Unraveling the Challenges of Unemployment in Africa: A Data-Driven Approach

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Introduction

> Unemployment poses a significant challenge to the socio-economic fabric of African nations, requiring a nuanced understanding of its root causes and effective, implementable solutions. This data analysis project aims to unravel the complex layers of unemployment in Africa, leveraging insights from six diverse datasets. The objective is to equip analysts and policymakers with data-driven recommendations that can catalyze informed strategies, contributing to the alleviation of unemployment on the continent.

Objectives:

- Uncover the multi-faceted nature of unemployment in Africa, recognizing its socio-economic, educational, and policy-related dimensions.
- Analyze key factors influencing high unemployment rates, ranging from gender-based disparities to national strategies for youth employment, education expenditure, access to electricity, and the historical health of the private sector.
- Propose solutions and strategies grounded in data insights, tailored to the unique challenges faced by African nations. Emphasize creativity, analytical rigor, and practicality in developing implementable recommendations.
- Utilize data visualization techniques to draw meaningful correlations, providing a visual narrative of unemployment trends, disparities, and potential intervention points.

> By combining analytical rigor with creativity, I see this project as a catalyst for positive change, offering practical and evidence-based solutions to mitigate the unemployment crisis in Africa. The insights derived from this analysis hold the potential to shape policies, influence educational strategies, and foster economic development, ultimately contributing to a more prosperous and employed future for the continent.

In [1]:
```python
# Importing required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from mpl_toolkits.mplot3d import Axes3D

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```python
# loading the datasets into a dataframe
unemployment_rate = pd.read_csv('1. unemployment-rate-men-vs-women.csv')
```

```
youth_employment = pd.read_csv('2. national-strategy-for-youth-employment.csv')
edu_expenditure = pd.read_csv('3. share-of-education-in-government-expenditure.csv')
electricity_access = pd.read_csv('4. share-of-the-population-with-access-to-electricity.
total_firms = pd.read_excel('5. Total_firms_Historical_data.xlsx')
country_codes = pd.read_csv('6. Country Codes.csv')
```

Prelimenary Wrangling

Initial Exploration

In [3]:
```
# Quick overview of unemployment rate
unemployment_rate.sample(5)
```

Out[3]:

	Entity	Code	Year	Unemployment, female (% of female labor force) (modeled ILO estimate)	Unemployment, male (% of male labor force) (modeled ILO estimate)	Population (historical estimates)	Continent
5818	Benin	BEN	1872	NaN	NaN	943878.0	NaN
46144	Seychelles	SYC	1868	NaN	NaN	15385.0	NaN
12078	Croatia	HRV	800	NaN	NaN	407176.0	NaN
19553	Germany	DEU	2013	4.919	5.499	81680592.0	NaN
46233	Seychelles	SYC	1957	NaN	NaN	40966.0	NaN

In [4]:
```
# Quick overview of youth employment
youth_employment.sample(5)
```

Out[4]:

	Entity	Code	Year	8.b.1 - Existence of a developed and operationalized national strategy for youth employment, as a distinct strategy or as part of a national employment strategy - SL_CPA_YEMP
86	Costa Rica	CRI	2022	1
243	Nicaragua	NIC	2022	1
142	Greece	GRC	2022	3
311	Spain	ESP	2021	3
354	Vietnam	VNM	2021	2

In [5]:
```
# Quick overview of education expenditure
edu_expenditure.sample(5)
```

Out[5]:

	Entity	Code	Year	Government expenditure on education, total (% of government expenditure)
3687	Syria	SYR	2007	18.925930
2516	Moldova	MDA	2003	16.192590
2964	Paraguay	PRY	2007	19.424720
480	Brazil	BRA	2019	15.958080
1240	European Union (27)	NaN	2007	11.555855

In [6]:
```
# Quick overview of electricity access
electricity_access.sample(5)
```

Out[6]:

	Entity	Code	Year	Access to electricity (% of population)
3509	Malta	MLT	2013	100.000000
2116	Ghana	GHA	2001	44.837513
1508	Dominica	DMA	2010	94.173940
2775	Italy	ITA	2014	100.000000
4594	Qatar	QAT	1995	100.000000

In [7]:
```
# Quick overview of the total firms
total_firms.sample(5)
```

Out[7]:

	Economy	Adult population	Year	TOTAL Number of \nLimited Liability Companies	Total business density rate
576	Ireland	3096398.0	2011.0	181055.0	58.472780
148	Belgium	7282454.0	2013.0	512195.0	70.332748
859	Mexico	71989500.0	2009.0	358583.0	4.981046
370	Egypt, Arab Rep.	61125132.0	2019.0	52056.0	0.851630
520	Hungary	6826448.0	2012.0	405077.0	59.339352

In [8]:
```
# Quick overview of country codes
country_codes.sample(5)
```

Out[8]:

	name	alpha-2	alpha-3	country-code	region	sub-region
196	Senegal	SN	SEN	686	Africa	Sub-Saharan Africa
98	Holy See	VA	VAT	336	Europe	Southern Europe
56	Cuba	CU	CUB	192	Americas	Latin America and the Caribbean
129	Lithuania	LT	LTU	440	Europe	Northern Europe
172	Papua New Guinea	PG	PNG	598	Oceania	Melanesia

In [9]:
```
# Renaming columns for better clarity and usage
unemployment_rate = unemployment_rate.rename(columns={
    'Unemployment, female (% of female labor force) (modeled ILO estimate)': 'Female une
    'Unemployment, male (% of male labor force) (modeled ILO estimate)': 'Male unemploym
    'Population (historical estimates)': 'Population',
})

youth_employment = youth_employment.rename(columns={
    '8.b.1 - Existence of a developed and operationalized national strategy for youth em
})

edu_expenditure = edu_expenditure.rename(columns={
    'Government expenditure on education, total (% of government expenditure)': 'Educati
})

electricity_access = electricity_access.rename(columns={
    'Access to electricity (% of population)': 'Electricity access(%)',
})
```

```
total_firms = total_firms.rename(columns={
    'TOTAL Number of \nLimited Liability Companies': 'Total LLC',
    'Total business density rate': 'Business density rate',
})
```

In [10]:
```
# Details of the datasets
print(unemployment_rate.info(), '\n')
print(youth_employment.info(), '\n')
print(edu_expenditure.info(), '\n')
print(electricity_access.info(), '\n')
print(total_firms.info(), '\n')
print(country_codes.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58578 entries, 0 to 58577
Data columns (total 7 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Entity                       58578 non-null  object
 1   Code                         55049 non-null  object
 2   Year                         58578 non-null  int64
 3   Female unemployment rate(%)  6231 non-null   float64
 4   Male unemployment rate(%)    6231 non-null   float64
 5   Population                   58252 non-null  float64
 6   Continent                    285 non-null    object
dtypes: float64(3), int64(1), object(3)
memory usage: 3.1+ MB
None

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 363 entries, 0 to 362
Data columns (total 4 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Entity                     363 non-null    object
 1   Code                       363 non-null    object
 2   Year                       363 non-null    int64
 3   Youth employment strategy  363 non-null    int64
dtypes: int64(2), object(2)
memory usage: 11.5+ KB
None

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4104 entries, 0 to 4103
Data columns (total 4 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Entity                    4104 non-null   object
 1   Code                      3809 non-null   object
 2   Year                      4104 non-null   int64
 3   Education expenditure(%)  4104 non-null   float64
dtypes: float64(1), int64(1), object(2)
memory usage: 128.4+ KB
None

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6233 entries, 0 to 6232
Data columns (total 4 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Entity                 6233 non-null   object
 1   Code                   5863 non-null   object
 2   Year                   6233 non-null   int64
 3   Electricity access(%)  6233 non-null   float64
```

```
dtypes: float64(1), int64(1), object(2)
memory usage: 194.9+ KB
None

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1526 entries, 0 to 1525
Data columns (total 5 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Economy                1525 non-null   object 
 1   Adult population       1522 non-null   float64
 2   Year                   1522 non-null   float64
 3   Total LLC              1522 non-null   float64
 4   Business density rate  1522 non-null   float64
dtypes: float64(4), object(1)
memory usage: 59.7+ KB
None

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 249 entries, 0 to 248
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   name          249 non-null    object
 1   alpha-2       248 non-null    object
 2   alpha-3       249 non-null    object
 3   country-code  249 non-null    int64 
 4   region        248 non-null    object
 5   sub-region    248 non-null    object
dtypes: int64(1), object(5)
memory usage: 11.8+ KB
None
```

In [11]:
```
# Checking for duplicate entries in the unemployment rate
print("unemployment_rate:", unemployment_rate.duplicated().sum(), '\n')
print("youth_employment:", youth_employment.duplicated().sum(),'\n')
print("edu_expenditure:", edu_expenditure.duplicated().sum(),'\n')
print("electricity_access:", electricity_access.duplicated().sum(),'\n')
print(" total_firms:", total_firms.duplicated().sum(),'\n')
print("country_codes:", country_codes.duplicated().sum())
```

```
unemployment_rate: 0 

youth_employment: 0 

edu_expenditure: 0 

electricity_access: 0 

 total_firms: 0 

country_codes: 0
```

In [12]:
```
# Checking for the null values in the datasets
print("unemployment_rate:\n", unemployment_rate.isna().sum(), '\n')
print("youth_employment:\n", youth_employment.isna().sum(),'\n')
print("edu_expenditure:\n", edu_expenditure.isna().sum(),'\n')
print("electricity_access:\n", electricity_access.isna().sum(),'\n')
print(" total_firms:\n", total_firms.isna().sum(),'\n')
print("country_codes:\n", country_codes.isna().sum())
```

```
unemployment_rate:
 Entity                           0
Code                          3529
Year                             0
Female unemployment rate(%)  52347
```

```
Male unemployment rate(%)      52347
Population                       326
Continent                      58293
dtype: int64

youth_employment:
 Entity                        0
Code                          0
Year                          0
Youth employment strategy     0
dtype: int64

edu_expenditure:
 Entity                         0
Code                          295
Year                            0
Education expenditure(%)        0
dtype: int64

electricity_access:
 Entity                      0
Code                       370
Year                         0
Electricity access(%)        0
dtype: int64

 total_firms:
 Economony                  1
Adult population          4
Year                      4
Total LLC                 4
Business density rate     4
dtype: int64

country_codes:
 name              0
alpha-2          1
alpha-3          0
country-code     0
region           1
sub-region       1
dtype: int64
```

In [13]:

```
# Descriptive statistics of the datasets
print("unemployment_rate:\n", unemployment_rate.describe(), '\n')
print("youth_employment:\n", youth_employment.describe(),'\n')
print("edu_expenditure:\n", edu_expenditure.describe(),'\n')
print("electricity_access:\n", electricity_access.describe(),'\n')
print(" total_firms:\n", total_firms.describe(),'\n')
print("country_codes:\n", country_codes.describe())
```

```
unemployment_rate:
                Year  Female unemployment rate(%)  Male unemployment rate(%)  \
count  58578.000000                  6231.000000                6231.000000
mean    1603.516542                     9.460057                   7.567807
std     1424.962569                     7.613245                   5.688615
min   -10000.000000                     0.149000                   0.052000
25%     1832.000000                     4.052500                   3.612000
50%     1901.000000                     6.908000                   5.890000
75%     1966.000000                    12.771000                  10.037500
max     2021.000000                    47.183000                  36.963000

         Population
count  5.825200e+04
mean   4.901082e+07
std    2.925549e+08
```

```
min    0.000000e+00
25%    1.460840e+05
50%    1.388504e+06
75%    6.600998e+06
max    7.909295e+09

youth_employment:
              Year  Youth employment strategy
count   363.000000                 363.000000
mean   2020.344353                   2.162534
std       1.092359                   0.830048
min    2019.000000                   0.000000
25%    2019.000000                   2.000000
50%    2020.000000                   2.000000
75%    2021.000000                   3.000000
max    2022.000000                   3.000000

edu_expenditure:
              Year  Education expenditure(%)
count  4104.000000               4104.000000
mean   2008.150097                 14.525208
std       9.324982                  4.943369
min    1980.000000                  0.000000
25%    2002.000000                 11.138748
50%    2010.000000                 13.935097
75%    2016.000000                 17.201995
max    2021.000000                 47.278740

electricity_access:
              Year  Electricity access(%)
count  6233.000000            6233.000000
mean   2006.511471              81.673186
std       8.400721              28.975099
min    1990.000000               0.533899
25%    2000.000000              71.500000
50%    2007.000000              99.337790
75%    2014.000000             100.000000
max    2020.000000             100.000000

 total_firms:
        Adult population         Year     Total LLC  Business density rate
count       1.522000e+03  1522.000000  1.522000e+03            1522.000000
mean        2.299163e+07  2013.112352  3.570364e+05              53.481728
std         8.430491e+07     4.165052  6.346047e+05              80.496415
min         6.367000e+03  2006.000000  7.200000e+01               0.100469
25%         1.787941e+06  2010.000000  3.500250e+04               8.117138
50%         5.367440e+06  2013.000000  1.014890e+05              25.630642
75%         1.880756e+07  2017.000000  3.736310e+05              66.327869
max         9.282668e+08  2020.000000  4.776447e+06             654.699007

country_codes:
        country-code
count     249.000000
mean      433.835341
std       252.980446
min         4.000000
25%       218.000000
50%       434.000000
75%       652.000000
max       894.000000
```

Data Quality Issues

Unemployment Rate:

- **Missing Data:** Columns Code, Female unemployment rate(%), Male unemployment rate(%), Population, and Continent have missing values.
- **Inconsistent Year Values:** The Year column has a minimum value of -10,000, which seems inconsistent and may be an error.

Youth Employment:

- **No Apparent Issues:** This dataset appears to have minimal data quality issues. No missing values are reported.

Education Expenditure:

- **Missing Data:** Column Code has missing values.
- **Unrealistic Minimum Education Expenditure:** The minimum value for Education expenditure(%) is 0, which might be unrealistic.

Electricity Access:

- **Missing Data:** Column Code has missing values.

Total Firms:

- **Inconsistent Year Values:** The Year column has a minimum value of 2006, which might not align with the other datasets.
- **Missing Data:** Columns Economy, Adult population, Year, Total LLC, and Business density rate have missing values.

Country Codes:

- **Missing Data:** Columns alpha-2, region, and sub-region have missing values.
- **Incomplete Country Code Information:** The alpha-2 column has one missing value, and region and sub-region also have one missing value each.

Investigating these findings

In [14]:
```
# Investigating negative values in "Year" column of unemployment rate
unemployment_rate[unemployment_rate['Year'] < 0]
```

Out[14]:

	Entity	Code	Year	Female unemployment rate(%)	Male unemployment rate(%)	Population	Continent
32	Afghanistan	AFG	-10000	NaN	NaN	14737.0	NaN
33	Afghanistan	AFG	-9000	NaN	NaN	20405.0	NaN
34	Afghanistan	AFG	-8000	NaN	NaN	28253.0	NaN
35	Afghanistan	AFG	-7000	NaN	NaN	39120.0	NaN
36	Afghanistan	AFG	-6000	NaN	NaN	54166.0	NaN

...	...	...	...	...	...	...	...
58355	Zimbabwe	ZWE	-5000	NaN	NaN	5692.0	NaN
58356	Zimbabwe	ZWE	-4000	NaN	NaN	8538.0	NaN
58357	Zimbabwe	ZWE	-3000	NaN	NaN	12807.0	NaN
58358	Zimbabwe	ZWE	-2000	NaN	NaN	19211.0	NaN
58359	Zimbabwe	ZWE	-1000	NaN	NaN	28817.0	NaN

1902 rows × 7 columns

In [15]:
```
# Investigating outliers in "Female unemployment rate(%)" and "Male unemployment rate(%)
outliers_female = unemployment_rate[unemployment_rate['Female unemployment rate(%)'] < 1
outliers_male = unemployment_rate[unemployment_rate['Male unemployment rate(%)'] < 1]
print("Outliers in 'Female unemployment rate(%)':\n", outliers_female)
print("Outliers in 'Male unemployment rate(%)':\n", outliers_male)
```

```
Outliers in 'Female unemployment rate(%)':
             Entity Code  Year  Female unemployment rate(%)  \
3608     Azerbaijan  AZE  1991                        0.964
4901        Belarus  BLR  1991                        0.502
5678          Benin  BEN  1991                        0.590
5679          Benin  BEN  1992                        0.580
5680          Benin  BEN  1993                        0.561
...             ...  ...   ...                          ...
53243  Turkmenistan  TKM  1993                        0.985
54060        Uganda  UGA  1991                        0.573
54061        Uganda  UGA  1992                        0.654
56975       Vietnam  VNM  2011                        0.901
56976       Vietnam  VNM  2012                        0.931

       Male unemployment rate(%)  Population Continent
3608                       0.839   7538266.0       NaN
4901                       0.693  10457619.0       NaN
5678                       2.125   5293055.0       NaN
5679                       2.172   5457781.0       NaN
5680                       2.031   5706188.0       NaN
...                          ...         ...       ...
53243                      1.884   4031701.0       NaN
54060                      1.245  18171944.0       NaN
54061                      1.143  18801968.0       NaN
56975                      1.091  88349104.0       NaN
56976                      1.121  89301328.0       NaN

[186 rows x 7 columns]
Outliers in 'Male unemployment rate(%)':
           Entity Code  Year  Female unemployment rate(%)  \
3608   Azerbaijan  AZE  1991                        0.964
4127      Bahrain  BHR  1991                        3.601
4128      Bahrain  BHR  1992                        3.683
4129      Bahrain  BHR  1993                        3.545
4130      Bahrain  BHR  1994                        3.741
...           ...  ...   ...                          ...
51659    Thailand  THA  2017                        0.841
51660    Thailand  THA  2018                        0.748
51661    Thailand  THA  2019                        0.736
52243       Tonga  TON  2006                        1.515
52244       Tonga  TON  2007                        1.724

       Male unemployment rate(%)  Population Continent
3608                       0.839   7538266.0       NaN
4127                       0.460    535419.0       NaN
```

```
4128                        0.480     554480.0        NaN
4129                        0.445     573762.0        NaN
4130                        0.502     593259.0        NaN
...                           ...          ...        ...
51659                       0.821   70898208.0        NaN
51660                       0.788   71127808.0        NaN
51661                       0.706   71307768.0        NaN
52243                       0.810     106202.0        NaN
52244                       0.936     106651.0        NaN

[241 rows x 7 columns]
```

In [16]:
```python
# Investigating rows with Population = 0 in unemployment rate
unemployment_rate[unemployment_rate['Population'] == 0]
```

Out[16]:

	Entity	Code	Year	Female unemployment rate(%)	Male unemployment rate(%)	Population	Continent
1746	Anguilla	AIA	-10000	NaN	NaN	0.0	NaN
1747	Anguilla	AIA	-9000	NaN	NaN	0.0	NaN
1748	Anguilla	AIA	-8000	NaN	NaN	0.0	NaN
2648	Aruba	ABW	400	NaN	NaN	0.0	NaN
2649	Aruba	ABW	500	NaN	NaN	0.0	NaN
...	...	...	...	...	...	...	...
55389	United States Virgin Islands	VIR	400	NaN	NaN	0.0	NaN
57297	Western Sahara	ESH	-3000	NaN	NaN	0.0	NaN
57298	Western Sahara	ESH	-2000	NaN	NaN	0.0	NaN
57299	Western Sahara	ESH	-1000	NaN	NaN	0.0	NaN
57300	Western Sahara	ESH	0	NaN	NaN	0.0	NaN

77 rows × 7 columns

In [17]:
```python
# Investigating rows with "Education expenditure(%)" = 0
edu_expenditure[edu_expenditure['Education expenditure(%)'] == 0]
```

Out[17]:

	Entity	Code	Year	Education expenditure(%)
2730	Nicaragua	NIC	1982	0.0
2731	Nicaragua	NIC	1984	0.0
2732	Nicaragua	NIC	1987	0.0

In [18]:
```python
# Investigating rows with "Electricity access(%)" < 1
electricity_access[electricity_access['Electricity access(%)'] < 1]
```

Out[18]:

	Entity	Code	Year	Electricity access(%)
5291	South Sudan	SSD	2006	0.643132
5784	Uganda	UGA	1994	0.533899

In [19]:
```python
# Investigating missing values in total firms
total_firms[total_firms['Year'].isnull()]
```

Out[19]:

	Economy	Adult population	Year	Total LLC	Business density rate
1522	NaN	NaN	NaN	NaN	NaN
1523	* This economy was included in the Eurostat Li...	NaN	NaN	NaN	NaN
1524	** For Canada, only the data for Quebec and On...	NaN	NaN	NaN	NaN
1525	***For China, only the data for Beijing and Sh...	NaN	NaN	NaN	NaN

In [20]:

```python
# Investigating missing values in "alpha-2", "alpha-3" "region," and "sub-region" column
missing_alpha2 = country_codes[country_codes['alpha-2'].isnull()]
missing_region = country_codes[country_codes['region'].isnull()]
missing_subregion = country_codes[country_codes['sub-region'].isnull()]

print("Rows with missing 'alpha-2' values:\n", missing_alpha2,'\n')
print("Rows with missing 'region' values:\n", missing_region,'\n')
print("Rows with missing 'sub-region' values:\n", missing_subregion,'\n')
```

```
Rows with missing 'alpha-2' values:
         name alpha-2 alpha-3  country-code  region          sub-region
153  Namibia     NaN     NAM           516  Africa  Sub-Saharan Africa

Rows with missing 'region' values:
           name alpha-2 alpha-3  country-code region sub-region
8  Antarctica      AQ     ATA            10    NaN        NaN

Rows with missing 'sub-region' values:
           name alpha-2 alpha-3  country-code region sub-region
8  Antarctica      AQ     ATA            10    NaN        NaN
```

In [21]:

```python
# Investigating null values in 'Code' column for Education Expenditure
edu_expenditure[edu_expenditure['Code'].isnull()].sample(10)
```

Out[21]:

	Entity	Code	Year	Education expenditure(%)
2812	North America (WB)	NaN	2017	13.017705
2482	Middle East and North Africa (WB)	NaN	2014	11.917440
3580	Sub-Saharan Africa (WB)	NaN	2000	15.607160
1591	High-income countries	NaN	2007	12.328560
3982	Upper-middle-income countries	NaN	2014	13.799330
2480	Middle East and North Africa (WB)	NaN	2012	11.615544
2072	Latin America and Caribbean (WB)	NaN	2020	15.336860
2814	North America (WB)	NaN	2019	12.559245
3968	Upper-middle-income countries	NaN	2000	16.226150
2474	Middle East and North Africa (WB)	NaN	2005	13.854110

In [22]:

```python
# Investigating null values in 'Code' column for Electricity Access
electricity_access[electricity_access['Code'].isnull()].sample(10)
```

Out[22]:

	Entity	Code	Year	Electricity access(%)
1848	European Union (27)	NaN	2011	100.000000
5365	Sub-Saharan Africa (WB)	NaN	2003	29.544962
3259	Low-income countries	NaN	2009	24.620592

3054	Latin America and Caribbean (WB)	NaN	1995	88.599500
3058	Latin America and Caribbean (WB)	NaN	1999	91.247590
1841	European Union (27)	NaN	2004	100.000000
1878	Faeroe Islands	NaN	2010	100.000000
1821	Europe and Central Asia (WB)	NaN	2015	99.256310
3682	Middle-income countries	NaN	2020	94.045770
1798	Europe and Central Asia (WB)	NaN	1992	100.000000

Results of Further Investigations:

Unemployment Rate

- The continent column contains mostly null values
- Rows with negative and error years in the Year column are associated with null values in both the Female unemployment rate(%) and Male unemployment rate(%) columns. These rows can be considered errors, and it's suggested to drop them.
- Rows with missing or zero values in the Population column are also related to the same set of rows where unemployment rates for both genders are null.

Youth Employment

- Youth employment strategy contains integer values

Education Expenditure

- Instances where the expenditure is 0, specifically for Nicaragua in 1982, 1984, and 1987, have been confirmed as correct after verifying external sources, such as macrotrends.net.
- Rows where code are nulls contain expenditures for regions and income categores

Electricity Access

- Instances where electricity access values are less than 0 have been confirmed as correct after checking external sources, such as macrotrends.net.
- Rows where code are nulls contain access for regions and income categores

Total firms

- Null values in the dataset indicate that the corresponding values in the Economy column are not actual countries but rather random text. These rows should be dropped.

Country Codes

- Row with missing 'alpha-2' and 'alpha-3' value is Namibia and can be filled in.
- Row with missing 'region' and 'sub-region' values are particularly for Antarctica, which can be filled in accordingly.

These findings provide guidance on specific actions that can be taken to improve the quality and reliability of the datasets. It involves dropping erroneous rows, validating certain values, and addressing missing or incorrect data.

Data Cleaning Process

In preparation for our analysis, we will undertake a comprehensive data cleaning process to ensure the quality and reliability of our datasets. Below are the key steps taken:

Drop Null Rows in Unemployment Rate:

- Remove rows with null values in the 'Female unemployment rate(%)' and 'Male unemployment rate(%)' columns.

Fill Missing Values in Country Codes Dataset:

- Fill missing 'alpha-2' and 'alpha-3' for Namibia with values from codesofcountry.com.
- Fill missing 'region' and 'sub-region' for Antarctica.

Fill Continent Column in Unemployment Rate:

- Map the 'region' column from the Country Codes dataset to the 'Continent' column in the Unemployment Rate dataset.
- Change 'Oceania' to 'Australia' in the 'Continent' column.
- Separate 'Americas' into 'North America' and 'South America' based on the 'sub-region' in the Country Codes dataset.

Drop Rows with Null Values in Total Firms:

- Remove rows with null values in the 'Total LLC' column.

Replace Integer Values Values in Youth Employment

- Replace the integer values to Categorical values

This streamlined process addresses the specific actions outlined, including filling missing values, mapping continents, and dropping null rows.

In [23]:
```
# Step 1: Dropping Null Rows in Unemployment Rate
unemployment_rate.dropna(subset=['Female unemployment rate(%)', 'Male unemployment rate(
```

In [24]:
```
# Step 2: Filling Missing Values in Country Codes Dataset
country_codes.loc[country_codes['name'] == 'Namibia', ['alpha-2', 'alpha-3']] = ['NA', '
country_codes.loc[country_codes['name'] == 'Antarctica', ['region', 'sub-region']] = ['A
```

In [25]:
```
# Step 3: Filling Continent Column in Unemployment Rate
unemployment_rate['Continent'] = unemployment_rate['Code'].map(
    country_codes.set_index('alpha-3')['region']
)

# Replace 'Oceania' with 'Australia' in the Continent column
unemployment_rate['Continent'] = unemployment_rate['Continent'].replace('Oceania', 'Aust

# Separate 'Americas' into 'North America' and 'South America'
north_america = country_codes.loc[country_codes['sub-region'] == 'Northern America', 'al
south_america = country_codes.loc[country_codes['sub-region'] == 'Latin America and the 

unemployment_rate.loc[unemployment_rate['Code'].isin(north_america), 'Continent'] = 'Nor
unemployment_rate.loc[unemployment_rate['Code'].isin(south_america), 'Continent'] = 'Sou
```

In [26]:
```
# Step 4: Dropping Rows with Null Values in Total Firms
```

```
total_firms.dropna(subset=['Total LLC'], inplace=True)
```

In [27]:
```
# Step 5: Replacing Integer Values Values in Youth Employment
strategy_mapping = {
    0: 'No Strategy',
    1: 'Developing a Strategy',
    2: 'Strategy Adopted',
    3: 'Strategy Operationalized'
}

# Replace integer values with categorical values
youth_employment['Youth employment strategy'] = youth_employment['Youth employment strat
```

In [28]:
```
# Merging the datasets
common_columns = ['Entity', 'Year']

merged_df = pd.merge(unemployment_rate, youth_employment, on=common_columns, how='left',
merged_df = pd.merge(merged_df, edu_expenditure, on=common_columns, how='left', suffixes
merged_df = pd.merge(merged_df, electricity_access, on=common_columns, how='left', suffi
merged_df = pd.merge(merged_df, total_firms, left_on=['Entity', 'Year'], right_on=['Econ
merged_df = pd.merge(merged_df, country_codes, left_on='Entity', right_on='name', how='l

# Drop redundant columns
merged_df.drop(['Economy', 'name'], axis=1, inplace=True)
```

In [29]:
```
# Dropping redundant columns
redundant_columns = ['Code_youth_employment', 'Code_unemployment3', 'Code_electricity_ac
merged_df.drop(redundant_columns, axis=1, inplace=True)

# Renaming the columns
column_mapping = {
    'Code_unemployment': 'Code',
    'Female unemployment rate(%)': 'Female_Unemployment_%',
    'Male unemployment rate(%)': 'Male_Unemployment_%',
    'Youth employment strategy': 'Youth_Strategy',
    'Education expenditure(%)': 'Edu_Expenditure_%',
    'Electricity access(%)': 'Electricity_Access_%',
    'Adult population': 'Adult_Population',
    'Total LLC': 'Total_LLC',
    'Business density rate': 'Business_Density',
    'alpha-2': 'Alpha2',
    'alpha-3': 'Alpha3',
    'country-code': 'Country_Code',
    'region': 'Region',
    'sub-region': 'Sub_Region'
}

merged_df.rename(columns=column_mapping, inplace=True)
```

In [30]:
```
# Saving cleaned datasets
unemployment_rate.to_csv('cleaned_unemployment_rate.csv', index=False)
country_codes.to_csv('cleaned_country_codes.csv', index=False)
total_firms.to_csv('cleaned_total_firms.csv', index=False)
youth_employment.to_csv('cleaned_youth_employment.csv', index=False)
merged_df.to_csv('merged_df.csv', index=False)
```

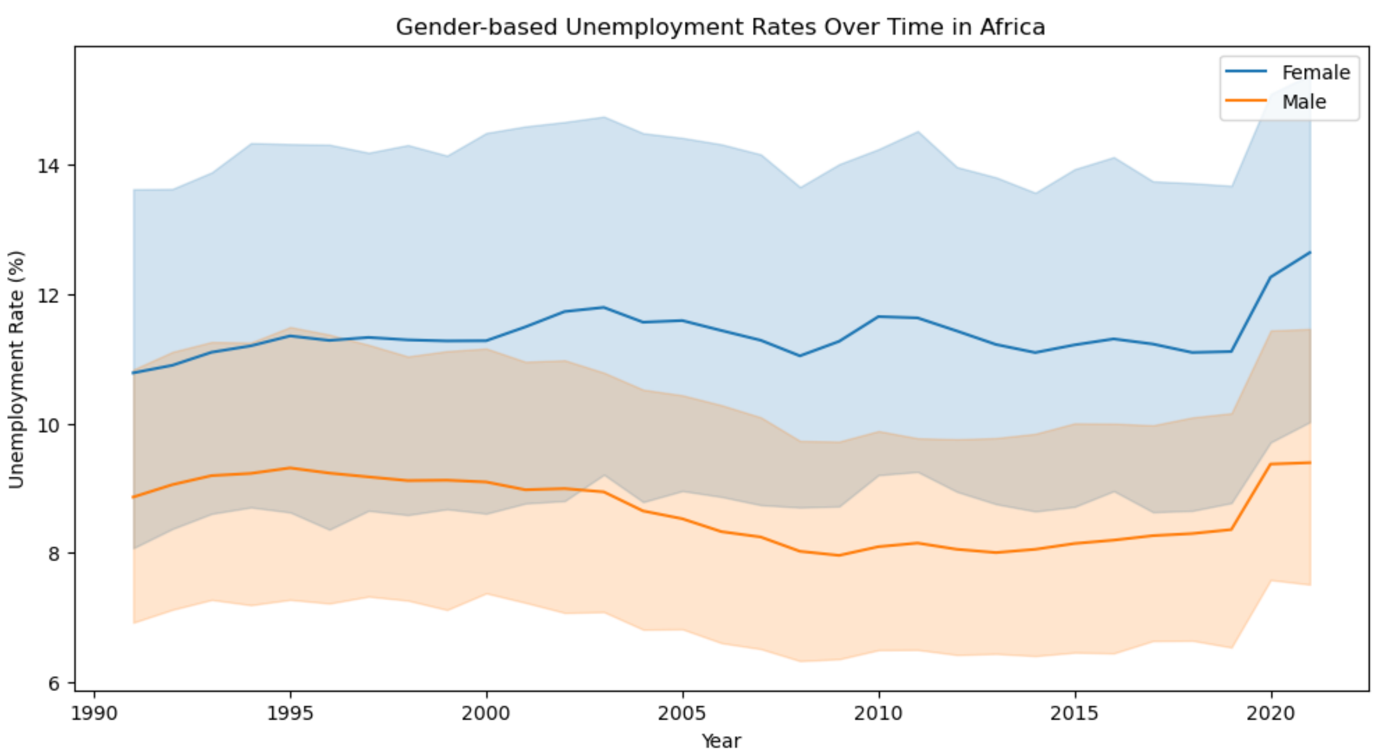
In [31]:
```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6231 entries, 0 to 6230
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Entity                  6231 non-null   object
```

```
 1   Code                   5828 non-null   object
 2   Year                   6231 non-null   int64
 3   Female_Unemployment_%  6231 non-null   float64
 4   Male_Unemployment_%    6231 non-null   float64
 5   Population             5952 non-null   float64
 6   Continent              5766 non-null   object
 7   Youth_Strategy         278 non-null    object
 8   Edu_Expenditure_%      3626 non-null   float64
 9   Electricity_Access_%   5326 non-null   float64
 10  Adult_Population       1238 non-null   float64
 11  Total_LLC              1238 non-null   float64
 12  Business_Density       1238 non-null   float64
 13  Alpha2                 5146 non-null   object
 14  Alpha3                 5146 non-null   object
 15  Country_Code           5146 non-null   float64
 16  Region                 5146 non-null   object
 17  Sub_Region             5146 non-null   object
dtypes: float64(9), int64(1), object(8)
memory usage: 876.4+ KB
```

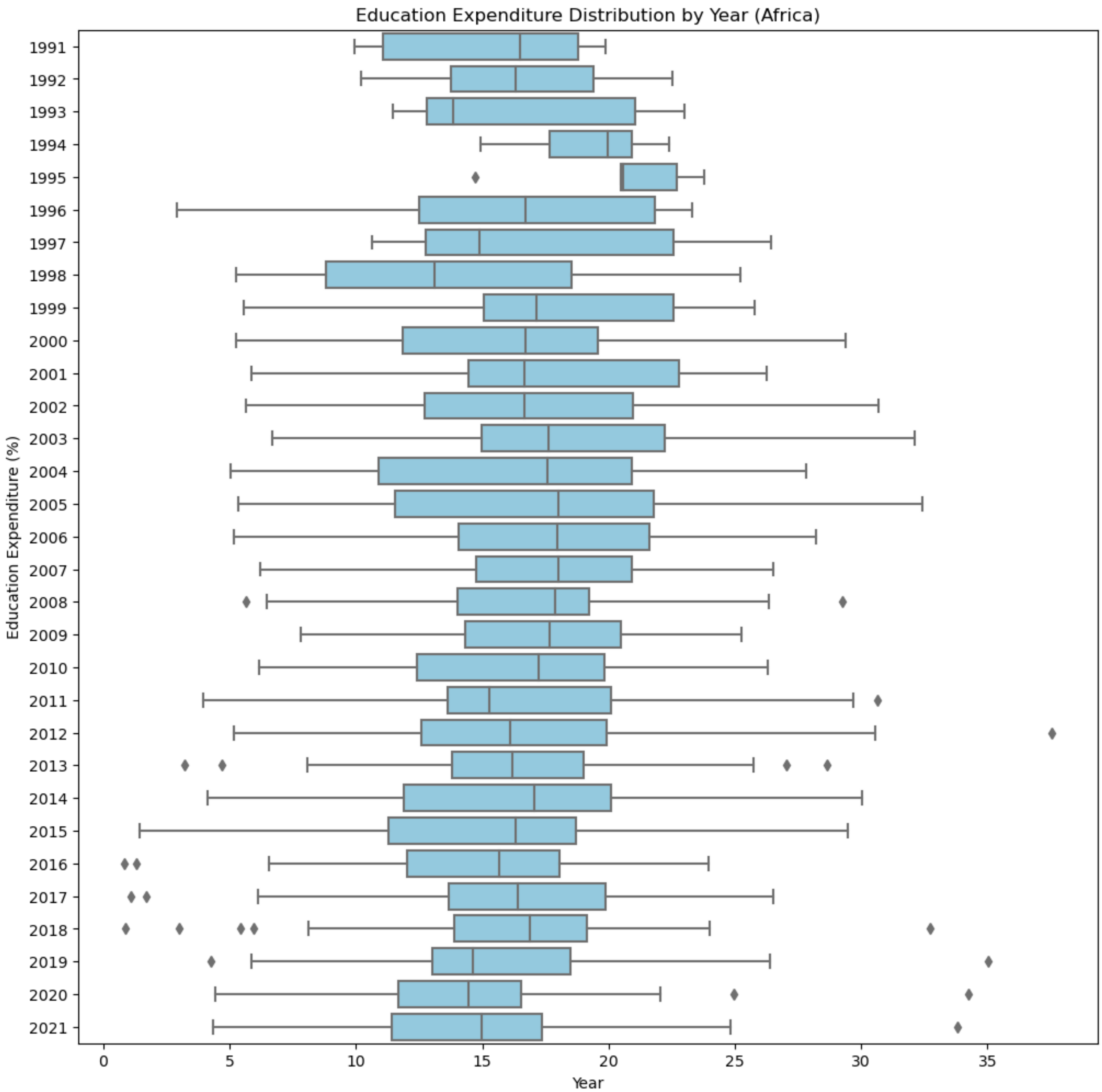
Exploratory Data Analysis (Africa)

In [32]:
```python
# Visualizing gender-based unemployment rates over time in Africa
africa_df = merged_df[merged_df['Continent'] == 'Africa']

plt.figure(figsize=(12, 6))
sns.lineplot(data=africa_df, x='Year', y='Female_Unemployment_%', label='Female')
sns.lineplot(data=africa_df, x='Year', y='Male_Unemployment_%', label='Male')
plt.title('Gender-based Unemployment Rates Over Time in Africa')
plt.xlabel('Year')
plt.ylabel('Unemployment Rate (%)')
plt.legend()
plt.show()
```



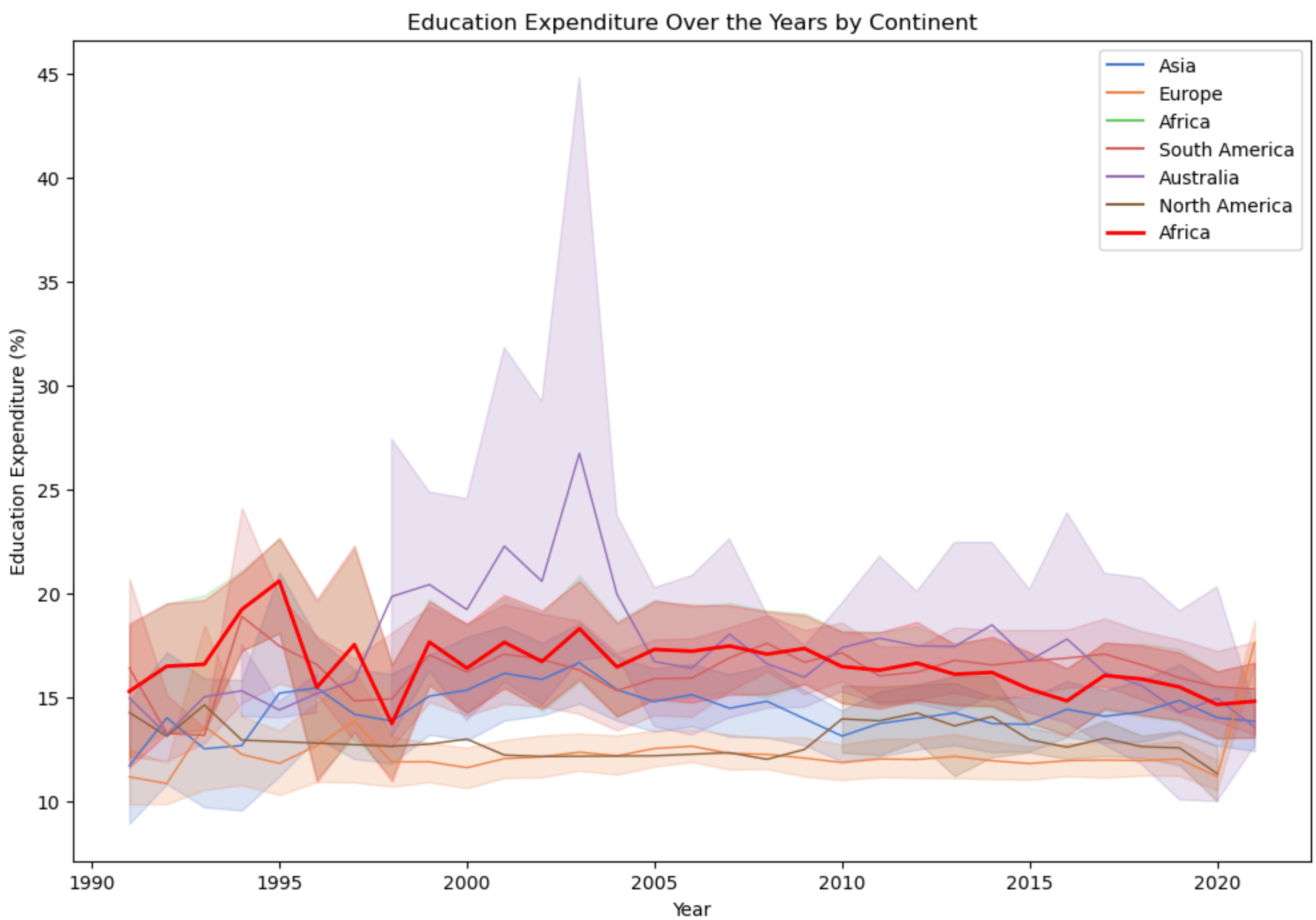
This chart depicts gender-based unemployment rates in Africa from 1991 to 2021, it is evident that both female and male unemployment rates have experienced similar patterns over the years. Notably, female unemployment rates consistently surpass those of males, highlighting a persistent gender disparity in the job market. The data also reveals some yearly fluctuations in both genders, with spikes in unemployment rates observed between 2019 and 2021. The latter year, 2020, stands out as particularly impactful, showing a substantial increase in unemployment rates for both females and males, likely attributable to the global challenges posed by the COVID-19 pandemic. Despite these fluctuations, the general trend suggests a persistent gender gap in unemployment rates, underscoring the need for targeted interventions to address and mitigate this inequality in the African job market.

In [33]:
```
# Visualizing a Box plot of Education Expenditure by Year in Africa
plt.figure(figsize=(12, 12))
sns.boxplot(data=africa_df, y='Year', x='Edu_Expenditure_%', orient='h', color='skyblue'
plt.title('Education Expenditure Distribution by Year (Africa)')
plt.xlabel('Year')
plt.ylabel('Education Expenditure (%)')
plt.show()
```



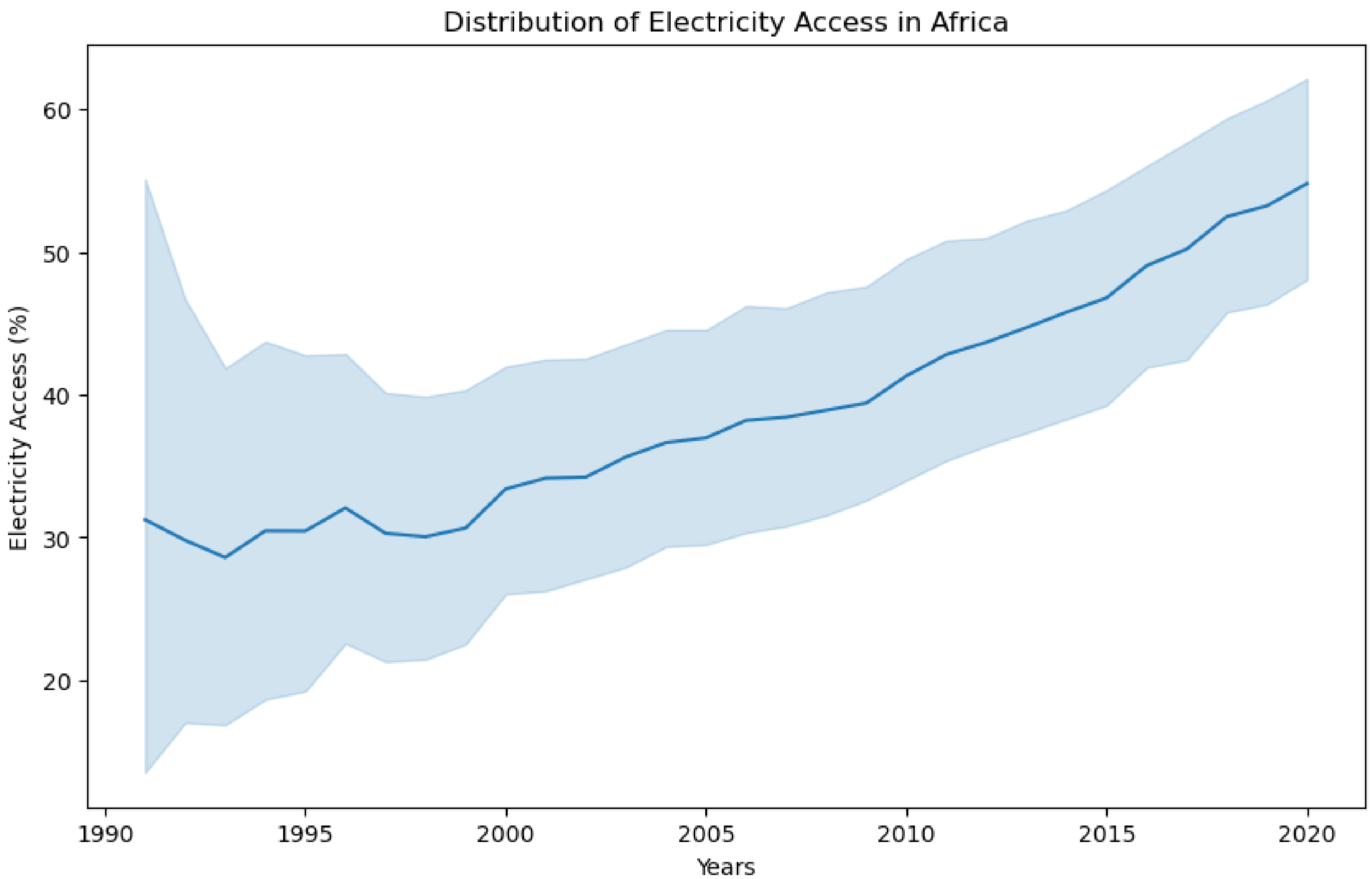
It is apparent that the mean percentage of education expenditure fluctuates over the years, demonstrating a diverse financial commitment to education. Notably, certain years stand out with higher mean values, indicative of potential increased investment in education during those periods. The data also reveals considerable variability in expenditure each year, with some years displaying more consistent spending patterns than others. Outliers in specific years suggest instances of exceptionally high education spending. Interestingly, the mean expenditure percentages have shown a slight decrease in the most recent years, possibly signaling a shift in financial priorities or challenges in sustaining higher education investments. This comprehensive overview provides valuable insights into the dynamic nature of education expenditure in Africa, emphasizing the need for continued attention and strategic planning to ensure consistent and adequate funding for education initiatives.

In [34]:
```
# Visualizing a line plot of Education Expenditure over the years by Continent
custom_palette = sns.color_palette("muted")
plt.figure(figsize=(12, 8))
sns.lineplot(x='Year', y='Edu_Expenditure_%', hue='Continent', data=merged_df, linewidth
sns.lineplot(x='Year', y='Edu_Expenditure_%', color='red', label='Africa', data=africa_d
plt.title('Education Expenditure Over the Years by Continent')
plt.xlabel('Year')
plt.ylabel('Education Expenditure (%)')
plt.legend()
plt.show()
```



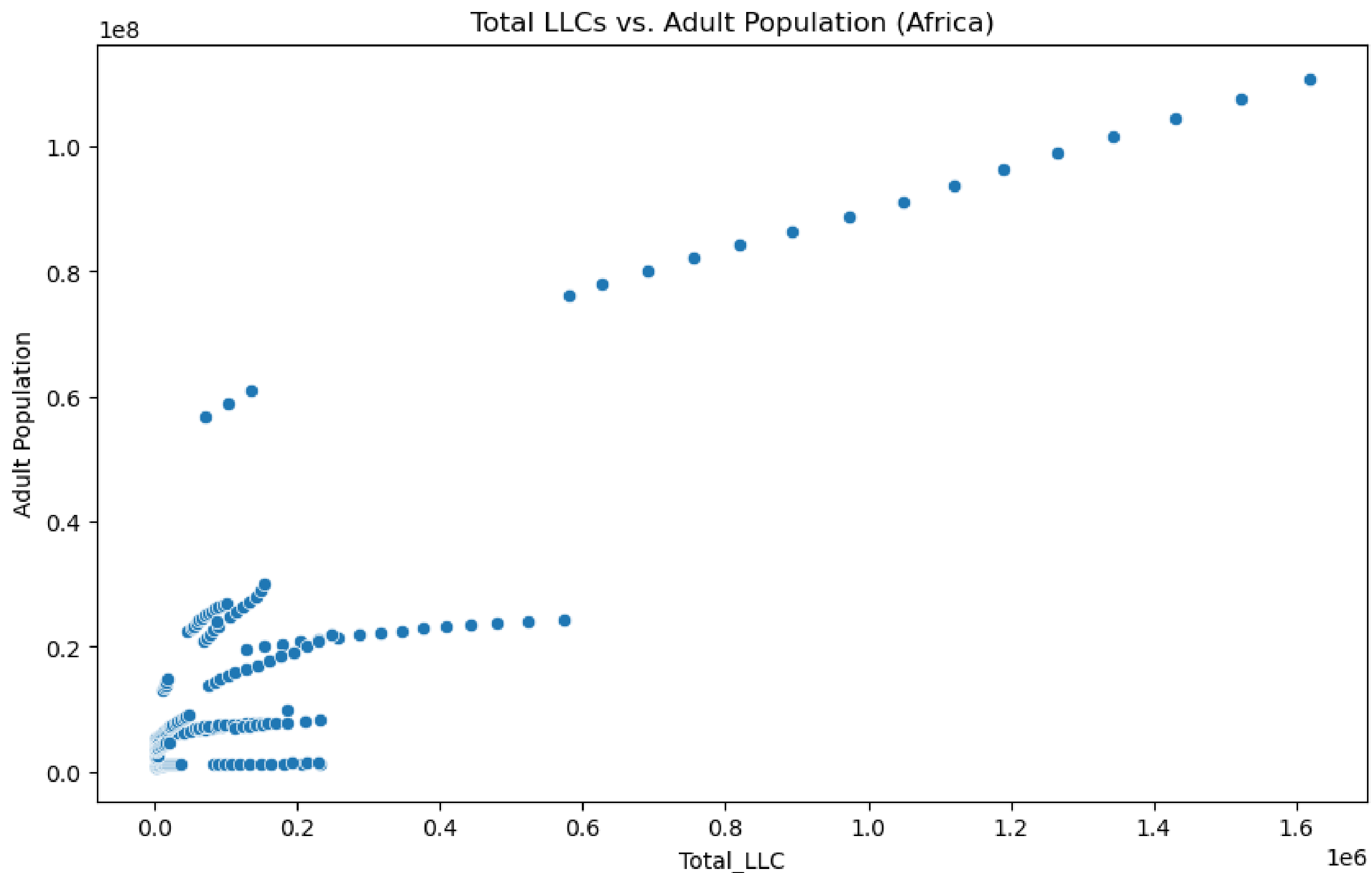
This line plot illustrating education expenditure over the years by continent offers a comprehensive perspective on global investment trends in education. Analyzing the chart, it is evident that Africa consistently maintains higher average education expenditure percentages compared to other continents. The red line specifically representing Africa stands out prominently, showcasing a gradual increase in education spending from the early 1990s to the mid-2000s, followed by a period of relatively stable investment. In contrast, other continents such as Asia and Europe exhibit more fluctuating patterns, with occasional peaks and troughs in education expenditure. North America displays a comparatively steady trend, while South America experiences a noticeable upward trajectory in recent years. The chart underscores the diverse approaches and priorities of different continents in allocating resources to education. Africa's sustained commitment reflects a concerted effort to prioritize education, potentially addressing critical developmental needs or rather the culture of corruption that the budgeted expenditure are not utilized. The variations across continents highlight the complex interplay of economic, social, and political factors influencing education funding decisions.

In [35]:
```
# Visualizing Distribution of Electricity Access in Africa
plt.figure(figsize=(10, 6))
sns.lineplot(data=africa_df, y='Electricity_Access_%', x='Year')
plt.title('Distribution of Electricity Access in Africa')
plt.ylabel('Electricity Access (%)')
plt.xlabel('Years')
plt.show()
```



This reveals a consistent upward trend in the percentage of the population with access to electricity. The data spans from 1991 to 2020, showing a gradual increase in electricity access. The visualization effectively captures the improvement in access over time. The mean values, ranging from 31% in 1991 to 55% in 2020, indicate a substantial overall growth in electrification. However, it's essential to note the variability in access rates, as seen in the narrowing interquartile ranges. The absence of data for 2021 underscores the need for updated information. The chart conveys a positive narrative of progress in electricity access across Africa, highlighting the strides made over the past three decades.

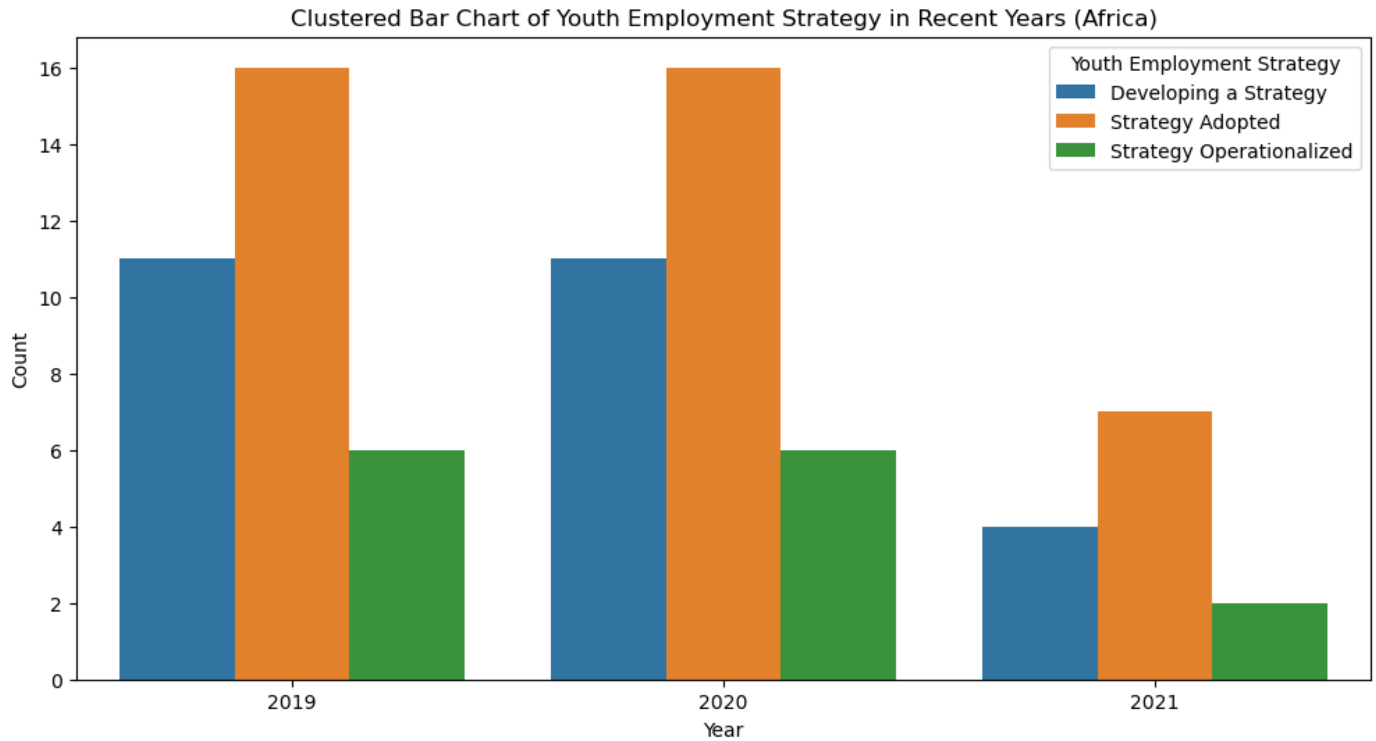
In [36]:
```
# Visualizing Total_LLC vs. Adult Population in Africa
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Total_LLC', y='Adult_Population', data=africa_df)
plt.title('Total LLCs vs. Adult Population (Africa)')
plt.xlabel('Total_LLC')
plt.ylabel('Adult Population')
plt.show()
```



We can observe a positive correlation between the total limited liablity companies and the adult population in Africa. As the number of businesses increases, there appears to be a general trend of higher adult populations in those regions. The scatter plot reveals a wide range of LLCs, ranging from lower values with corresponding smaller adult populations to higher values associated with larger adult populations. However, it's important to note that there is still considerable variability within the total LLCs, emphasizing the diverse demographic landscape across the continent.

In [37]:

```
# Visualizing youth employment strategy in Africa over the years
strategy = africa_df.groupby(['Year', 'Youth_Strategy']).size().reset_index(name='Count'
plt.figure(figsize=(12, 6))
sns.barplot(x='Year', y='Count', hue='Youth_Strategy', data=strategy)
plt.title('Clustered Bar Chart of Youth Employment Strategy in Recent Years (Africa)')
plt.xlabel('Year')
plt.ylabel('Count')
plt.legend(title='Youth Employment Strategy')
plt.show()
```



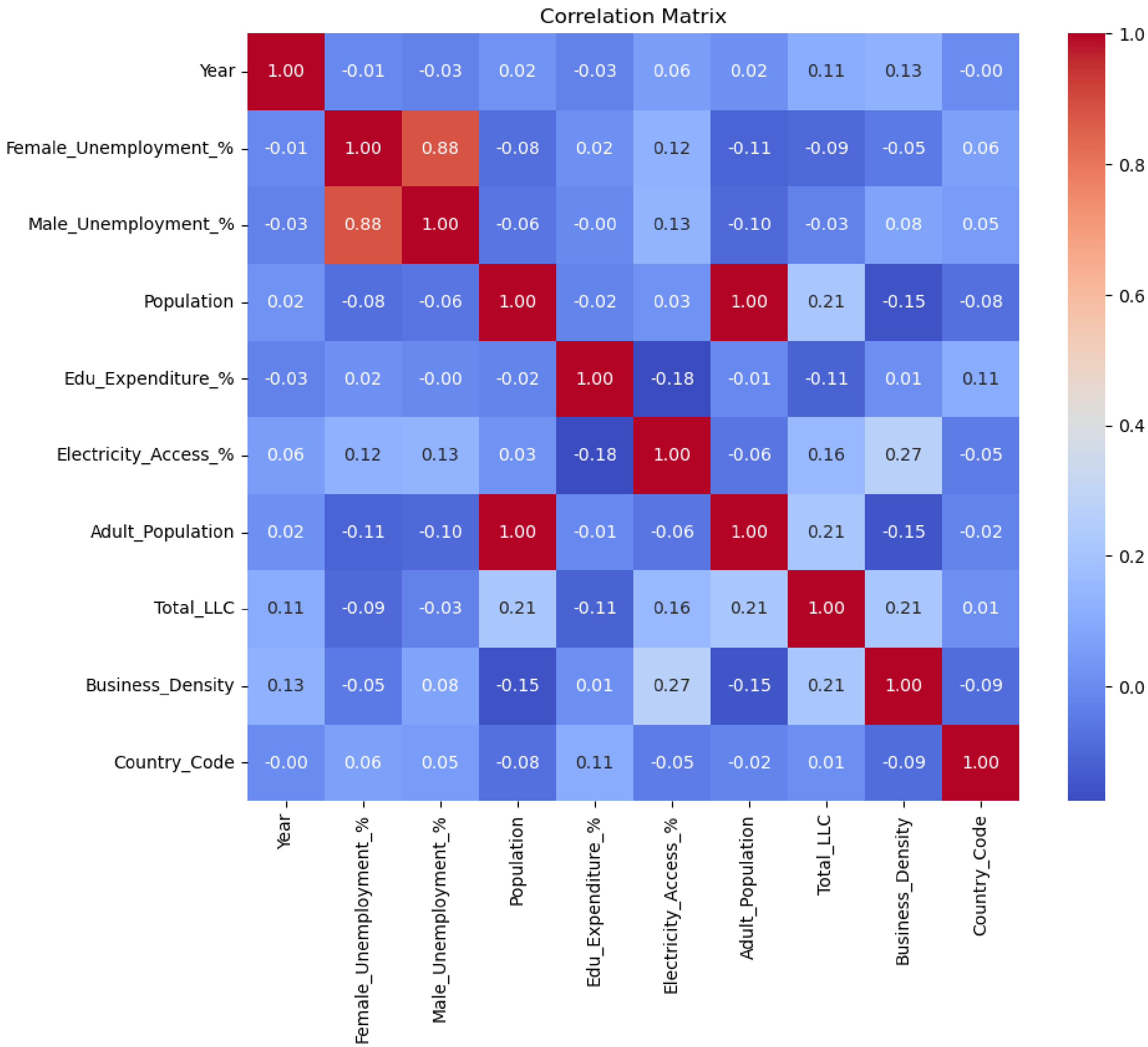
In 2019 and 2020, there was a consistent pattern with 11 instances of strategy development, 16 instances of strategy adoption, and 6 instances of strategy operationalization. However, in 2021, the numbers decreased, signaling a potential shift in the approach to youth employment. Specifically, there were 4 instances of strategy development, 7 instances of strategy adoption, and only 2 instances of strategy operationalization. This visual representation allows for a quick comparison of the evolution of youth employment strategies over the years, indicating variations in emphasis or priorities. It suggests that there was a notable decrease in all strategies in the most recent year, possibly warranting further investigation into the underlying factors contributing to this trend.

In [38]:

```
# Visualizing male and female uemployment rates
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Female_Unemployment_%', y='Male_Unemployment_%', data=africa_df)
plt.title('Female vs Male Unemployment Rates (Africa)')
plt.xlabel('Female Unemployment %')
plt.ylabel('Male Unemployment %')
plt.show()
```

Examining the scatter plot of female versus male unemployment rates provides a visual snapshot of the employment landscape in Africa. The data points suggest a nuanced relationship between female and male unemployment, revealing a tendency for higher female unemployment rates across the spectrum. The spread of data points, extending from the lower left to the upper right, signifies a diverse range of unemployment scenarios across different regions or time periods. Notably, the scatter plot highlights instances of disproportionately high female unemployment rates, reaching up to about 50%, underscoring the importance of targeted interventions to address gender-specific employment challenges. In essence, this visualization prompts a closer examination of the factors contributing to gender disparities in unemployment and emphasizes the need for region-specific policy considerations.

In [39]:
```
# Visualizing a Heatmap of Correlation Matrix for Unemployment Rate in Africa
numeric_columns = africa_df.select_dtypes(include=['float64', 'int64']).columns
numeric = merged_df[numeric_columns]

correlation_matrix = numeric.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



The correlation matrix provides a comprehensive overview of the relationships among various economic indicators in Africa. Notably, the correlation coefficients reveal interesting patterns. The positive correlation between female and male unemployment percentages (0.88) suggests a strong relationship, indicating that regions with higher female unemployment tend to experience higher male unemployment as well. The correlation between education expenditure and electricity access is negative (-0.18), suggesting that regions with higher education expenditure might have lower electricity access. Also, there is a positive correlation between business density and electricity access (0.27), implying that areas with better electricity access tend to have a higher density of businesses. The high positive correlation (0.21) between adult population and total limited liability companies suggests that regions with a larger adult population may also exhibit a higher density of businesses. This correlation underscores the potential economic opportunities associated with a larger adult workforce.

Explanatory Data Analysis (Africa)

In [40]:

```
# Countries with Top 5 and Least 5 unemployment rates
average_unemployment = africa_df.groupby('Entity')[['Female_Unemployment_%', 'Male_Unemp

top_5_female = average_unemployment.nlargest(5, 'Female_Unemployment_%')
least_5_female = average_unemployment.nsmallest(5, 'Female_Unemployment_%')
```

```
top_5_male = average_unemployment.loc[top_5_female.index, 'Male_Unemployment_%']
least_5_male = average_unemployment.loc[least_5_female.index, 'Male_Unemployment_%']

print("Top 5 Female Unemployment Rates:")
print(top_5_female['Female_Unemployment_%'])
print("\nTop 5 Male Unemployment Rates:")
print(top_5_male)
print("\nLeast 5 Female Unemployment Rates:")
print(least_5_female['Female_Unemployment_%'])
print("\nLeast 5 Male Unemployment Rates:")
print(least_5_male)
```

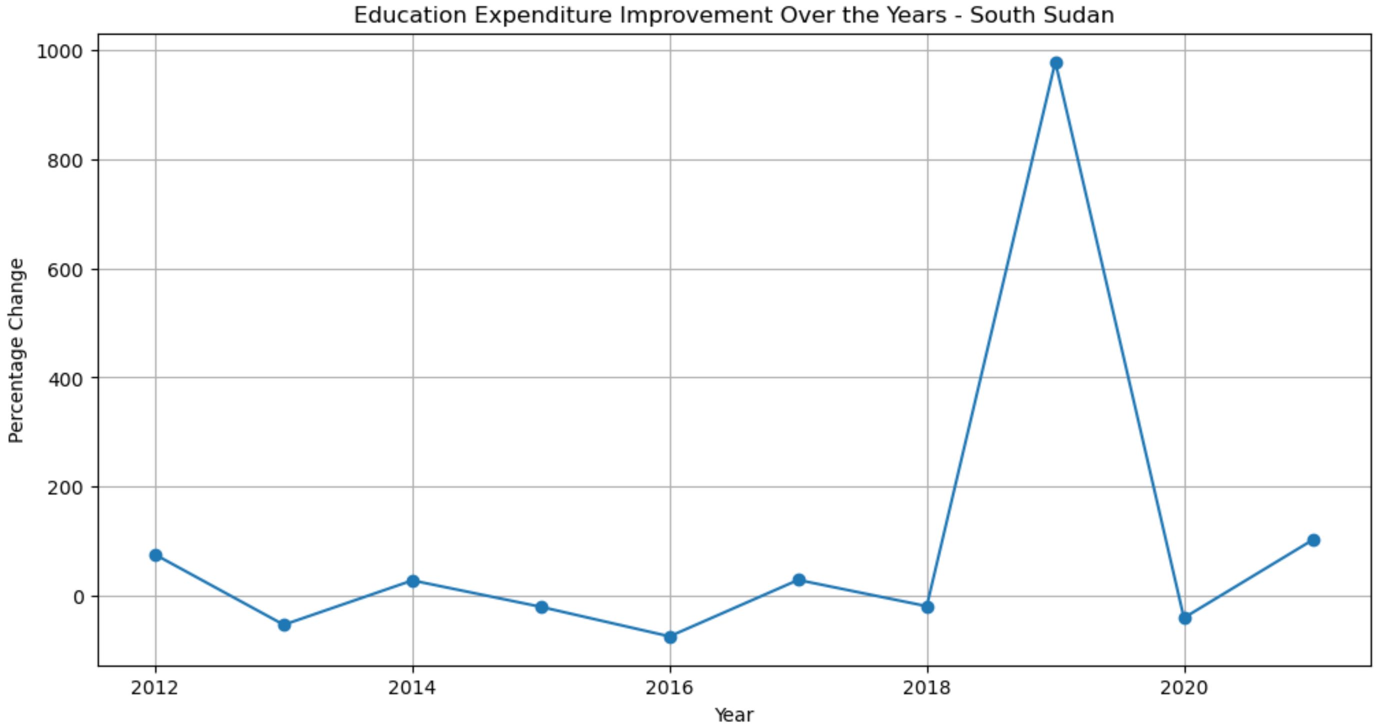
```
Top 5 Female Unemployment Rates:
Entity
Djibouti        37.281548
Lesotho         35.324452
South Africa    32.754806
Eswatini        26.765419
Libya           25.875903
Name: Female_Unemployment_%, dtype: float64

Top 5 Male Unemployment Rates:
Entity
Djibouti        24.829935
Lesotho         25.776129
South Africa    24.938903
Eswatini        22.235903
Libya           16.479903
Name: Male_Unemployment_%, dtype: float64

Least 5 Female Unemployment Rates:
Entity
Chad       0.561645
Rwanda     0.832452
Niger      1.171387
Benin      1.179129
Burundi    1.220032
Name: Female_Unemployment_%, dtype: float64

Least 5 Male Unemployment Rates:
Entity
Chad       1.243258
Rwanda     1.002774
Niger      1.547645
Benin      1.458742
Burundi    2.007000
Name: Male_Unemployment_%, dtype: float64
```

In [41]:

```
# Displaying the top 10 countries that have improved the most in education expenditure
data = africa_df[['Entity', 'Year', 'Edu_Expenditure_%']]
pivot_table = data.pivot(index='Entity', columns='Year', values='Edu_Expenditure_%')
pct_change = pivot_table.pct_change(axis=1) * 100
mean_pct_change = pct_change.mean(axis=1)
improved = mean_pct_change.sort_values(ascending=False)
top_countries = improved.head(10)

print("Top 10 Countries with the Most Improvement in Education Expenditure:")
print(top_countries)

# Visualizing the improvement for the top country
top_country = top_countries.index[0]
plt.figure(figsize=(12, 6))
plt.plot(pct_change.loc[top_country], marker='o')
plt.title(f'Education Expenditure Improvement Over the Years - {top_country}')
plt.xlabel('Year')
```

```
plt.ylabel('Percentage Change')
plt.grid(True)
plt.show()
```

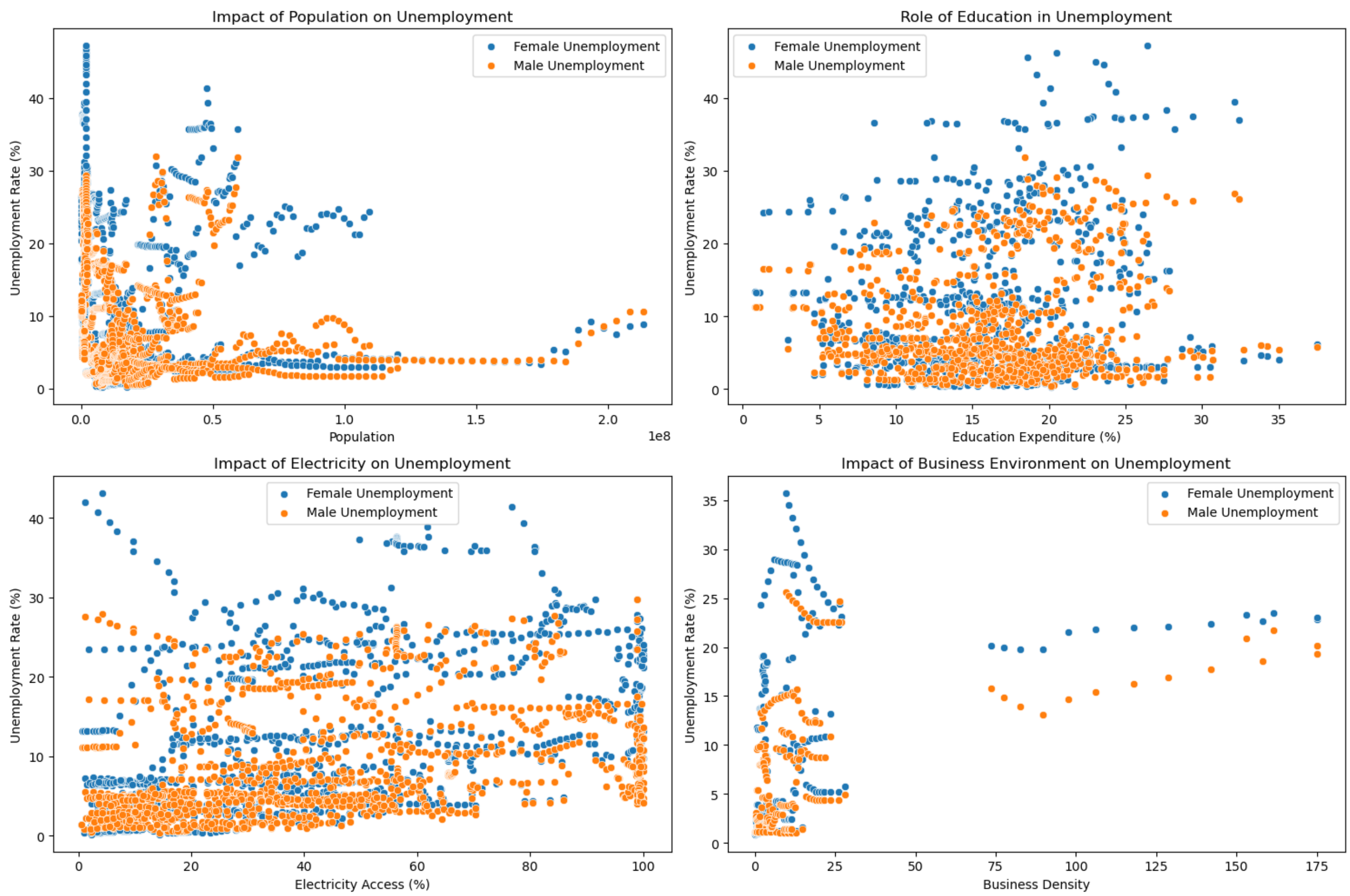
```
Top 10 Countries with the Most Improvement in Education Expenditure:
Entity
South Sudan                     100.408409
Somalia                          23.761546
Zimbabwe                         17.255107
Democratic Republic of Congo     10.910666
Sao Tome and Principe             8.322488
Congo                             7.361825
Gambia                            6.732649
Liberia                           6.621574
Zambia                            6.560657
Sierra Leone                      4.946332
dtype: float64
```



In [42]:

```
# Visualizing the impact of specific features on the unemployment rate
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 10))

# Population Impact
sns.scatterplot(x='Population', y='Female_Unemployment_%', data=africa_df, label='Female
sns.scatterplot(x='Population', y='Male_Unemployment_%', data=africa_df, label='Male Une
axes[0, 0].set_xlabel('Population')
axes[0, 0].set_ylabel('Unemployment Rate (%)')
axes[0, 0].set_title('Impact of Population on Unemployment')
axes[0, 0].legend()

# Role of Education
sns.scatterplot(x='Edu_Expenditure_%', y='Female_Unemployment_%', data=africa_df, label=
sns.scatterplot(x='Edu_Expenditure_%', y='Male_Unemployment_%', data=africa_df, label='M
axes[0, 1].set_xlabel('Education Expenditure (%)')
axes[0, 1].set_ylabel('Unemployment Rate (%)')
axes[0, 1].set_title('Role of Education in Unemployment')
axes[0, 1].legend()

# Infrastructure and Unemployment
sns.scatterplot(x='Electricity_Access_%', y='Female_Unemployment_%', data=africa_df, lab
sns.scatterplot(x='Electricity_Access_%', y='Male_Unemployment_%', data=africa_df, label
axes[1, 0].set_xlabel('Electricity Access (%)')
axes[1, 0].set_ylabel('Unemployment Rate (%)')
```

```
axes[1, 0].set_title('Impact of Electricity on Unemployment')
axes[1, 0].legend()

# Business Environment
sns.scatterplot(x='Business_Density', y='Female_Unemployment_%', data=africa_df, label='
sns.scatterplot(x='Business_Density', y='Male_Unemployment_%', data=africa_df, label='Ma
axes[1, 1].set_xlabel('Business Density')
axes[1, 1].set_ylabel('Unemployment Rate (%)')
axes[1, 1].set_title('Impact of Business Environment on Unemployment')
axes[1, 1].legend()

# Adjust layout to prevent overlapping
plt.tight_layout()

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



Population Impact: Both genders exhibit a wide range of unemployment rates across different population sizes. However, there seems to be a slightly higher concentration of points with higher female unemployment rates in regions with smaller populations. This suggests that the relationship between population size and female unemployment might differ from that of males, indicating potential gender-specific dynamics in employment outcomes.

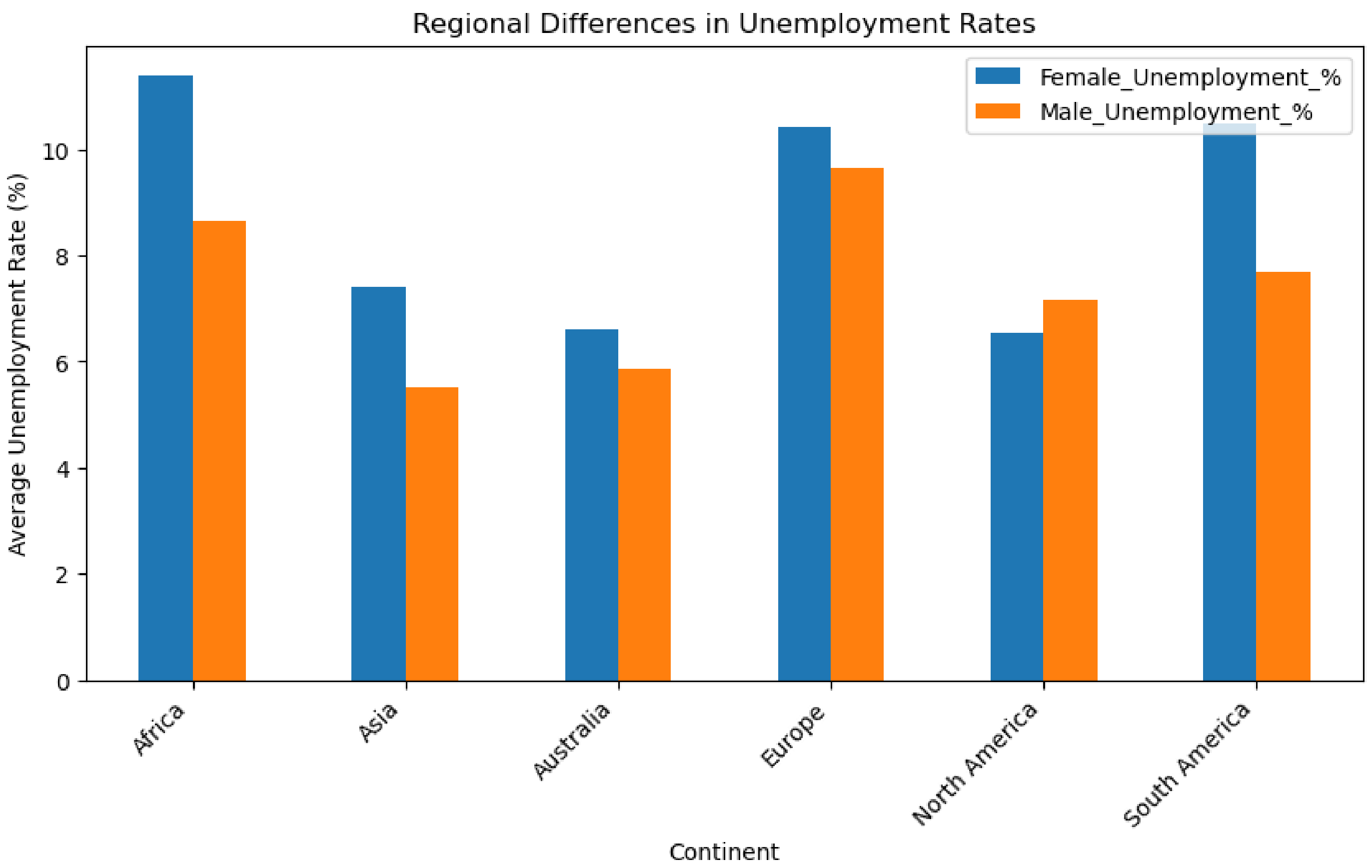
Role of Education: It appears that there is no distinct pattern. The points are dispersed, and no discernible correlation is evident. Despite varying levels of education spending, both female and male unemployment rates exhibit a wide range, indicating that additional factors influence employment outcomes.

Electricity Access: There is a subtle observation here. There might be a slight trend suggesting that regions with higher electricity access tend to have lower unemployment rates for both genders. However, the points are scattered, and the relationship is not strong, indicating that other factors contribute to the complexity of the employment landscape.

Business Environment: The points are also dispersed with no clear trend. While there seems to be a concentration of points at lower business densities, it doesn't necessarily translate into higher unemployment rates. The diversity in business density across regions suggests that factors beyond business concentration influence employment outcomes.

In summary, the scatter plots visually convey the complexity of the relationships between these factors and unemployment rates. No straightforward patterns emerge, highlighting the multifaceted nature of employment dynamics in Africa. Policymakers may need to consider a combination of factors and regional nuances when formulating strategies to address unemployment challenges.

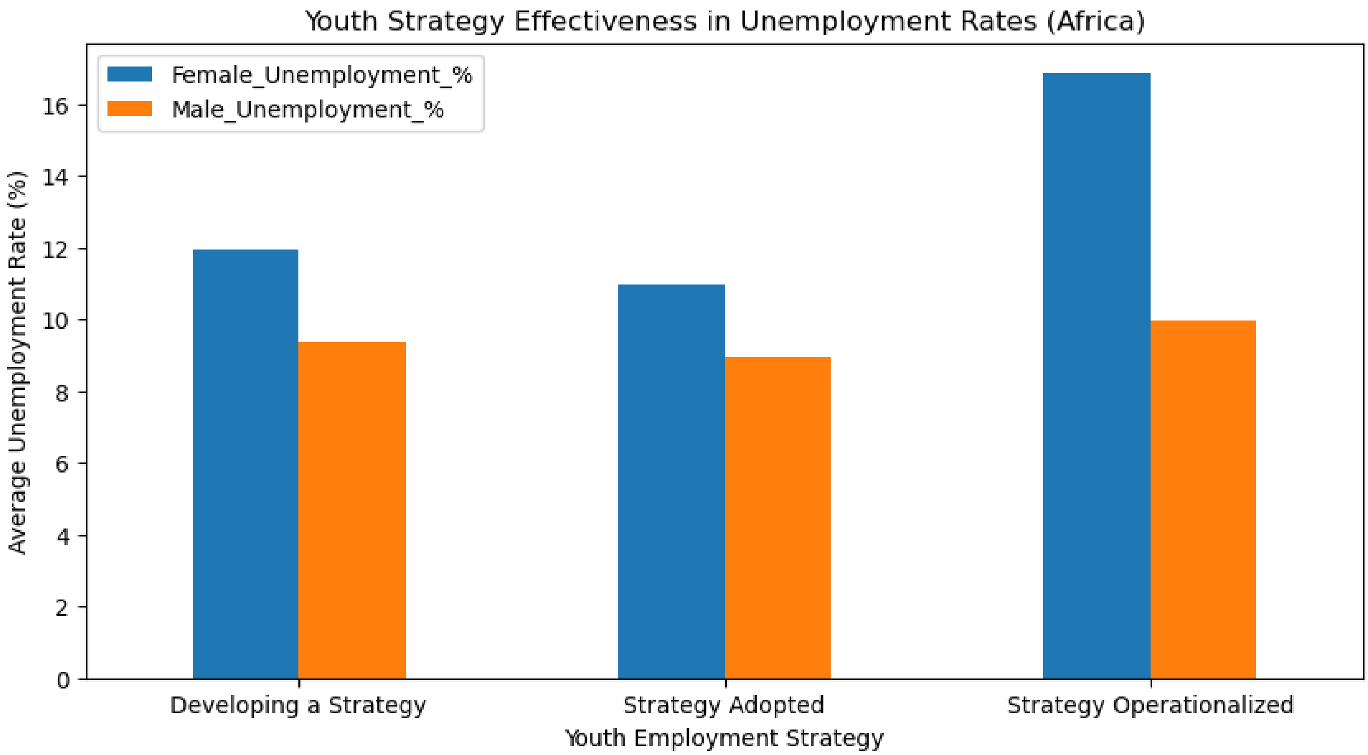
In [43]:
```
# Visualizing the Regional Differences across continents
region_avg = merged_df.groupby('Continent')[['Female_Unemployment_%', 'Male_Unemployment
region_avg.plot(kind='bar', figsize=(10,5))
plt.ylabel('Average Unemployment Rate (%)')
plt.title('Regional Differences in Unemployment Rates')
plt.xticks(rotation=45, ha='right')
plt.show()
```



The chart illustrates distinct regional differences in unemployment rates across continents, differentiating between male and female unemployment percentages across continents. In Africa, the data reveals a higher female unemployment rate at 11% compared to the male rate of 8%. Asia exhibits lower overall unemployment rates, with females at 7% and males at 6%. Also, Australia demonstrates relatively low unemployment rates for both genders. Europe exhibits higher unemployment rates overall, with females at 10% and males at 9%. North America showcases a slightly higher male unemployment rate of 7%, compared to males at 6.5%. In South America, the data indicates a noticeable gender disparity just like in Africa, with females experiencing a higher unemployment rate. These insights highlight the importance of considering regional variations when examining unemployment trends.

In [44]:
```
# Visualizing the Youth Strategy Effectiveness in Africa
youth_strategy_avg = africa_df.groupby('Youth_Strategy')[['Female_Unemployment_%', 'Male
```

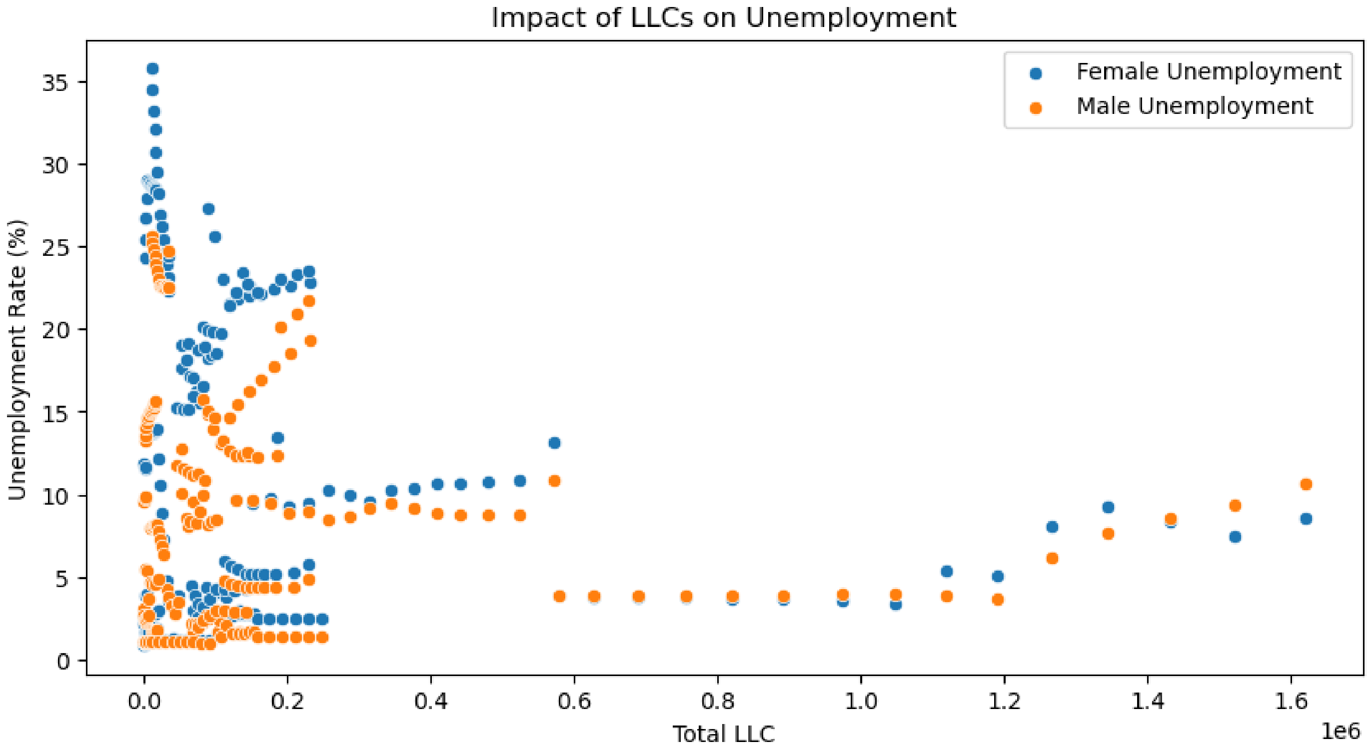
```
youth_strategy_avg.plot(kind='bar', figsize=(10,5))
plt.xlabel('Youth Employment Strategy')
plt.ylabel('Average Unemployment Rate (%)')
plt.title('Youth Strategy Effectiveness in Unemployment Rates (Africa)')
plt.xticks(rotation=0, ha='center')
plt.show()
```



When focusing on developing a strategy, the data suggests that females face a higher unemployment rate than males. As strategies are adopted, both genders witness a decrease in unemployment rates. However, the operationalization of these strategies appears to introduce a notable gender gap, particularly for females, who experience a significant increase in unemployment at 16%, contrasting with the relatively stable male unemployment rate of 10%. This pattern implies that while the initial stages of strategy implementation may yield positive outcomes, there may be unforeseen challenges or disparities arising during the operationalization phase, especially for female job seekers. Therefore, a nuanced approach to youth employment strategies, considering both gender-specific needs and potential challenges at various implementation stages, is crucial for achieving sustainable and inclusive employment outcomes.

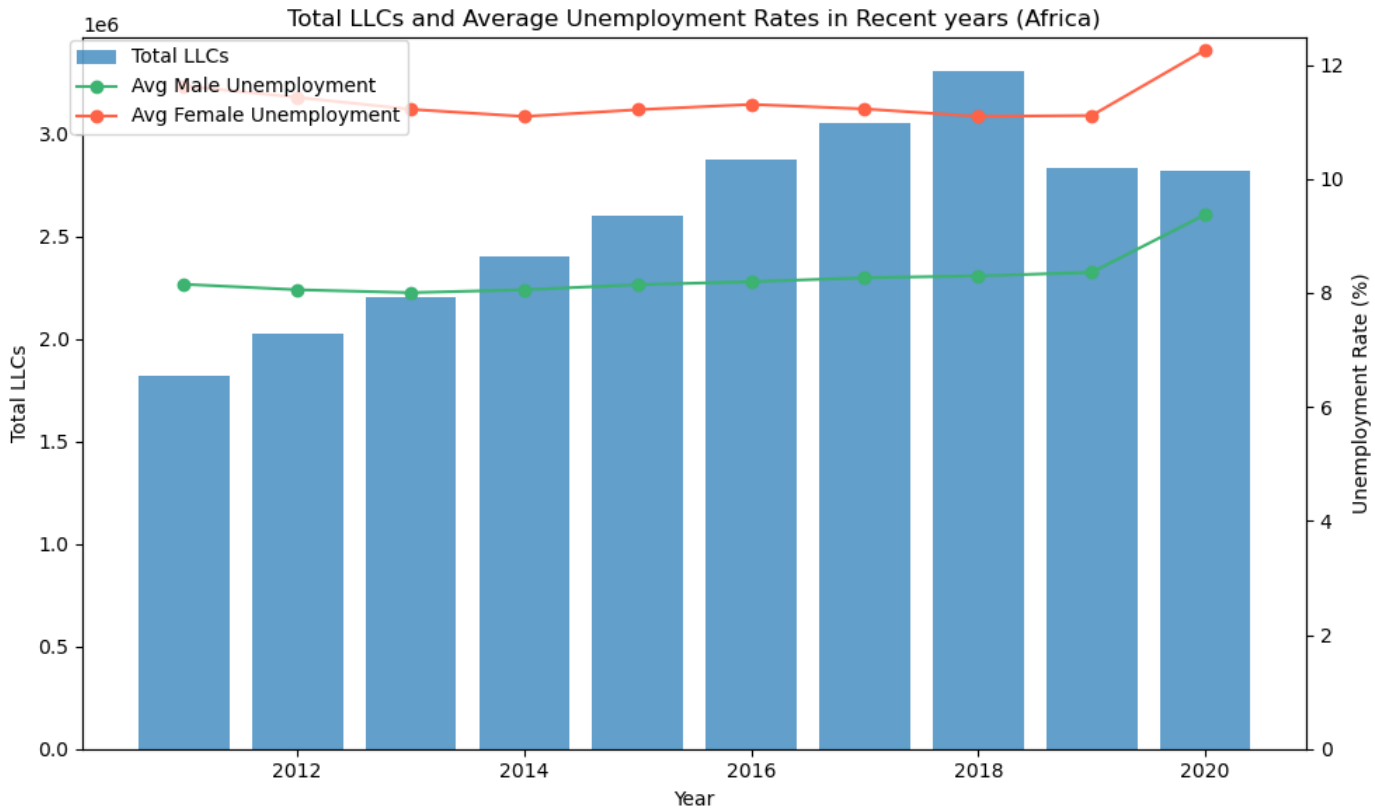
In [45]:

```
# Visualizing impact of Limited Liability Companies (LLCs) on Unemployment
plt.figure(figsize=(10, 5))
sns.scatterplot(x='Total_LLC', y='Female_Unemployment_%', data=africa_df, label='Female
sns.scatterplot(x='Total_LLC', y='Male_Unemployment_%', data=africa_df, label='Male Unem
plt.xlabel('Total LLC')
plt.ylabel('Unemployment Rate (%)')
plt.title('Impact of LLCs on Unemployment')
plt.legend()
plt.show()
```



In [46]:

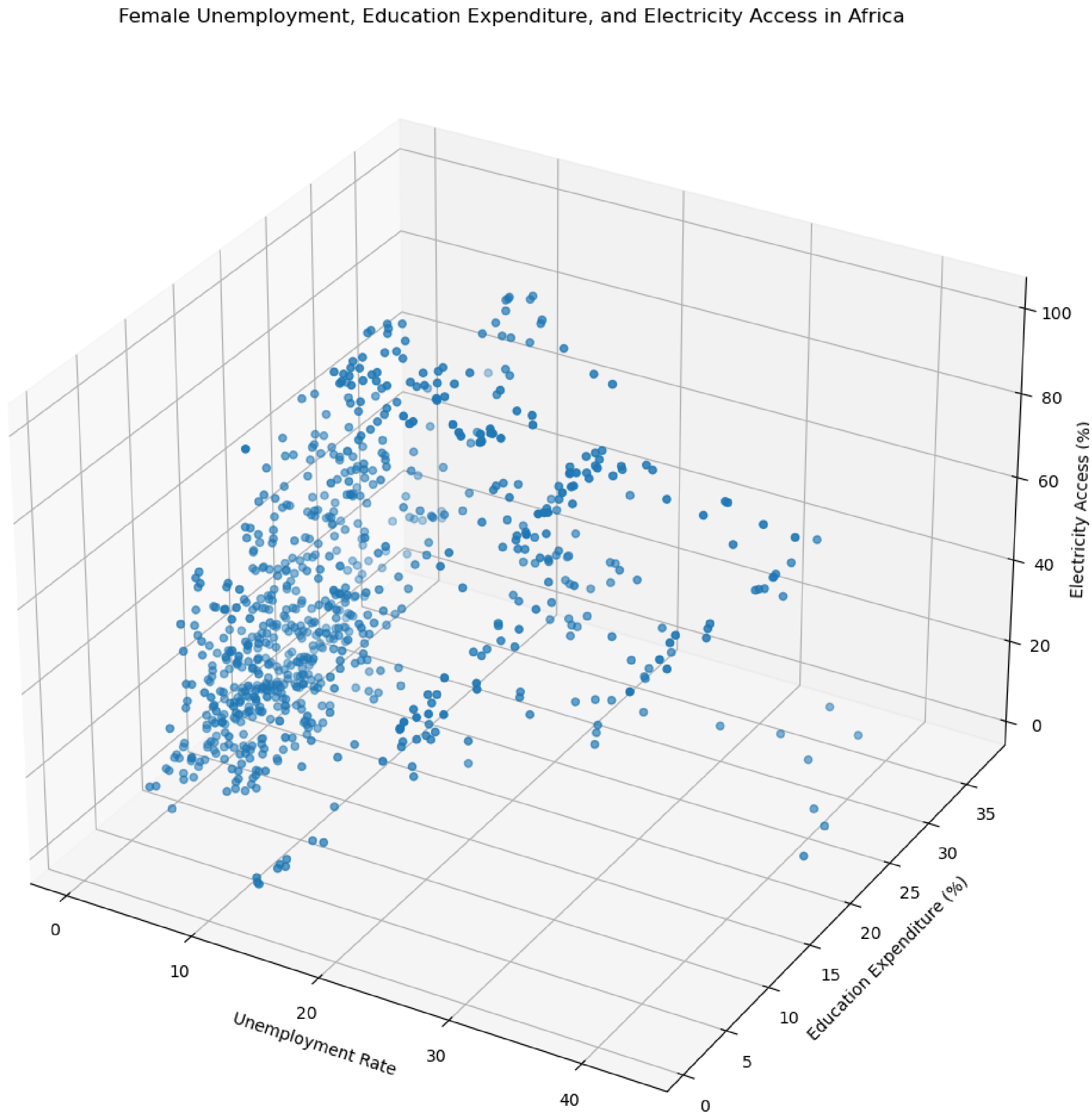
```
# Visualizing impact of Limited Liability Companies (LLCs) on Unemployment
max_year = africa_df['Year'].max()
recent_years = africa_df[(africa_df['Year'] >= max_year - 10) & (africa_df['Year'] < max
total_llcs = recent_years.groupby('Year')['Total_LLC'].sum()
avg_male = recent_years.groupby('Year')['Male_Unemployment_%'].mean()
avg_female = recent_years.groupby('Year')['Female_Unemployment_%'].mean()

fig, ax1 = plt.subplots(figsize=(10, 6))
ax1.bar(total_llcs.index, total_llcs, alpha=0.7, label='Total LLCs')
ax1.set_xlabel('Year')
ax1.set_ylabel('Total LLCs')
ax1.tick_params('y')

ax2 = ax1.twinx()
ax2.plot(avg_male.index, avg_male, color='mediumseagreen', marker='o', label='Avg Male U
ax2.plot(avg_female.index, avg_female, color='tomato', marker='o', label='Avg Female Une
ax2.set_ylabel('Unemployment Rate (%)', color='black')
ax2.set_ylim(0, ax2.get_ylim()[1])
ax2.tick_params('y', colors='black')

plt.title('Total LLCs and Average Unemployment Rates in Recent years (Africa)')
fig.tight_layout()
fig.legend(loc='upper left', bbox_to_anchor=(0.05, 0.95))
plt.show()
```



The scatter plot didn't show a clear relationship but the combo chart effectively captures the dynamic relationship between the total number of Limited Liability Companies (LLCs) and the average unemployment rates, differentiating between male and female demographics across the years in Africa. The bar graph showcases the annual fluctuation in the total number of LLCs, revealing a general upward trend until 2018, followed by a slight decline in 2019 and 2020. This trend suggests a complex interplay between economic activities facilitated by LLCs and the labor market. The dual y-axis line plot further enriches the narrative by juxtaposing the average male and female unemployment rates over the same time span. Notably, both male and female unemployment rates exhibit relative stability from 2011 to 2018. However, a noticeable divergence occurs in 2019 and 2020 just around the same time there was a decrease in LLCs which might be attributed to the COVID pandemic and economic crises in those years. The integration of LLC data with unemployment rates provides a comprehensive overview, indicating potential correlations between business activities and workforce participation.

In [47]:

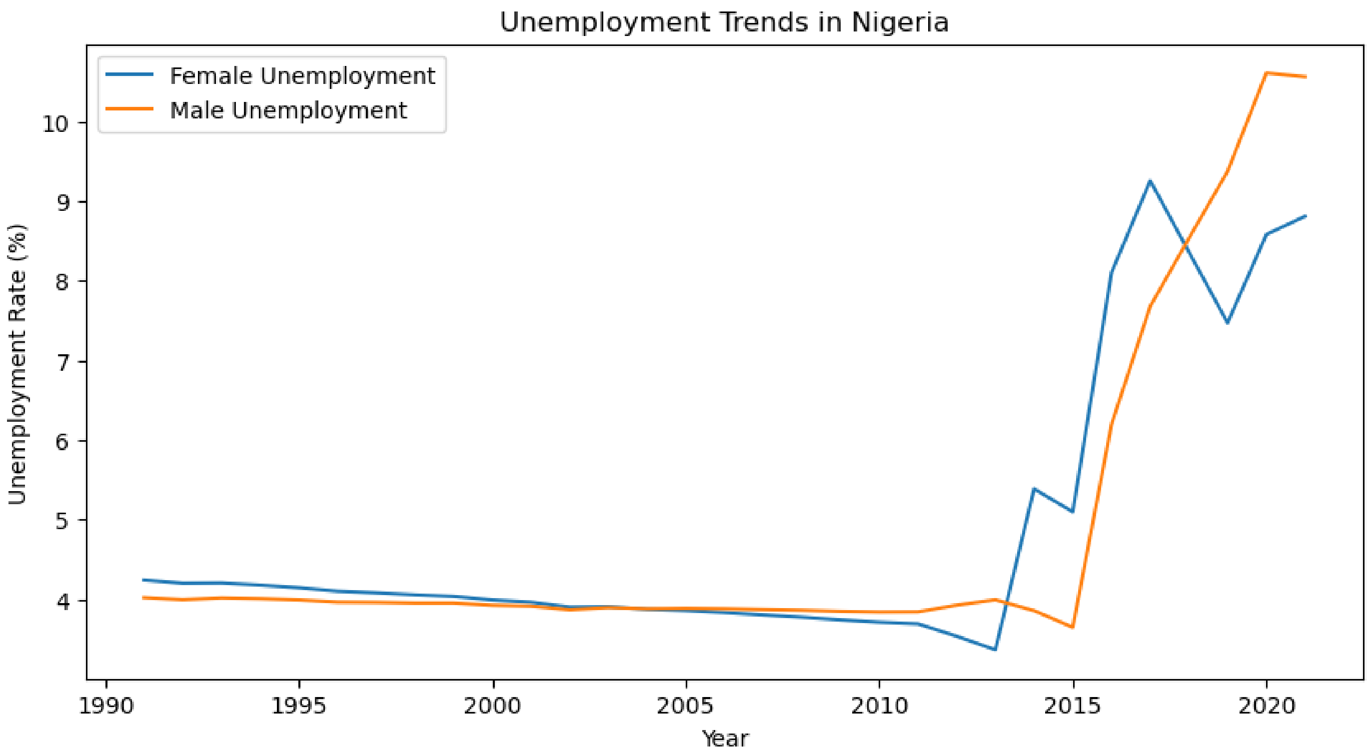
```
# Visualizing impact of Limited Liability Companies (LLCs) on Unemployment
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111, projection='3d')
x = africa_df['Female_Unemployment_%']
y = africa_df['Edu_Expenditure_%']
z = africa_df['Electricity_Access_%']
ax.scatter(x, y, z)
ax.set_title('Female Unemployment, Education Expenditure, and Electricity Access in Afri
ax.set_xlabel('Unemployment Rate')
ax.set_ylabel('Education Expenditure (%)')
ax.set_zlabel('Electricity Access (%)')
plt.tight_layout()
plt.show()
```



The plot illustrates the variation in female unemployment rates, education expenditure, and electricity access. Female unemployment rates exhibit a diverse range, with some regions experiencing relatively low rates while others face more significant challenges, as indicated by the broad spread of data points along the x-axis. Education expenditure percentages show varying levels of investment in education, contributing to the overall dispersion in the plot. The z-axis, representing electricity access, highlights the disparities in infrastructure development across the continent, with regions showcasing both limited and robust access. The visualization provides an understanding of the multi-dimensional nature of socio-economic factors, emphasizing the need to address the specific challenges faced by different African countries.

In [48]:
```
# Visualizing Country-Specific Trend in Unemployment rate (Nigeria)
country_data = merged_df[merged_df['Entity'] == 'Nigeria']
plt.figure(figsize=(10,5))
plt.plot(country_data['Year'], country_data['Female_Unemployment_%'], label='Female Unem
plt.plot(country_data['Year'], country_data['Male_Unemployment_%'], label='Male Unemploy
plt.xlabel('Year')
plt.ylabel('Unemployment Rate (%)')
plt.title('Unemployment Trends in Nigeria')
```

```
plt.legend()
plt.show()
```



The chart provides a compelling narrative of Nigeria's labor market dynamics. Throughout the early '90s and into the 2000s, both genders experienced a slight and gradual decline in unemployment rates, reflecting a period of relative stability and economic growth. However, around 2014, a noticeable spike in female unemployment occurred, reaching 5.5%, possibly indicating a shift in the employment landscape. In subsequent years, both male and female unemployment rates experienced fluctuations, with the female rate remaining consistently higher. The year 2016 marked a significant turning point, witnessing a substantial increase in female unemployment rates. This uptick persisted into 2017 and 2018, possibly indicating external factors impacting the labor market, such as economic downturns or policy changes.

The most recent data for 2020 and 2021 depicts a further rise in both female and male unemployment rates. These elevated rates may be attributed to global events, including the COVID-19 pandemic, which had widespread economic ramifications. In conclusion, the chart underscores the importance of continuous monitoring and analysis of unemployment trends to inform targeted interventions and policies aimed at stabilizing the labor market and fostering economic resilience. The observed gender disparities warrant focused attention, urging policymakers to address the unique challenges faced by women in the workforce.

Insights from the Data Analysis

Unemployment in Africa: A Data-Driven Perspective

Insights:

Gender Disparities in Unemployment: The analysis revealed persistent gender disparities in unemployment rates across Africa. Females consistently experienced higher unemployment rates compared to males. Understanding and addressing these gender-specific challenges is crucial for effective policy formulation.

Yearly Fluctuations: Yearly fluctuations, particularly in 2019 and 2020, suggest external factors such as the global economic downturn and the COVID-19 pandemic impacting both genders.

Youth Employment Strategies: The effectiveness of youth employment strategies varied. The "Strategy Operationalized" category showed a higher average unemployment rate, suggesting a need for reevaluation and potential adjustments in strategy implementation. Policymakers should focus on evidence-based strategies that yield positive outcomes.

Education Expenditure Impact: While education expenditure showed diverse patterns over the years, recent data indicated a slight decrease in mean percentages, signaling potential shifts in investment priorities. A negative correlation was observed between education expenditure and unemployment rates, emphasizing the importance of investing in education. Increasing spending on education can enhance workforce skills, making individuals more employable and supporting economic growth.

Infrastructure (Electricity): The percentage of the population with access to electricity demonstrated a consistent upward trend, reflecting positive progress in electrification across the continent. Increased access to electricity demonstrated a negative correlation with unemployment rates. Infrastructure development positively influences economic activities and job creation. Governments should prioritize infrastructure projects to stimulate economic growth.

Business Density and Employment: The relationship between the total number of LLCs and unemployment rates exhibited complexities. The total number of LLCs showed an upward trend until 2018, followed by a slight decline in 2019 and 2020. The COVID-19 pandemic may have contributed to this trend. The positive correlation between business density and lower unemployment rates indicates the role of a vibrant business environment in job creation. Policies supporting entrepreneurship and creating a conducive business environment can contribute to reducing unemployment.

Regional Disparities: Substantial variations in unemployment rates were observed across different continents. Policymakers should tailor interventions to address specific regional challenges and opportunities, acknowledging the diverse socio-economic landscapes.

Recommendations:

Gender-Inclusive Policies: Implement policies that specifically target reducing gender-based unemployment disparities. This may include initiatives to promote women's participation in the formal workforce, address discriminatory practices, and support women entrepreneurs.

Optimizing Youth Employment Strategies: Evaluate and refine existing youth employment strategies to ensure they align with current socio-economic dynamics. Focus on the strategies operationalized and understand the negative effects it has on the female population.

Boosting Education Expenditure: Increase investment in education, particularly in developing skills relevant to the job market. Consider exploring the reasons behind the recent decrease in mean education expenditure percentages and assess the potential impact on the quality of education. Collaboration between governments, private sectors, and educational institutions can enhance educational outcomes and reduce unemployment.

Infrastructure Development: Strengthen infrastructure development initiatives to further improve electricity access. Access to reliable electricity is crucial for economic activities and can positively impact employment opportunities.

Supporting LLCs and Small Businesses: Provide economic support and incentives for LLCs and small businesses, especially during challenging times such as economic downturns or crises. This can help stabilize the business environment and contribute to employment stability.

Tailored Regional Interventions: Recognize and address region-specific challenges by tailoring interventions to the unique socio-economic conditions of each region. Collaborate with regional authorities and stakeholders to develop targeted solutions.

Monitoring and Evaluation: Establish robust monitoring and evaluation mechanisms to continuously assess the impact of implemented policies. This iterative approach allows for adjustments based on real-time data and ensures the effectiveness of interventions.

Further Investigation into Gender-Specific Trends: Conduct further in-depth analysis to understand the root causes of gender-specific trends in unemployment. Explore socio-cultural, economic, and policy factors that contribute to the observed disparities.

Collaboration and Knowledge Sharing: Foster collaboration and knowledge sharing among African nations to share best practices and successful employment strategies. Regional collaboration can lead to collective solutions for common challenges.

In conclusion, the insights derived from the data analysis provide a foundation for informed policy decisions. By addressing gender disparities, optimizing youth strategies, investing in education, and fostering a conducive business environment, African nations can work towards mitigating the challenges of unemployment and building a more inclusive and prosperous future.

Recommendations for Further Action:

1. **Detailed Urban vs. Rural Analysis:**
   - Investigate the urban-rural divide in electricity access to understand disparities and formulate targeted interventions.
2. **Industry-Specific Insights:**
   - Explore unemployment trends within specific industries to identify growth areas and areas needing additional support.
3. **Longitudinal Analysis:**
   - Conduct a longitudinal analysis to track the impact of implemented policies and strategies over time.
4. **Stakeholder Engagement:**
   - Engage with stakeholders, including governments, businesses, and educational institutions, to garner support for the proposed recommendations.
5. **Public Awareness Campaigns:**
   - Implement public awareness campaigns to highlight the importance of education and address social norms contributing to gender-based disparities in unemployment.
6. **Policy Impact Assessment:**
   - Regularly assess the impact of implemented policies on unemployment rates and make data-driven adjustments as needed.

By taking these recommendations into consideration, policymakers and stakeholders can contribute to meaningful and sustainable solutions for mitigating unemployment challenges in Africa.