Task 1: Data Preparation (Primary.csv only, the others are prepared for tasks)

In [1]:
```python
import pandas as pd
primary_filepathog = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_Data
pogdf = pd.read_csv(primary_filepathog, encoding='latin1')
```

In [2]:
```python
pogdf.head()
```

Out[2]:

	column A	column B	column C	column D	column E	column F	column G	column H	column I	column J	column K	colu
0	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	T pe
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	15%	2%	22%	0%	61%	Demographic and Health Survey	2(
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	39%	NaN	NaN	NaN	NaN	Multiple Indicator Cluster Survey	2(
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	81%	69%	89%	46%	99%	Demographic and Health Survey	2(
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	34%	30%	49%	7%	75%	Multiple Indicator Cluster Survey	2

In [3]:
```python
pogdf.isnull().any()
```

Out[3]:
```
column A      False
column B      False
column C      False
column  D     False
column E      False
column F      False
column G       True
column H       True
column I       True
column J       True
column K      False
column L      False
dtype: bool
```

In [4]:
```python
duplicates = pogdf.duplicated()
print(f"Number of duplicate rows: {duplicates.sum()}")
```

```
Number of duplicate rows: 0
```

In [5]:

```
#now that we know which columns have missing values, I want to check how many missin
missing_values = pogdf.isnull().sum()
print("Missing values per column:\n", missing_values)
```

```
Missing values per column:
 column A      0
column B      0
column C      0
column  D     0
column E      0
column F      0
column G     11
column H      8
column I     18
column J     21
column K      0
column L      0
dtype: int64
```

In [6]:

```
#here is how I will be cleaning the data
#first I will pull the csv into a dataframe
#i till skip the first row as it is just the columns by letters which isn't the most
#to remember or analyze

file_path_test = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSci
dftest = pd.read_csv(file_path_test, skiprows=1)

output_file_path_test = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_I
dftest.to_csv(output_file_path_test, index=False)
dftest.head()
```

Out[6]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Time period
0	AGO	Angola	SSA	ESA	Lower middle income (LM)	15%	2%	22%	0%	61%	Demographic and Health Survey	2015-16
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	39%	NaN	NaN	NaN	NaN	Multiple Indicator Cluster Survey	2011-12
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	81%	69%	89%	46%	99%	Demographic and Health Survey	2015-16
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	34%	30%	49%	7%	75%	Multiple Indicator Cluster Survey	2019
4	BRB	Barbados	LAC	LAC	High income (H)	63%	54%	68%	9%	97%	Multiple Indicator Cluster Survey	2012

In [7]:

```python
import numpy as np

file_path_test = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSci
dftest = pd.read_csv(file_path_test, skiprows=1)

# Function for converting the percentage string value to float
def percentage_to_float(x):
    if isinstance(x, str) and x.endswith('%'):
        return float(x[:-1]) / 100
    return x

# Converting the string percentage values to float
cols_to_convert = ['Total',
                   'Rural (Residence)',
                   'Urban (Residence)',
                   'Poorest (Wealth quintile)',
                   'Richest (Wealth quintile)']
for col in cols_to_convert:
    dftest[col] = dftest[col].apply(percentage_to_float)

# Replacing the empty 'NaN' values in 'Rural (Residence)' and 'Urban (Residence)'
#columns with the mean of other non-empty countries in the same 'Region'
cols_to_fill = ['Rural (Residence)',
                'Urban (Residence)',
                'Poorest (Wealth quintile)',
                'Richest (Wealth quintile)']

for col in cols_to_fill:
    dftest[col] = dftest.groupby('Region')[col].apply(lambda x: x.fillna(round(x.mea

output_file_path_test = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_I
dftest.to_csv(output_file_path_test, index=False)
dftest.head()
```

Out[7]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Time period
0	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.15	0.02	0.22	0.00	0.61	Demographic and Health Survey	2015-16
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.39	0.26	0.47	0.22	0.80	Multiple Indicator Cluster Survey	2011-12
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81	0.69	0.89	0.46	0.99	Demographic and Health Survey	2015-16
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.34	0.30	0.49	0.07	0.75	Multiple Indicator Cluster Survey	2019
4	BRB	Barbados	LAC	LAC	High income (H)	0.63	0.54	0.68	0.09	0.97	Multiple Indicator Cluster Survey	2012

In [8]:

```python
#using regex to handle the 'Time period' values in the last column
#basically to ensure all he values in the column are in the 2010's
import re

def handle_time_period(value):
    # Case 1: If format is like '2015-16' or '2011-12'
    if re.match(r'\d{4}-\d{2}', value):
        return value[:2] + value[-2:]

    # Case 2: If the value is something outlandish like '2562'
    if int(value) > 2019 or int(value) < 2010:
        return '20' + value[-2:]

    # Case 3: If the value is like '2027'
    if int(value) > 2019:
        return '201' + value[-1]

    # Case 4: If the value is like '2012-99'
    if re.match(r'\d{4}-\d{2}', value) and int(value[-2:]) > 19:
        return '20' + value[-2:]

    # Case 5: If the value is like '2018-2019'
    if re.match(r'\d{4}-\d{4}', value):
        return value[-4:]

    # Case 6: If the value is like '2076'
    if int(value) > 2019 and int(value[-1]) > 0:
        return '20' + value[-1]

    return value

# Applying the function to the 'Time period' column
dftest['Time period'] = dftest['Time period'].apply(handle_time_period)

output_file_path_test = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_
dftest.to_csv(output_file_path_test, index=False)

dftest.head(59)
```

29	GNB	Guinea-Bissau	SSA	WCA	Low income (L)	0.02	0.01	0.04	0.00	0.05	Multiple Indicator Cluster Survey	2019
30	HTI	Haiti	LAC	LAC	Low income (L)	0.18	0.10	0.33	0.00	0.60	Demographic and Health Survey	2017
31	IND	India	SA	SA	Lower middle income (LM)	0.07	0.04	0.14	0.00	0.33	Demographic and Health Survey	2016
32	IDN	Indonesia	EAP	EAP	Lower middle income (LM)	0.17	0.09	0.24	0.05	0.44	SUSENAS	2019
33	IRQ	Iraq	MENA	MENA	Upper middle income (UM)	0.46	0.33	0.53	0.14	0.83	Multiple Indicator Cluster Survey	2018

In [9]:

```
#I am removing the following columns as I feel they aren't relevant to the analysis .
columns_to_remove1 = ['Rural (Residence)','Urban (Residence)','Poorest (Wealth quint
dftest = dftest.drop(columns=columns_to_remove1)
dftest.head()
```

Out[9]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.15
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.39
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.34
4	BRB	Barbados	LAC	LAC	High income (H)	0.63

In [10]:

```
#now that I have the dataset I wanted, i will convert the string values into floats
#this will allow me to analyze the data numerically

def percentage_to_float(value):
    if isinstance(value, str) and value.endswith('%'):
        return float(value[:-1]) / 100
    else:
        return value

columns_to_convert = ['Total']

for column in columns_to_convert:
    dftest[column] = dftest[column].apply(percentage_to_float)

dftest.head()
```

Out[10]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.15
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.39
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.34
4	BRB	Barbados	LAC	LAC	High income (H)	0.63

Task 2.1: I am choosing the following:

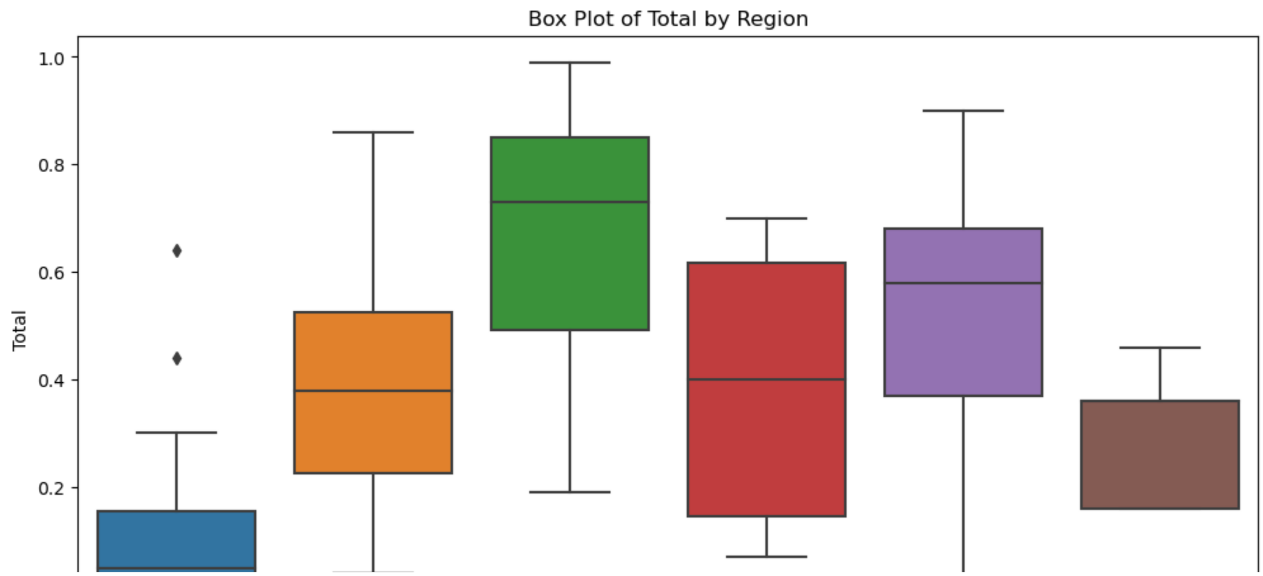
Nominal Value: 'Region; Ordinal Value: 'Income Group'; Numerical Value: 'Total';

In [11]:

```
#my data is now cleaned as I have the rows that I want to analyze
import seaborn as sns
import matplotlib.pyplot as plt
```

In [12]:

```python
plt.figure(figsize=(12, 6))
sns.boxplot(x='Region', y='Total', data=dftest)
plt.title('Box Plot of Total by Region')
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()
```



In [13]:

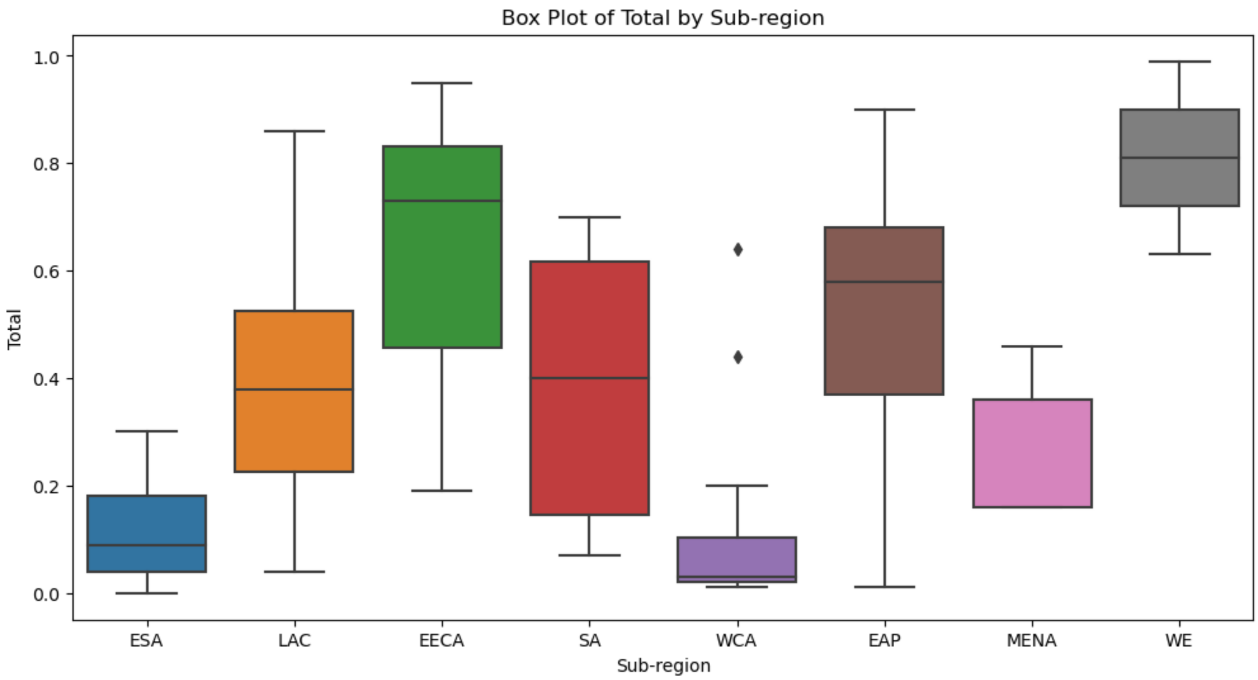
```python
#As we can witness, there are outliers on the 'SSA' region

def detect_outliers(region_df):
    Q1 = region_df['Total'].quantile(0.25)
    Q3 = region_df['Total'].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = region_df[(region_df['Total'] < lower_bound) | (region_df['Total'] > u
    return outliers

region_groups = dftest.groupby('Region')

outliers = pd.concat([detect_outliers(group) for _, group in region_groups])

outliers.head()
```

Out[13]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
25	GMB	Gambia	SSA	WCA	Low income (L)	0.64
60	STP	Sao Tome and Principe	SSA	WCA	Lower middle income (LM)	0.44

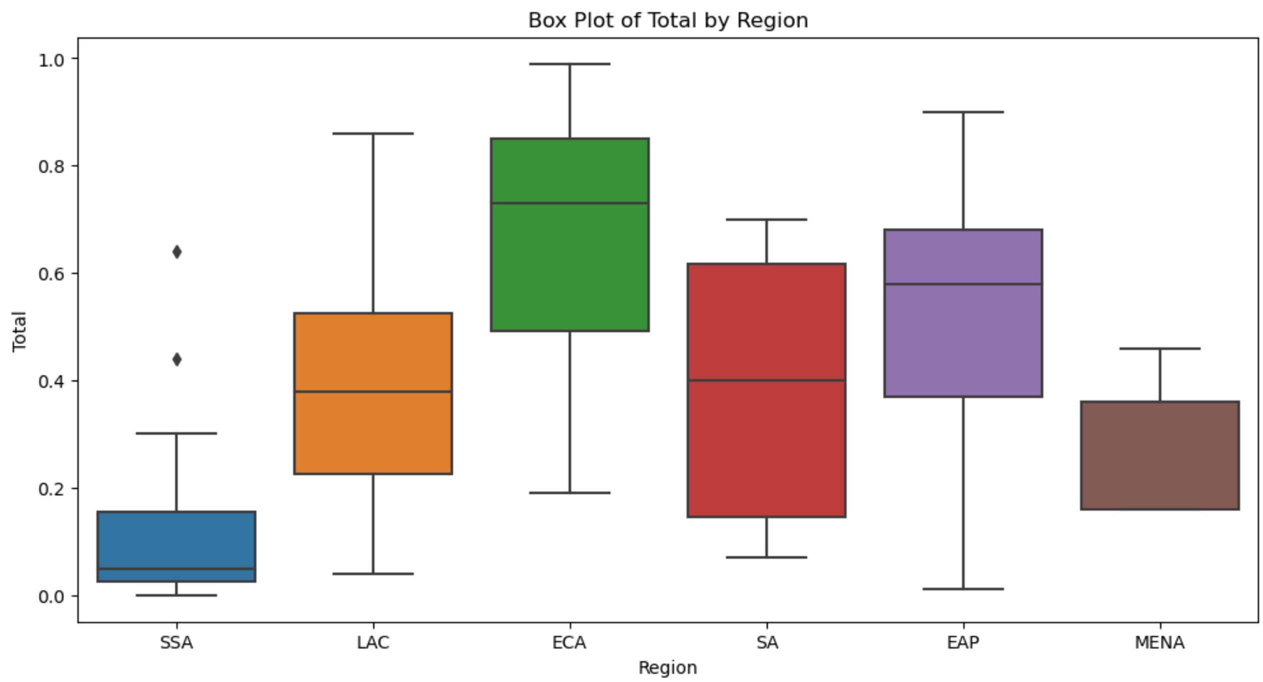
In [14]:

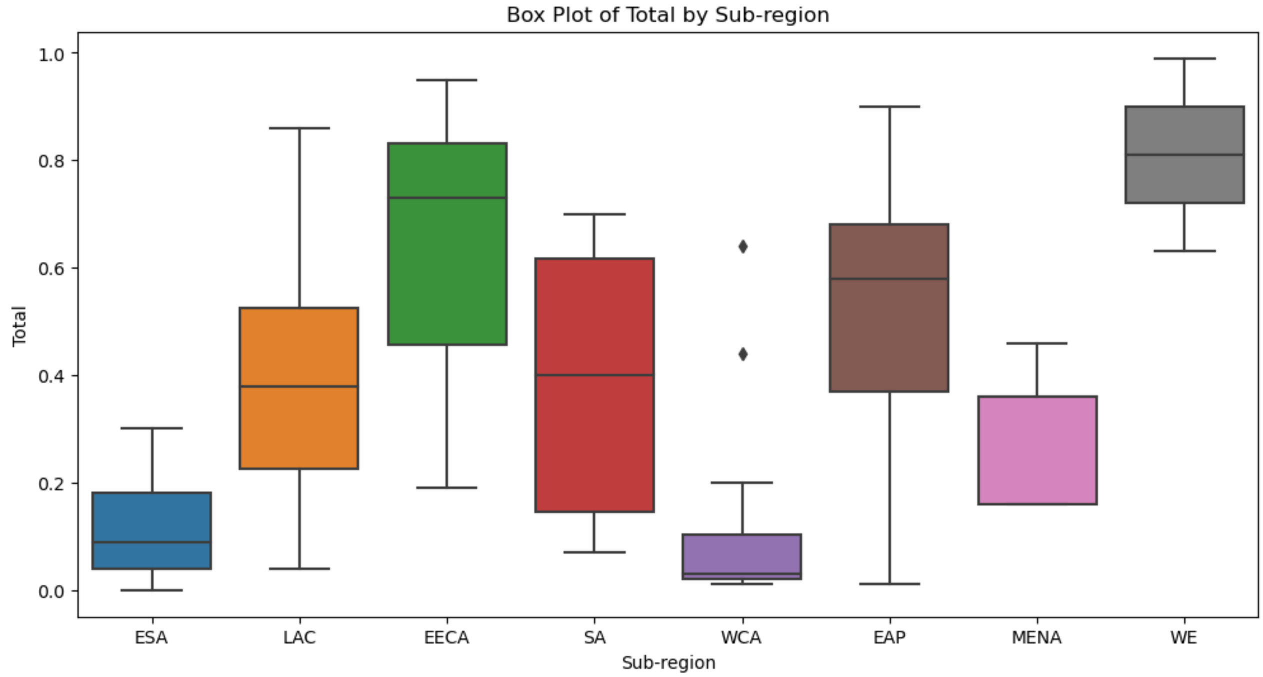
```
#I want to explore and analyze these so we can make a good inference as to what make:
#To do this, I am going to visualize a similar boxplot, with the Sub-region and Tota.
#my reasoning for this is that maybe Sub-region migh be a better predictor of the To
# and Income Group

plt.figure(figsize=(12, 6))
sns.boxplot(x='Sub-region', y='Total', data=dftest)
plt.title('Box Plot of Total by Sub-region')
plt.xlabel('Sub-region')
plt.ylabel('Total')
plt.show()
```

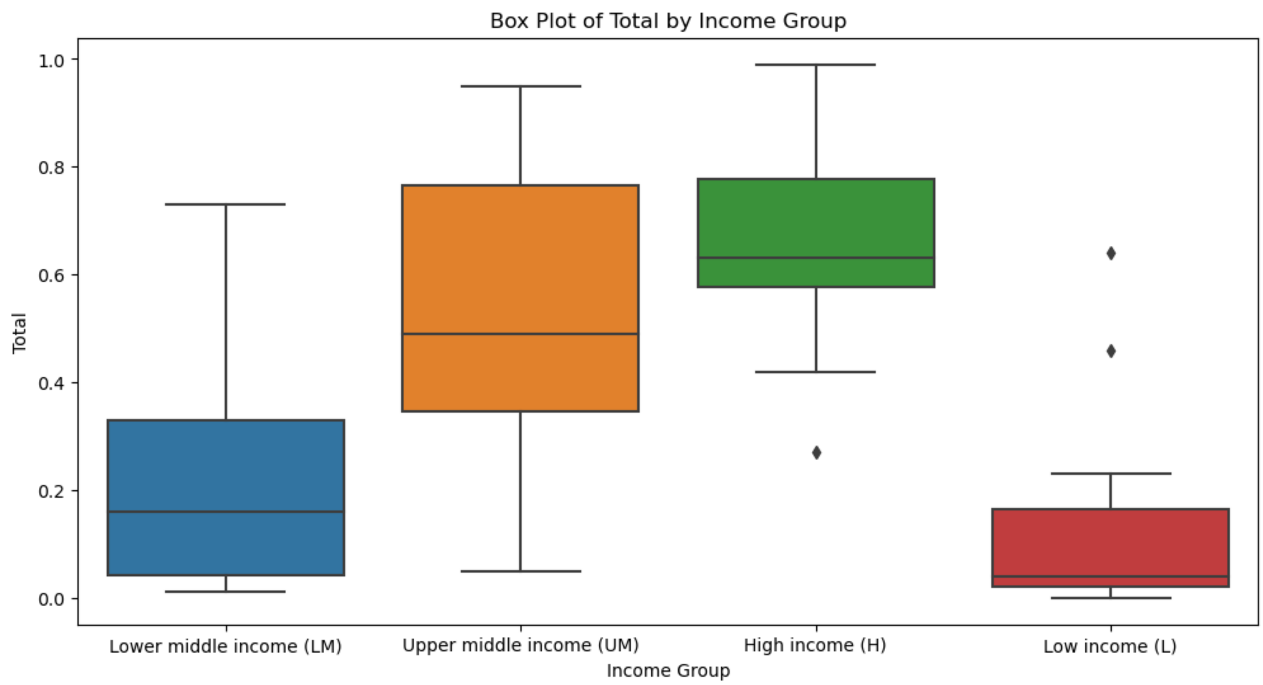


In [15]:

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Region', y='Total', data=dftest)
plt.title('Box Plot of Total by Region')
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()

plt.figure(figsize=(12, 6))
sns.boxplot(x='Sub-region', y='Total', data=dftest)
plt.title('Box Plot of Total by Sub-region')
plt.xlabel('Sub-region')
plt.ylabel('Total')
plt.show()

plt.figure(figsize=(12, 6))
sns.boxplot(x='Income Group', y='Total', data=dftest)
plt.title('Box Plot of Total by Income Group')
plt.xlabel('Income Group')
plt.ylabel('Total')
plt.show()
```

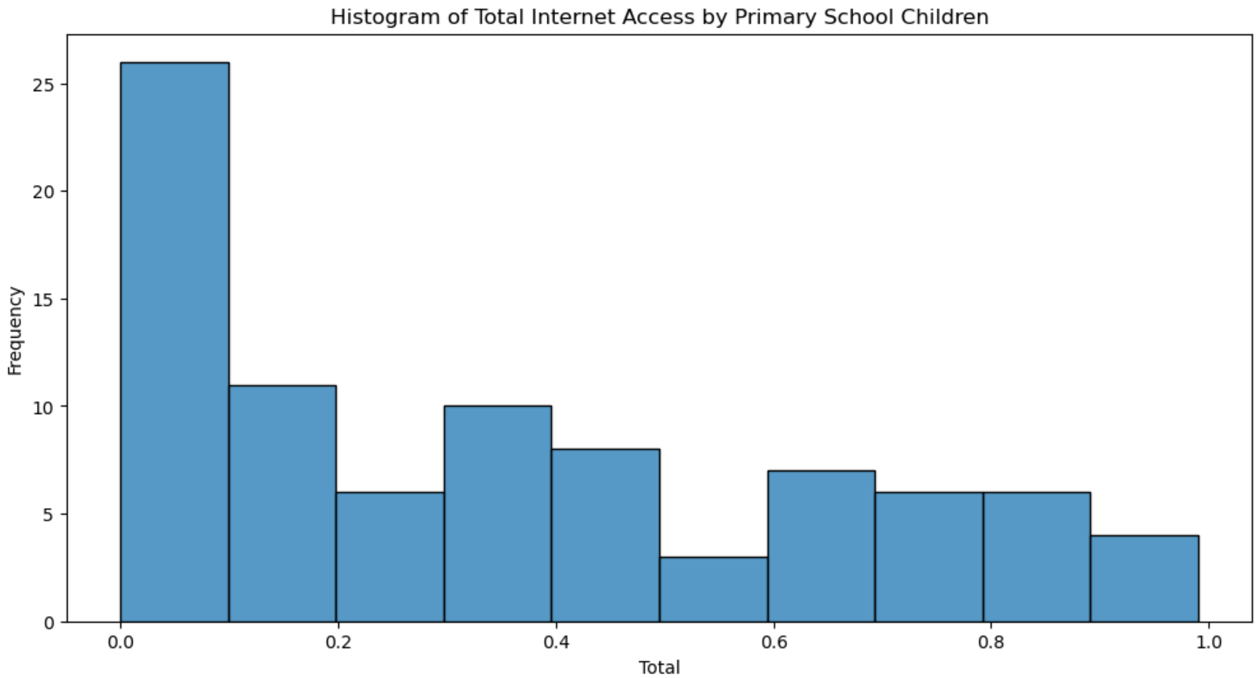



Box Plot of Total by Sub-region
Total
Sub-region
ESA
LAC
EECA
SA
WCA
EAP
MENA
WE
0.0
0.2
0.4
0.6
0.8
1.0


Box Plot of Total by Income Group
Total
Income Group
Lower middle income (LM)
Upper middle income (UM)
High income (H)
Low income (L)
0.0
0.2
0.4
0.6
0.8
1.0

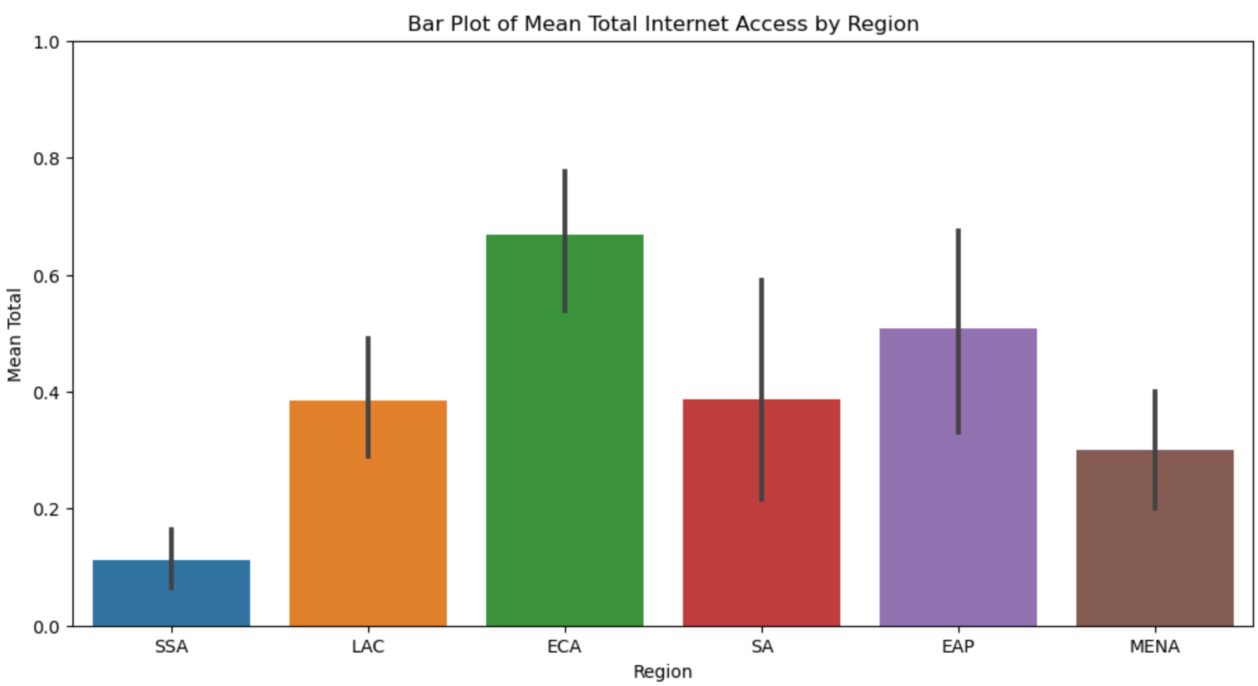
In [16]:

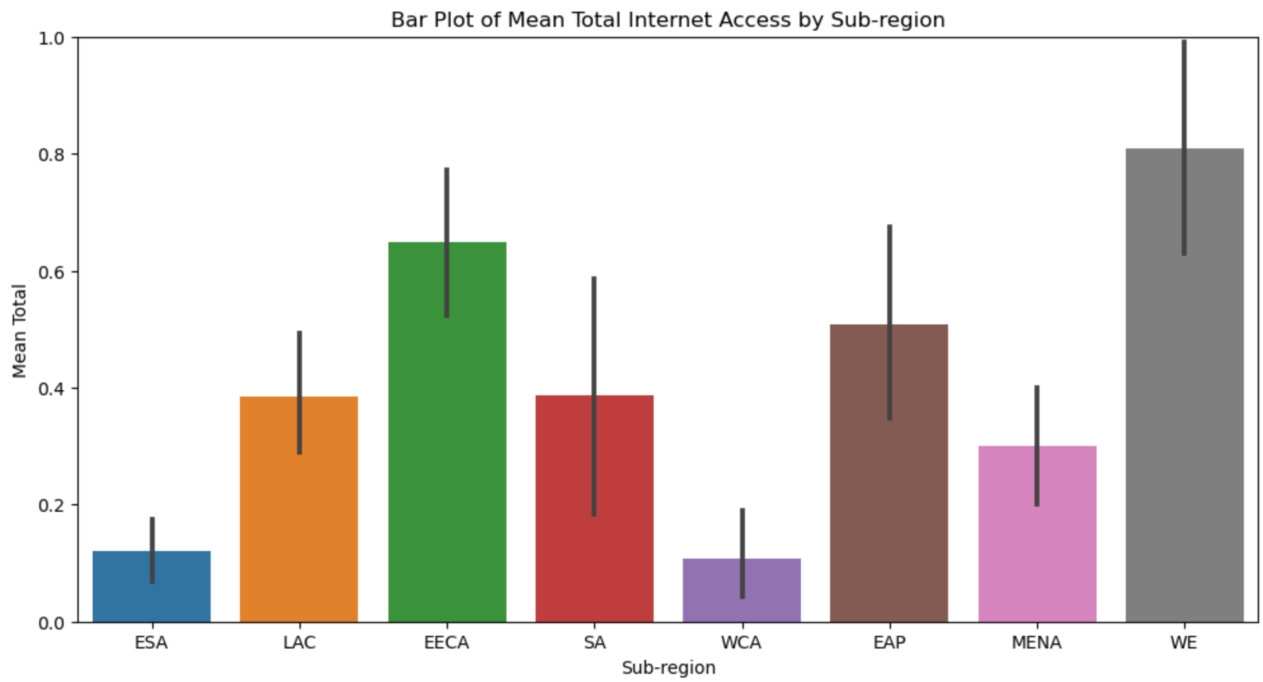
```
#I wanted to see he spread of data across the Primary school children data
#for this, I employed a Histogram
#as we can see, most of the data is aggregated towards only 1% of of primary schoolc
#internet access


plt.figure(figsize=(12, 6))
sns.histplot(data=dftest, x='Total', bins=10)
plt.title('Histogram of Total Internet Access by Primary School Children')
plt.xlabel('Total')
plt.ylabel('Frequency')
plt.show()

```

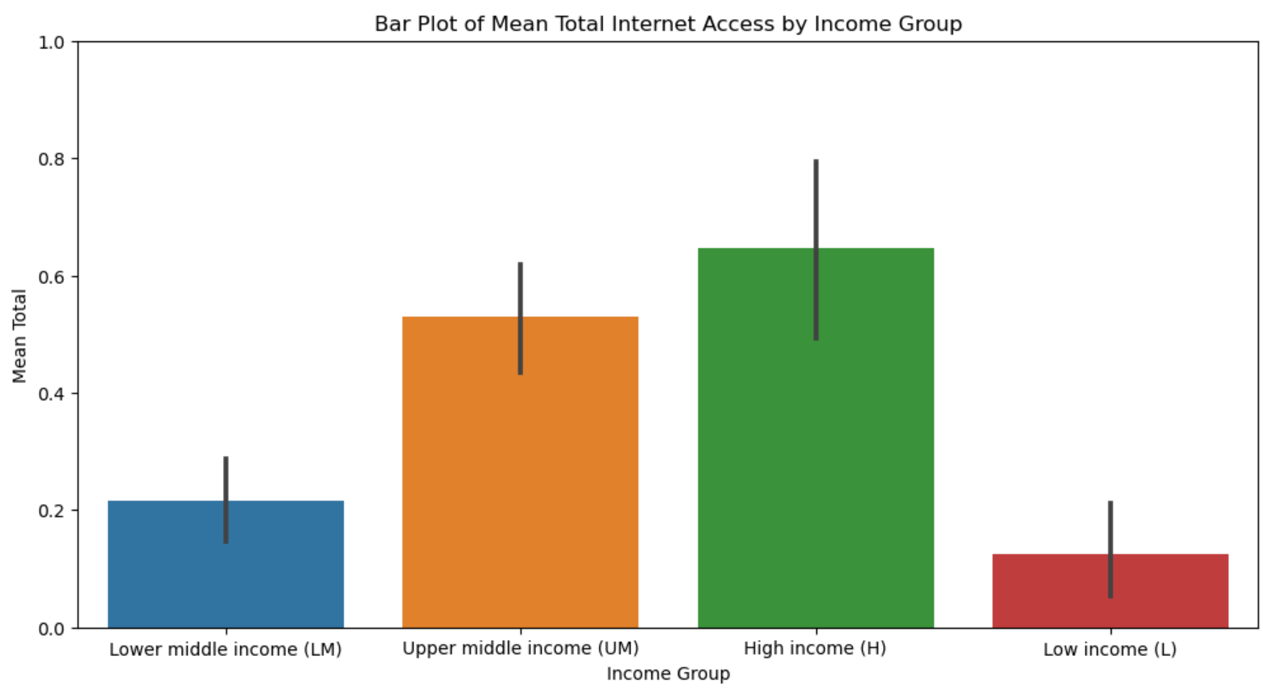


In [17]:

```python
plt.figure(figsize=(12, 6))
ax1 = sns.barplot(x='Region', y='Total', data=dftest)
plt.title('Bar Plot of Mean Total Internet Access by Region')
plt.xlabel('Region')
plt.ylabel('Mean Total')

# Setting the y-axis range from 0 to 1 to accomodate percent values
ax1.set_ylim(0, 1)

plt.show()

plt.figure(figsize=(12, 6))
ax2 = sns.barplot(x='Sub-region', y='Total', data=dftest)
plt.title('Bar Plot of Mean Total Internet Access by Sub-region')
plt.xlabel('Sub-region')
plt.ylabel('Mean Total')

ax2.set_ylim(0, 1)

plt.show()

plt.figure(figsize=(12, 6))
ax3 = sns.barplot(x='Income Group', y='Total', data=dftest)
plt.title('Bar Plot of Mean Total Internet Access by Income Group')
plt.xlabel('Income Group')
plt.ylabel('Mean Total')

ax3.set_ylim(0, 1)

plt.show()

```

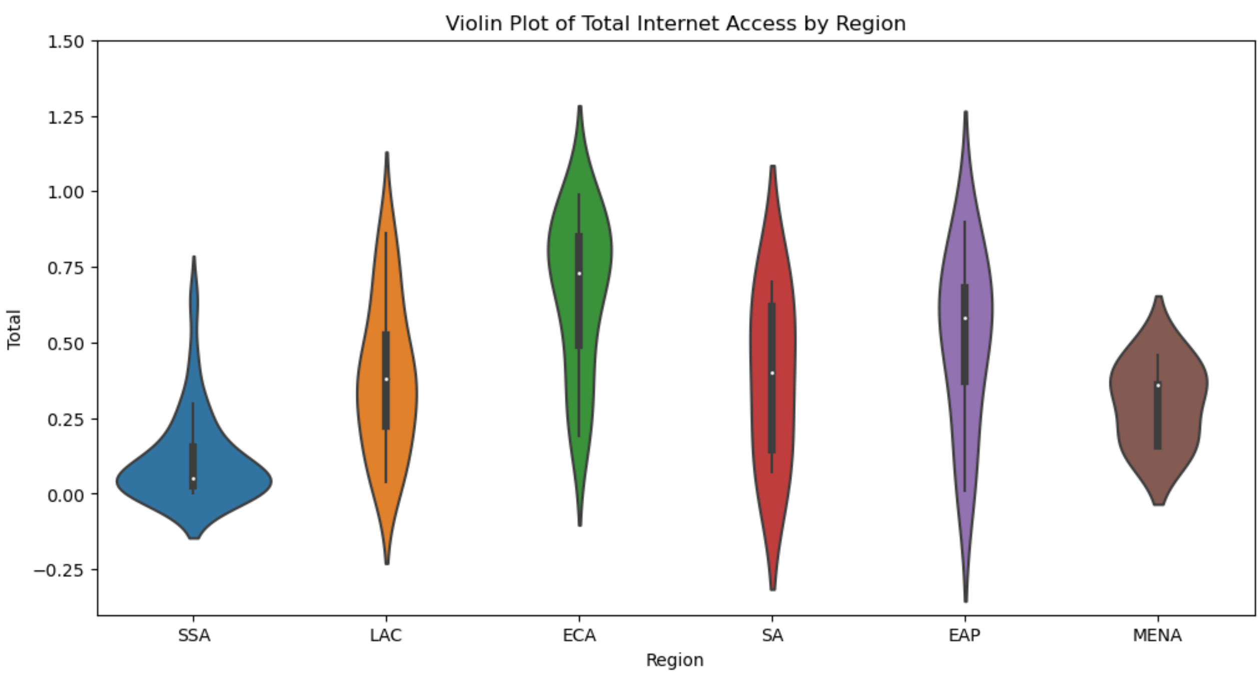


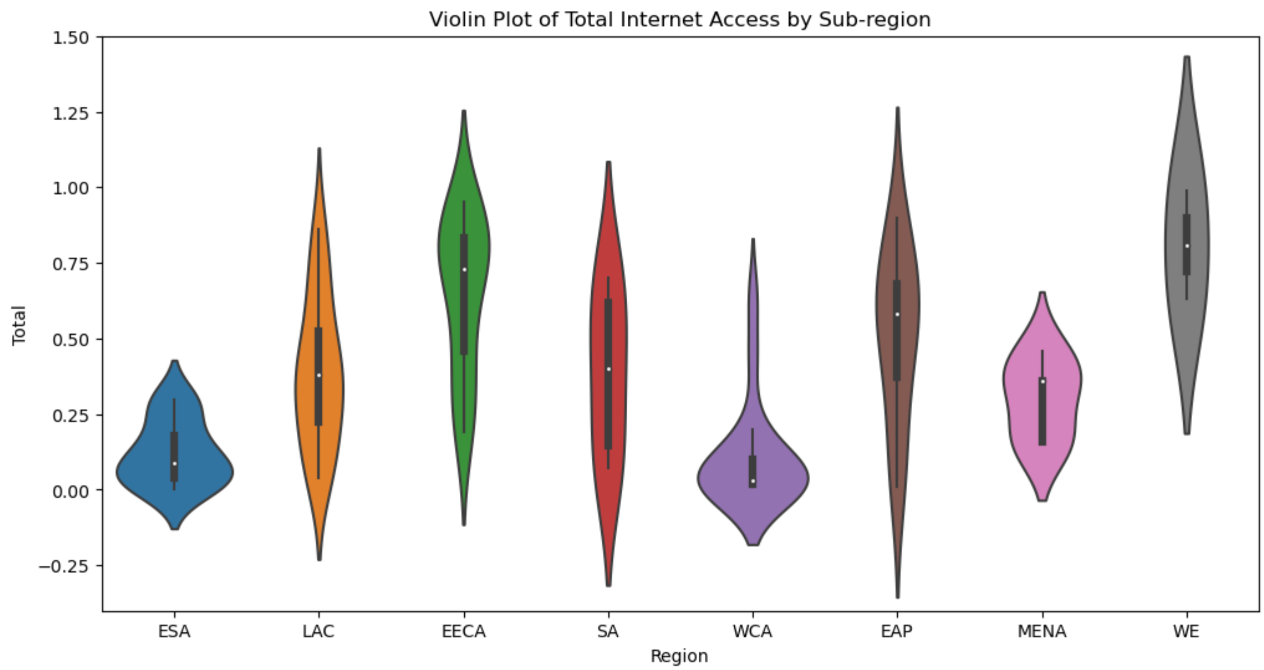

Bar Plot of Mean Total Internet Access by Sub-region
Mean Total
1.0
0.8
0.6
0.4
0.2
0.0
ESA
LAC
EECA
SA
WCA
EAP
MENA
WE
Sub-region


Bar Plot of Mean Total Internet Access by Income Group
Mean Total
1.0
0.8
0.6
0.4
0.2
0.0
Lower middle income (LM)
Upper middle income (UM)
High income (H)
Low income (L)
Income Group

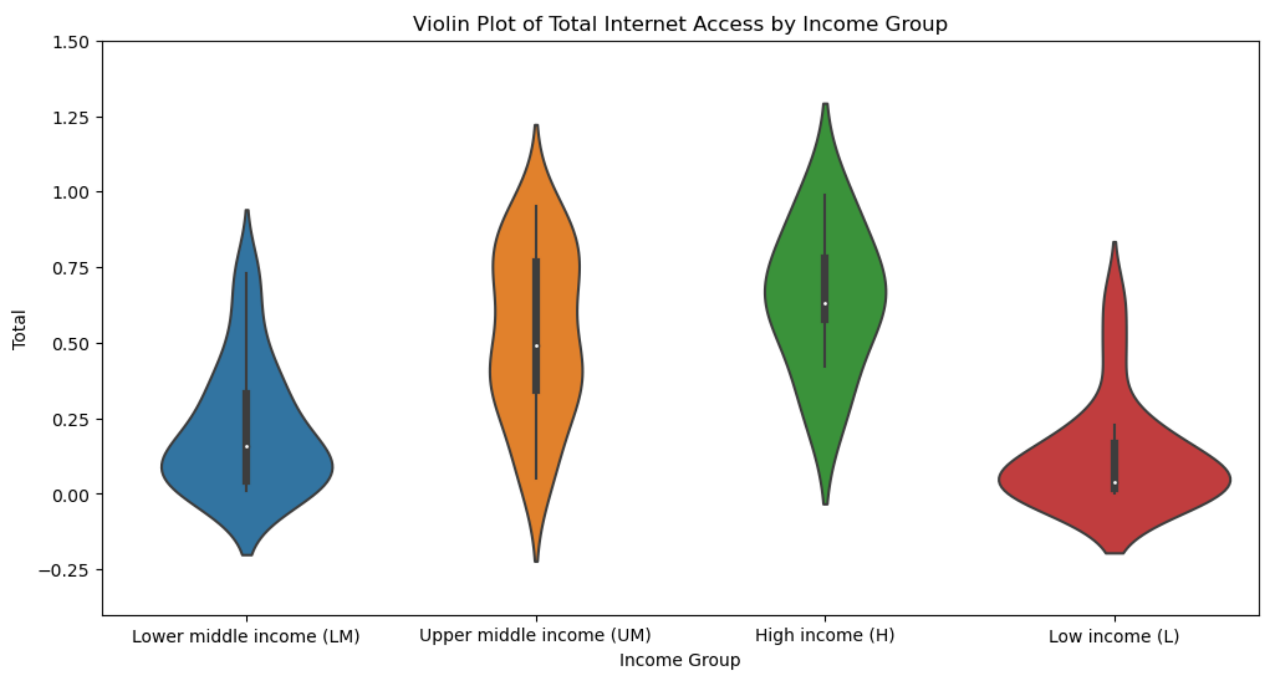
In [18]:

```
plt.figure(figsize=(12, 6))
ax1 = sns.violinplot(x='Region', y='Total', data=dftest)
plt.title('Violin Plot of Total Internet Access by Region')
plt.xlabel('Region')
plt.ylabel('Total')

# Settting the y-axis range from -0.30 to 1.50 to accomodate the full violin plot
ax1.set_ylim(-0.40, 1.50)

plt.show()

plt.figure(figsize=(12, 6))
ax2 = sns.violinplot(x='Sub-region', y='Total', data=dftest)
plt.title('Violin Plot of Total Internet Access by Sub-region')
plt.xlabel('Region')
plt.ylabel('Total')

ax2.set_ylim(-0.40, 1.50)

plt.show()

plt.figure(figsize=(12, 6))
ax3 = sns.violinplot(x='Income Group', y='Total', data=dftest)
plt.title('Violin Plot of Total Internet Access by Income Group')
plt.xlabel('Income Group')
plt.ylabel('Total')

ax3.set_ylim(-0.40, 1.50)

plt.show()

```





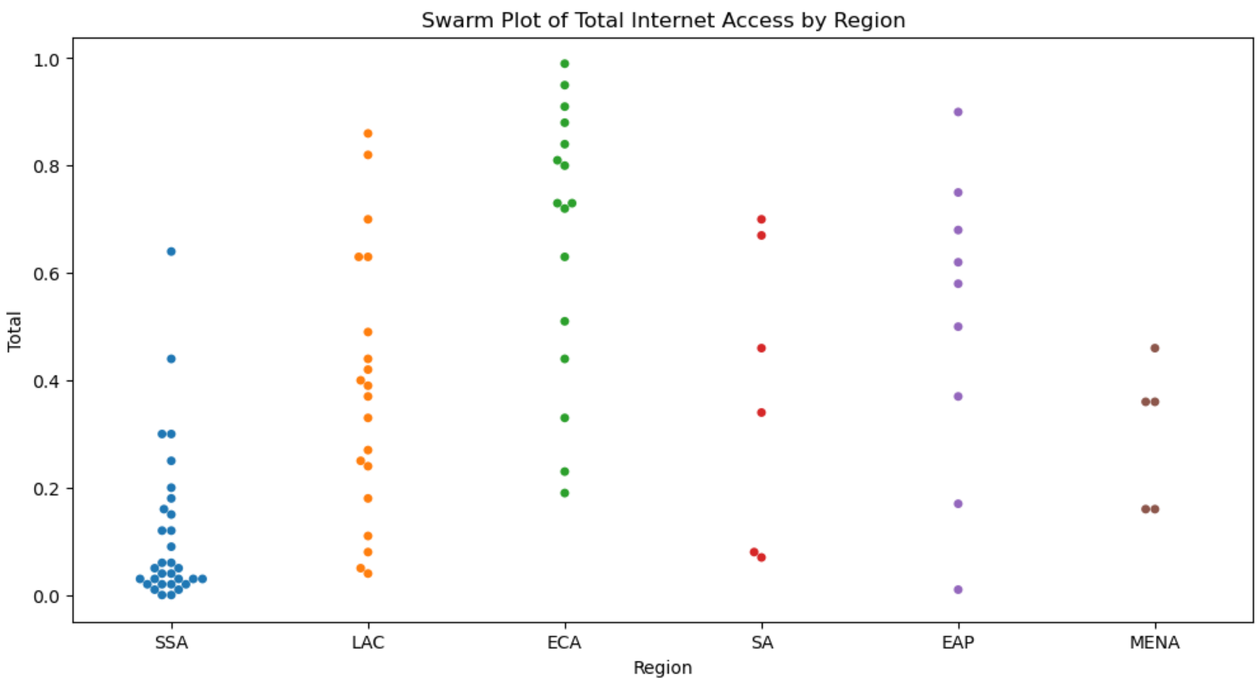
Violin Plot of Total Internet Access by Sub-region
Total
Region
ESA
LAC
EECA
SA
WCA
EAP
MENA
WE
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25

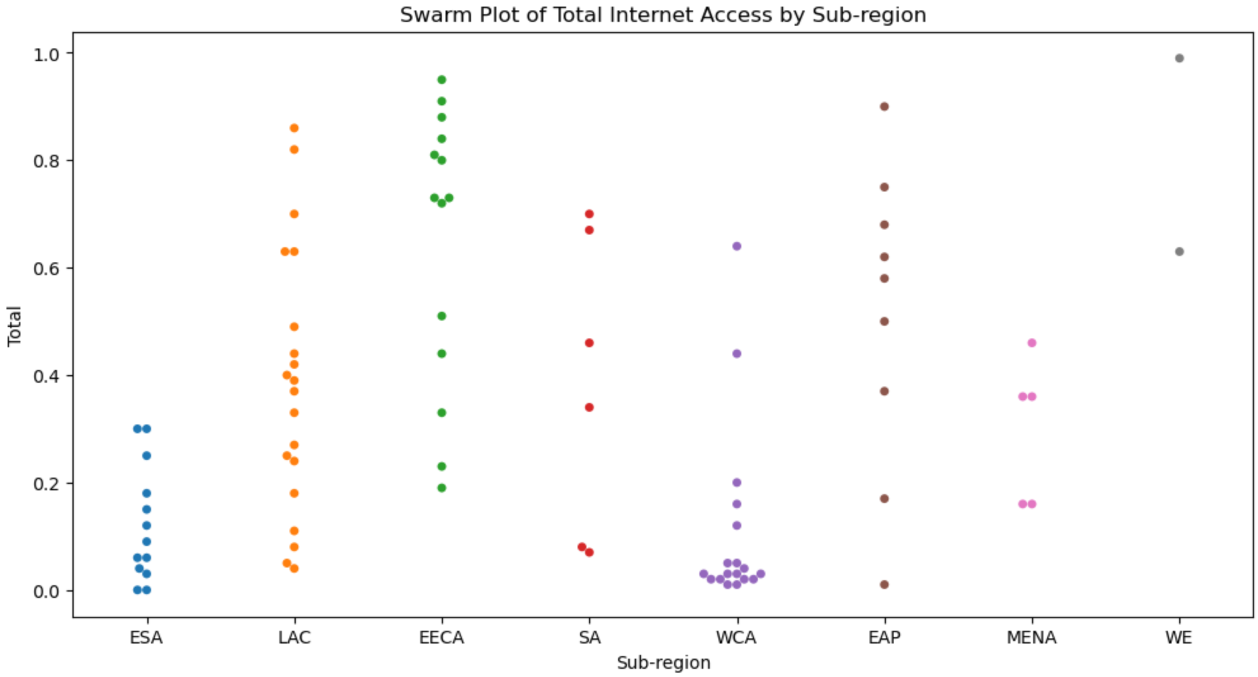


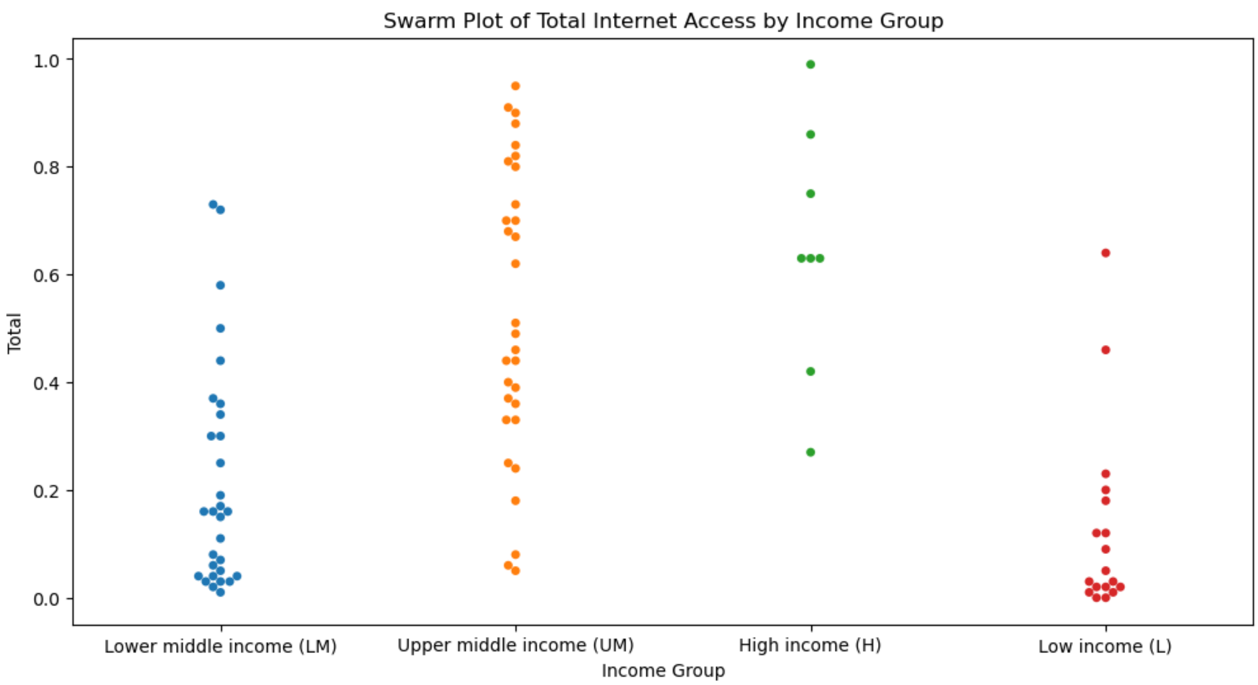
Violin Plot of Total Internet Access by Income Group
Total
Income Group
Lower middle income (LM)
Upper middle income (UM)
High income (H)
Low income (L)
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25

In [19]:

```
plt.figure(figsize=(12, 6))
sns.swarmplot(x='Region', y='Total', data=dftest)
plt.title('Swarm Plot of Total Internet Access by Region')
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()

plt.figure(figsize=(12, 6))
sns.swarmplot(x='Sub-region', y='Total', data=dftest)
plt.title('Swarm Plot of Total Internet Access by Sub-region')
plt.xlabel('Sub-region')
plt.ylabel('Total')
plt.show()

plt.figure(figsize=(12, 6))
sns.swarmplot(x='Income Group', y='Total', data=dftest)
plt.title('Swarm Plot of Total Internet Access by Income Group')
plt.xlabel('Income Group')
plt.ylabel('Total')
plt.show()
```

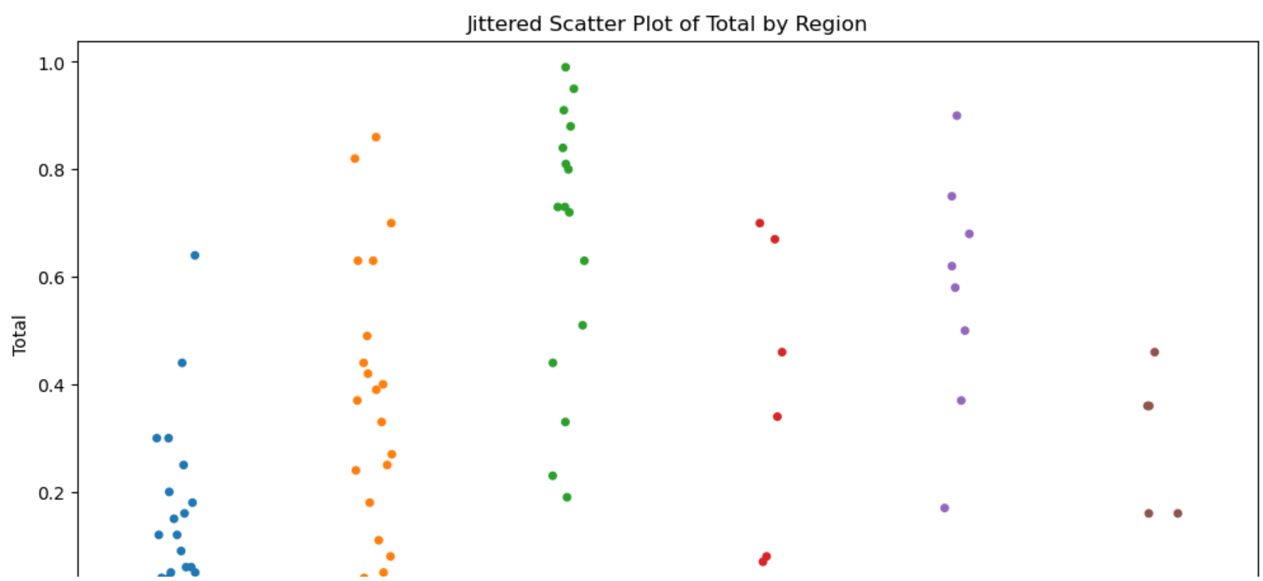



Swarm Plot of Total Internet Access by Sub-region
Total
Sub-region
ESA
LAC
EECA
SA
WCA
EAP
MENA
WE
0.0
0.2
0.4
0.6
0.8
1.0


Swarm Plot of Total Internet Access by Income Group
Total
Income Group
Lower middle income (LM)
Upper middle income (UM)
High income (H)
Low income (L)
0.0
0.2
0.4
0.6
0.8
1.0

In [20]:

```
#I am using a Jittered Plot to see a messier version of the swarm plot so i can get
#an idea of how much variation there is in between the data


plt.figure(figsize=(12, 6))
sns.stripplot(x='Region', y='Total', data=dftest, jitter=True, edgecolor='gray')
plt.title('Jittered Scatter Plot of Total by Region')
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()

plt.figure(figsize=(12, 6))
sns.stripplot(x='Sub-region', y='Total', data=dftest, jitter=True, edgecolor='gray')
plt.title('Jittered Scatter Plot of Total by Sub-region')
plt.xlabel('Sub-region')
plt.ylabel('Total')
plt.show()

plt.figure(figsize=(12, 6))
sns.stripplot(x='Income Group', y='Total', data=dftest, jitter=True, edgecolor='gray
plt.title('Jittered Scatter Plot of Total by Income Group')
plt.xlabel('Income Group')
plt.ylabel('Total')
plt.show()

```



Task 1: ANOVA ANALYSIS FOR NUMERICAL VALUE SUBSTITUTION

Here, I am evaluating the effectiveness of 'Total', 'Region', and 'Income Group' by virtue of their 'Total' value predictive power

In [21]:

```
#anova analysis to determine which is a better predictor of 'Total', 'Region', 'Sub-

from scipy.stats import f_oneway

# ANOVA calculation for 'Region' and 'Total'
region_groups = dftest.groupby('Region')['Total'].apply(list)
region_anova_results = f_oneway(*region_groups)
print(f"Region - F statistic: {region_anova_results.statistic:.2f}, P-value: {region_

#'Sub-region' and 'Total'
sub_region_groups = dftest.groupby('Sub-region')['Total'].apply(list)
sub_region_anova_results = f_oneway(*sub_region_groups)
print(f"Sub-region - F statistic: {sub_region_anova_results.statistic:.2f}, P-value:

#'Income Group' and 'Total'
income_group_groups = dftest.groupby('Income Group')['Total'].apply(list)
income_group_anova_results = f_oneway(*income_group_groups)
print(f"Income Group - F statistic: {income_group_anova_results.statistic:.2f}, P-va

```

```
Region - F statistic: 15.30, P-value: 0.00000
Sub-region - F statistic: 10.93, P-value: 0.00000
Income Group - F statistic: 20.17, P-value: 0.00000
```

In [22]:

```
#eta squared test to determine prediction and effective power of a categorical varia
def eta_squared(f_statistic, df_between, df_within):
    return f_statistic * df_between / (f_statistic * df_between + df_within)

region_eta_squared = eta_squared(region_anova_results.statistic, len(region_groups) -
income_group_eta_squared = eta_squared(income_group_anova_results.statistic, len(inco
sub_region_eta_squared = eta_squared(sub_region_anova_results.statistic, len(sub_reg


print(f"Region - Eta-squared: {region_eta_squared:.4f}")
print(f"Income Group - Eta-squared: {income_group_eta_squared:.4f}")
print(f"Sub-region - Eta-squared: {sub_region_eta_squared:.4f}")

```

```
Region - Eta-squared: 0.4857
Income Group - Eta-squared: 0.4216
Sub-region - Eta-squared: 0.4921
```

In [23]:
```python
#from the above Eta-squared value, We have inferred that the Sub-region is the best p
#'total' percent of children, however, I want to undersand how feasible this is to be
#as a substitute for the mean if one seems o be missing, given this need, I feel I w
#if in case, I want to compute and substitute a value for a missing value in a regio

region_counts = dftest['Region'].value_counts()
print("Region Counts:")
print(region_counts)

subregion_counts = dftest['Sub-region'].value_counts()
print("\nSub-region Counts:")
print(subregion_counts)

income_group_counts = dftest['Income Group'].value_counts()
print("\nIncome Group Counts:")
print(income_group_counts)

```

```
Region Counts:
SSA     31
LAC     20
ECA     16
EAP      9
SA       6
MENA     5
Name: Region, dtype: int64

Sub-region Counts:
LAC     20
WCA     18
EECA    14
ESA     13
EAP      9
SA       6
MENA     5
WE       2
Name: Sub-region, dtype: int64

Income Group Counts:
Upper middle income (UM)    31
Lower middle income (LM)    30
Low income (L)              18
High income (H)              8
Name: Income Group, dtype: int64
```

Task 2.2: Total School Age.csv data preparation and visualization

In this section, I will clean and substitute the missing values in the Total School Age csv I will employ the same methods that I used for preparing Primary.csv in Task 1

In [24]:
```python
signment1_DataSciWithPython_s3970066/Global database on school-age digital connectivity-C
```

In [25]:
```python
df3 = pd.read_csv(file_path3, encoding='latin1')
```

In [26]:
```
df3.describe()
```
Out[26]:

	column A	column B	column C	column D	column E	column F	column G	column H	column I	column J	column K	column L
count	88	88	88	88	88	88	78	81	71	70	88	88
unique	88	88	7	9	6	59	40	56	34	45	27	21
top	ISO3	Countries and areas	SSA	LAC	Upper middle income (UM)	3%	1%	52%	0%	99%	Multiple Indicator Cluster Survey	2018
freq	1	1	31	20	32	5	12	4	24	6	45	16

In [27]:
```
duplicates3 = df3.duplicated()
print(f"Number of duplicate rows: {duplicates3.sum()}")
```
```
Number of duplicate rows: 0
```

In [28]:
```
df_transposed3 = df3.T
duplicates3 = df_transposed3.duplicated()
print(f"Number of duplicate columns: {duplicates3.sum()}")
duplicate_column_names3 = df_transposed3.index[duplicates3].tolist()
print("Duplicate column names:", duplicate_column_names3)
```
```
Number of duplicate columns: 0
Duplicate column names: []
```

In [29]:
```
df3.isnull().any()
```
Out[29]:
```
column A      False
column B      False
column C      False
column  D     False
column E      False
column F      False
column G       True
column H       True
column I       True
column J       True
column K      False
column L      False
dtype: bool
```

In [30]:
```
df3.isnull().sum()
```
Out[30]:
```
column A       0
column B       0
column C       0
column  D      0
column E       0
column F       0
column G      10
column H       7
column I      17
column J      18
column K       0
column L       0
dtype: int64
```

In [31]:

```
#removing the first 'column' row
file_path_test3 = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSc
dftest3 = pd.read_csv(file_path_test3, skiprows=1)
output_file_path_test3 = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_
dftest3.to_csv(output_file_path_test3, index=False)
dftest3.head()
```

Out[31]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Time period
0	DZA	Algeria	MENA	MENA	Upper middle income (UM)	24%	9%	32%	1%	77%	Multiple Indicator Cluster Survey	2018-19
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	17%	2%	24%	0%	62%	Demographic and Health Survey	2015-16
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	40%	NaN	NaN	NaN	NaN	Multiple Indicator Cluster Survey	2011-12
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	81%	71%	88%	47%	99%	Demographic and Health Survey	2015-16
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	37%	33%	52%	9%	76%	Multiple Indicator Cluster Survey	2019

In [32]:

```
#printing out every single row with missing values in the School Age Dataset
missing_values_df_test3 = dftest3.loc[dftest3['Rural (Residence)'].isnull() | dftest3
```

In [33]:

```
missing_values_df_test3.head(100)
```

Out[33]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Tim perio
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	40%	NaN	NaN	NaN	NaN	Multiple Indicator Cluster Survey	2011 1
7	BOL	Bolivia (Plurinational State of)	LAC	LAC	Lower middle income (LM)	12%	4%	17%	NaN	NaN	EDSA	201
16	CHN	China	EAP	EAP	Upper middle income (UM)	57%	50%	91%	NaN	90%	CHARLS	201
24	ECU	Ecuador	LAC	LAC	Upper middle income (UM)	42%	20%	53%	NaN	NaN	ENSANUT	201
25	EGY	Egypt	MENA	MENA	Lower middle income (LM)	17%	9%	29%	NaN	NaN	2015 Household Income, Expenditure and Consump...	201
37	KEN	Kenya	SSA	ESA	Lower middle income (LM)	32%	NaN	24%	NaN	NaN	STEP Skills Measurement Household Survey 2013 ...	201
46	MEX	Mexico	LAC	LAC	Upper middle income (UM)	41%	11%	52%	NaN	NaN	ENSANUT	201
49	MAR	Morocco	MENA	MENA	Lower middle income (LM)	18%	12%	23%	NaN	NaN	Morocco Household and Youth Survey 2010	201
52	NIC	Nicaragua	LAC	LAC	Lower middle income (LM)	4%	NaN	NaN	NaN	NaN	Nicaragua National Demographic and Health Surv...	2011 1
53	NER	Niger	SSA	WCA	Low income (L)	3%	NaN	NaN	NaN	NaN	National Survey on Household Living Conditions...	2014 1
54	NGA	Nigeria	SSA	WCA	Lower middle income (LM)	3%	NaN	NaN	NaN	NaN	General Household Survey, Panel 2018-2019, Wave 4	2018 201
57	PER	Peru	LAC	LAC	Upper middle income (UM)	26%	1%	34%	NaN	NaN	ENDES	201
59	LCA	Saint Lucia	LAC	LAC	Upper middle income (UM)	48%	48%	44%	12%	NaN	Multiple Indicator Cluster Survey	201
64	SOM	Somalia	SSA	ESA	Low income (L)	13%	NaN	NaN	NaN	NaN	Somalia High Frequency Survey	2017 1

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Tim perio
65	ZAF	South Africa	SSA	ESA	Upper middle income (UM)	20%	NaN	NaN	NaN	NaN	South Africa Living Conditions Survey 2014-15	2014 1
80	UKR	Ukraine	ECA	EECA	Lower middle income (LM)	71%	NaN	71%	NaN	NaN	STEP Skills Measurement Household Survey 2013 ...	201
81	GBR	United Kingdom	ECA	WE	High income (H)	99%	NaN	NaN	NaN	NaN	UK Data Archive Information for the Study 8298...	201
82	URY	Uruguay	LAC	LAC	High income (H)	63%	47%	65%	35%	NaN	Multiple Indicator Cluster Survey	2012 9
84	VNM	Viet Nam	EAP	EAP	Lower middle income (LM)	62%	NaN	62%	NaN	NaN	STEP Skills Measurement Household Survey 2012 ...	201

In [34]:

```
#I am going to be choosing Rural (Residence), and Urban (Residence) for analysis in 
#for this, like I did for task 1, I will be converting the % string values to float

def percentage_to_float(value):
    if isinstance(value, str) and value.endswith('%'):
        return float(value[:-1]) / 100
    else:
        return value

columns_to_convert = ['Total', 'Rural (Residence)', 'Urban (Residence)']

for column in columns_to_convert:
    dftest3[column] = dftest3[column].apply(percentage_to_float)

#removing unwanted last four columns
#columns_to_remove = ['Poorest (Wealth quintile)', 'Richest (Wealth quintile)', 'Data
#dftest3 = dftest3.drop(columns=columns_to_remove)

dftest3.head()
```

Out[34]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Time period
0	DZA	Algeria	MENA	MENA	Upper middle income (UM)	0.24	0.09	0.32	1%	77%	Multiple Indicator Cluster Survey	2018-19
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.17	0.02	0.24	0%	62%	Demographic and Health Survey	2015-16
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.40	NaN	NaN	NaN	NaN	Multiple Indicator Cluster Survey	2011-12
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81	0.71	0.88	47%	99%	Demographic and Health Survey	2015-16
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.37	0.33	0.52	9%	76%	Multiple Indicator Cluster Survey	2019

In [35]:

```
columns_to_remove = ['Poorest (Wealth quintile)', 'Richest (Wealth quintile)', 'Data
dftest3 = dftest3.drop(columns=columns_to_remove)
dftest3.head()
```

Out[35]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)
0	DZA	Algeria	MENA	MENA	Upper middle income (UM)	0.24	0.09	0.32
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.17	0.02	0.24
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.40	NaN	NaN
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81	0.71	0.88
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.37	0.33	0.52

In [36]:

```
file_path = "/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSciWithPy
dftest3.to_csv(file_path, index=False)
```

In [37]:

```

file_path = "/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSciWithPy
dftest3cleaned1 = pd.read_csv(file_path)

dftest3cleaned1.head()
```

Out[37]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)
0	DZA	Algeria	MENA	MENA	Upper middle income (UM)	0.24	0.09	0.32
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.17	0.02	0.24
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.40	NaN	NaN
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81	0.71	0.88
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.37	0.33	0.52

In [38]:

```python

# Calculating the mean values for 'Rural (Residence)' and 'Urban (Residence)' per Re
mean_values = dftest3cleaned1.groupby('Region').agg({
    'Rural (Residence)': np.nanmean,
    'Urban (Residence)': np.nanmean
}).reset_index()


# Function to substitute NaN values with the mean value based on the Region's mean
def replace_nan_with_mean(row, mean_values):
    region = row['Region']
    mean_rural = mean_values.loc[mean_values['Region'] == region, 'Rural (Residence)
    mean_urban = mean_values.loc[mean_values['Region'] == region, 'Urban (Residence)

    row['Rural (Residence)'] = round(row['Rural (Residence)'] if pd.notna(row['Rural
    row['Urban (Residence)'] = round(row['Urban (Residence)'] if pd.notna(row['Urban

    return row


# Substituting NaN values into dftest3cleaned1
dftest3cleaned1 = dftest3cleaned1.apply(lambda row: replace_nan_with_mean(row, mean_

dftest3cleaned1.head()

```

Out[38]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)
0	DZA	Algeria	MENA	MENA	Upper middle income (UM)	0.24	0.09	0.32
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.17	0.02	0.24
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.40	0.27	0.49
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81	0.71	0.88
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.37	0.33	0.52

In [39]:

```
dftest3cleaned1.head(50)
```

Out[39]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)
0	DZA	Algeria	MENA	MENA	Upper middle income (UM)	0.24	0.09	0.32
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.17	0.02	0.24
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.40	0.27	0.49
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81	0.71	0.88
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.37	0.33	0.52
5	BRB	Barbados	LAC	LAC	High income (H)	0.66	0.61	0.69
6	BEN	Benin	SSA	WCA	Low income (L)	0.04	0.01	0.07
7	BOL	Bolivia (Plurinational State of)	LAC	LAC	Lower middle income (LM)	0.12	0.04	0.17
8	BIH	Bosnia and Herzegovina	ECA	EECA	Upper middle income (UM)	0.59	0.51	0.76
9	BRA	Brazil	LAC	LAC	Upper middle income (UM)	0.83	0.51	0.89
10	BGR	Bulgaria	ECA	EECA	Upper middle income (UM)	0.76	0.66	0.81
11	BFA	Burkina Faso	SSA	WCA	Low income (L)	0.01	0.01	0.04
12	CMR	Cameroon	SSA	WCA	Lower middle income (LM)	0.05	0.00	0.10
13	CAF	Central African Republic	SSA	WCA	Low income (L)	0.04	0.01	0.09
14	TCD	Chad	SSA	WCA	Low income (L)	0.02	0.01	0.08
15	CHL	Chile	LAC	LAC	High income (H)	0.86	0.70	0.89
16	CHN	China	EAP	EAP	Upper middle income (UM)	0.57	0.50	0.91
17	COL	Colombia	LAC	LAC	Upper middle income (UM)	0.36	0.05	0.48
18	CRI	Costa Rica	LAC	LAC	Upper middle income (UM)	0.72	0.61	0.78
19	CIV	C™te d'Ivoire	SSA	WCA	Lower middle income (LM)	0.03	0.01	0.05
20	CUB	Cuba	LAC	LAC	Upper middle income (UM)	0.04	0.01	0.06
21	COD	Democratic Republic of the Congo	SSA	WCA	Low income (L)	0.01	0.00	0.02
22	DJI	Djibouti	SSA	ESA	Lower middle income (LM)	0.06	0.01	0.11
23	DOM	Dominican Republic	LAC	LAC	Upper middle income (UM)	0.24	0.10	0.29
24	ECU	Ecuador	LAC	LAC	Upper middle income (UM)	0.42	0.20	0.53
25	EGY	Egypt	MENA	MENA	Lower middle income (LM)	0.17	0.09	0.29
26	GMB	Gambia	SSA	WCA	Low income (L)	0.65	0.47	0.75
27	GEO	Georgia	ECA	EECA	Upper middle income (UM)	0.85	0.72	0.93
28	GHA	Ghana	SSA	WCA	Lower middle income (LM)	0.17	0.10	0.26

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)
29	GTM	Guatemala	LAC	LAC	Upper middle income (UM)	0.09	0.03	0.18
30	GNB	Guinea-Bissau	SSA	WCA	Low income (L)	0.02	0.02	0.04
31	HTI	Haiti	LAC	LAC	Low income (L)	0.21	0.11	0.36
32	IND	India	SA	SA	Lower middle income (LM)	0.09	0.05	0.17
33	IDN	Indonesia	EAP	EAP	Lower middle income (LM)	0.19	0.10	0.26
34	IRQ	Iraq	MENA	MENA	Upper middle income (UM)	0.49	0.35	0.56
35	JPN	Japan	EAP	EAP	High income (H)	0.78	0.83	0.77
36	JOR	Jordan	MENA	MENA	Upper middle income (UM)	0.38	0.35	0.38
37	KEN	Kenya	SSA	ESA	Lower middle income (LM)	0.32	0.07	0.24
38	KIR	Kiribati	EAP	EAP	Lower middle income (LM)	0.51	0.33	0.69
39	KGZ	Kyrgyzstan	ECA	EECA	Lower middle income (LM)	0.74	0.69	0.83
40	LAO	Lao People's Democratic Republic	EAP	EAP	Lower middle income (LM)	0.02	0.01	0.04
41	LSO	Lesotho	SSA	ESA	Lower middle income (LM)	0.32	0.22	0.52
42	MDG	Madagascar	SSA	ESA	Low income (L)	0.11	0.06	0.27
43	MDV	Maldives	SA	SA	Upper middle income (UM)	0.70	0.69	0.72
44	MLI	Mali	SSA	WCA	Low income (L)	0.05	0.03	0.14
45	MRT	Mauritania	SSA	WCA	Lower middle income (LM)	0.03	0.01	0.06
46	MEX	Mexico	LAC	LAC	Upper middle income (UM)	0.41	0.11	0.52
47	MNG	Mongolia	EAP	EAP	Lower middle income (LM)	0.37	0.13	0.49
48	MNE	Montenegro	ECA	EECA	Upper middle income (UM)	0.82	0.74	0.86
49	MAR	Morocco	MENA	MENA	Lower middle income (LM)	0.18	0.12	0.23

In [40]:

```
file_path3 = "/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSciWithI
dftest3cleaned1.to_csv(file_path3, index=False)
```

In [41]:

```python

file_path = "/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSciWithPy
dftest3cleaned2 = pd.read_csv(file_path)

dftest3cleaned2.head()
```

Out[41]:

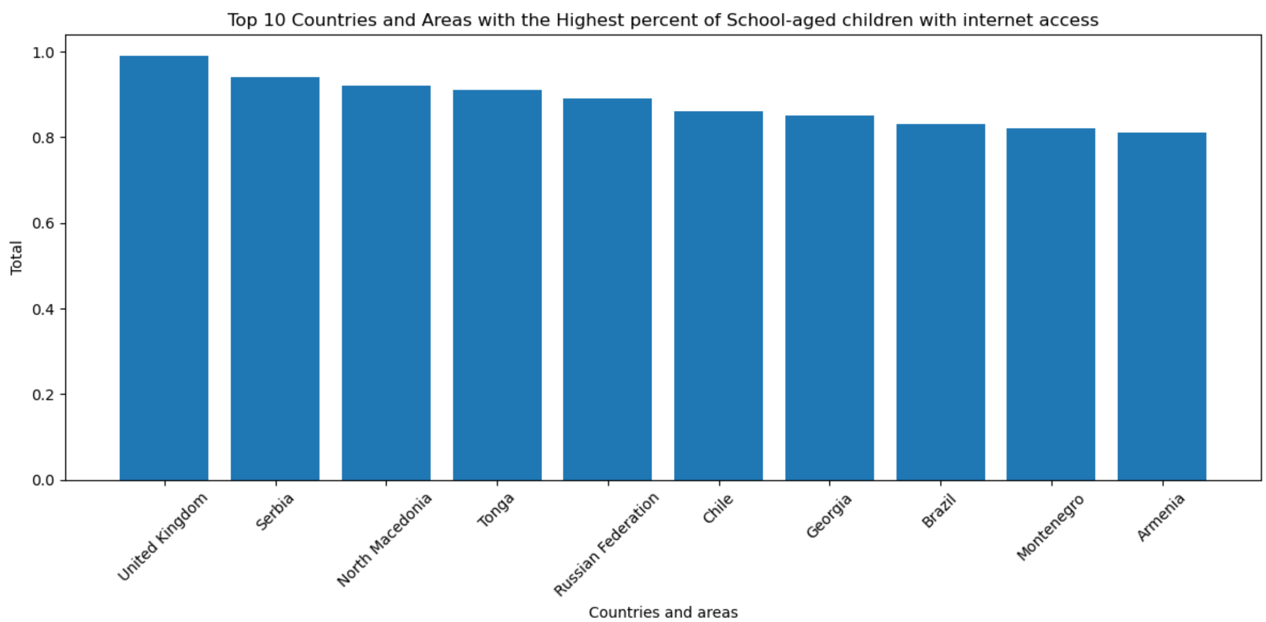
	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)
0	DZA	Algeria	MENA	MENA	Upper middle income (UM)	0.24	0.09	0.32
1	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.17	0.02	0.24
2	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.40	0.27	0.49
3	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81	0.71	0.88
4	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.37	0.33	0.52

Task 2.2: Top 10 Countries and areas with the Highest percent of School-aged children with internet access

This is the start of Task 2.2's objectives

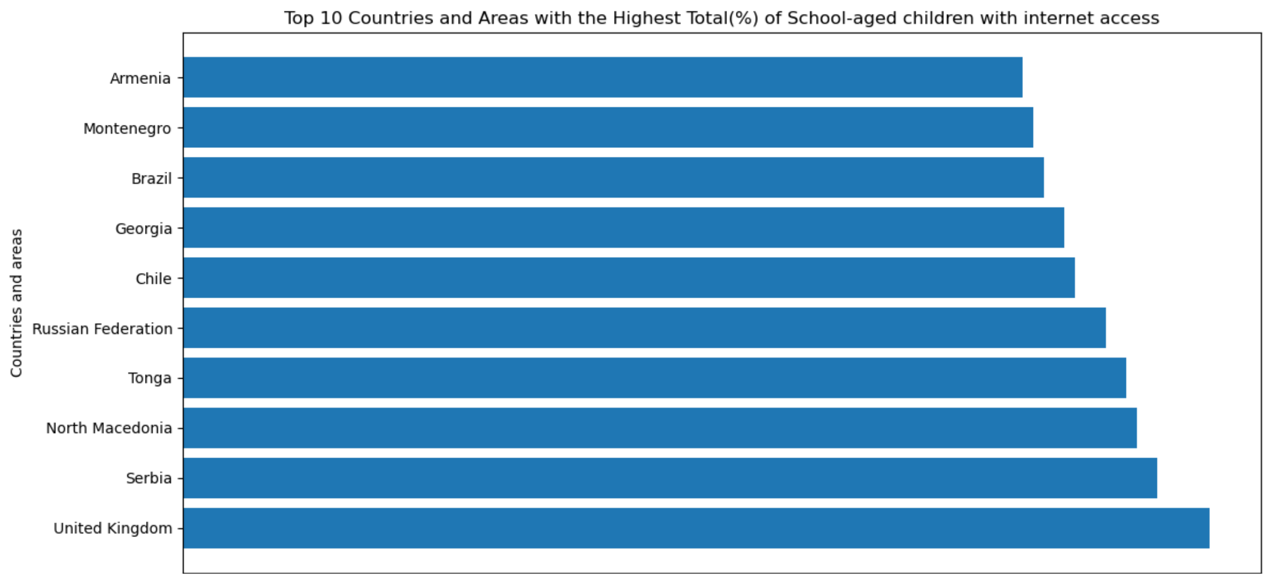
In [42]:

```


dftest3cleaned2 = dftest3cleaned2.sort_values(by='Total', ascending=False)

#selecting top 10 rows based on their 'Total' value
top_10 = dftest3cleaned2.head(10)

# Bar graph for displaying the top 10 countries with highest total percent of schoolc
plt.figure(figsize=(12, 6))
plt.bar(top_10['Countries and areas'], top_10['Total'])
plt.xlabel('Countries and areas')
plt.ylabel('Total')
plt.title('Top 10 Countries and Areas with the Highest percent of School-aged childre
plt.xticks(rotation=45)

plt.tight_layout()
plt.show()

```

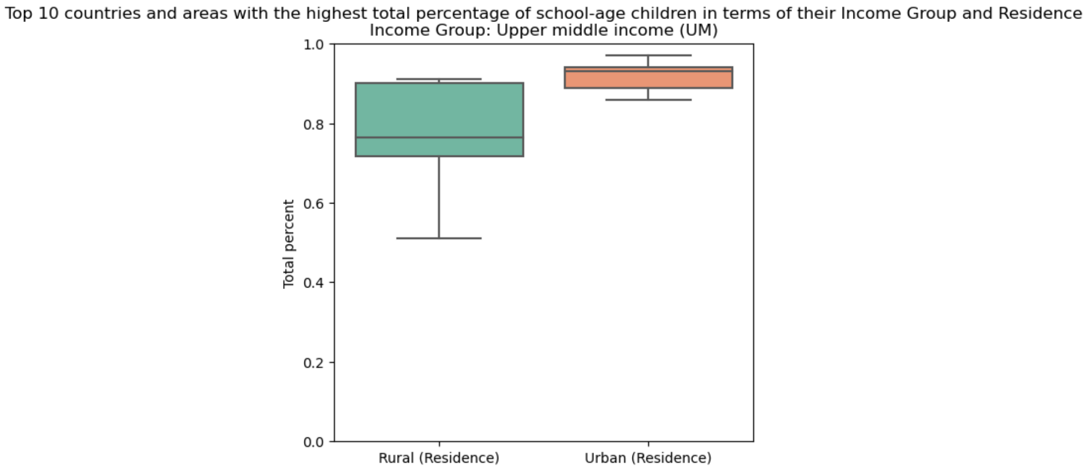


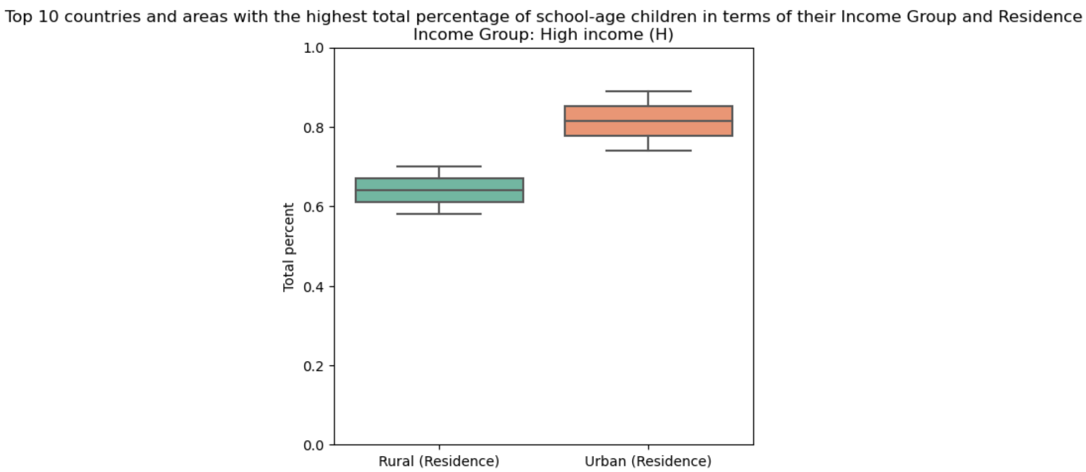
In [43]:

```
#horizintal version of the above graph
plt.figure(figsize=(12, 6))
plt.barh(top_10['Countries and areas'], top_10['Total'])
plt.xlabel('Total')
plt.ylabel('Countries and areas')
plt.title('Top 10 Countries and Areas with the Highest Total(%) of School-aged childr
plt.tight_layout()
plt.show()
```



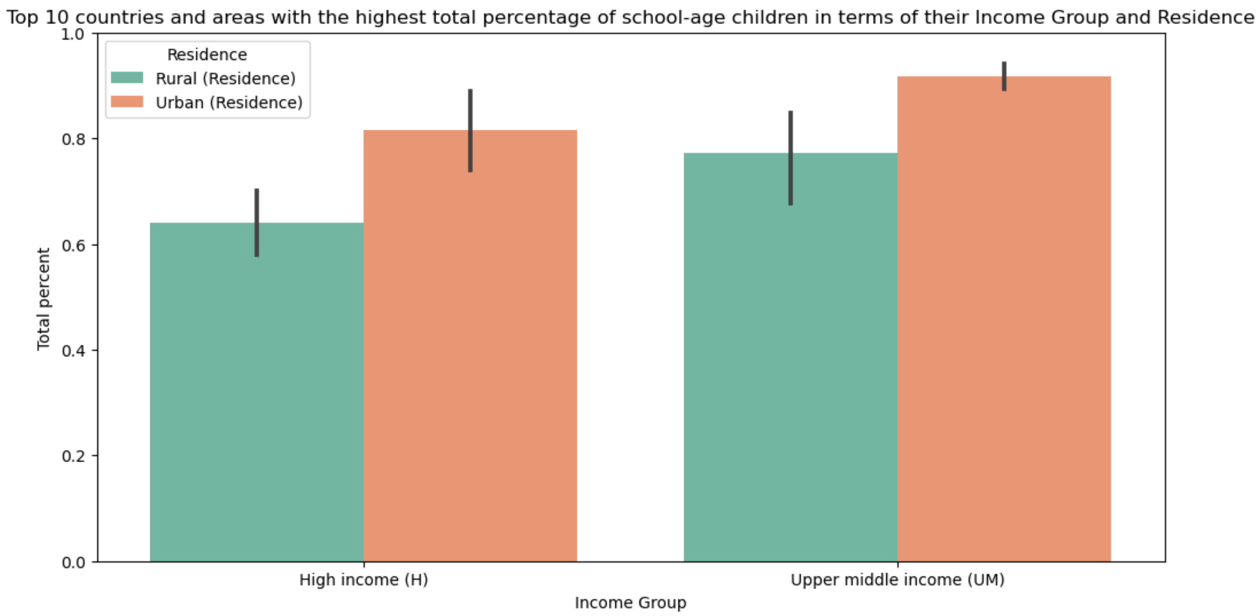
```
In [44]:
#here, I am visualizing the top 10 countries which I pulled into a dataframe
#and depictted in a bar graph above, but am delineating by the Top 10's Income Group:
#to see the relationship between Income group and the rural versus urban residence
#in internet connectivitty


dftest3cleaned2 = dftest3cleaned2.sort_values(by='Total', ascending=False)

top_10 = dftest3cleaned2.head(10)

fig, axes = plt.subplots(2, 2, figsize=(12, 12))
income_groups = ['Upper middle income (UM)', 'Lower middle income (LM)', 'High income

for i, income_group in enumerate(income_groups):
    row = i // 2
    col = i % 2

    top_10_income_group = top_10[top_10['Income Group'] == income_group]

    if not top_10_income_group.empty:
        ax = sns.boxplot(data=top_10_income_group[['Rural (Residence)', 'Urban (Resid
        ax.set_xticklabels(['Rural (Residence)', 'Urban (Residence)'])
        ax.set_ylabel('Total percent')
        ax.set_ylim(0, 1)
        ax.yaxis.grid(False)
        axes[row, col].set_title(f'Top 10 countries and areas with the highest total
    else:
        axes[row, col].set_axis_off()

plt.subplots_adjust(hspace=0.3)
plt.show()
```


Top 10 countries and areas with the highest total percentage of school-age children in terms of their Income Group and Residence
Income Group: Upper middle income (UM)
Total percent
1.0
0.8
0.6
0.4
0.2
0.0
Rural (Residence)
Urban (Residence)


Top 10 countries and areas with the highest total percentage of school-age children in terms of their Income Group and Residence
Income Group: High income (H)
Total percent
1.0
0.8
0.6
0.4
0.2
0.0
Rural (Residence)
Urban (Residence)

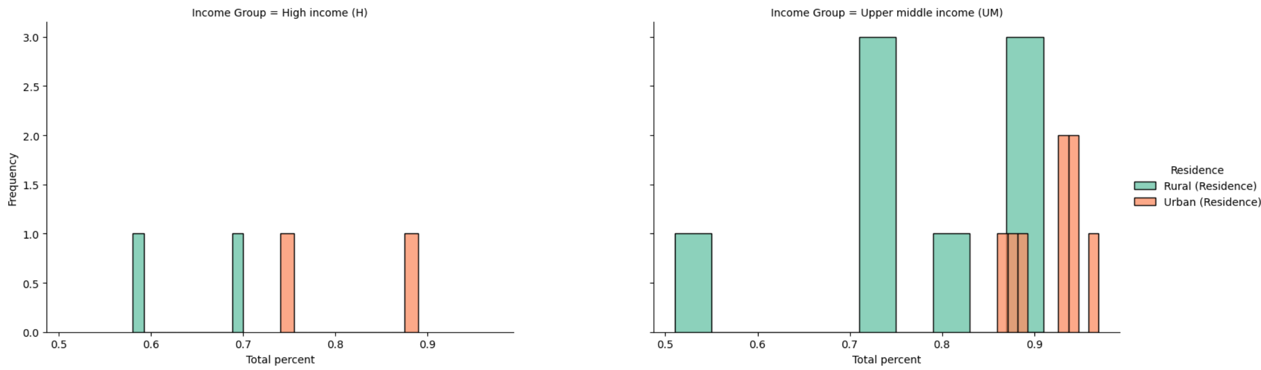
In [45]:

```
#here, i am separating the bar graphs to be able to visualize the two
#relevant income groups more effectiveely I will create a groupeed Bar plot
#these are visually quite explainable to a viewer and I think that makes it a favora
#visualization method


#melting the data to fit into a grouped bar plot
melted_data = pd.melt(top_10, id_vars=['Income Group'], value_vars=['Rural (Residence

plt.figure(figsize=(12, 6))
ax = sns.barplot(data=melted_data, x='Income Group', y='Total percent', hue='Residenc
plt.title('Top 10 countries and areas with the highest total percentage of school-age
plt.ylabel('Total percent')


ax.set_ylim(0, 1)

plt.show()
```



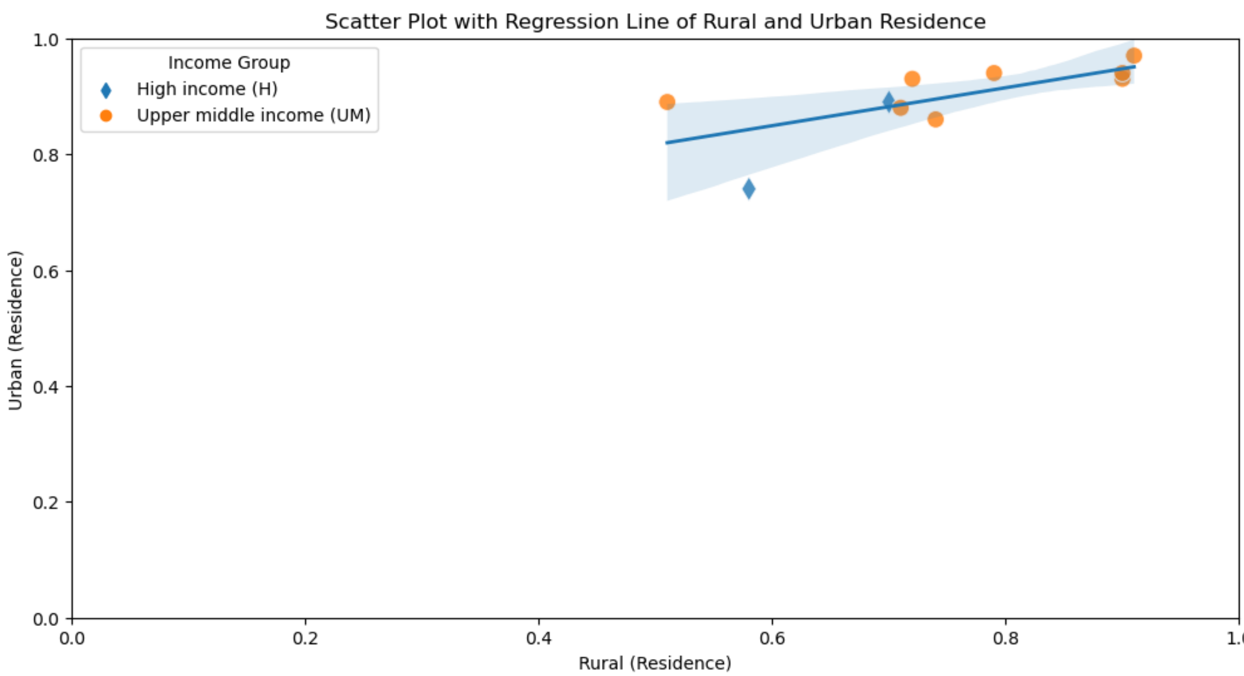
In [46]:

```
# Here I am Melting the data to have the columns, 'Residence' and 'Total percent'
#however, i am going to be visualizing how many individual values we have per catego
#this is important as it gives a better understanding of what kind of data visualiza
melted_data = pd.melt(top_10, id_vars=['Income Group'], value_vars=['Rural (Residence

# Faceted Histogram will help me in grasping how many individual values are present
#for me to be able to visualize and make inferences with
g = sns.FacetGrid(melted_data, col='Income Group', hue='Residence', palette='Set2', c
g.map(sns.histplot, 'Total percent', bins=10, alpha=0.75)
g.add_legend(title='Residence')
g.set_axis_labels('Total percent', 'Frequency')
g.fig.subplots_adjust(wspace=0.3, hspace=0.3)
plt.show()
```



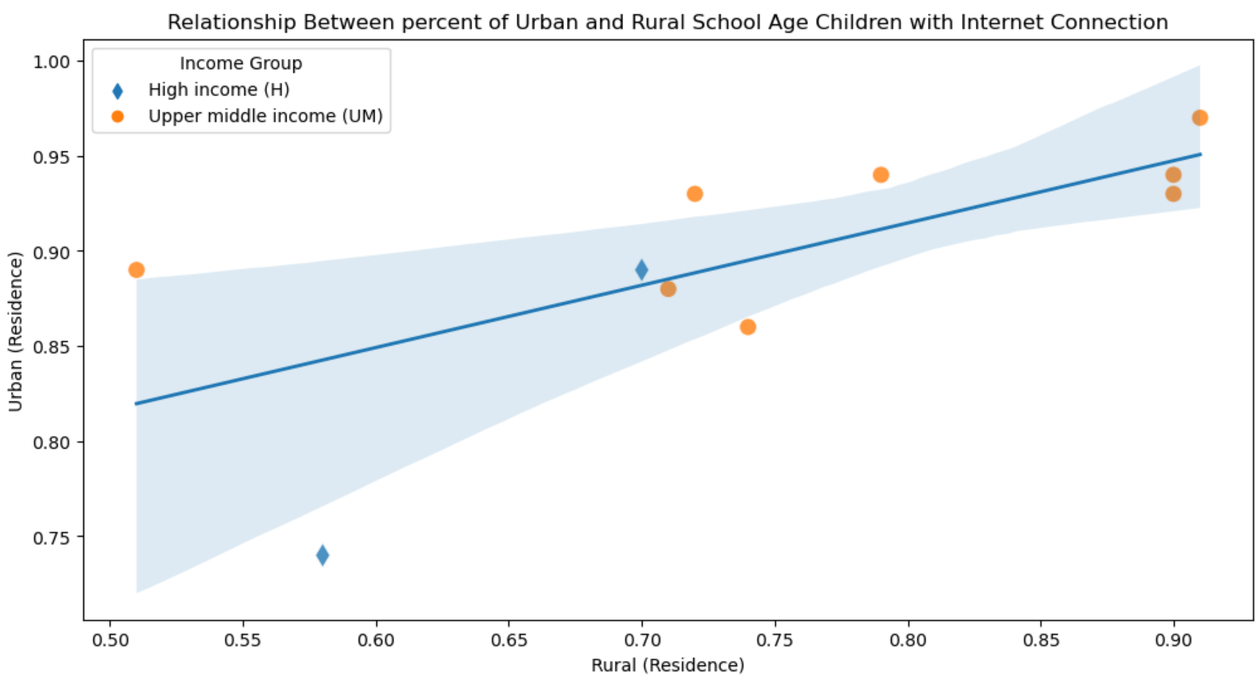
In [47]:

```
#Here I want to visualize the relationship between the urban and rural residence
#with a Scatter plot

plt.figure(figsize=(12, 6))

#First I am going to define markers for each income group
markers = {'Upper middle income (UM)': 'o', 'Lower middle income (LM)': 's', 'High inco


sns.scatterplot(x='Rural (Residence)', y='Urban (Residence)', hue='Income Group', data=

# This regression line will help in visualizing the relationship between urban and rura
sns.regplot(x='Rural (Residence)', y='Urban (Residence)', data=top_10, scatter=False, l

plt.title('Scatter Plot with Regression Line of Rural and Urban Residence')
plt.xlabel('Rural (Residence)')
plt.ylabel('Urban (Residence)')

# Here, i am setting the y-axis range from 0 to 1 so that we see the clear spread acros
#percentages, in the next cell, I will zoom into the relevant section of this scatter p
#examine the relationship in more detail
plt.ylim(0, 1)
plt.xlim(0,1)

plt.legend(title='Income Group', loc='upper left')

plt.show()

```



In [48]:

```
#zoomed in scatter plot
#given that the previous scatter plot gave a birds eye view of the data, It prompts
#a zoomed in view of the data as well

plt.figure(figsize=(12, 6))

#First I am going to define markers for each income group
markers = {'Upper middle income (UM)': 'o', 'Lower middle income (LM)': 's', 'High in

sns.scatterplot(x='Rural (Residence)', y='Urban (Residence)', hue='Income Group', dat

# This regression line will help in visualizing the relationship between urban and ru
#given that this graph will be zoomed in, it will be easier to make inferences
sns.regplot(x='Rural (Residence)', y='Urban (Residence)', data=top_10, scatter=False

plt.title('Relationship Between percent of Urban and Rural School Age Children with I
plt.xlabel('Rural (Residence)')
plt.ylabel('Urban (Residence)')

plt.legend(title='Income Group', loc='upper left')

plt.show()

```



Task 2.3: Preparing Secondary.csv data for comparative analysis with cleaned Primary.csv data

In this part, I am cleaning Secondary.csv's data and handling the anomalies so that I can compare the results to the Primary.csv data to see if the results mirror their respective regions

In [49]:

```
#cleaning Secondary.csv
file_path_test2 = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_DataSci
dftest2 = pd.read_csv(file_path_test2, skiprows=1)
output_file_path_test2 = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_
dftest2.to_csv(output_file_path_test2, index=False)
dftest2.head()
```

Out[49]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Time period
0	AGOA	Angola	SSA	ESA	Lower middle income (LM)	24%	2%	33%	0%	69%	Demographic and Health Survey	2015-16
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	45%	NaN	NaN	NaN	NaN	Multiple Indicator Cluster Survey	2011-12
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	85%	78%	91%	54%	100%	Demographic and Health Survey	2015-16
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	42%	38%	57%	13%	79%	Multiple Indicator Cluster Survey	2019
4	BRB	Barbados	LAC	LAC	High income (H)	76%	76%	76%	4%	100%	Multiple Indicator Cluster Survey	2012

In [50]:

```
#converting the data in the 'Total' column to numeric to enable analysis

def percentage_to_float(value):
    if isinstance(value, str) and value.endswith('%'):
        return float(value[:-1]) / 100
    else:
        return value

columns_to_convert = ['Total']

for column in columns_to_convert:
    dftest2[column] = dftest2[column].apply(percentage_to_float)

dftest2.head()
```

Out[50]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total	Rural (Residence)	Urban (Residence)	Poorest (Wealth quintile)	Richest (Wealth quintile)	Data source	Time period
0	AGOA	Angola	SSA	ESA	Lower middle income (LM)	0.24	2%	33%	0%	69%	Demographic and Health Survey	2015-16
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.45	NaN	NaN	NaN	NaN	Multiple Indicator Cluster Survey	2011-12
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.85	78%	91%	54%	100%	Demographic and Health Survey	2015-16
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.42	38%	57%	13%	79%	Multiple Indicator Cluster Survey	2019
4	BRB	Barbados	LAC	LAC	High income (H)	0.76	76%	76%	4%	100%	Multiple Indicator Cluster Survey	2012

In [51]:

```
columns_to_remove2 = ['Rural (Residence)','Urban (Residence)','Poorest (Wealth quintile)
dftest2 = dftest2.drop(columns=columns_to_remove2)
dftest2.head()
```

Out[51]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGOA	Angola	SSA	ESA	Lower middle income (LM)	0.24
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.45
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.85
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.42
4	BRB	Barbados	LAC	LAC	High income (H)	0.76

In [52]:

```
output_file_path2 = '/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignment1_Datas
dftest2.to_csv(output_file_path2, index=False)
```

In [53]:
```python
dftest.head()
```
Out[53]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.15
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.39
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.81
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.34
4	BRB	Barbados	LAC	LAC	High income (H)	0.63

In [54]:
```python
dftest2.head()
```
Out[54]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGOA	Angola	SSA	ESA	Lower middle income (LM)	0.24
1	ARG	Argentina	LAC	LAC	Upper middle income (UM)	0.45
2	ARM	Armenia	ECA	EECA	Upper middle income (UM)	0.85
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.42
4	BRB	Barbados	LAC	LAC	High income (H)	0.76

In [55]:
```python
dftesttask3 = dftest[dftest['Income Group'] == 'Lower middle income (LM)']
dftesttask3.head()
```
Out[55]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGO	Angola	SSA	ESA	Lower middle income (LM)	0.15
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.34
6	BOL	Bolivia (Plurinational State of)	LAC	LAC	Lower middle income (LM)	0.11
11	CMR	Cameroon	SSA	WCA	Lower middle income (LM)	0.04
18	CIV	C™te d'Ivoire	SSA	WCA	Lower middle income (LM)	0.02

In [56]:
```python
dftest2task3 = dftest2[dftest2['Income Group'] == 'Lower middle income (LM)']

dftest2task3.head()
```
Out[56]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGOA	Angola	SSA	ESA	Lower middle income (LM)	0.24
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.42
10	CMR	Cameroon	SSA	WCA	Lower middle income (LM)	0.07
17	CIV	C™te d'Ivoire	SSA	WCA	Lower middle income (LM)	0.03
20	DJI	Djibouti	SSA	ESA	Lower middle income (LM)	0.09

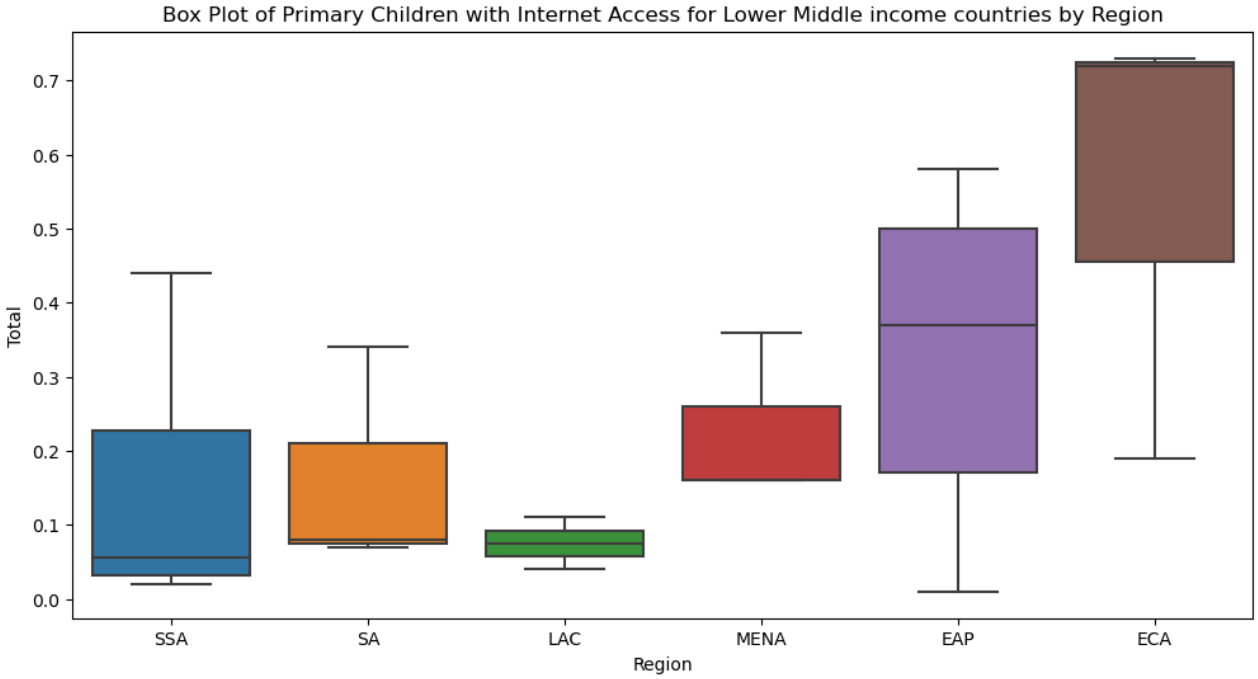
In [57]:
```python
file_path_primarylm_task3 = "/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignmen

dftesttask3.to_csv(file_path_primarylm_task3, index=False)

```

In [58]:

```
file_path_secondarylm_task3 = "/Users/amayiyer/Desktop/DatSci_Python/s3970066/Assignm

dftest2task3.to_csv(file_path_secondarylm_task3, index=False)
```

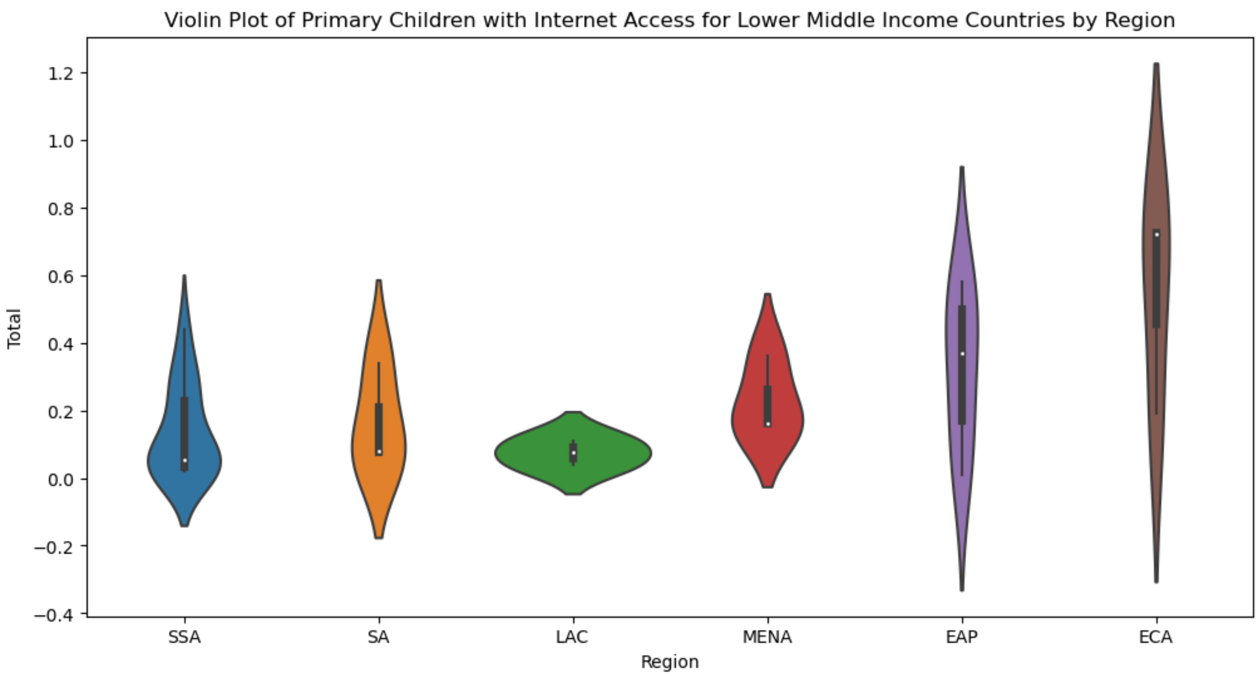
In [59]:

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Region', y='Total', data=dftesttask3)
plt.title('Box Plot of Primary Children with Internet Access for Lower Middle income
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()
```



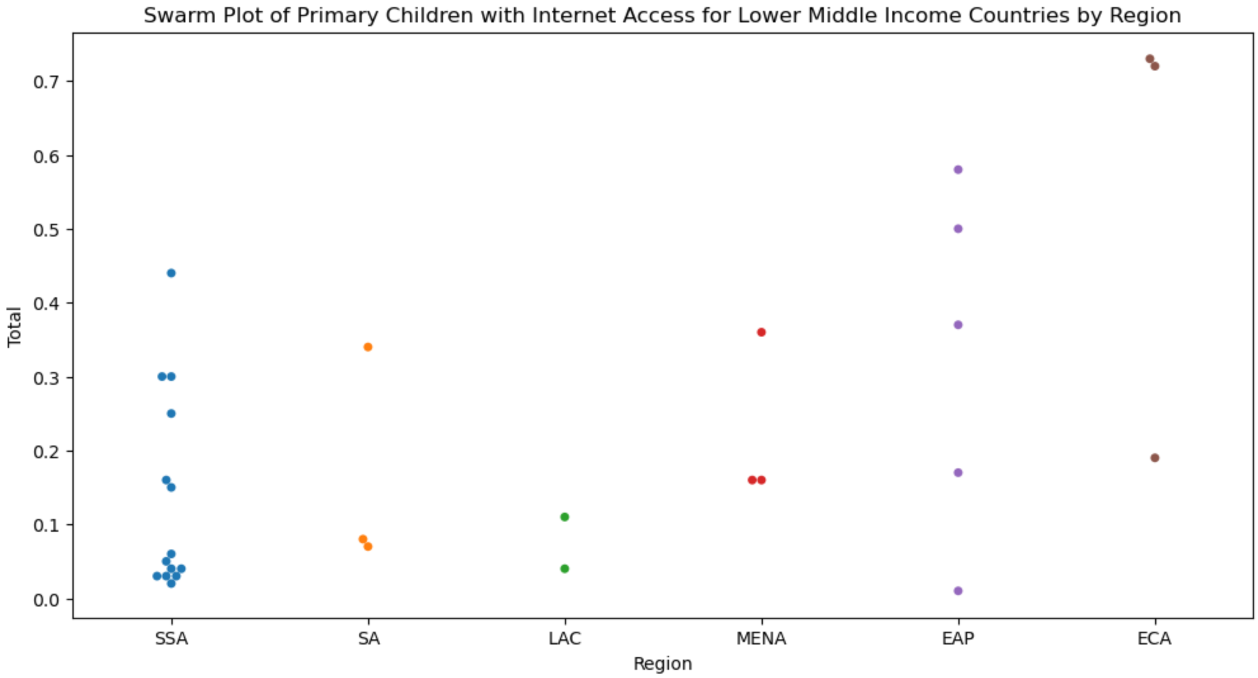
In [60]:

```python

plt.figure(figsize=(12, 6))
sns.violinplot(x='Region', y='Total', data=dftesttask3)
plt.title('Violin Plot of Primary Children with Internet Access for Lower Middle Inco
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()

```



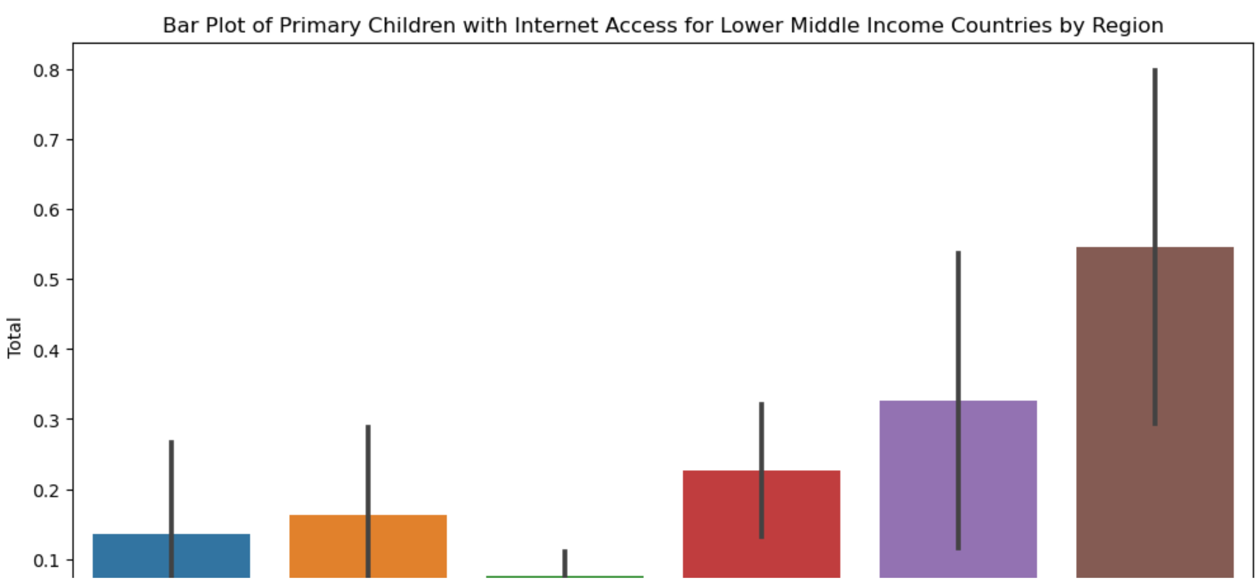
In [61]:

```
plt.figure(figsize=(12, 6))
sns.swarmplot(x='Region', y='Total', data=dftesttask3)
plt.title('Swarm Plot of Primary Children with Internet Access for Lower Middle Incor
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()
```



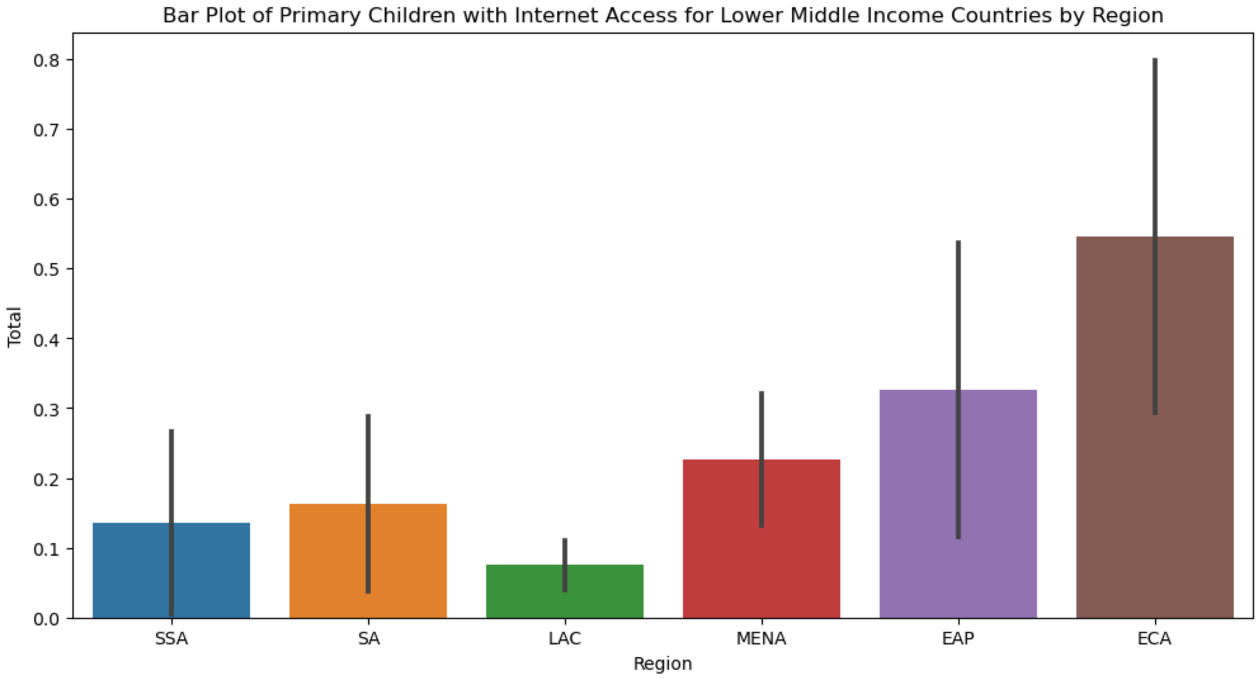
In [62]:

```
plt.figure(figsize=(12, 6))
sns.barplot(x='Region', y='Total', data=dftesttask3, ci='sd')
plt.title('Bar Plot of Primary Children with Internet Access for Lower Middle Income
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()
```



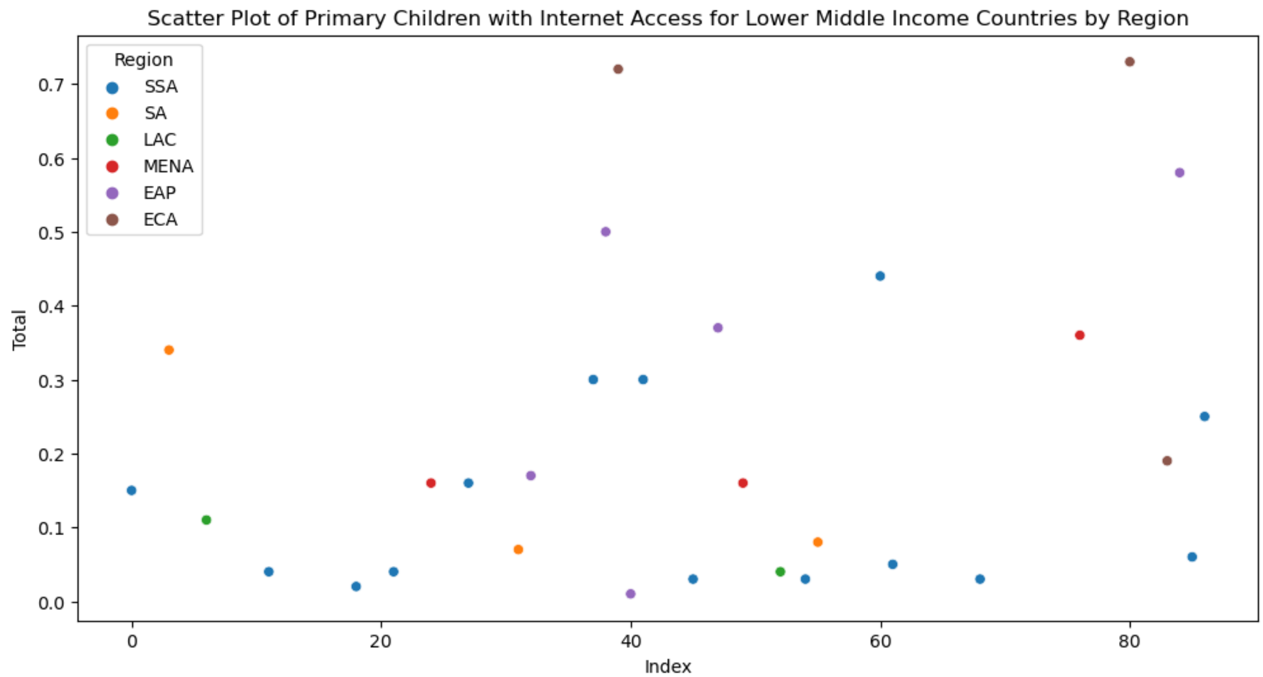
In [63]:

```python

plt.figure(figsize=(12, 6))
sns.barplot(x='Region', y='Total', data=dftesttask3, ci='sd')
plt.title('Bar Plot of Primary Children with Internet Access for Lower Middle Income
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()

```



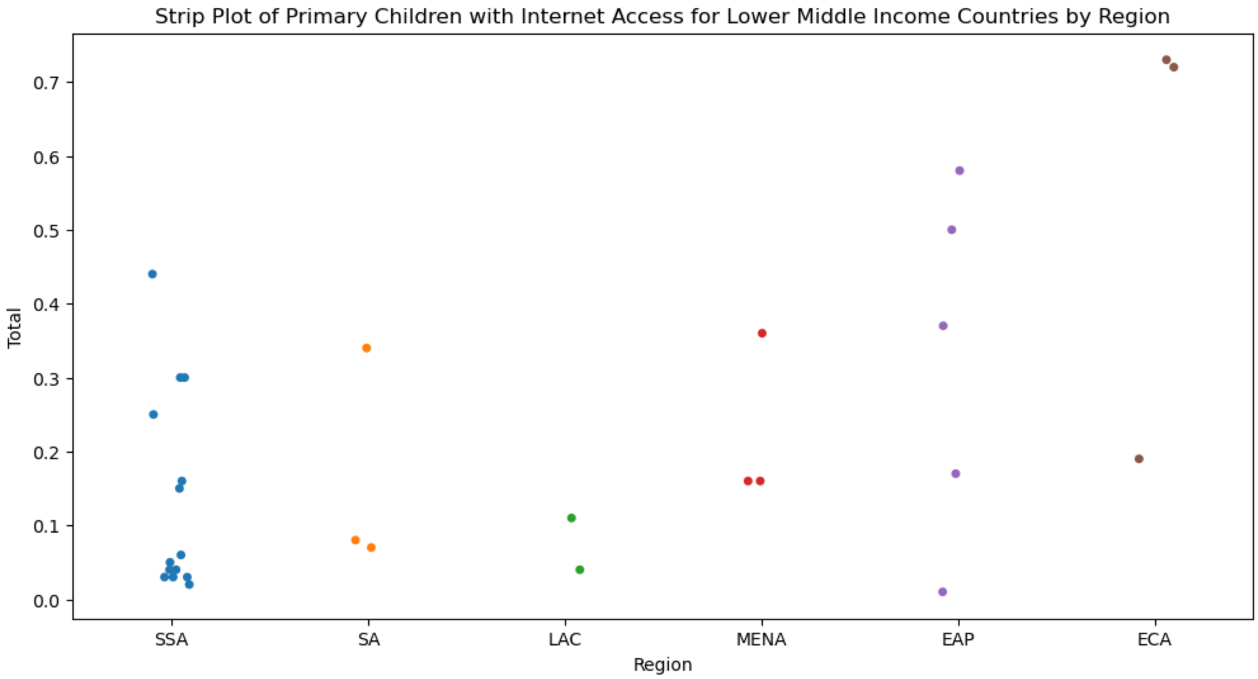
In [64]:

```python

plt.figure(figsize=(12, 6))
sns.scatterplot(x=dftesttask3.index, y='Total', hue='Region', data=dftesttask3)
plt.title('Scatter Plot of Primary Children with Internet Access for Lower Middle Inc
plt.xlabel('Index')
plt.ylabel('Total')
plt.show()

```



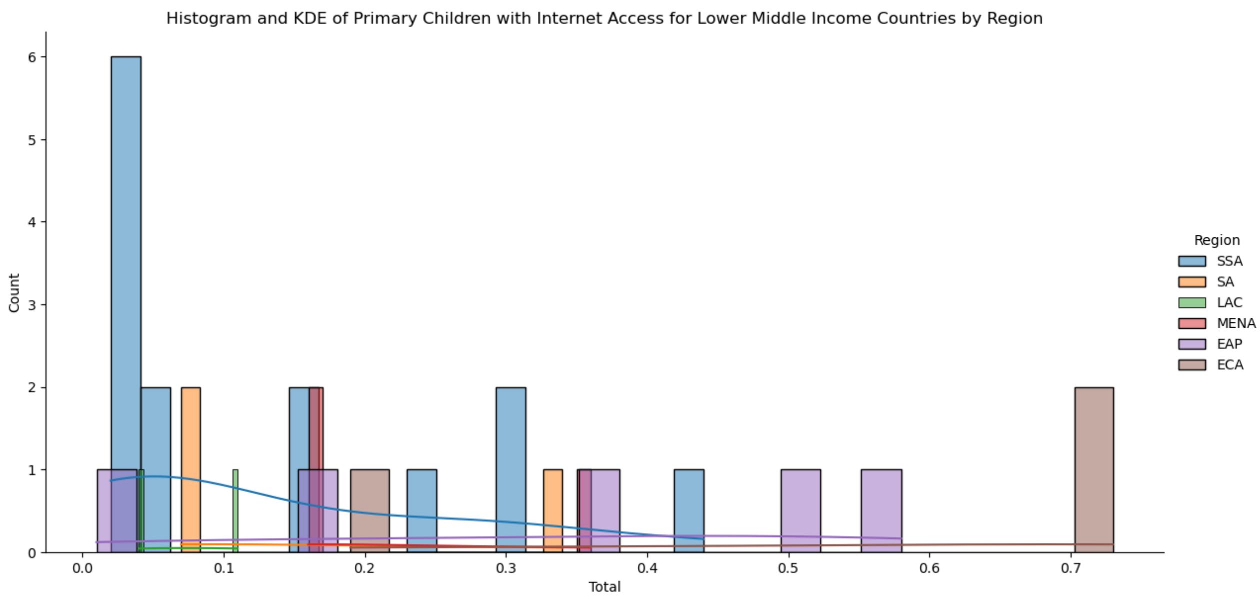
In [65]:

```
plt.figure(figsize=(12, 6))
sns.stripplot(x='Region', y='Total', data=dftesttask3, jitter=True)
plt.title('Strip Plot of Primary Children with Internet Access for Lower Middle Incor
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()
```



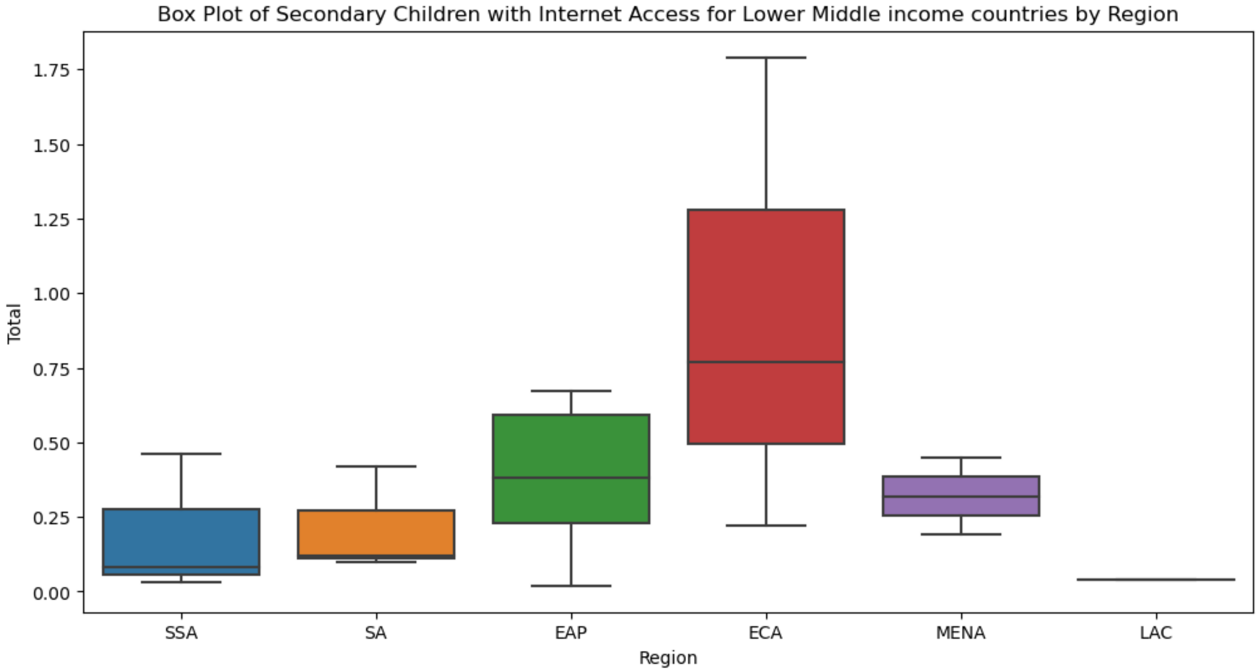
In [66]:

```
#I am visualizing the following data in a Faceted histogram to get an idea of how mai
#regions in the datasets have a low % of internet connectivity

import seaborn as sns
import matplotlib.pyplot as plt

g = sns.FacetGrid(dftesttask3, hue='Region', height=6, aspect=2)
g.map(sns.histplot, 'Total', kde=True, bins=20)
g.add_legend()
plt.title('Histogram and KDE of Primary Children with Internet Access for Lower Middl
plt.xlabel('Total')
plt.show()
```



In [67]:

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Region', y='Total', data=dftest2task3)
plt.title('Box Plot of Secondary Children with Internet Access for Lower Middle incor
plt.xlabel('Region')
plt.ylabel('Total')
plt.show()
```



In [68]:
```
dftest2task3.head(50)
```

Out[68]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGOA	Angola	SSA	ESA	Lower middle income (LM)	0.24
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.42
10	CMR	Cameroon	SSA	WCA	Lower middle income (LM)	0.07
17	CIV	C™te d'Ivoire	SSA	WCA	Lower middle income (LM)	0.03
20	DJI	Djibouti	SSA	ESA	Lower middle income (LM)	0.09
24	GHA	Ghana	SSA	WCA	Lower middle income (LM)	0.20
28	IND	India	SA	SA	Lower middle income (LM)	0.12
29	IDN	Indonesia	EAP	EAP	Lower middle income (LM)	0.23
34	KEN	Kenya	SSA	ESA	Lower middle income (LM)	0.39
35	KIR	Kiribati	EAP	EAP	Lower middle income (LM)	0.59
36	KGZ	Kyrgyzstan	ECA	EECA	Lower middle income (LM)	0.77
37	LAO	Lao People's Democratic Republic	EAP	EAP	Lower middle income (LM)	0.02
38	LSO	Lesotho	SSA	ESA	Lower middle income (LM)	0.38
42	MRT	Mauritania	SSA	WCA	Lower middle income (LM)	0.04
43	MNG	Mongolia	EAP	EAP	Lower middle income (LM)	0.38
45	MAR	Morocco	MENA	MENA	Lower middle income (LM)	0.19
48	NIC	Nicaragua	LAC	LAC	Lower middle income (LM)	0.04
50	NGA	Nigeria	SSA	WCA	Lower middle income (LM)	0.04
51	PAK	Pakistan	SA	SA	Lower middle income (LM)	0.10
55	STP	Sao Tome and Principe	SSA	WCA	Lower middle income (LM)	0.46
56	SEN	Senegal	SSA	WCA	Lower middle income (LM)	0.07
63	SDN	Sudan	SSA	ESA	Lower middle income (LM)	0.05
71	TUN	Tunisia	MENA	MENA	Lower middle income (LM)	0.45
75	UKR	Ukraine	ECA	EECA	Lower middle income (LM)	1.79
78	UZB	Uzbekistan	ECA	EECA	Lower middle income (LM)	0.22
79	VNM	Viet Nam	EAP	EAP	Lower middle income (LM)	0.67
80	ZMB	Zambia	SSA	ESA	Lower middle income (LM)	0.07
81	ZWE	Zimbabwe	SSA	ESA	Lower middle income (LM)	0.29

In [69]:

```python
#because of Ukraine's total value being over 1, I am handling the anomaly by
#making it 0.79, along with this, I will also handle other similarly anomalous values
#although Ukraine is the only main anomaly here

def adjust_total(value):
    if value < 0:
        return -value
    elif value > 1:
        return value - int(value)
    else:
        return value


dftest2task3['Total'] = dftest2task3['Total'].apply(adjust_total)


dftest2task3.head(50)
```

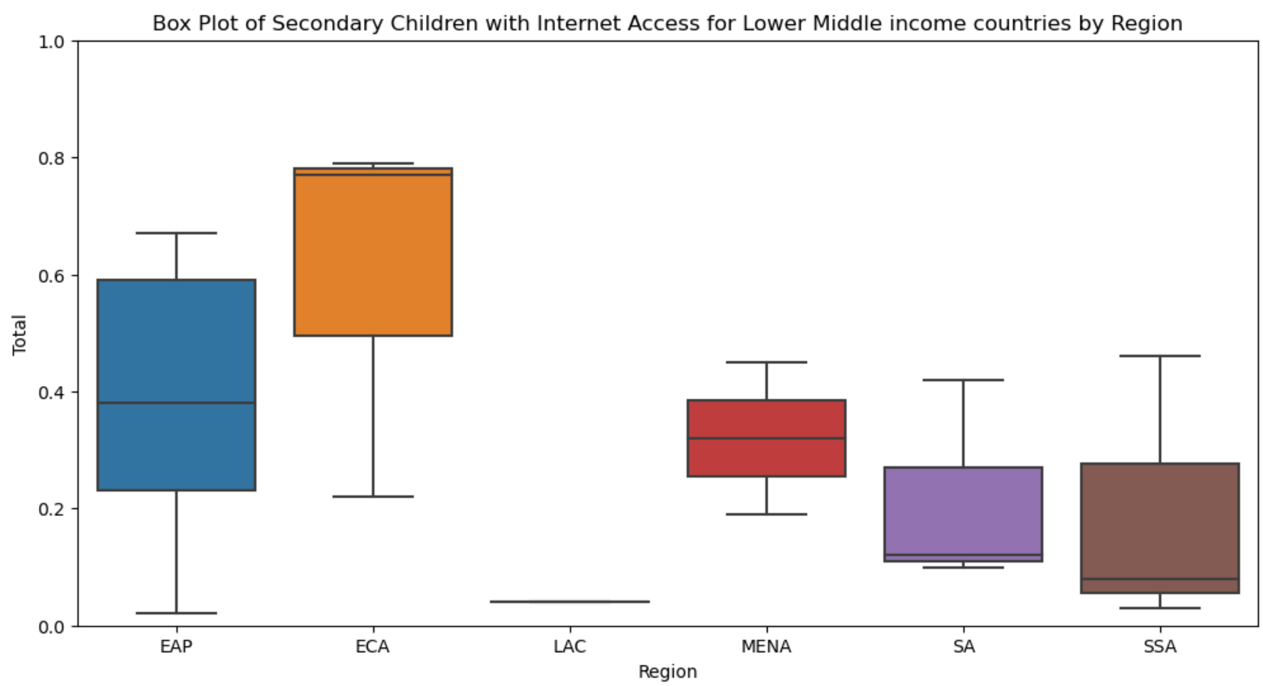
```
/var/folders/8y/9bzf6lrd1kggm5429dypyz2r0000gn/T/ipykernel_40815/3478238393.py:14: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  dftest2task3['Total'] = dftest2task3['Total'].apply(adjust_total)
```

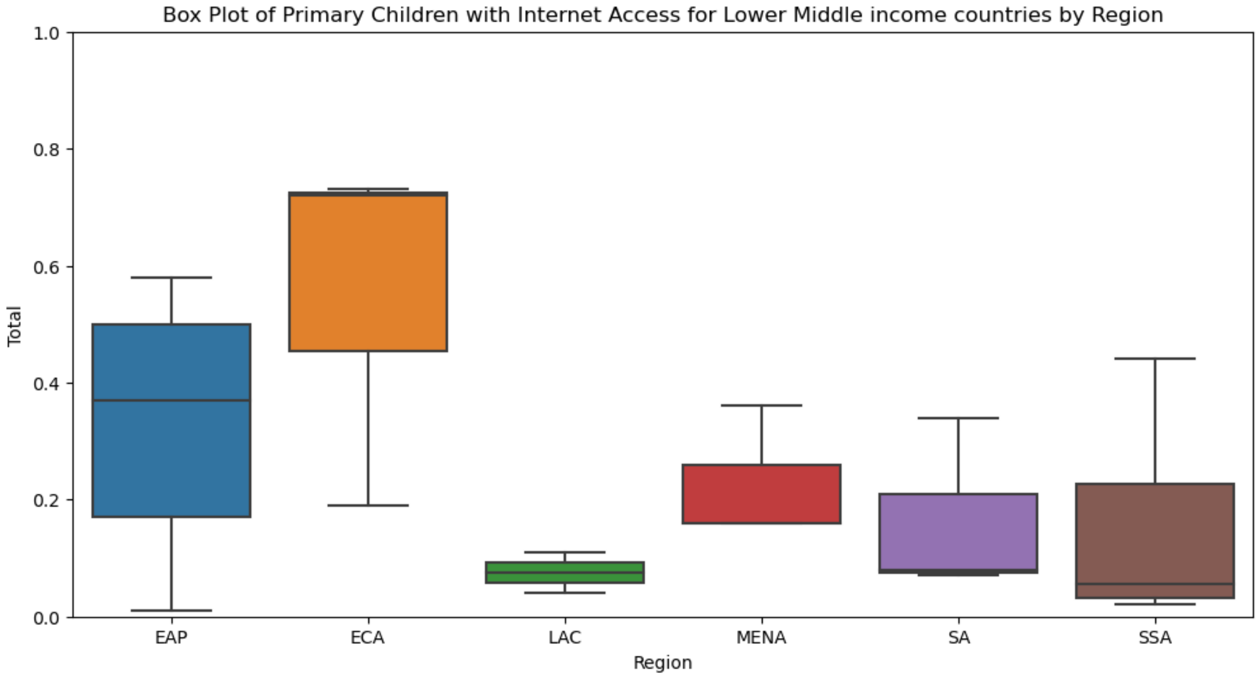
Out[69]:

	ISO3	Countries and areas	Region	Sub-region	Income Group	Total
0	AGOA	Angola	SSA	ESA	Lower middle income (LM)	0.24
3	BGD	Bangladesh	SA	SA	Lower middle income (LM)	0.42
10	CMR	Cameroon	SSA	WCA	Lower middle income (LM)	0.07
17	CIV	C™te d'Ivoire	SSA	WCA	Lower middle income (LM)	0.03
20	DJI	Djibouti	SSA	ESA	Lower middle income (LM)	0.09

In [70]:

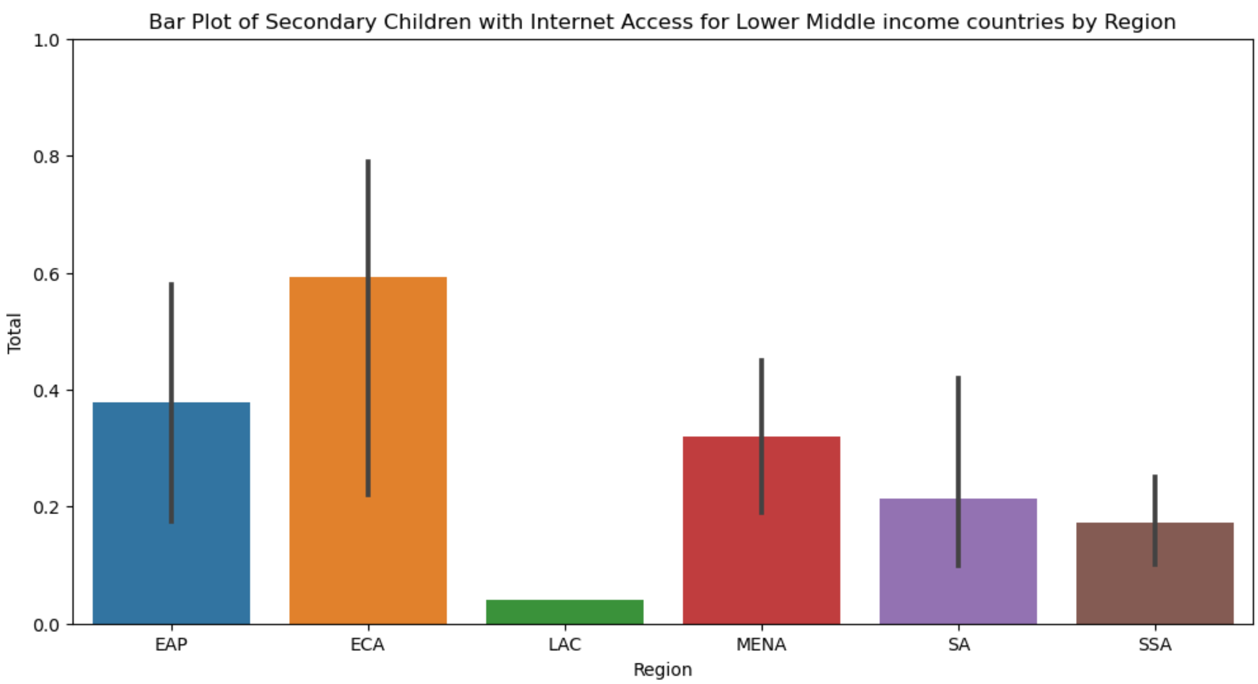
```python
#the next few graphs will consist of a similar pattern as I just want to
#visualize them in as many ways possible
region_order = ['EAP', 'ECA', 'LAC', 'MENA', 'SA', 'SSA']

plt.figure(figsize=(12, 6))
ax1 = sns.boxplot(x='Region', y='Total', data=dftest2task3, order=region_order)
plt.title('Box Plot of Secondary Children with Internet Access for Lower Middle inco
plt.xlabel('Region')
plt.ylabel('Total')

ax1.set_ylim(0, 1)

plt.show()

plt.figure(figsize=(12, 6))
ax2 = sns.boxplot(x='Region', y='Total', data=dftesttask3, order=region_order)
plt.title('Box Plot of Primary Children with Internet Access for Lower Middle income
plt.xlabel('Region')
plt.ylabel('Total')

ax2.set_ylim(0, 1)

plt.show()

```

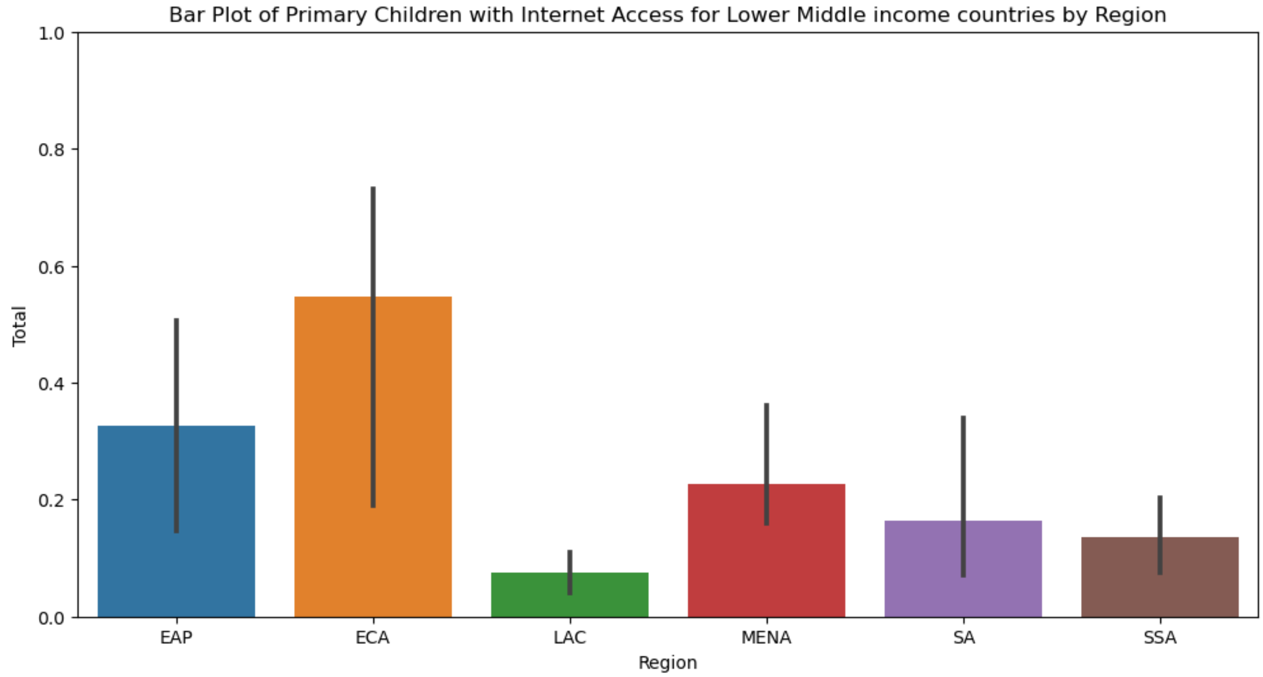



Box Plot of Primary Children with Internet Access for Lower Middle income countries by Region
Total
Region
EAP
ECA
LAC
MENA
SA
SSA
0.0
0.2
0.4
0.6
0.8
1.0

In [71]:

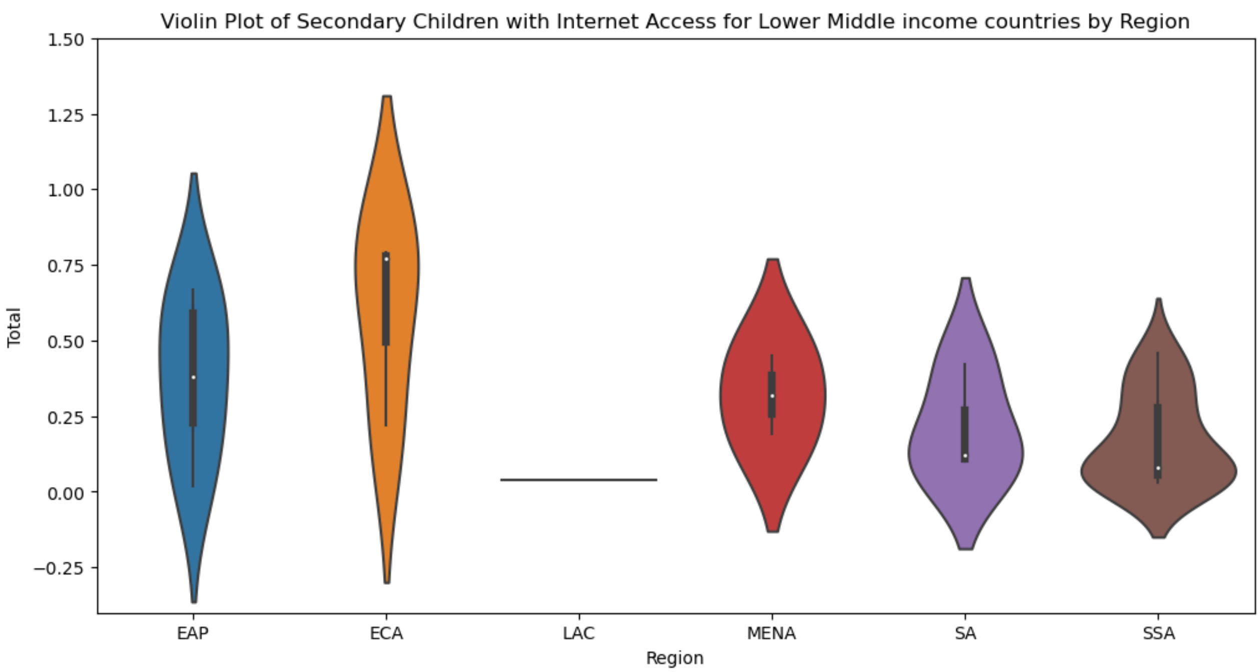
```
region_order = ['EAP', 'ECA', 'LAC', 'MENA', 'SA', 'SSA']

plt.figure(figsize=(12, 6))
ax1 = sns.barplot(x='Region', y='Total', data=dftest2task3, order=region_order)
plt.title('Bar Plot of Secondary Children with Internet Access for Lower Middle incor
plt.xlabel('Region')
plt.ylabel('Total')

ax1.set_ylim(0, 1)

plt.show()

plt.figure(figsize=(12, 6))
ax2 = sns.barplot(x='Region', y='Total', data=dftesttask3, order=region_order)
plt.title('Bar Plot of Primary Children with Internet Access for Lower Middle income
plt.xlabel('Region')
plt.ylabel('Total')

ax2.set_ylim(0, 1)

plt.show()

```

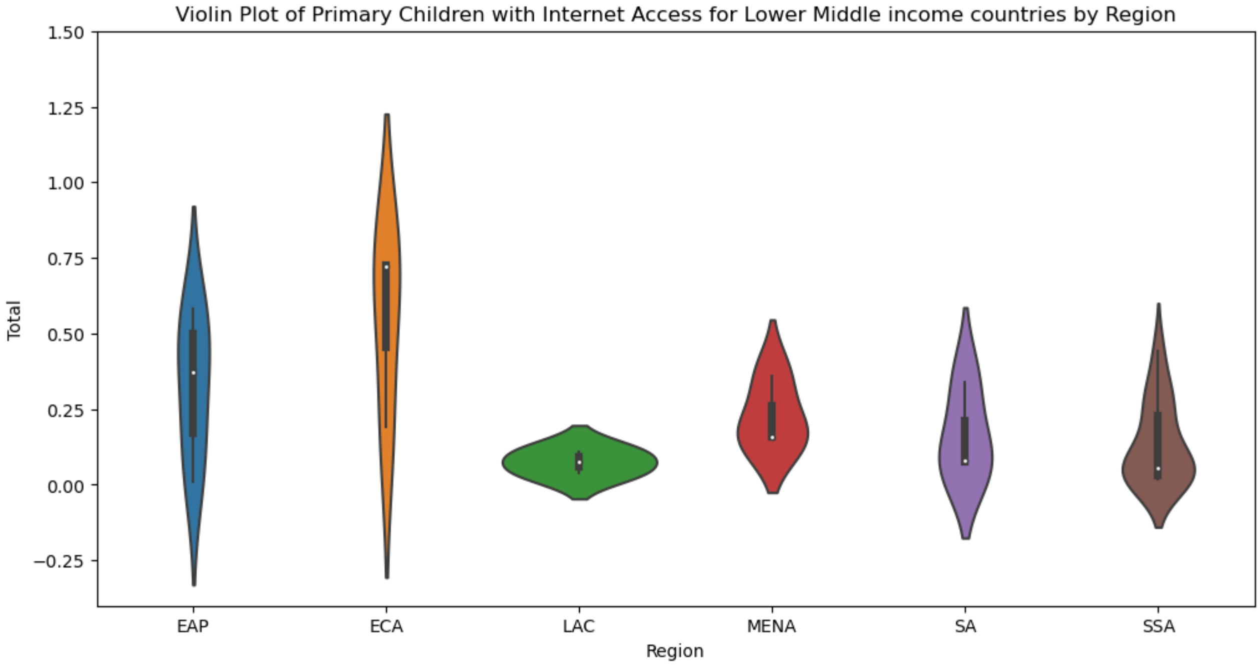



Bar Plot of Primary Children with Internet Access for Lower Middle income countries by Region
Total
1.0
0.8
0.6
0.4
0.2
0.0
EAP
ECA
LAC
MENA
SA
SSA
Region

In [72]:

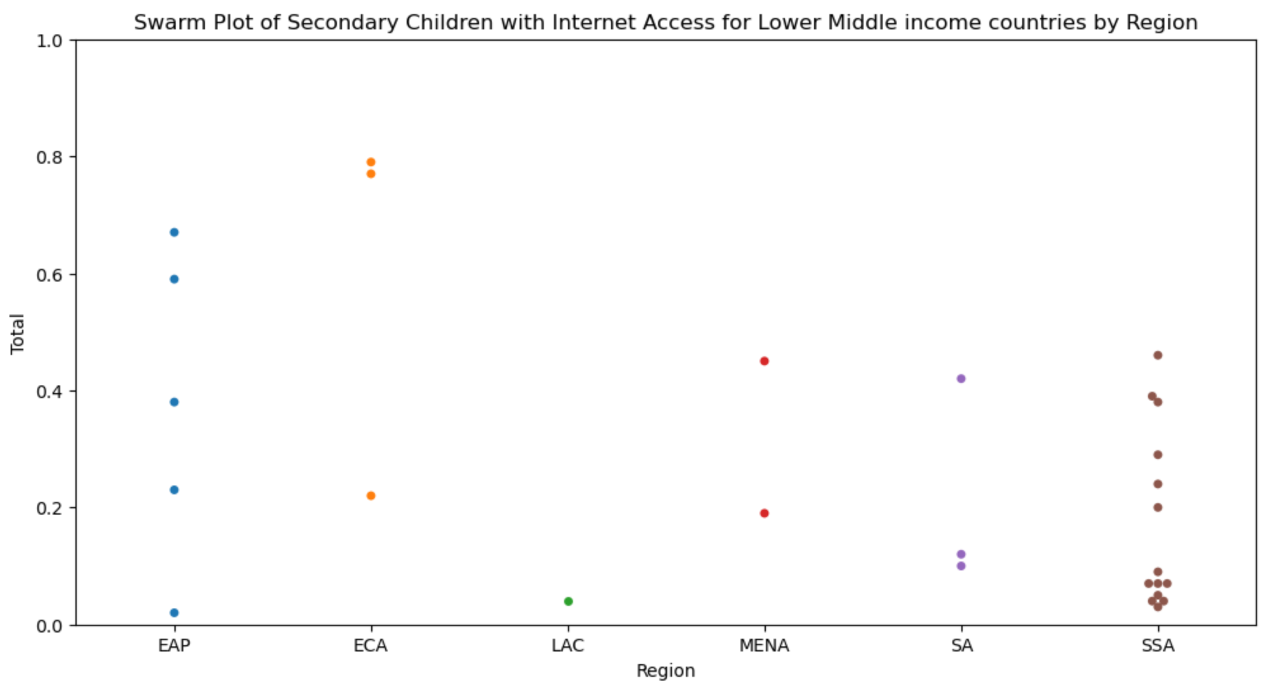
```
region_order = ['EAP', 'ECA', 'LAC', 'MENA', 'SA', 'SSA']

plt.figure(figsize=(12, 6))
ax1 = sns.violinplot(x='Region', y='Total', data=dftest2task3, order=region_order)
plt.title('Violin Plot of Secondary Children with Internet Access for Lower Middle i
plt.xlabel('Region')
plt.ylabel('Total')

ax1.set_ylim(-0.4, 1.5)

plt.show()

plt.figure(figsize=(12, 6))
ax2 = sns.violinplot(x='Region', y='Total', data=dftesttask3, order=region_order)
plt.title('Violin Plot of Primary Children with Internet Access for Lower Middle inco
plt.xlabel('Region')
plt.ylabel('Total')

ax2.set_ylim(-0.4, 1.5)

plt.show()

```

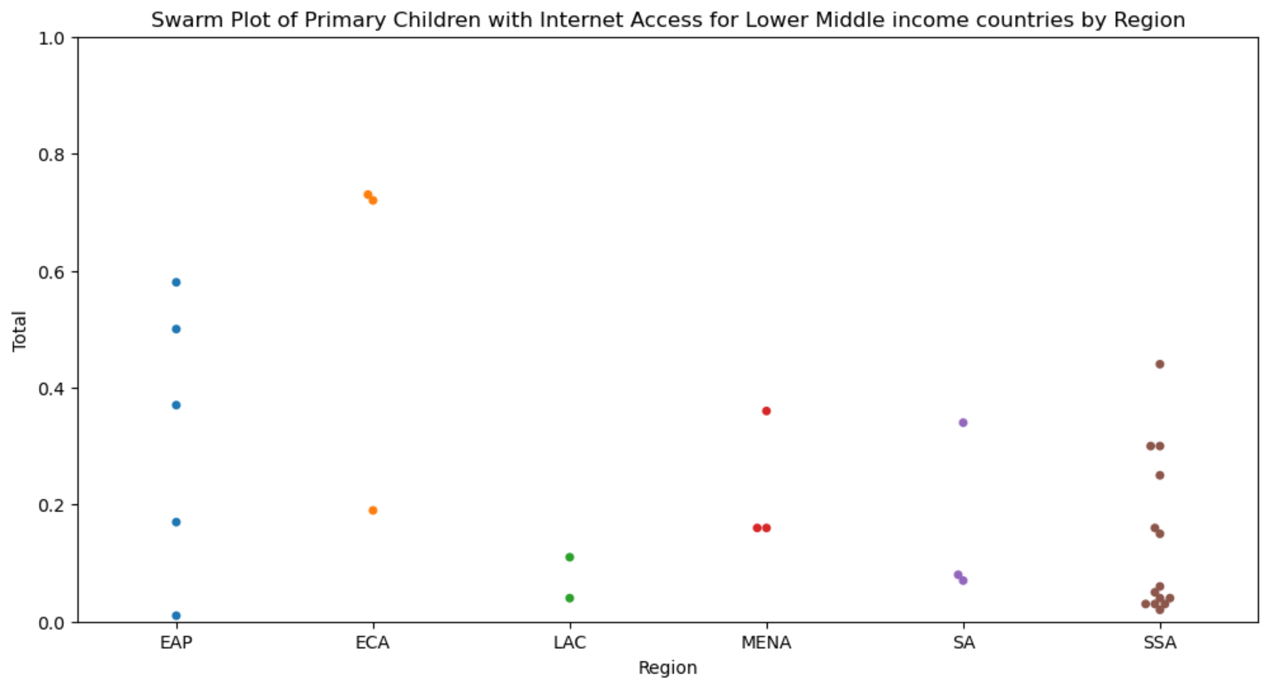



Violin Plot of Primary Children with Internet Access for Lower Middle income countries by Region
Total
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
EAP
ECA
LAC
MENA
SA
SSA
Region

In [73]:

```
region_order = ['EAP', 'ECA', 'LAC', 'MENA', 'SA', 'SSA']

plt.figure(figsize=(12, 6))
ax1 = sns.swarmplot(x='Region', y='Total', data=dftest2task3, order=region_order)
plt.title('Swarm Plot of Secondary Children with Internet Access for Lower Middle inc
plt.xlabel('Region')
plt.ylabel('Total')

ax1.set_ylim(0, 1)

plt.show()

plt.figure(figsize=(12, 6))
ax2 = sns.swarmplot(x='Region', y='Total', data=dftesttask3, order=region_order)
plt.title('Swarm Plot of Primary Children with Internet Access for Lower Middle inco
plt.xlabel('Region')
plt.ylabel('Total')

ax2.set_ylim(0, 1)

plt.show()
```




Swarm Plot of Primary Children with Internet Access for Lower Middle income countries by Region
Total
Region
0.0
0.2
0.4
0.6
0.8
1.0
EAP
ECA
LAC
MENA
SA
SSA