Introduction to data analysis using pandas

Pandas is a popular open source Python package for data science, data engineering, analytics, and machine learning.

This notebook will give you a gentle introduction to pandas, but the exercises have been deisgned to allow you to complete them in multiple ways so feel free to google and find different functions. For more helpful documentation, check out these resources:

Completely new to coding?

- If you are new to google colab you can watch an introduction to it here.
- If you have never used python before you can read an introduction to the language here

New to pandas?

- Introduction to Pandas in colab: https://colab.google/articles/pandas
- Pandas documentation introduction: https://pandas.pydata.org/docs/user_guide/10min.html

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Data we are using for analysis

This data is from the NSHBSA Open Data Portal, and is called the 'Prescription Cost analysis' dataset.

https://opendata.nhsbsa.net/dataset/prescription-cost-analysis-pca-monthly-data

This data is open source, which means:

- We can share it openly
- It has no security concerns

This is a monthly dataset that describes how many medicines were prescribed across all GP Practices in england, per NHS Region, and what they cost. This is 'real data', so actually describes real anti-depressant prescribing in England. We have merged, simplified and filtered all these monthly files into a single dataset.

The data is being read into this notebook using this github repo link below (do not delete).

In [2]:
```
! git clone https://github.com/nhsengland/Digdata
```

```
Cloning into 'Digdata'...
remote: Enumerating objects: 40, done.
remote: Counting objects: 100% (40/40), done.
remote: Compressing objects: 100% (40/40), done.
remote: Total 40 (delta 21), reused 1 (delta 0), pack-reused 0 (from 0)
Receiving objects: 100% (40/40), 238.24 KiB | 1.21 MiB/s, done.
Resolving deltas: 100% (21/21), done.
```

pca_regional_drug_summary_df

This dataset now contains 6 columns:

- *YEAR*: The year in the format YYYY. There are 4 years-worth of prescribing information in the dataset.
- *YEAR_MONTH*: The year and month, in the format YYYYMM, where 202401 is the same as January 2024. There are 46 year-month values in the data.
- *REGION*: The NHS Region. There are 7 regions in the data.
- *DRUG*: The name of the anti-depressant medicine. There are 32 of these in the data.
- *ITEMS*: How many items were prescribed.

- *COST*: The combined cost for all those items.

In a sentence we could describe this dataset as:

- Per English NHS Region and per year-month, the volume and cost of each antidepressant drug prescribed.

And what we are going to do with this data is:

- Understand national and regional prescribing volumes and costs
- Understand national and regional prescribing trends
- Understand monthly and annual trends
- And finally, maybe even predict future monthly anti-depressant prescribing volumes

In [3]:
```
pca_regional_drug_summary_df = pd.read_csv('/content/Digdata/BSA_ODP_PCA_REGIONAL_DRUG_SUMMARY.csv')

display(pca_regional_drug_summary_df)
```

	YEAR	YEAR_MONTH	REGION_NAME	BNF_CHEMICAL_SUBSTANCE	ITEMS	COST
0	2021	202101	EAST OF ENGLAND	Agomelatine	183	7405.37
1	2021	202101	LONDON	Agomelatine	411	18227.63
2	2021	202101	MIDLANDS	Agomelatine	252	12344.56
3	2021	202101	NORTH EAST AND YORKSHIRE	Agomelatine	366	11183.06
4	2021	202101	NORTH WEST	Agomelatine	119	4783.72
...	...	...	...	...	...	...
9450	2024	202410	MIDLANDS	Vortioxetine	5989	149309.82
9451	2024	202410	NORTH EAST AND YORKSHIRE	Vortioxetine	6687	139779.09
9452	2024	202410	NORTH WEST	Vortioxetine	5430	124510.32
9453	2024	202410	SOUTH EAST	Vortioxetine	7018	178709.85
9454	2024	202410	SOUTH WEST	Vortioxetine	1992	50313.78

9455 rows × 6 columns

pca_regional_summary_df

So we can see that the original data differs in a few ways:

- It only contains antidepressant drugs
- It doesn't contain BNF Chapter and BNF Section information

The BNF stands for the *British National Formulary*. The BNF is structured hierarchically into Chapters, Sections and Chemical Substances (Drugs).

For example:

- Amitriptyline hydrochloride is an actual antidepressant *DRUG*
- Amitriptyline hydrochloride is one of many *DRUG* within the 'Antidepressant drugs' *BNF_SECTION*
- Antidepressant drugs is one of many *BNF_SECTION* within the '04: Central Nervous System' *BNF_CHAPTER*
- And there are 23 *BNF_CHAPTER* (although very little prescribing stems from some of the chapters)

In summary, BNF chapters are split into sections, which are then split into actual drugs (i.e. a hierarchy).

In [4]:
```
pca_regional_summary_df = pd.read_csv('/content/Digdata/BSA_ODP_PCA_REGIONAL_SUMMARY.csv')

display(pca_regional_summary_df)
```

	YEAR_MONTH	REGION_NAME	ITEMS	COST
0	202101	EAST OF ENGLAND	796466	3406002.61
1	202101	LONDON	678021	3205663.66
2	202101	MIDLANDS	1249416	5698605.43
3	202101	NORTH EAST AND YORKSHIRE	1428677	5741978.96
4	202101	NORTH WEST	1003963	4435228.70
...	...	...	...	...
317	202410	MIDLANDS	1515794	3650020.71
318	202410	NORTH EAST AND YORKSHIRE	1845998	3766629.55
319	202410	NORTH WEST	1196871	2687352.76
320	202410	SOUTH EAST	972188	2852364.46
321	202410	SOUTH WEST	746315	1883877.39

322 rows × 4 columns

Part 1 Pandas introduction: Transforming and Aggregating Data

Printing data

There are a few methods you can use to view your dataframe, given the name df:

```
# shows you the top 5 rows of a dataframe
df.head(5)

# this displays your dataframe
display(df)

# this displays the datatype of each column
df.info()

# this prints a list of columns in the df
df.columns
```

Selecting data

To view only one, or multiple columns in the dataframe, use the following syntax:

```
#this will display a single column, 'prescription_count'
df['prescription_count']

#this will display both 'prescription_count' and 'gp_practice'. Remember to use double brackets to
view multiple columns!
df[['prescription_count', 'gp_practice']]
```

Aggregating data

To read more:

- grouby documentation
- sort_values documentation

```
# this calculates the total number stored in 'prescription_count', so the total count of
prescriptions
df['prescription_count'].sum()

# this calculates the total number of prescriptions, grouped by GP practice
df.groupby('gp_practice', as_index=False)['prescription_count'].sum()

# this sorts the values of the df by the values in column 'cost' from low to high
df.sort_values(by=['cost'])
```

Filtering data

To read more:

- Filtering to a column value
- Using the query method

```python
# this filters to a specific value within a column, in this instance where the year is 2023
df[df['year']==2023]

# this filters to where drug counts are greater than 100
df[df['drug_count']>100]

# this also filters to where drug counts are greater than 100
df.query('drug_count > 100')
```

Part 1: Transforming and Aggregating Data Exercises

Question 1: Nationally, calculate the top 10 prescribed anti-depressants across the whole time frame, sorted from biggest from smallest.

In [5]:
```python
# Calculate the top 10 prescribed anti-depressants
pca_regional_drug_summary_df.groupby('BNF_CHEMICAL_SUBSTANCE')['ITEMS'].sum().sort_values(ascending=False).head
```

Out[5]:

	BNF_CHEMICAL_SUBSTANCE	ITEMS
0	Sertraline hydrochloride	85402251
1	Amitriptyline hydrochloride	59272937
2	Citalopram hydrobromide	52891620
3	Mirtazapine	46335570
4	Fluoxetine hydrochloride	28211759
5	Venlafaxine	21447209
6	Duloxetine hydrochloride	14262656
7	Escitalopram	6580386
8	Paroxetine hydrochloride	4886615
9	Trazodone hydrochloride	4861813

Question 2: Calculate the monthly national cost of Mirtazapine prescribing

In [6]:
```python
# Calculate the monthly national cost of Mirtazapine prescribing
pca_regional_drug_summary_df[
    pca_regional_drug_summary_df["BNF_CHEMICAL_SUBSTANCE"] == "Mirtazapine"
].groupby("YEAR_MONTH")["COST"].sum().reset_index()
```

Out[6]:

	YEAR_MONTH	COST
0	202101	2380030.90
1	202102	2249220.63
2	202103	2523008.14
3	202104	2039348.02
4	202105	1935629.32
5	202106	2055820.88
6	202107	1609248.23
7	202108	1539582.17
8	202109	1621383.70
9	202110	1356643.04
10	202111	1429072.08
11	202112	1496540.76
12	202201	1174913.49
13	202202	1094983.89
14	202203	1248772.91
15	202204	1141081.07
16	202205	1190452.94
17	202206	1155918.28
18	202207	1060524.71
19	202208	1097570.56
20	202209	1107894.62
21	202210	1096392.40
22	202211	1125694.74
23	202212	1153658.07
24	202301	1137624.14
25	202302	1046988.40
26	202303	1202506.98
27	202304	1076691.16
28	202305	1151848.40
29	202306	1170895.45
30	202307	1067405.39
31	202308	1093233.80
32	202309	1083696.99
33	202310	1137520.24
34	202311	1197370.59
35	202312	1189870.33
36	202401	1295778.19
37	202402	1197220.63
38	202403	1206946.43
39	202404	1259733.88
40	202405	1287895.19
41	202406	1196151.06
42	202407	1479650.60
43	202408	1319024.11
44	202409	1292033.75
45	202410	1302293.45

Question 3: What is the annual spend of Sertraline hydrochloride prescribing in the Midlands region?

In [7]:
```python
# Calculate the annual spend of Sertraline hydrochloride prescribing in the Midlands region
pca_regional_drug_summary_df[
    (pca_regional_drug_summary_df["BNF_CHEMICAL_SUBSTANCE"] == "Sertraline hydrochloride") &
    (pca_regional_drug_summary_df["REGION_NAME"] == "MIDLANDS")
].groupby("YEAR")["COST"].sum().reset_index()
```

Out[7]:

	YEAR	COST
0	2021	17477276.46
1	2022	6433863.59
2	2023	7600322.04
3	2024	8094889.16

Part 2: Data Visualisation

Visualising is an important tool in both analytics and data science.

Visualising data can help us better understand data and see trends in data, amongst other things.

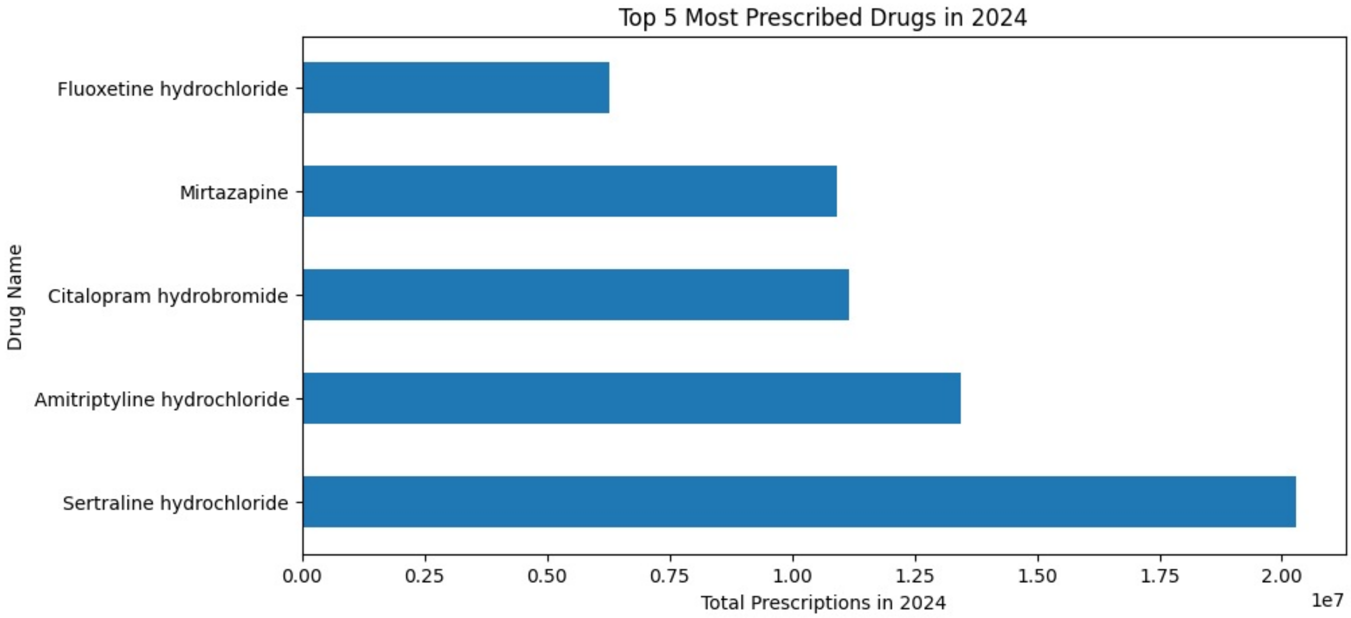
There are several packages which you can explore through these links here:

- A good start point for data visualisations in pandas can be found here- https://www.geeksforgeeks.org/pandas-built-in-data-visualization-ml/
- Introduction to the python package matplotlib - https://www.geeksforgeeks.org/python-introduction-matplotlib/
- Introduction to the python package seaborn - https://www.geeksforgeeks.org/introduction-to-seaborn-python/

Part 2: Data Visualisation Exercises

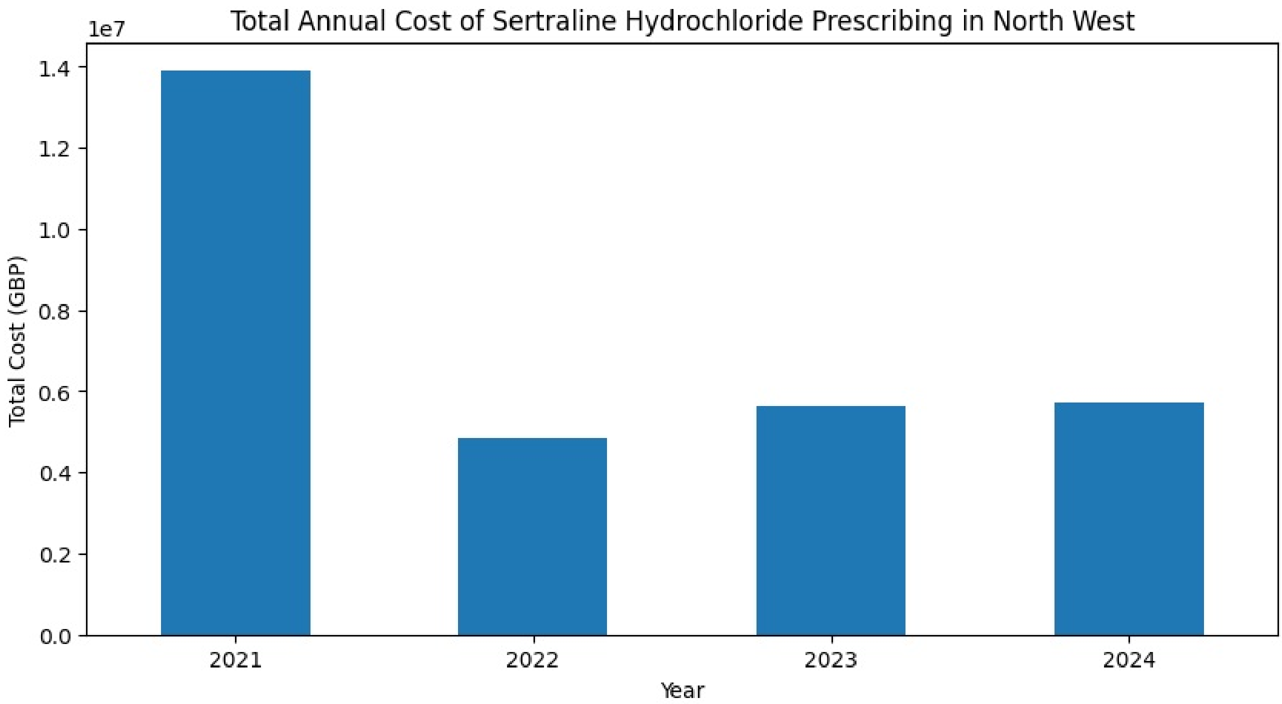
Question 1: Create a horizontal bar chart of the top 5 most prescribed drugs in 2024, arranged in order.

In [8]:
```python
# Filter data for 2024 and get the top 5 prescribed drugs
top_5_drugs_2024 = pca_regional_drug_summary_df[
    pca_regional_drug_summary_df["YEAR"] == 2024
].groupby("BNF_CHEMICAL_SUBSTANCE")["ITEMS"].sum().sort_values(ascending = False).head(5)

# Plot the horizontal bar char
top_5_drugs_2024.plot(kind="barh", figsize=(10, 5))

# Customize labels and title
plt.xlabel("Total Prescriptions in 2024")
plt.ylabel("Drug Name")
plt.title("Top 5 Most Prescribed Drugs in 2024")
plt.show()
```



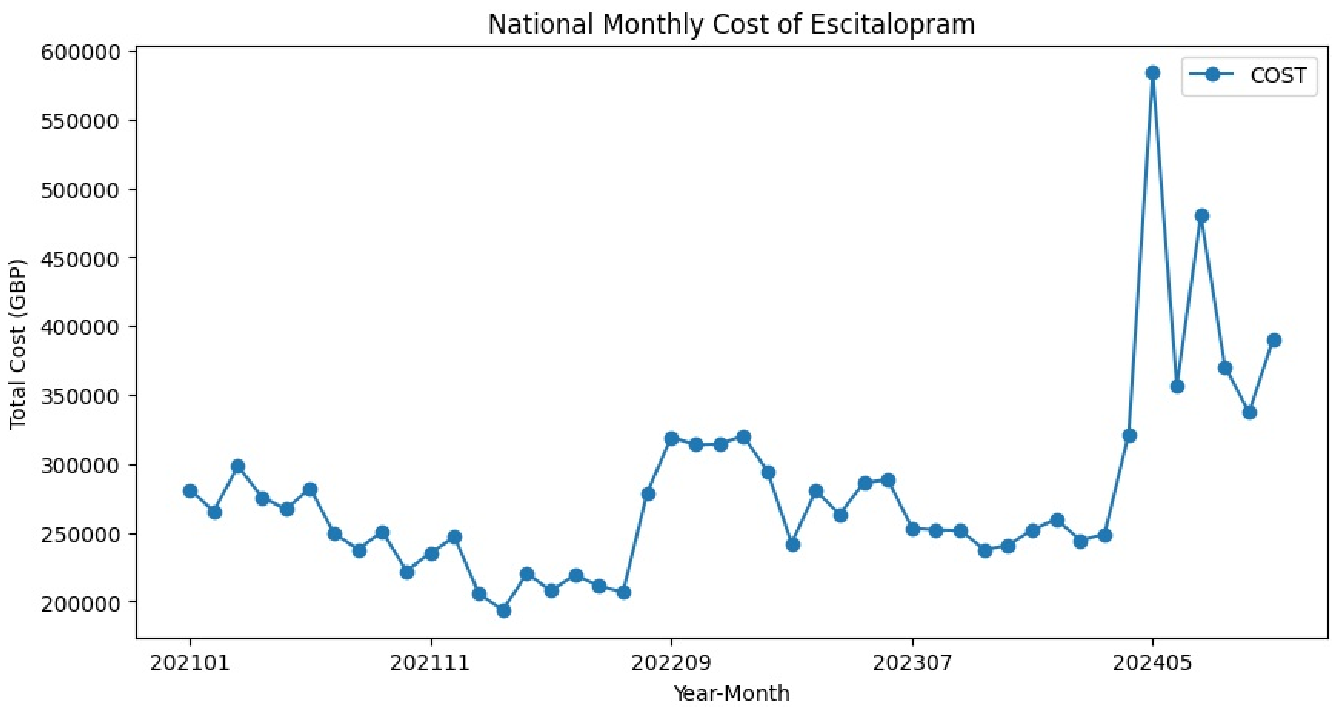
Question 2: Create a vertical bar chart showing the total annual cost of Sertraline hydrochloride prescribing in the NORTH WEST region.

In [9]:
```python
# Filter data for Sertraline hydrochloride in the North West region
sertraline_northwest_annual_cost = pca_regional_drug_summary_df[
    (pca_regional_drug_summary_df["BNF_CHEMICAL_SUBSTANCE"] == "Sertraline hydrochloride") &
    (pca_regional_drug_summary_df["REGION_NAME"] == "NORTH WEST")
].groupby("YEAR")["COST"].sum()

# Plot the vertical bar chart
sertraline_northwest_annual_cost.plot(kind="bar", figsize=(10, 5))

# Customize labels and title
plt.xlabel("Year")
plt.ylabel("Total Cost (GBP)")
plt.title("Total Annual Cost of Sertraline Hydrochloride Prescribing in North West")
plt.xticks(rotation=0)
plt.show()
```



Question 3: Create a line chart of the nationally monthly cost (rounded to the nearest pound) of escitalopram.

In [10]:
```python
# Filter data for Escitalopram and calculate the monthly national cost
escitalopram_monthly_cost = pca_regional_drug_summary_df[
    pca_regional_drug_summary_df["BNF_CHEMICAL_SUBSTANCE"] == "Escitalopram"
].groupby("YEAR_MONTH")["COST"].sum().round(0).reset_index()

# Convert YEAR_MONTH to string for proper x-axis labeling
escitalopram_monthly_cost["YEAR_MONTH"] = escitalopram_monthly_cost["YEAR_MONTH"].astype(str)

# Plot the line chart
escitalopram_monthly_cost.plot(x="YEAR_MONTH", y="COST", kind="line", figsize=(10, 5), marker="o")

# Customize labels and title
plt.xlabel("Year-Month")
plt.ylabel("Total Cost (GBP)")
plt.title("National Monthly Cost of Escitalopram")
plt.show()
```



Part 3: Data Metrics and Insights

Advanced analysis introduction

- Introduction to statistics in pandas
- Pivot tables

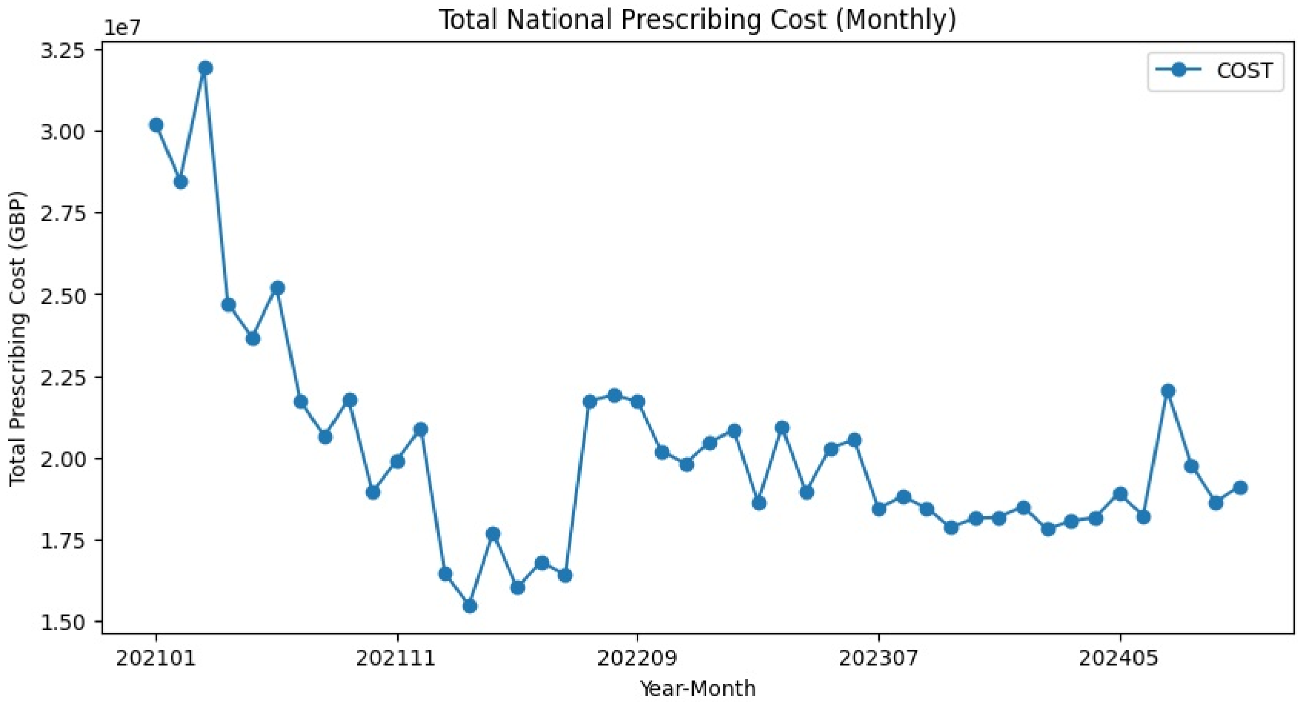
```
# this gives a summary of some descriptive statistics for the dataframe
df.describe()

# this will return the average number in the drug count field
df['drug_count'].mean()

# this will return the minimum value, the lowest observed value
df['drug_count'].min()

# this will return the maximum value, the highest observed value
df['drug_count'].max()

# this will pivot the df so each row represents a year, the columns are now the regions and the values are the summed count of the items within the column 'drug_count'
df.pivot_table(index='year', columns='region', values='drug_count', aggfunc=sum)
```

Part 3: Data Metrics and Insight Exercises

For these exercises, you will need to use the dataframe pca_regional_drug_summary_df

Question 1: For context, create a monthly line chart showing total national prescribing cost

In [11]:
```
# Aggregate total national prescribing cost per month
monthly_cost = pca_regional_drug_summary_df.groupby("YEAR_MONTH")["COST"].sum().reset_index()

# Convert YEAR_MONTH to string for proper x-axis labeling
monthly_cost["YEAR_MONTH"] = monthly_cost["YEAR_MONTH"].astype(str)

# Plot the line chart
monthly_cost.plot(x="YEAR_MONTH", y="COST", kind="line", figsize=(10, 5), marker="o")

# Customize labels and title
plt.xlabel("Year-Month")
plt.ylabel("Total Prescribing Cost (GBP)")
plt.title("Total National Prescribing Cost (Monthly)")
plt.show()
```



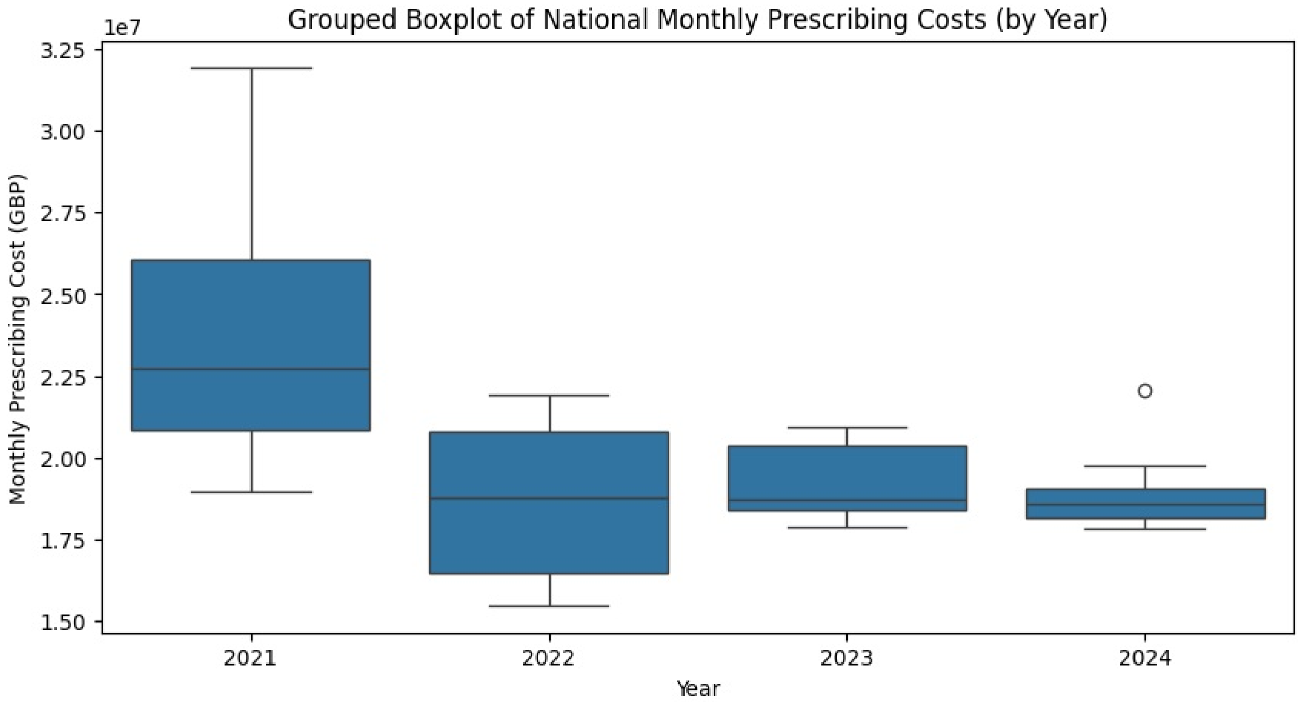
Question 2: Create *annual* summary statistics, for the min, Q1, median, Q3 and maximum national monthly prescribing cost (i.e. all drugs across all regions)

In [12]:
```
# Calculate national monthly prescribing cost per year
national_monthly_cost = pca_regional_drug_summary_df.groupby(["YEAR", "YEAR_MONTH"])["COST"].sum()

# Calculate summary statistics for the national monthly prescribing cost
national_monthly_stats = national_monthly_cost.groupby("YEAR").describe(percentiles=[0.25, 0.5, 0.75]).reset_in

# Rename columns for clarity
national_monthly_stats.columns = ["YEAR", "Min", "Q1(25%)", "Median (50%)", "Q3(75%)", "Max"]

# Display the results
print(national_monthly_stats)
```

```
   YEAR          Min       Q1(25%)  Median (50%)       Q3(75%)          Max
0  2021  18949756.25  2.083549e+07  2.272424e+07  2.603658e+07  31933609.64
1  2022  15453991.47  1.645837e+07  1.875420e+07  2.077687e+07  21914896.72
2  2023  17859075.18  1.836279e+07  1.872291e+07  2.034416e+07  20934041.83
3  2024  17802904.89  1.816383e+07  1.856003e+07  1.905628e+07  22071625.09
```

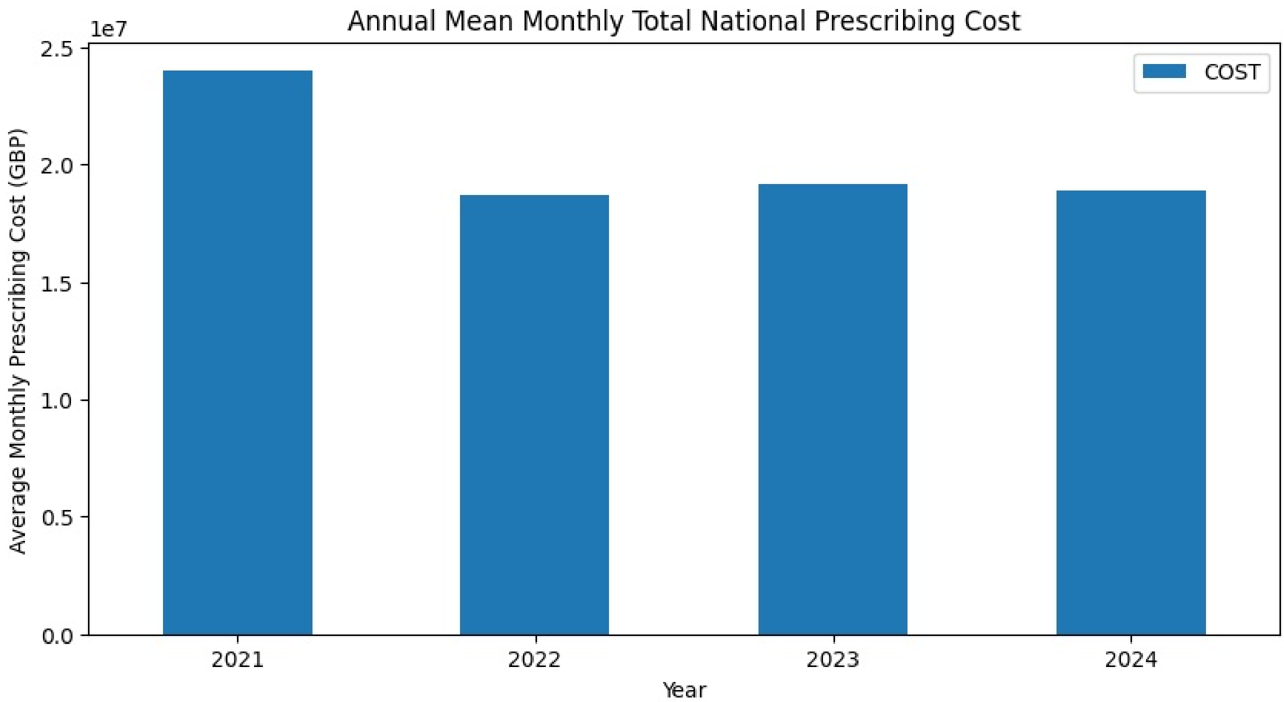
Question 3: Create a grouped boxplot that shows the above information (4 boxplots, 1 per year)

In [13]:
```
# Create a grouped boxplot
plt.figure(figsize=(10, 5))
sns.boxplot(x="YEAR", y="COST", data=national_monthly_cost.reset_index())

# Customize labels and title
plt.xlabel("Year")
plt.ylabel("Monthly Prescribing Cost (GBP)")
plt.title("Grouped Boxplot of National Monthly Prescribing Costs (by Year)")
plt.show()
```



Question 4: Calculate the annual *mean* monthly total national prescribing cost and display in a vertical barchart

In [14]:
```
# Calculate the annual mean monthly total national prescribing cost
annual_mean_cost = national_monthly_cost.groupby("YEAR").mean().reset_index()

# Plot the vertical bar chart
annual_mean_cost.plot(x="YEAR", y="COST", kind="bar", figsize=(10, 5))

# Customize labels and title
plt.xlabel("Year")
plt.ylabel("Average Monthly Prescribing Cost (GBP)")
plt.title("Annual Mean Monthly Total National Prescribing Cost")
plt.xticks(rotation=0)
plt.show()
```

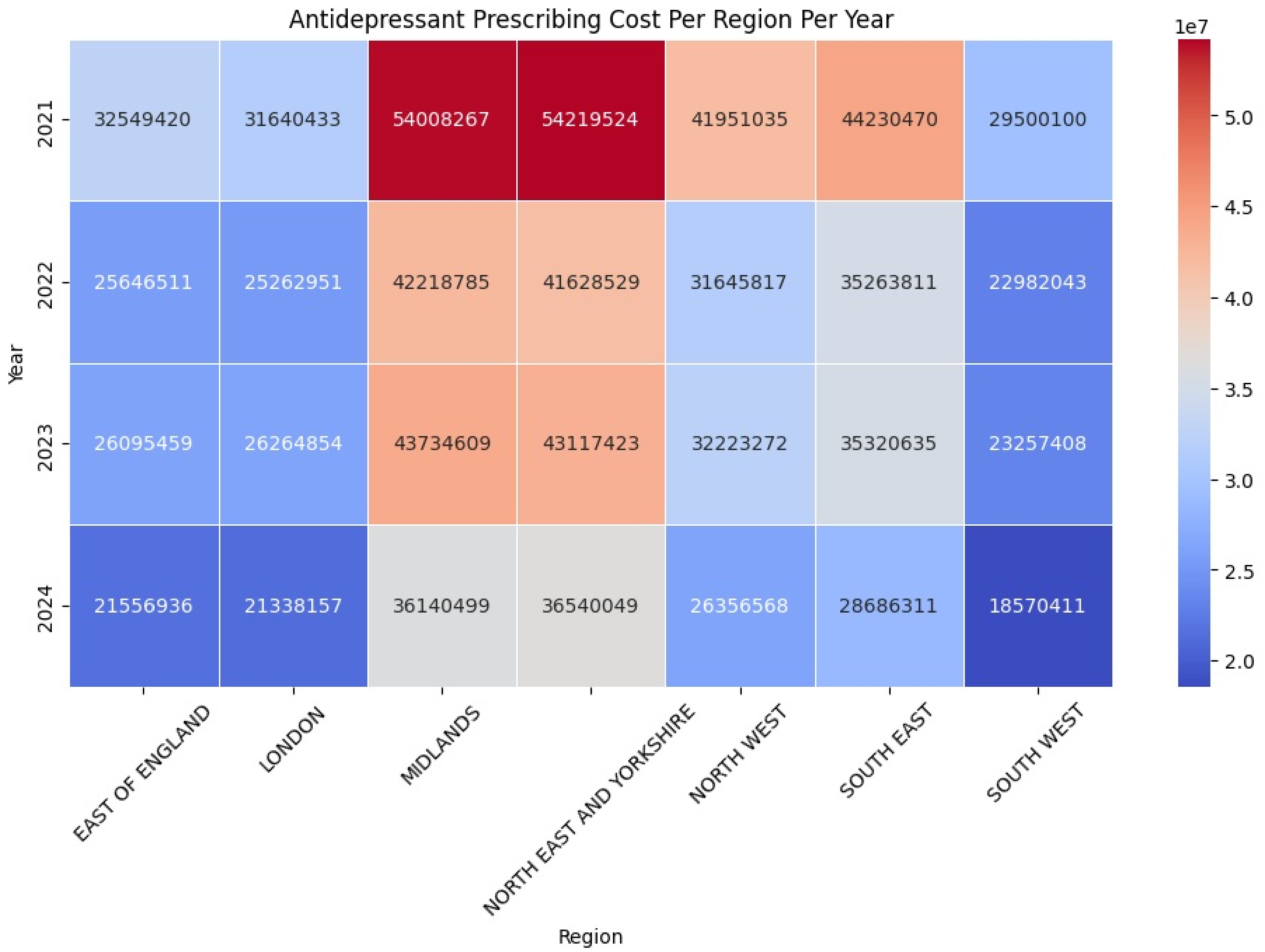


Question 5: Create a (pivoted) table that shows the cost of anti-depressant prescribing per region per year?

Note: Each row should be a year and each column should be a region.

In [15]:
```
# Create a pivot table for antidepressant prescribing cost per region per year
drug_cost_pivot = pca_regional_drug_summary_df.pivot_table(index="YEAR", columns="REGION_NAME", values="COST", a
```

```python
# Display the pivot table by heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(drug_cost_pivot, annot=True, fmt=".0f", cmap="coolwarm", linewidths=0.5)

# Customize labels
plt.xlabel("Region")
plt.ylabel("Year")
plt.title("Antidepressant Prescribing Cost Per Region Per Year")
plt.xticks(rotation=45)
plt.show()
```



Report Task

You are a Public Health Analyst and you have been asked to write a report. This report will describe and analyse antidepressant prescribing, looking at volume and cost, both nationally and regionally. The title of this report is 'Longitudinal Analysis of Antidepressant Prescribing'. Longitudinal just means the analysis is over an extended period of time, which we have with 4 years of monthly data. The report is to be split into two sections:

Part One: To set the context for the report, this will be overall national and regional figures

Part Two: The will be followed-up by a more exploratory analysis that delves into antidepressant prescribing cost trends.

Part Two Extension: Those attempting the extension task can then look at creating standardised metrics to understand more specific prescribing patterns.

In [15]:

```python

```

Part One

Part One is a directed analysis and the same content needs to be covered by both streams. These required content for Part One is:

1. Create two vertical bar charts for comparison. First, create a bar chart showing the total annual antidepressant prescribing (items). Second, create a bar chart that shows the total antidepressant prescribing cost. Describe the trend of each chart and compare the charts against each other.
2. Create two tables for comparison. First, create a table showing the total annual antidepressant prescribing per region (items).

Second, create a table showing the annual antidepressant prescribing cost per region. Describe some regional changes and contrasts between 2021 and 2024.

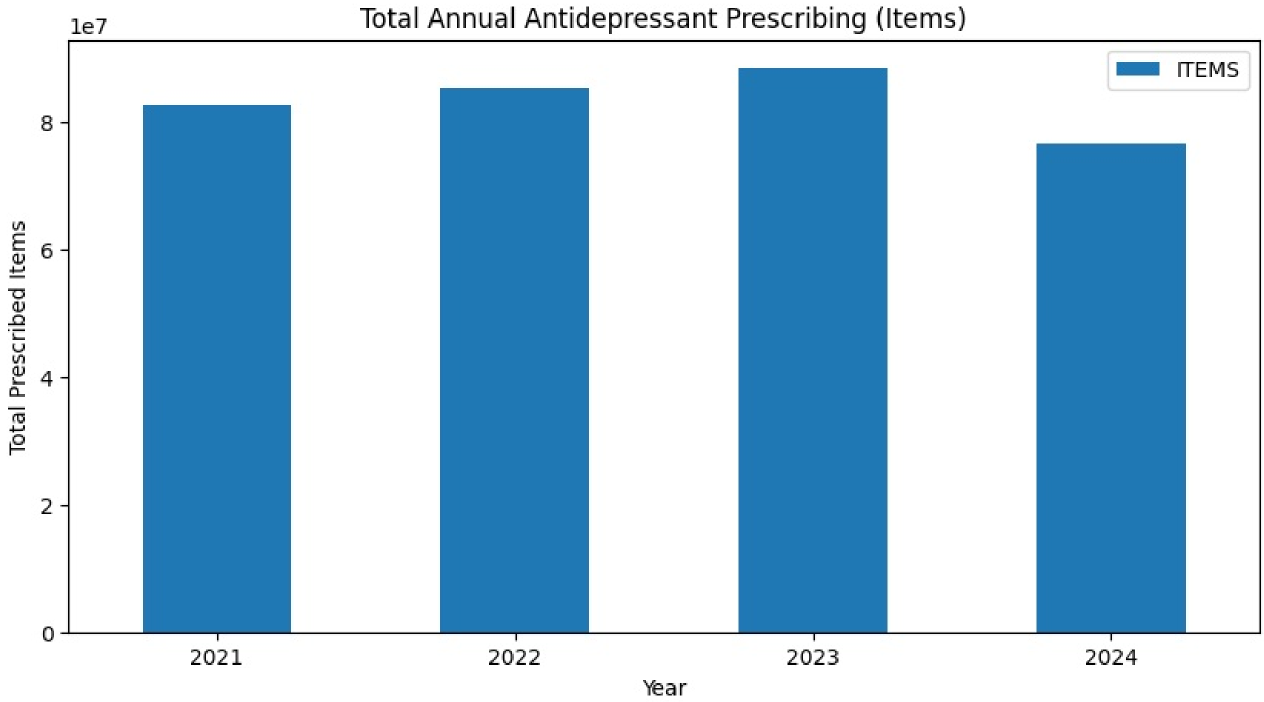
3. By now you may have noticed there are contrasts between antidepressant prescribing volumes and costs. Next, we will create two horizontal bar charts for comparison. First, create an ordered bar chart showing the 10 most prescribed antidepressants across the four years (items). Second, create an ordered bar chart that shows antidepressants with the greatest total prescribing cost across the entire four year period.. Highlight and describe any differences between the charts.

Try and make text between sections flow, so the report reads well. The findings from part one may inform how you approach part two.

1.1 Total Annual Prescribing Volume (Items)

The bar chart below illustrates the total number of antidepressant items prescribed annually across England.

In [16]:
```
# Calculate total annual antidepressant prescribing volume (items)
annual_drug_items = pca_regional_drug_summary_df.groupby("YEAR")["ITEMS"].sum().reset_index()

# Plot the vertical bar chart for prescribing volume
annual_drug_items.plot(x="YEAR", y="ITEMS", kind="bar", figsize=(10, 5))

# Customize labels and title
plt.xlabel("Year")
plt.ylabel("Total Prescribed Items")
plt.title("Total Annual Antidepressant Prescribing (Items)")
plt.xticks(rotation=0)
plt.show()
```



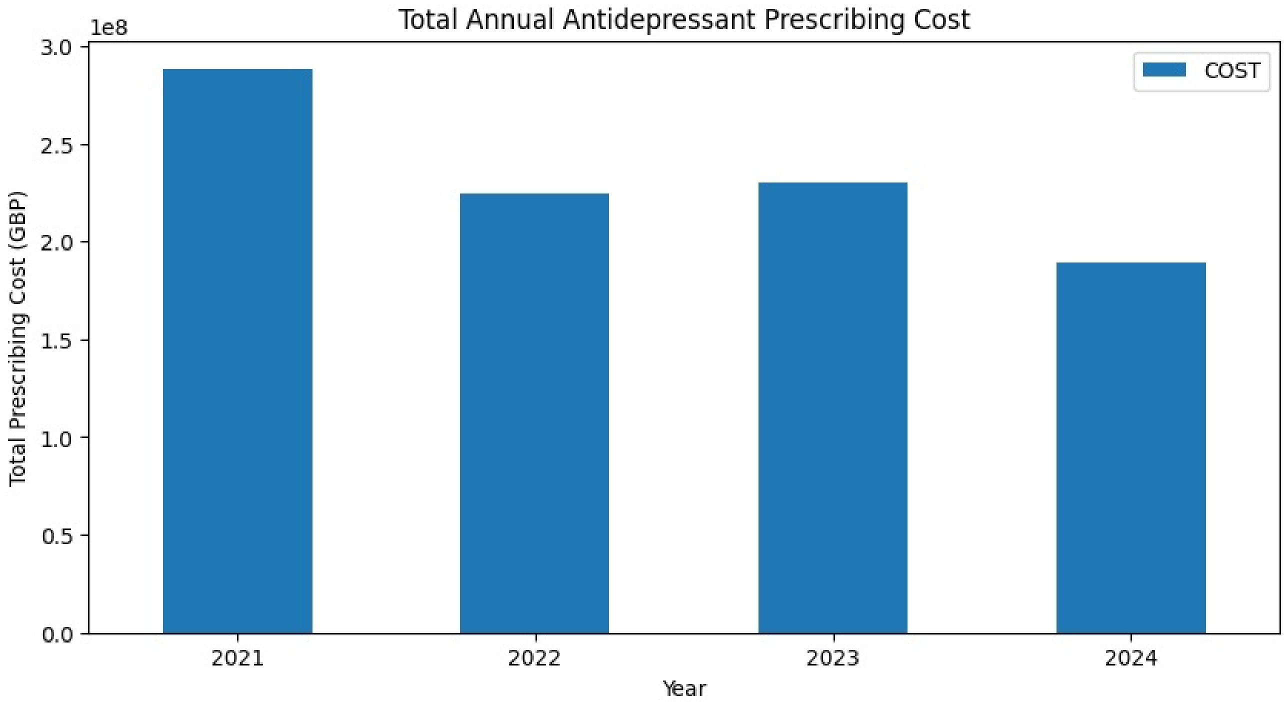
The chart illustrates the total number of antidepressant items prescribed annually over the four years.

- The first three years increased year by year, showing a steady rise in antidepressant prescribing volume.
- The fourth year fell slightly, indicating a potential shift in prescribing patterns, policy changes, or alternative treatment approaches.

1.2 Total Annual Prescribing Cost

The following bar chart visualizes the total annual cost of antidepressant prescribing across England.

In [17]:
```
# Calculate total annual antidepressant prescribing cost
annual_drug_cost = pca_regional_drug_summary_df.groupby("YEAR")["COST"].sum().reset_index()

# Plot the vertical bar chart for prescribing cost
annual_drug_cost.plot(x="YEAR", y="COST", kind="bar", figsize=(10, 5))

# Customize labels and title
plt.xlabel("Year")
plt.ylabel("Total Prescribing Cost (GBP)")
plt.title("Total Annual Antidepressant Prescribing Cost")
plt.xticks(rotation=0)
plt.show()
```



The chart above illustrates the total cost of antidepressant prescribing over the four years.

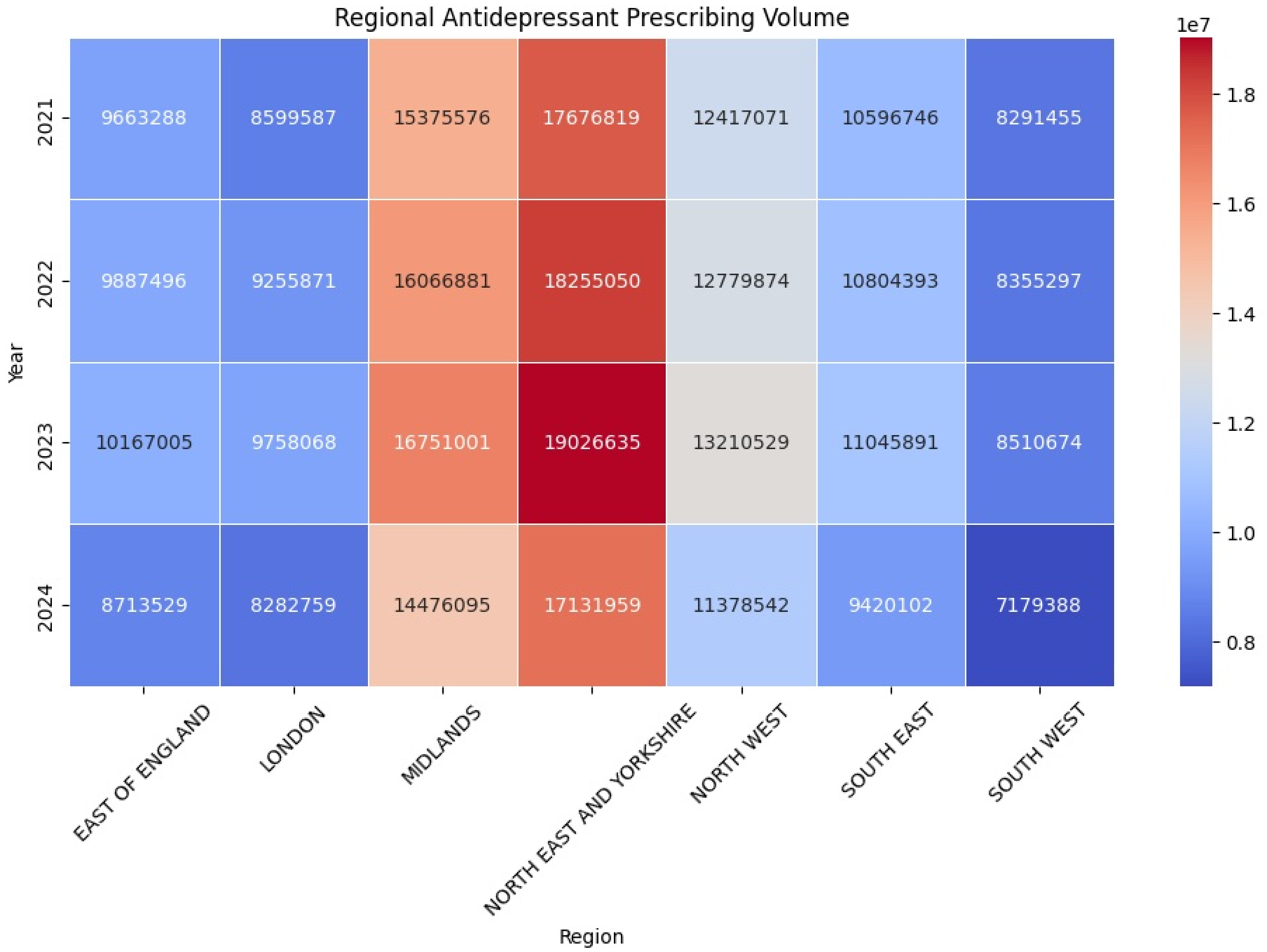
- The total cost has steadily declined over the past four years, suggesting a reduction in overall NHS expenditure on antidepressants.
- In contrast to the trend of rising items, we can conclude that the unit drug price is also gradually decreasing.

1.3 Regional Antidepressant Prescribing Volume

The heatmap below displays the total number of antidepressant items prescribed per region per year.

In [18]:

```
# Create a pivot table for antidepressant prescribing volume per region per year
drug_items_pivot = pca_regional_drug_summary_df.pivot_table(index="YEAR", columns="REGION_NAME", values="ITEMS"

# Display the pivot table by heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(drug_items_pivot, annot=True, fmt=".0f", cmap="coolwarm", linewidths=0.5)

# Customize labels
plt.xlabel("Region")
plt.ylabel("Year")
plt.title("Regional Antidepressant Prescribing Volume")
plt.xticks(rotation=45)
plt.show()
```



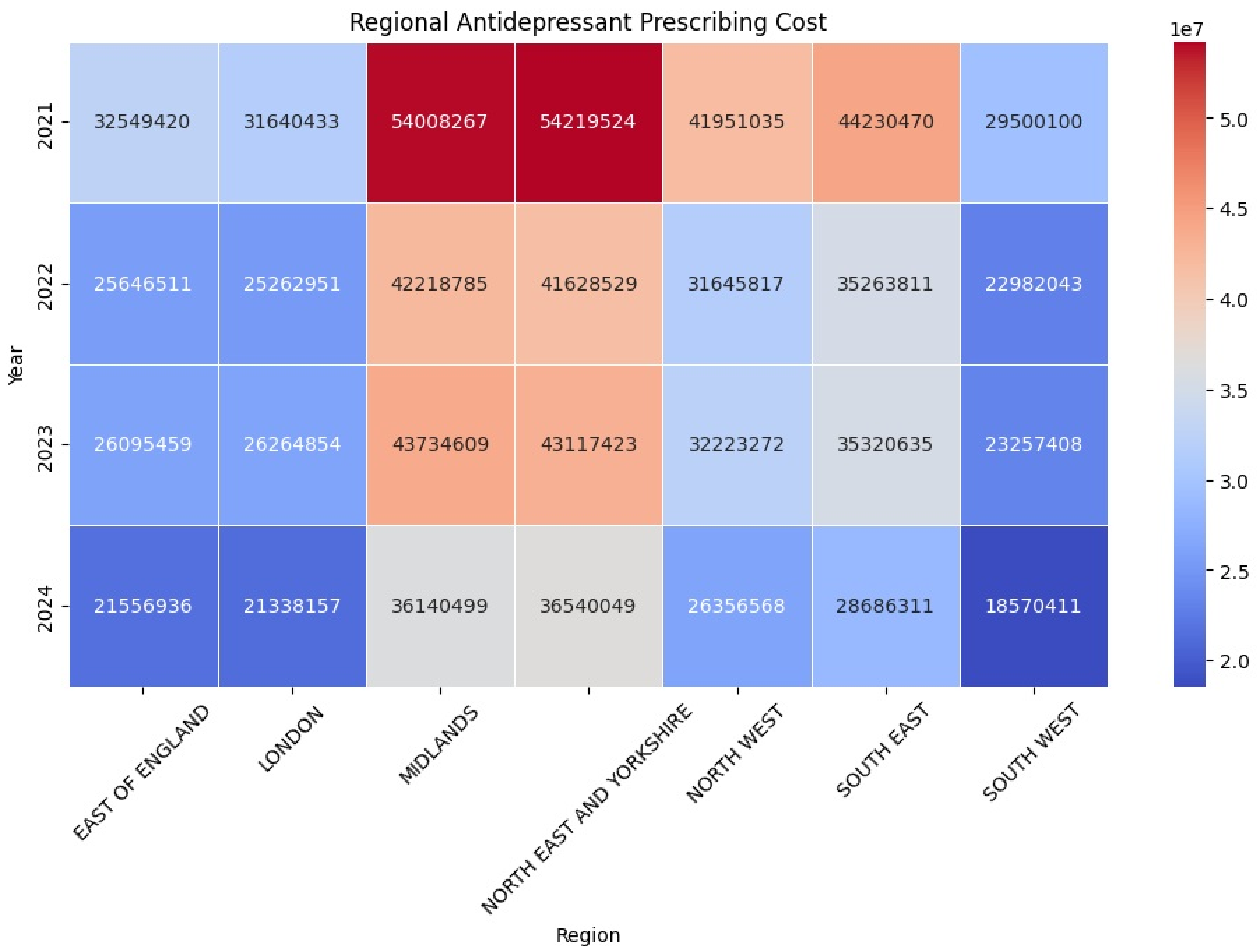
The table above highlights regional variations in antidepressant prescribing volume over the four years.

- Highest Prescribing Regions: The North East and Yorkshire consistently had the highest number of prescribed items each year.
- Fluctuations in Prescriptions: Some regions, such as London and the South West, show relatively stable prescribing volumes, while others experience noticeable year-to-year changes.
- 2024 Decline: There appears to be a decrease in prescribing volume in 2024 across most regions.

1.4 Regional Antidepressant Prescribing Cost

The heatmap below displays the total cost of antidepressant prescriptions per region per year.

In [19]:
```
# Display the pivot table by heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(drug_cost_pivot, annot=True, fmt=".0f", cmap="coolwarm", linewidths=0.5)

# Customize labels
plt.xlabel("Region")
plt.ylabel("Year")
plt.title("Regional Antidepressant Prescribing Cost")
plt.xticks(rotation=45)
plt.show()
```



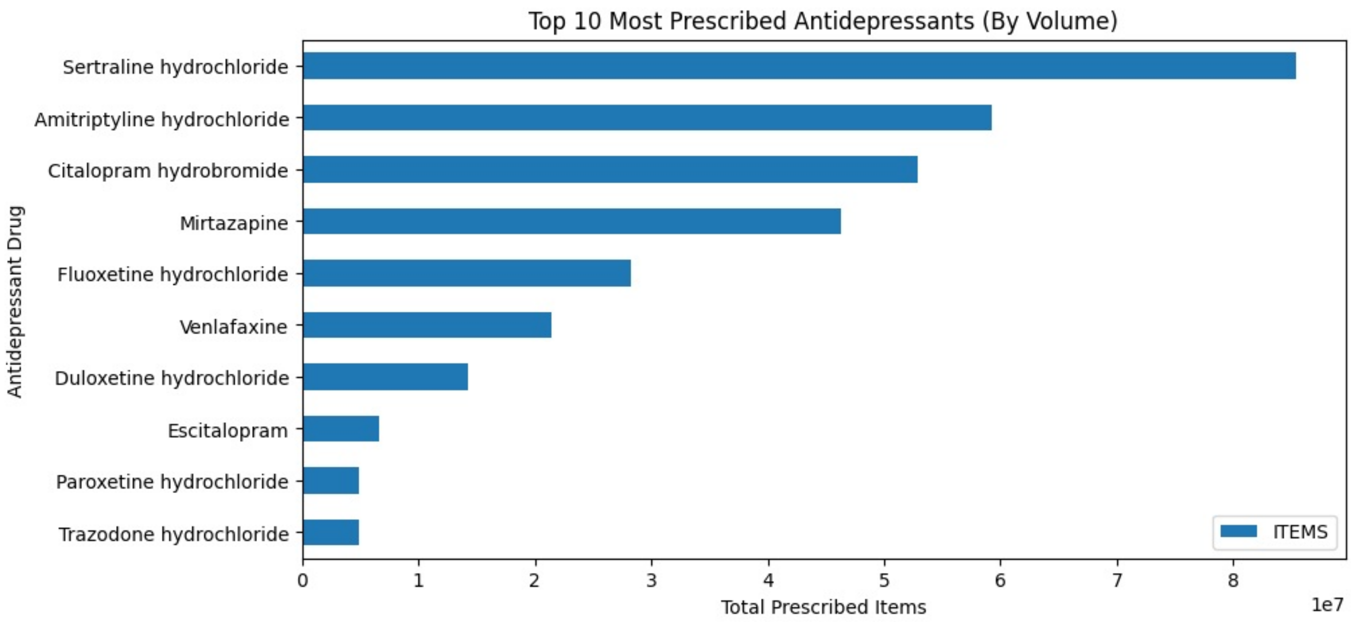
The heatmap above highlights regional variations in antidepressant prescribing costs over the four years.

- Cost Decreases Over Time: Prescription costs significantly reduced from 2021 to 2024, with some regions experiencing a significant drop.
- Cost vs. Volume Trends: While the North East and Yorkshire region had the highest prescribing volume, the Midlands and North East and Yorkshire regions had the highest total prescribing costs in earlier years.
- Regional Disparities: The differences in total costs vs. volume suggest that some regions prescribe higher-cost antidepressants while others focus on lower-cost alternatives.

1.5 The following horizontal bar chart ranks the top 10 antidepressants by total prescribing volume over the four years.

In [20]:

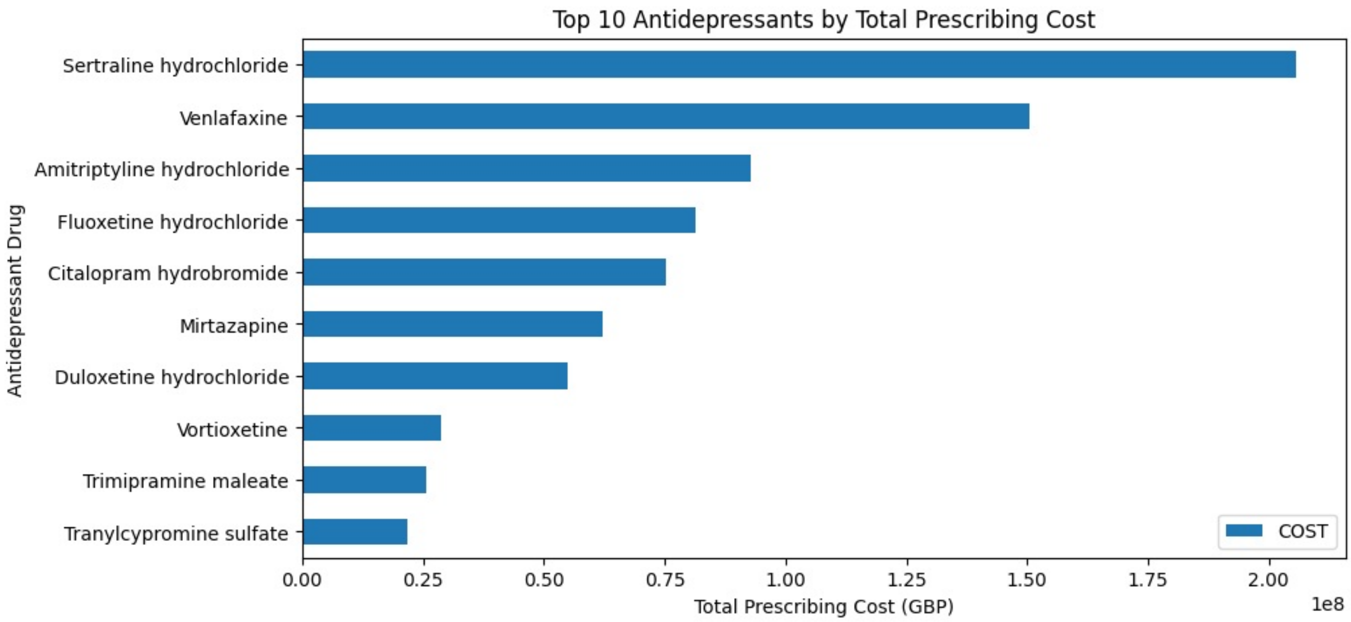
```
# Aggregate total prescriptions per drug over the four-year period
top_10_prescribed_drugs = (
    pca_regional_drug_summary_df.groupby("BNF_CHEMICAL_SUBSTANCE")["ITEMS"].sum()
    .reset_index()
    .sort_values(by="ITEMS", ascending=False)
    .head(10)
)

# Plot the horizontal bar chart
top_10_prescribed_drugs = top_10_prescribed_drugs.sort_values(by="ITEMS", ascending=True)
top_10_prescribed_drugs.plot(x="BNF_CHEMICAL_SUBSTANCE", y="ITEMS", kind="barh", figsize=(10, 5))

# Customize labels and title
plt.xlabel("Total Prescribed Items")
plt.ylabel("Antidepressant Drug")
plt.title("Top 10 Most Prescribed Antidepressants (By Volume)")
plt.show()
```



The top 10 most prescribed antidepressants show that Sertraline hydrochloride is the most commonly used antidepressant, followed by Amitriptyline hydrochloride and Citalopram hydrobromide.

1.6 The following horizontal bar chart ranks the top 10 antidepressants by total prescribing cost over the four years.

In [21]:
```
# Aggregate total cost per drug over the four-year period
top_10_costly_drugs = (
    pca_regional_drug_summary_df.groupby("BNF_CHEMICAL_SUBSTANCE")["COST"].sum()
    .reset_index()
    .sort_values(by="COST", ascending=False)
    .head(10)
)

# Plot the horizontal bar chart
top_10_costly_drugs = top_10_costly_drugs.sort_values(by="COST", ascending=True)
top_10_costly_drugs.plot(x="BNF_CHEMICAL_SUBSTANCE", y="COST", kind="barh", figsize=(10, 5))

# Customize labels and title
plt.xlabel("Total Prescribing Cost (GBP)")
plt.ylabel("Antidepressant Drug")
plt.title("Top 10 Antidepressants by Total Prescribing Cost")
plt.show()
```



Comparing the top 10 most prescribed drugs with the top 10 highest-cost drugs, key differences emerge:

- Sertraline hydrochloride remains a top-prescribed drug but does not dominate cost rankings. This suggests it is a widely used but relatively low-cost antidepressant.
- Higher-cost medications like Vortioxetine appear in the top-cost category but are not among the most prescribed, indicating its higher unit price.

- Amitriptyline hydrochloride is highly prescribed and costly, suggesting that it plays a significant role in prescribing volume and total NHS expenditure.

1.7 Key Takeaways from Part One

- Prescribing volume and cost trends do not always align. Some drugs are widely used but inexpensive, while others have lower prescribing volume, significantly impacting NHS costs.
- Regional prescribing patterns vary. Certain regions prescribe more antidepressants overall, while others spend more due to drug selection.
- The 2024 data show a reduction in prescribing volume and costs. This may indicate policy changes, generics availability, or shifts in prescribing practices.

Part Two (Longitudinal Analysis)

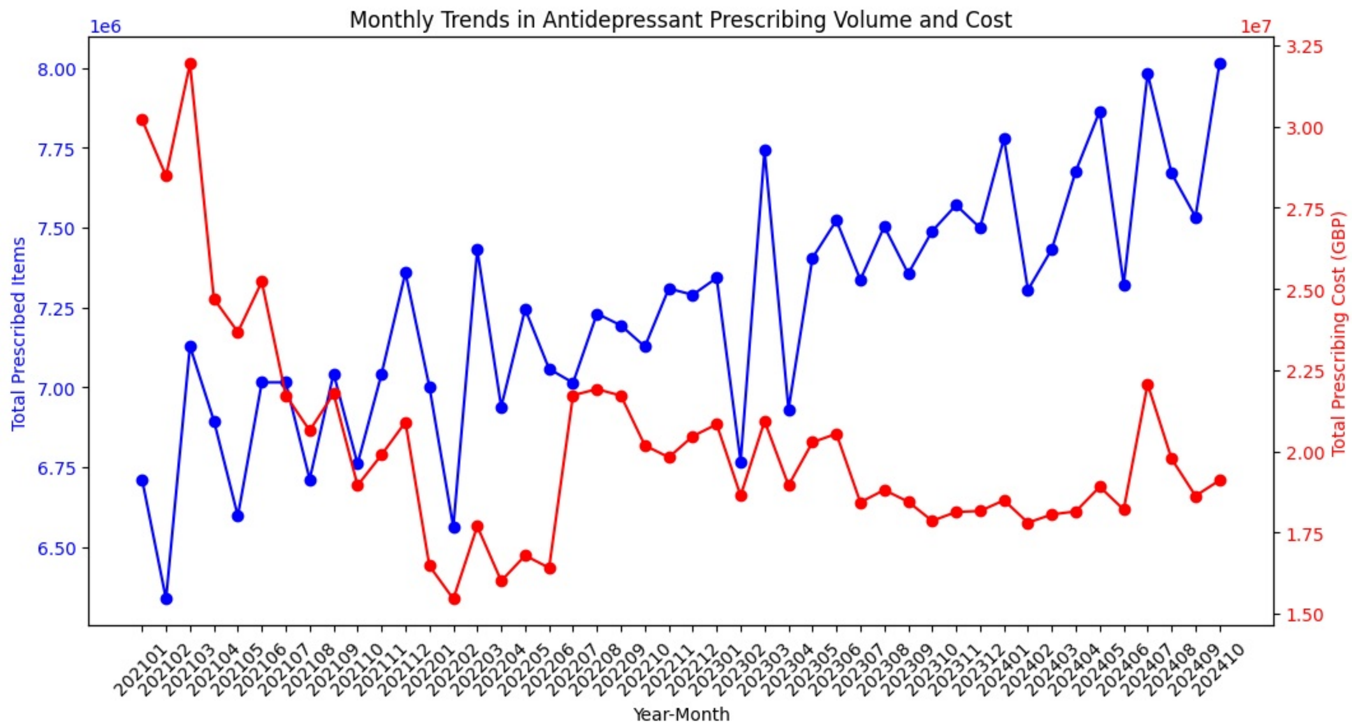
Now you have a good understanding around national and regional antidepressant prescribing volume and cost trends. You will be given various topics or points to explore, and you will decide what approach or charts best does this. To supplement the initial analysis, you will now:

- Look at the longitudinal (monthly) trend for all antidepressant items and for the cost of antidepressant prescribing
- Then, explore the data and find the antidepressant drugs that are driving these monthly item and cost trends.
- Then give a high-level summary to your work and findings.

The line chart below shows monthly prescribing trends for both total items prescribed and total cost.

In [22]:

```
# Aggregate monthly prescribing volume and cost
monthly_trends = (
    pca_regional_drug_summary_df.groupby("YEAR_MONTH")[["ITEMS", "COST"]]
    .sum()
    .reset_index()
)

# Convert YEAR_MONTH to string for proper x-axis labeling
monthly_trends["YEAR_MONTH"] = monthly_trends["YEAR_MONTH"].astype(str)

# Plot the monthly trends
fig, ax1 = plt.subplots(figsize=(12, 6))

# Plot prescribing volume
ax1.plot(monthly_trends["YEAR_MONTH"], monthly_trends["ITEMS"], color="blue", marker="o", label="Total Prescrib
ax1.set_xlabel("Year-Month")
ax1.set_ylabel("Total Prescribed Items", color="blue")
ax1.tick_params(axis="y", labelcolor="blue")

# Create second y-axis for prescribing cost
ax2 = ax1.twinx()
ax2.plot(monthly_trends["YEAR_MONTH"], monthly_trends["COST"], color="red", marker="o", label="Total Cost (GBP)
ax2.set_ylabel("Total Prescribing Cost (GBP)", color="red")
ax2.tick_params(axis="y", labelcolor="red")

# Customize labels and title
plt.title("Monthly Trends in Antidepressant Prescribing Volume and Cost")
plt.setp(ax1.xaxis.get_majorticklabels(), rotation=45)
plt.show()
```



The chart above illustrates the monthly trends in total antidepressant prescribing volume (blue) and total prescribing cost (red).

- Fluctuations in Volume and Cost: Both prescribing volume and costs exhibit cyclical trends, likely influenced by supply seasonality or other season-related factors.
- Cost Reductions Despite Consistent Volume: There are periods where costs drop significantly while the prescribing volume remains stable.
- Potential Policy Impacts in 2024: The downward trends towards the end of the timeline could indicate new NHS prescribing policies or shifts in mental health treatment approaches.

Part Two Extension (Antidepressant Case studies)

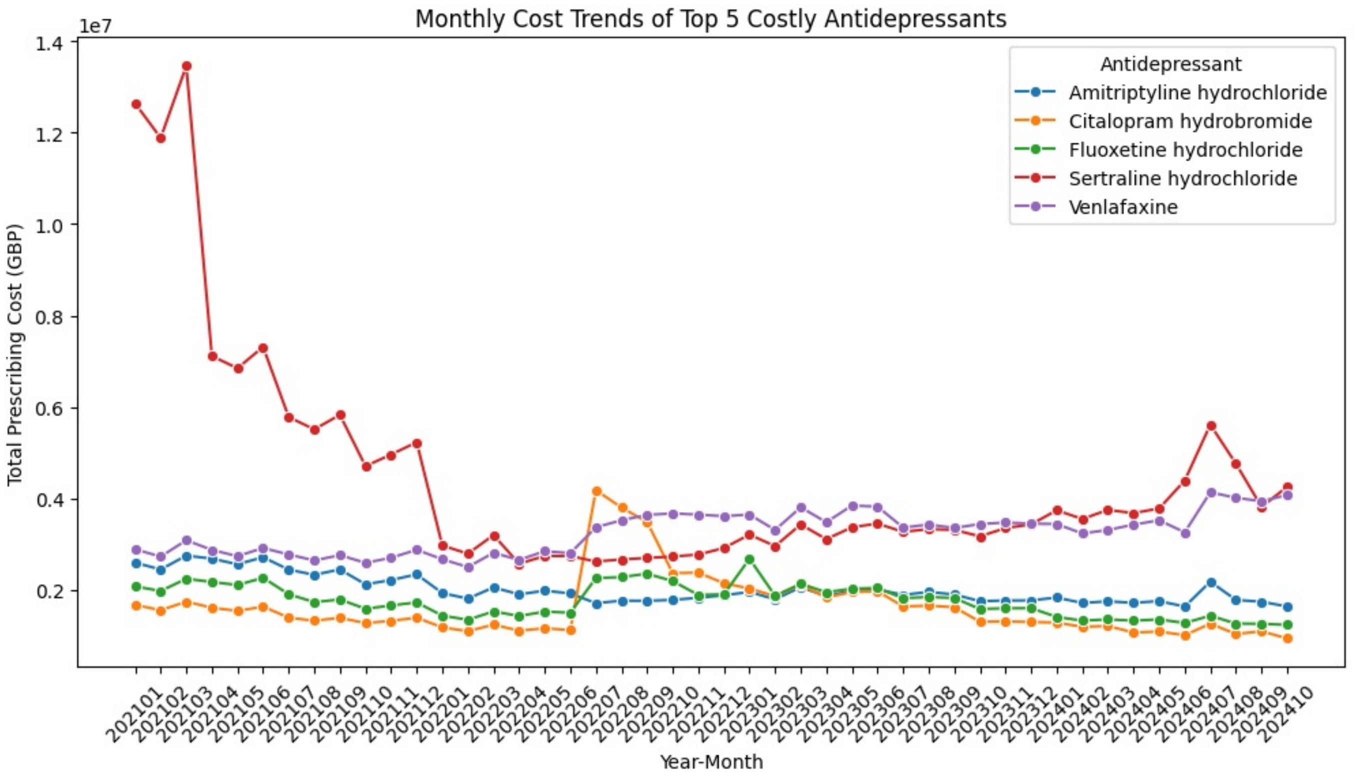
The extension is only to be attempted if you completed the data_metrics_and_insights learning material and exercises. The analyses within this section will delve a bit deeper into antidepressant prescribing costs.

- Focus one one or more antidepressants that play a significant role in national volume and cost trends
- Percentage of total antidepressant volume or cost from a drug
- Mean cost per item in relation a drug
- Distribution of mean cost per item values for a drug
- Anything else you think might be informative or relevant (be creative!)
- Then give a high-level summary to your work and findings.

The line chart below analyses the top 5 costly antidepressants' monthly prescribing cost fluctuations.

In [23]:
```
# Identify the top 5 drugs contributing to total cost trends
top_5_costly_drugs = (
    pca_regional_drug_summary_df.groupby("BNF_CHEMICAL_SUBSTANCE")["COST"]
    .sum()
    .sort_values(ascending=False)
    .head(5)
    .index.tolist()
)

# Filter dataset for only these top 5 drugs
top_costly_drugs_trends = pca_regional_drug_summary_df[
    pca_regional_drug_summary_df["BNF_CHEMICAL_SUBSTANCE"].isin(top_5_costly_drugs)
]

# Aggregate monthly cost trends for these drugs
top_costly_drugs_monthly = (
    top_costly_drugs_trends.groupby(["YEAR_MONTH", "BNF_CHEMICAL_SUBSTANCE"])["COST"]
    .sum()
    .reset_index()
)

# Convert YEAR_MONTH to string for proper x-axis labeling
top_costly_drugs_monthly["YEAR_MONTH"] = top_costly_drugs_monthly["YEAR_MONTH"].astype(str)

# Plot the monthly trends of top 5 costly drugs
```

```
plt.figure(figsize=(12, 6))
sns.lineplot(
    data=top_costly_drugs_monthly,
    x="YEAR_MONTH",
    y="COST",
    hue="BNF_CHEMICAL_SUBSTANCE",
    marker="o"
)

# Customize labels and title
plt.xlabel("Year-Month")
plt.ylabel("Total Prescribing Cost (GBP)")
plt.title("Monthly Cost Trends of Top 5 Costly Antidepressants")
plt.xticks(rotation=45)
plt.legend(title="Antidepressant")
plt.show()
```



The line chart above displays the monthly cost trends for the top 5 most expensive antidepressants over four years.

- Only Sertraline hydrochloride has seen a sharp decline in cost among the five most costly antidepressants over these four years.
- The cost of the other four antidepressants has remained almost unchanged, indicating stable pricing or consistent demand.
- The decline in total prescribing cost in the fourth year (2024) is primarily driven by the cost reduction of Sertraline hydrochloride. This suggests potential pricing adjustments, increased generic use, or changes in NHS procurement strategies.

Conclusion

This longitudinal analysis provides valuable insights into antidepressant prescribing trends, cost fluctuations, and regional disparities over the four years.

- The volume of prescriptions increased for the first three years but declined slightly in 2024. This suggests stabilization or external influences, such as policy changes or alternative treatment approaches.
- Total prescribing costs have steadily declined over the past four years, even though prescription volumes have remained high. Sertraline hydrochloride played a key role in these cost reductions. Among the five most costly antidepressants, only Sertraline hydrochloride showed a significant decline in cost, while the others remained relatively stable. This suggests that price reductions for sertraline hydrochloride primarily drove the overall cost decrease in 2024.
- Regional variations reveal differences in prescribing behaviour and cost efficiency. Some regions prescribe more antidepressants, while others spend more on fewer items, likely due to drug selection differences or localized prescribing guidelines.

Next Steps

To further investigate these trends and provide additional policy recommendations, the following steps include:

1. Examining cost efficiency per item

- Calculating the mean cost per item across different antidepressants.

- Identifying drugs with the highest cost per prescription and evaluating if lower-cost alternatives exist.

2. Assessing the percentage contribution of key drugs to total costs

- Determining which antidepressants account for the highest share of NHS spending.
- Exploring potential savings if prescribing patterns shifted to cost-effective alternatives.

3. Investigating the prescribing behavior of high-cost vs. high-volume drugs

- Understanding why certain drugs remain expensive despite consistent prescribing levels.
- Analyzing if these drugs offer unique benefits over cheaper alternatives or if cost-containment measures could be implemented.

4. Exploring further regional trends

- Identifying regions that have successfully reduced costs and examining best practices.
- Comparing NHS procurement strategies across regions to optimize cost efficiency nationally.