nlargest(5, 'Difference')
plt.show()


# Display'top5' and 'lowest5'
print("Top 5 Cities with the highest Difference:")
print(top5)

print("\nLowest 5 Cities with the lowest Difference:")
print(lowest5)
```



```
Top 5 Cities with the highest Difference:
        Cities  Difference
22  Diyarbakır          10
77    İstanbul          10
27     Erzurum           9
9        Aydın           6
29   Gaziantep           5

Lowest 5 Cities with the lowest Difference:
        Cities  Difference
48    Kırşehir          -2
50      Manisa          -2
46  Kırklareli          -2
47   Kırıkkale          -2
34     Isparta          -3
```

We see from this table that health expenditures caused the most change in these cities, and health expenditures were mostly used to increase the number of hospitals in these cities.

Research Questions and Proposed tests

Are there any correlations between years of healthy living and healthcare expenditures?

Our hypothesis is, higher healthcare expenditures correlate positively with an increase in the years of healthy living among the population. Regression analysis model can be used, such as linear regression, to identify relationships between healthcare expenditure (independent variable) and years of healthy living (dependent variable). Correlation analysis can also be used to determine the strength and direction of the relationship.

In [40]:
```
expenditures = expenditures[expenditures["Expenditures"]=="Total health expe
expenditures=expenditures.drop("Expenditures",axis=1)
expenditures.reset_index(inplace=True,drop=True)
years = [2008, 2010, 2012, 2014, 2016, 2019, 2022]
selected_columns = [col for col in expenditures.columns if col in years]
expenditures = expenditures[selected_columns]
expenditures = expenditures.T
expenditures.columns = ["Expenditures"]
expenditures
```

Out[40]:

	Expenditures
2008	57739
2010	61677
2012	74188
2014	94749
2016	119755
2019	201030
2022	606835

In [41]:

```python
age_groups = ['15-24', '25-34', '35-44', '45-54', '55-64', '75+']
new_index_value = health_with_ages.iloc[:,0]
health_with_ages.index = [new_index_value]
health_with_ages=health_with_ages.drop("Ages",axis=1)
health_with_ages = health_with_ages.astype(float)

print(health_with_ages)


def findcorrelation(df):
    correlation=df.corr()
    names=df.columns.to_list()
    print(f"Correlation between {names[0]} and {names[1]}  is :",correlation


age_ranges = ["15-24", "25-34", "35-44", "45-54", "55-64", "75+"]

health_with_ages_list = []

for age_range in age_ranges:
    temp = health_with_ages.loc[age_range].T
    health_with_ages_list.append(temp)

for i in health_with_ages_list:
    df = pd.merge(i,expenditures,left_index=True, right_index=True)
    findcorrelation(df)
```

```
25-34   75.901548  80.545748  85.296996  76.667881  81.075248  79.774367
35-44   63.265173  65.212058  73.682511  62.534223  66.958897  65.985747
45-54   51.782979  53.840895  60.473288  47.833804  49.201874  48.850269
55-64   38.294831  40.113756  45.408718  38.229355  40.725837  38.388261
75+     21.837342  17.457172  17.911589  17.899089  14.025103  14.824537

0            2022
Ages
15-24   87.201652
25-34   81.126461
35-44   69.676422
45-54   55.402543
55-64   42.879847
75+     17.202585
Correlation between ('15-24',) and Expenditures  is : -0.0500467833218255
1
Correlation between ('25-34',) and Expenditures  is : 0.15501361821520007
Correlation between ('35-44',) and Expenditures  is : 0.3182353986717579
Correlation between ('45-54',) and Expenditures  is : 0.1591551755447171
```

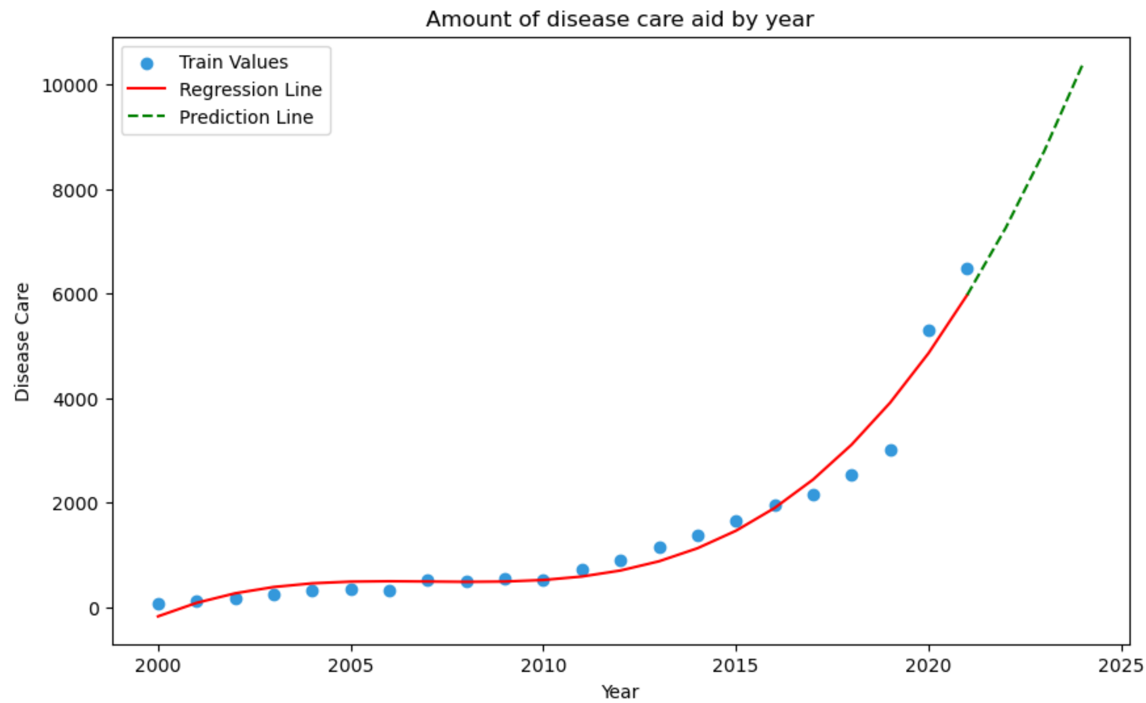
Does healthcare spending affect obesity in a positive way?

Our hypothesis is, increased healthcare spending leads to a reduction in obesity rates due to better healthcare services and preventative programs. Logistic regression model can be applied to predict the probability of obesity prevalence based on healthcare spending. This method can handle binary outcomes (e.g., obese vs. not obese) and model the relationship with spending.

How do healthcare expenditures affect social assistance programs such as disease care?

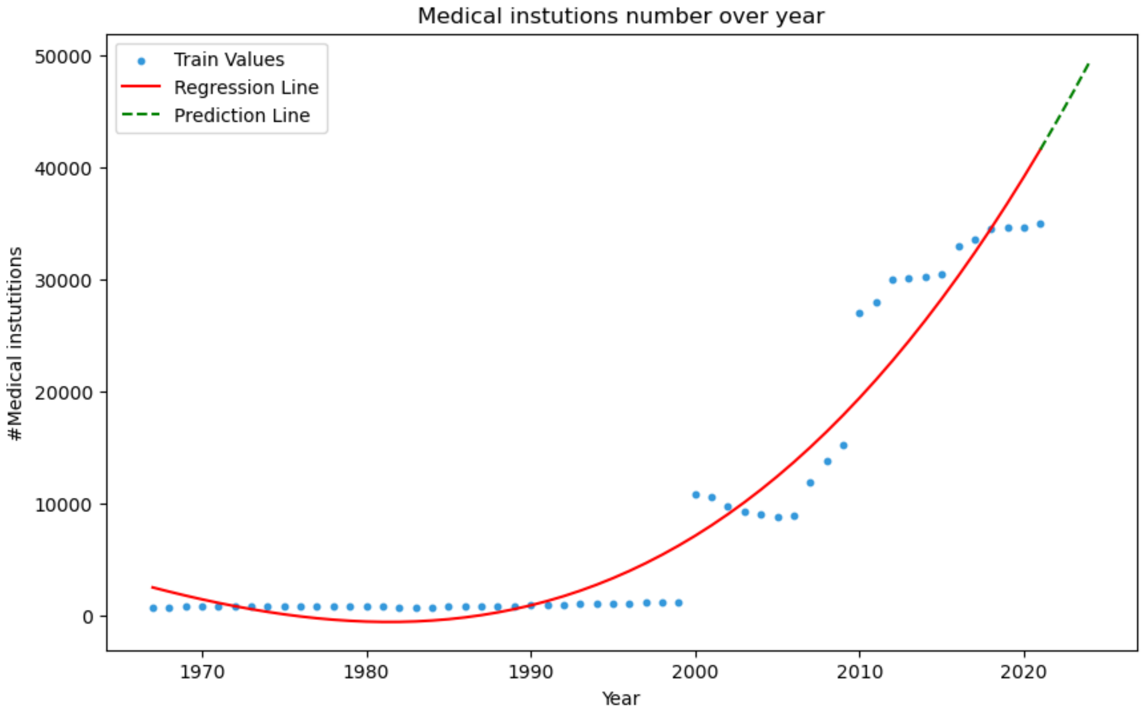
Our hypothesis is higher healthcare expenditures improve the effectiveness and reach of social assistance programs, leading to better disease care outcomes. A multivariate regression model could be used to analyze how different levels of healthcare spending impact various aspects of social assistance programs (e.g., program availability, quality of care).

In [42]:
```
x = healthcare_last.iloc[:,1].values.reshape(-1,1)
y = healthcare_last.iloc[:, 0].values.reshape(-1,1)
poly = PolynomialFeatures(degree=3)

future_years = np.array(range(2021, 2025)).reshape(-1, 1)

X_train_poly = poly.fit_transform(x)
X_test_future = poly.fit_transform(future_years)

polynomial = LinearRegression()
polynomial.fit(X_train_poly, y)

future_test_pred = polynomial.predict(X_test_future)
poly_regression = polynomial.predict(X_train_poly)


fig = plt.subplots(figsize=(10, 6))
plt.scatter(x,y, color='#3498DB')
plt.plot(x, poly_regression, color='red')
plt.plot(future_years, future_test_pred, color='green', linestyle='dashed')
plt.legend(['Train Values', 'Regression Line','Prediction Line'],prop={'size
plt.title("Amount of disease care aid by year")
plt.xlabel('Year')
plt.ylabel("Disease Care")
plt.show()
```



Did the healthcare expenditures lead to critical change in hospital and bed capacities?

In [43]:
```
x = hospitalnumber.iloc[:, :-1].values
y = hospitalnumber.iloc[:, 1].values
poly = PolynomialFeatures(degree=3)
future_years = np.array(range(2021,2025)).reshape(-1, 1)

X_train_poly = poly.fit_transform(x)
X_test_future = poly.fit_transform(future_years)

polynomial = LinearRegression()
polynomial.fit(X_train_poly,y)

future_test_pred = polynomial.predict(X_test_future)
poly_regression = polynomial.predict(X_train_poly)


fig = plt.subplots(figsize=(10, 6))
plt.scatter(x,y, color='#3498DB',s=10)
plt.plot(x, poly_regression, color='red')
plt.plot(future_years, future_test_pred, color='green', linestyle='dashed')
plt.legend(['Train Values', 'Regression Line','Prediction Line'],prop={'size
plt.title("Medical instutions number over year")
plt.xlabel('Year')
plt.ylabel("#Medical instutitions")

plt.xticks()
plt.show()
```



Our hypothesis is, increases in healthcare expenditures have significantly contributed to the expansion of hospital and bed capacities. Time series analysis or interrupted time series analysis would be suitable to examine changes over time, especially if you have data pre- and post-expenditure changes.

Is the distribution of health expenditures by province balanced based on the changing number of hospitals?

Our hypothesis is: The distribution of health expenditures across provinces is not balanced and does not correspond proportionally to the number of hospitals. Cluster analysis could be used to group provinces based on similarities in expenditure and hospital numbers, identifying patterns and imbalances in distribution.

Has the pandemic created a crucial change in health expenditures?

Our hypothesis is: The onset of the pandemic has led to a significant increase in health expenditures due to increased demand for medical services and resources. Interrupted time series analysis or a difference-in-differences approach could be effective in assessing the impact of the pandemic as an 'interruption' or 'treatment' on healthcare spending trends.

Potential products or how to convert this project to a service or product

"Focused Expenditure Prediction & Optimization": This service uses advanced machine learning algorithms to analyze current healthcare expenditure trends, identifying areas of high spending and their impacts. It then forecasts future expenditure patterns and effects, focusing on key areas like hospital infrastructure, obesity management, or public health programs. Based on these predictions, the service recommends the most efficient allocation of resources and strategies to optimize healthcare outcomes, guiding decision-makers towards more effective and targeted health investments. This approach aims to maximize the impact of healthcare spending by aligning it with the most critical health needs and trends.

To develop the "Focused Expenditure Prediction & Optimization" service, machine learning models will be trained using historical healthcare data, identifying key expenditure areas and their impacts. These models will forecast future spending patterns and assess potential outcomes of different health indicators. Optimization algorithms will then recommend efficient resource allocations, focusing on maximizing health impacts. The system will incorporate continuous learning, regularly updating with new data to refine predictions and maintain accuracy in its recommendations.

Any issues related to data engineering

1. Machine Learning Model Maintenance:

For our project, Machine Learning Model Maintenance entails regularly updating and retraining the predictive models with new healthcare data to adapt to changing health trends and policies, ensuring ongoing accuracy and relevance in forecasting healthcare expenditures and optimization recommendations.

2. Scalability:

The system should be scalable to handle increasing amounts of data and users. This involves using scalable architectures like cloud services and designing databases that can grow without performance degradation.

3. Data Quality and Consistency:

Ensuring high-quality, accurate, and consistent data is crucial. This involves cleaning, normalizing, and standardizing data from diverse sources to avoid issues like missing values, duplicates, or inconsistent formats.

Any issues related ethics

In the project, data utilization is legally unrestricted and can be leveraged as long as the government agrees to share it, posing no current issues in terms of access permissions or ethics.

Our dataset, which includes the number of hospitals, encompasses data from various institutions like university hospitals, state hospitals, and private hospitals. Currently, the project utilizes only state hospital data. However, if the project is expanded to include data from private hospitals, permission may need to be obtained from these private institutions for data access.

Conclusion

In conclusion, our project, "Health Status & Expenditures," has shed light on the intricate relationships between healthcare expenditures and key factors such as the number of hospitals by province, obesity rates, hospital bed capacities, social assistance programs, and individual health status. We have observed that the relationships among certain datasets align with our expectations, paving the way for accurate predictions through machine learning algorithms.