EduPulse: School & Student Insights Dashboard

Project Objective

The objective of this project is to simulate and analyze a comprehensive education dataset to uncover insights into school performance trends across regions and demographic groups.

The goal is to support data-driven decisions aimed at improving educational outcomes for children, particularly in the post-COVID era.

Key Questions to be Addressed

1. How did COVID-19 impact student performance across academic terms and years?
2. Which regions or school types consistently performed better?
3. Is there a relationship between household income and student academic scores?
4. What is the impact of parental education on student performance?

Step 1: Data Generation

- Synthetic datasets will be programmatically generated using Python to simulate real-world school systems.

In [52]:
```
import pandas as pd
import numpy as np
from faker import Faker
import random
import os

fake = Faker()

# Parameters
num_students = 1000
num_schools = 10
num_years = 5
terms = ["Term1", "Term2", "Term3"]
subjects = ["Math", "English", "Science", "Social Studies", "ICT"]

# Lookup tables
school_types = pd.DataFrame({
    "SchoolType_ID": ["TYP-0001", "TYP-0002"],
```

```
    "SchoolType": ["Public", "Private"]
})

boarding_statuses = pd.DataFrame({
    "BoardingStatus_ID": ["BRD-0001", "BRD-0002"],
    "BoardingStatus": ["Boarding", "Day"]
})

countries = ["Utopia", "Val Verde", "Wakanda", "Montalei"]
country_df = pd.DataFrame({
    "Country_ID": [f"CTR-{str(i+1).zfill(4)}" for i in range(len(countries))],
    "Country": countries
})

regions = [fake.state() for _ in range(10)]
region_df = pd.DataFrame({
    "Region_ID": [f"REG-{str(i+1).zfill(4)}" for i in range(len(regions))],
    "Region": regions
})

counties = [fake.city() for _ in range(10)]
county_df = pd.DataFrame({
    "County_ID": [f"CNT-{str(i+1).zfill(4)}" for i in range(len(counties))],
    "County": counties
})

education_levels = ["None", "Primary", "Secondary", "Vocational", "Tertiary"]
parent_edu_df = pd.DataFrame({
    "ParentEdu_ID": [f"PED-{str(i+1).zfill(4)}" for i in range(len(education_levels
    "Parent_Education": education_levels
})

income_brackets = ["<20K", "20K-50K", "50K-100K", "100K-200K", ">200K"]
income_df = pd.DataFrame({
    "Income_ID": [f"INC-{str(i+1).zfill(4)}" for i in range(len(income_brackets))],
    "Household_Income": income_brackets
})

# Schools
schools = pd.DataFrame({
    "School_ID": [f"SCH-{str(i+1).zfill(4)}" for i in range(num_schools)],
    "School_Name": [fake.company() for _ in range(num_schools)],
    "SchoolType_ID": np.random.choice(school_types["SchoolType_ID"], size=num_schoo
    "BoardingStatus_ID": np.random.choice(boarding_statuses["BoardingStatus_ID"], s
    "Country_ID": np.random.choice(country_df["Country_ID"], size=num_schools),
    "Region_ID": np.random.choice(region_df["Region_ID"], size=num_schools),
    "County_ID": np.random.choice(county_df["County_ID"], size=num_schools)
})

# Students
students = pd.DataFrame({
    "Student_ID": [f"STU-{str(i+1).zfill(5)}" for i in range(num_students)],
    "Student_Name": [fake.name() for _ in range(num_students)],
    "Gender": np.random.choice(["M", "F"], size=num_students),
    "School_ID": np.random.choice(schools["School_ID"], size=num_students),
    "ParentEdu_ID": np.random.choice(parent_edu_df["ParentEdu_ID"], size=num_studen
```

```
    "Income_ID": np.random.choice(income_df["Income_ID"], size=num_students)
})

# Performance records
records = []
for student in students["Student_ID"]:
    for year in range(1, num_years + 1):
        for term in terms:
            for subject in subjects:
                records.append({
                    "Student_ID": student,
                    "Year": 2018 + year,
                    "Term": term,
                    "Subject": subject,
                    "Score": np.random.randint(20, 100)
                })

performance_df = pd.DataFrame(records)

# Export all to Excel
schools.to_excel("schools.xlsx", index=False)
school_types.to_excel("school_types.xlsx", index=False)
boarding_statuses.to_excel("boarding_statuses.xlsx", index=False)
country_df.to_excel("countries.xlsx", index=False)
region_df.to_excel("regions.xlsx", index=False)
county_df.to_excel("counties.xlsx", index=False)
students.to_excel("students.xlsx", index=False)
parent_edu_df.to_excel("parent_education.xlsx", index=False)
income_df.to_excel("household_income.xlsx", index=False)
performance_df.to_excel("performance.xlsx", index=False)

print("All Excel files exported successfully.")
```

```
All Excel files exported successfully.
```

Step 2: Data Export & Excel Staging

- Generated data was exported into structured Excel sheets for initial validation and backup.
- Ensured integrity and proper format alignment for SQL ingestion. Replaced all country specific regions and counties with fictitious data

Step 3: SQL Database Modeling

1. Designed a Star Schema model in SQL for performance-efficient analysis.
2. Tables were normalized and loaded into a SQL server 2025 database.

3. Foreign key relationships linked students to their schools, Performance, and household details.

Step 4: Connecting SQL to Python

In [53]:
```python
from sqlalchemy import create_engine

# For Windows Authentication
server = 'DESKTOP-SC0AHMQ'  # Your sql server
database = 'EduPulse'

connection_string = f'mssql+pyodbc://@{server}/{database}?driver=ODBC+Driver+17+for
engine = create_engine(connection_string)
```

In [54]:
```python
#Test the connection:

import warnings
from sqlalchemy import exc as sa_exc
from sqlalchemy import text

# Suppress the specific SQLAlchemy warning about server version
warnings.filterwarnings('ignore',
                        message='Unrecognized server version info.*',
                        category=sa_exc.SAWarning)


try:
    with engine.connect() as conn:
        result = conn.execute(text("SELECT GETDATE()"))
        print("Connection successful. SQL Server current date/time:")
        for row in result:
            print(row[0])
except Exception as e:
    print("Connection failed:", e)
```

```
Connection successful. SQL Server current date/time:
2025-07-31 10:19:20.410000
```

In [55]:
```python
# Run a test query

with engine.connect() as conn:
    result = conn.execute(text("SELECT TOP 5 * FROM dbo.schools"))
    for row in result:
        print(row)
```

```
('SCH-0001', 'Smith-Gomez', 'TYP-0001', 'BRD-0002', 'CTR-0003', 'REG-0008', 'CNT-000
5')
('SCH-0002', 'Cook Ltd', 'TYP-0001', 'BRD-0001', 'CTR-0004', 'REG-0002', 'CNT-0001')
('SCH-0003', 'Williams, Valentine and Russell', 'TYP-0002', 'BRD-0001', 'CTR-0003',
'REG-0002', 'CNT-0005')
('SCH-0004', 'Edwards-Harding', 'TYP-0001', 'BRD-0002', 'CTR-0001', 'REG-0007', 'CNT
-0008')
('SCH-0005', 'Jones Group', 'TYP-0002', 'BRD-0001', 'CTR-0003', 'REG-0001', 'CNT-000
2')
```

Step 5: Load SQL Tables into Pandas

In [56]:

```python
import pandas as pd

df_schools = pd.read_sql("SELECT * FROM dbo.schools", engine)
df_boarding_status = pd.read_sql("SELECT * FROM dbo.boarding_status", engine)
df_counties = pd.read_sql("SELECT * FROM dbo.counties", engine)
df_countries = pd.read_sql("SELECT * FROM dbo.countries", engine)
df_household_income = pd.read_sql("SELECT * FROM dbo.household_income", engine)
df_parent_education = pd.read_sql("SELECT * FROM dbo.parent_education", engine)
df_performance = pd.read_sql("SELECT * FROM dbo.performance", engine)
df_regions = pd.read_sql("SELECT * FROM dbo.regions", engine)
df_school_types = pd.read_sql("SELECT * FROM dbo.school_types", engine)
df_students = pd.read_sql("SELECT * FROM dbo.students", engine)


# Preview performance
df_performance.head()
```

Out[56]:

	Student_ID	Year	Term	Subject	Score
0	STU-00943	2023	Term3	Math	62
1	STU-00943	2023	Term3	English	57
2	STU-00943	2023	Term3	Science	78
3	STU-00943	2023	Term3	Social Studies	57
4	STU-00943	2023	Term3	ICT	77

Step 6: Data Cleaning

In [57]:

```python
# 6.1 Check for missing values on Schools table
print(df_schools.isnull().sum())
```

```
School_ID            0
School_Name          0
SchoolType_ID        1
BoardingStatus_ID    0
Country_ID           0
Region_ID            0
County_ID            0
dtype: int64
```

In [58]:
```python
# View rows where SchoolType_ID is null
df_schools[df_schools['SchoolType_ID'].isnull()]
```

Out[58]:

	School_ID	School_Name	SchoolType_ID	BoardingStatus_ID	Country_ID	Region_ID	Co
7	SCH-0008	Keith, White and James	None	BRD-0001	CTR-0004	REG-0006	CN

- Handle Missing: Fill with Previous Value (Forward Fill)
- For demo purposes, missing school type will be filled using forward-fill to maintain data consistency in the dashboard.
- In production environments, we would validate and correct this at the source.

In [59]:
```python
# If the missing value is the first row, ffill won't work unless there's something
# We will use bfill() after ffill() to catch both directions if needed:

df_schools['SchoolType_ID']= df_schools['SchoolType_ID'].ffill()
df_schools['SchoolType_ID']=df_schools['SchoolType_ID'].bfill()
```

In [60]:
```python
# Confirm it's filled
print(df_schools.isnull().sum())
```

```
School_ID            0
School_Name          0
SchoolType_ID        0
BoardingStatus_ID    0
Country_ID           0
Region_ID            0
County_ID            0
dtype: int64
```

In [61]:
```python
# 6.2 Check for missing values on fact table performance
print(df_performance.isnull().sum())
```

```
Student_ID    0
Year          0
Term          0
Subject       0
Score         0
dtype: int64
```

- No missing value

Step 7: Exploratory Data Analysis (EDA)

7.1 Check Basic Information

In [62]:
```
df_schools.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   School_ID          10 non-null     object
 1   School_Name        10 non-null     object
 2   SchoolType_ID      10 non-null     object
 3   BoardingStatus_ID  10 non-null     object
 4   Country_ID         10 non-null     object
 5   Region_ID          10 non-null     object
 6   County_ID          10 non-null     object
dtypes: object(7)
memory usage: 692.0+ bytes
```

In [63]:
```
df_schools.head()
```

Out[63]:

	School_ID	School_Name	SchoolType_ID	BoardingStatus_ID	Country_ID	Region_ID	Co
0	SCH-0001	Smith-Gomez	TYP-0001	BRD-0002	CTR-0003	REG-0008	CN
1	SCH-0002	Cook Ltd	TYP-0001	BRD-0001	CTR-0004	REG-0002	CN
2	SCH-0003	Williams, Valentine and Russell	TYP-0002	BRD-0001	CTR-0003	REG-0002	CN
3	SCH-0004	Edwards-Harding	TYP-0001	BRD-0002	CTR-0001	REG-0007	CN
4	SCH-0005	Jones Group	TYP-0002	BRD-0001	CTR-0003	REG-0001	CN

In [64]:
```
# View the first 10 records on performance dataframe
df_performance.head(10)
```

Out[64]:

	Student_ID	Year	Term	Subject	Score
0	STU-00943	2023	Term3	Math	62
1	STU-00943	2023	Term3	English	57
2	STU-00943	2023	Term3	Science	78
3	STU-00943	2023	Term3	Social Studies	57
4	STU-00943	2023	Term3	ICT	77
5	STU-00944	2019	Term1	Math	22
6	STU-00944	2019	Term1	English	70
7	STU-00944	2019	Term1	Science	20
8	STU-00944	2019	Term1	Social Studies	66
9	STU-00944	2019	Term1	ICT	90

In [65]:

```
#  Value Counts

print(df_schools['SchoolType_ID'].value_counts())
```

```
SchoolType_ID
TYP-0002    6
TYP-0001    4
Name: count, dtype: int64
```

In [66]:

```
# For percentages
print(df_students['Gender'].value_counts(normalize=True) * 100)
```

```
Gender
M    51.948052
F    48.051948
Name: proportion, dtype: float64
```

In [67]:

```
print(df_performance['Term'].unique())
```

```
['Term3' 'Term1' 'Term2']
```

In [68]:

```
print(df_performance['Subject'].unique())
```

```
['Math' 'English' 'Science' 'Social Studies' 'ICT']
```

7.2 Numerical Descriptive Stats

In [69]:

```
df_counties.describe()
```

Out[69]:

	County_ID	County
count	10	10
unique	10	10
top	CNT-0001	Zantora
freq	1	1

In [70]:

```
df_household_income.describe()
```

Out[70]:

	Income_ID	Household_Income
count	5	5
unique	5	5
top	INC-0001	<20K
freq	1	1

7.3 Check for Duplicates

In [71]:

```
# full row duplicates
duplicate_schools = df_schools.duplicated().sum()
print(f"Duplicate schools: {duplicate_schools}")
```

```
Duplicate schools: 0
```

In [72]:

```
# Count duplicates on students
num_duplicates = df_students.duplicated(subset=['Student_Name', 'Gender', 'School_I
print(f"Duplicate students before removal: {num_duplicates}")
```

```
Duplicate students before removal: 1
```

In [73]:

```
# View duplicated student
df_students[df_students.duplicated(subset=['Student_Name', 'Gender', 'School_ID', '
```

Out[73]:

	Student_ID	Student_Name	Gender	School_ID	ParentEdu_ID	Income_ID
10	STU-00010_DUP	Robert Lester	M	SCH-0002	PED-0002	INC-0004

7.4 Handle Duplicates

- We will remove duplicates

In [74]:

```
df_students_cleaned = df_students.drop_duplicates(subset=['Student_Name', 'Gender',
```

In [75]:

```
# confirm duplicate removal
```

```
num_duplicates_after = df_students_cleaned.duplicated(subset=['Student_Name', 'Gend
print(f"Duplicates after removal: {num_duplicates_after}")
```

```
Duplicates after removal: 0
```

7.5 Join all datsets into one unified DataFrame for analysis.

- We shall use Left Join to keep all rows from the performance table (df_performance)

In [76]:
```
# Merge performance with student details
df_overall_performance = df_performance.merge(df_students, on='Student_ID', how='le
print(df_overall_performance.head())
```

```
  Student_ID  Year   Term         Subject  Score   Student_Name Gender  \
0  STU-00943  2023  Term3            Math     62  Brittany Howe      F
1  STU-00943  2023  Term3         English     57  Brittany Howe      F
2  STU-00943  2023  Term3         Science     78  Brittany Howe      F
3  STU-00943  2023  Term3  Social Studies     57  Brittany Howe      F
4  STU-00943  2023  Term3             ICT     77  Brittany Howe      F

  School_ID ParentEdu_ID Income_ID
0  SCH-0006     PED-0005  INC-0004
1  SCH-0006     PED-0005  INC-0004
2  SCH-0006     PED-0005  INC-0004
3  SCH-0006     PED-0005  INC-0004
4  SCH-0006     PED-0005  INC-0004
```

In [77]:
```
#  Also merge with schools
df_overall_performance = df_overall_performance.merge(df_schools, on='School_ID',ho

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
```

In [78]:
```
#  Also merge with parent_education
df_overall_performance = df_overall_performance.merge(df_parent_education, on='Pare

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
```

In [79]:
```
#  Also merge with school_types
df_overall_performance = df_overall_performance.merge(df_school_types, on='SchoolTy

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
```

In [80]:
```
#  Also merge with household_income
df_overall_performance = df_overall_performance.merge(df_household_income, on='Inco

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
```

In [81]:
```
#  Also merge with countries
df_overall_performance = df_overall_performance.merge(df_countries, on='Country_ID'

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
```

In [82]:
```
#  Also merge with counties
df_overall_performance = df_overall_performance.merge(df_counties, on='County_ID',h

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
```

In [83]:
```
#  Also merge with regions
df_overall_performance = df_overall_performance.merge(df_regions, on='Region_ID',ho

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
```

In [84]:
```
#  Also merge with boarding_status
df_overall_performance = df_overall_performance.merge(df_boarding_status, on='Board

# drop the _sch suffix columns
df_overall_performance.drop(columns=[col for col in df_overall_performance.columns
df_overall_performance.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 75000 entries, 0 to 74999
Data columns (total 23 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Student_ID          75000 non-null  object
 1   Year                75000 non-null  int64 
 2   Term                75000 non-null  object
 3   Subject             75000 non-null  object
 4   Score               75000 non-null  int64 
 5   Student_Name        75000 non-null  object
 6   Gender              75000 non-null  object
 7   School_ID           75000 non-null  object
 8   ParentEdu_ID        75000 non-null  object
 9   Income_ID           75000 non-null  object
 10  School_Name         75000 non-null  object
 11  SchoolType_ID       75000 non-null  object
 12  BoardingStatus_ID   75000 non-null  object
 13  Country_ID          75000 non-null  object
 14  Region_ID           75000 non-null  object
 15  County_ID           75000 non-null  object
 16  Parent_Education    75000 non-null  object
 17  SchoolType          75000 non-null  object
 18  Household_Income    75000 non-null  object
 19  Country             75000 non-null  object
 20  County              75000 non-null  object
 21  Region              75000 non-null  object
 22  BoardingStatus      75000 non-null  object
dtypes: int64(2), object(21)
memory usage: 13.2+ MB
```

* Fully joined table can now be used for further analysis. We will remove all ID columns except Student_ID & School_ID

In [85]:
```
df_merged_performance = df_overall_performance[[col for col in df_overall_performan

# Confirm all required columns

df_merged_performance.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 75000 entries, 0 to 74999
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Student_ID        75000 non-null  object
 1   Year              75000 non-null  int64 
 2   Term              75000 non-null  object
 3   Subject           75000 non-null  object
 4   Score             75000 non-null  int64 
 5   Student_Name      75000 non-null  object
 6   Gender            75000 non-null  object
 7   School_ID         75000 non-null  object
 8   School_Name       75000 non-null  object
 9   Parent_Education  75000 non-null  object
 10  SchoolType        75000 non-null  object
 11  Household_Income  75000 non-null  object
 12  Country           75000 non-null  object
 13  County            75000 non-null  object
 14  Region            75000 non-null  object
 15  BoardingStatus    75000 non-null  object
dtypes: int64(2), object(14)
memory usage: 9.2+ MB
```

Step 8 Key analyses:

8.1. Term & Year Performance Trends

In [86]:
```
# Total score per student per year and term
student_total = (
    df_merged_performance.groupby(['Student_ID', 'Year', 'Term'])['Score']
    .sum()
    .reset_index(name='total_score')
)

# Then get the average total_score across students per year and term
term_year_total = (
    student_total.groupby(['Year', 'Term'])['total_score']
    .mean()
    .reset_index()
    .pivot(index='Year', columns='Term', values='total_score')
    .sort_index()
```

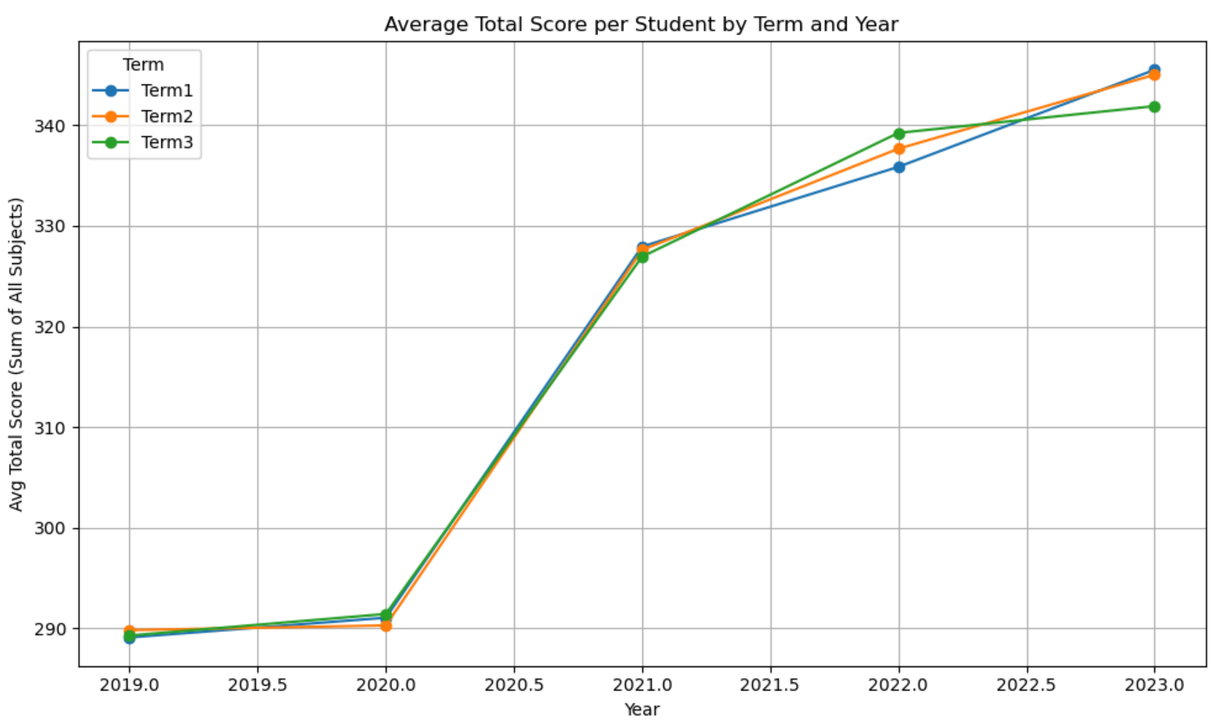
```
)

term_year_total
```

Out[86]:

Term	Term1	Term2	Term3
Year			
2019	289.115	289.840	289.301
2020	291.072	290.305	291.443
2021	327.949	327.613	326.949
2022	335.867	337.673	339.243
2023	345.516	345.022	341.905

In [87]:

```
# Visualize

import matplotlib.pyplot as plt

term_year_total.plot(marker='o', figsize=(10,6))
plt.title("Average Total Score per Student by Term and Year")
plt.xlabel("Year")
plt.ylabel("Avg Total Score (Sum of All Subjects)")
plt.grid(True)
plt.legend(title='Term')
plt.tight_layout()
plt.show()
```



Key Observations: Term & Year Performance Trends

1. Significant Growth Post-2020: There is a clear jump in total scores from 2020 to 2021, indicating a strong post-COVID recovery.

2. Consistent Improvement: Scores steadily increased from 2019 (avg ~289) to 2023 (avg ~344), suggesting improvements in teaching quality, learning strategies, or student support.

3. Peak Performance: The highest total scores were observed in 2023, with Term 1 leading at 345.52, closely followed by Term 2.

4. Pre-COVID Stability: From 2019 to 2020, scores were relatively flat, indicating a stable but low-performing system.

- **Term-wise Insight:**

1. Term 3 had the highest scores in 2022 but slightly dipped in 2023, possibly due to end-of-year fatigue or exam scheduling.

2. Term 1 and Term 2 show strong, consistent growth year over year.

8.2. Regional comparison

- To understand which regions performed better, we'll compute and visualize the total subject scores grouped by Region

In [88]:

```
# Step 1: Total score per student per region, year and term
student_region_total = (
    df_merged_performance.groupby(['Student_ID', 'Region', 'Year', 'Term'])['Score'
    .sum()
    .reset_index(name='total_score')
)

# Step 2: Average total_score across students per region, year and term
region_term_year_avg = (
    student_region_total.groupby(['Region', 'Year', 'Term'])['total_score']
    .mean()
    .reset_index()
    .pivot_table(index=['Year', 'Term'], columns='Region', values='total_score')
    .sort_index()
)

region_term_year_avg
```

Out[88]:

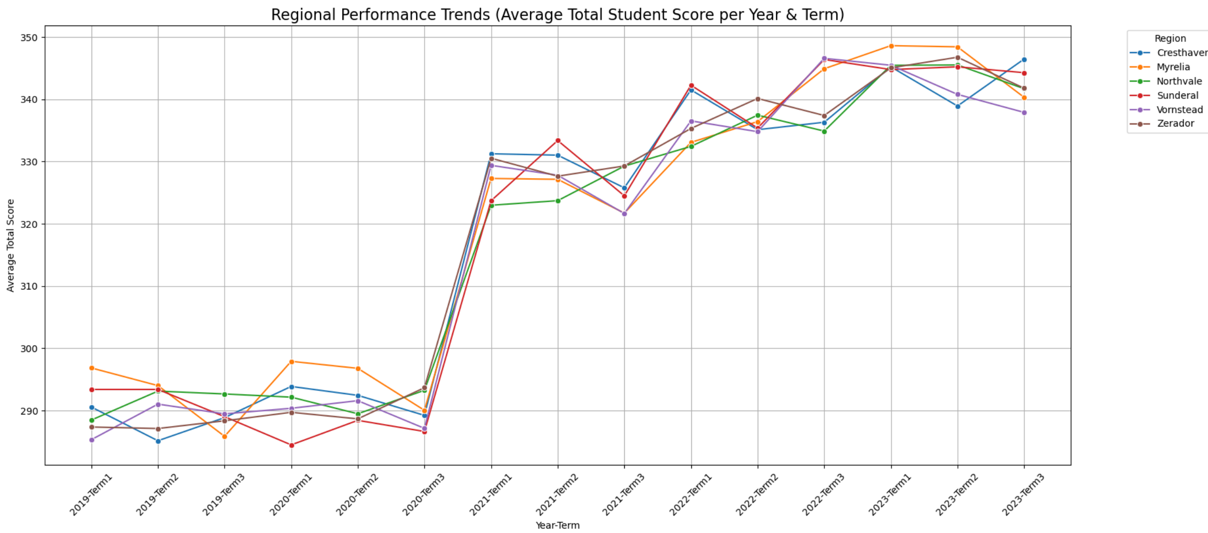
Year	Term	Cresthaven	Myrelia	Northvale	Sunderal	Vornstead	Zerador
2019	Term1	290.571429	296.849462	288.477064	293.395349	285.321429	287.362694
	Term2	285.152381	294.010753	293.123853	293.395349	291.035714	287.116580
	Term3	288.866667	285.860215	292.669725	289.023256	289.473214	288.357513
2020	Term1	293.876190	297.913978	292.155963	284.488372	290.366071	289.720207
	Term2	292.447619	296.784946	289.486239	288.430233	291.589286	288.668394
	Term3	289.228571	290.043011	293.256881	286.639535	287.142857	293.676166
2021	Term1	331.257143	327.290323	322.981651	323.709302	329.392857	330.538860
	Term2	331.028571	327.150538	323.720183	333.383721	327.803571	327.652850
	Term3	325.780952	321.720430	329.270642	324.500000	321.660714	329.295337
2022	Term1	341.514286	333.086022	332.435780	342.267442	336.535714	335.318653
	Term2	335.123810	336.419355	337.454128	335.383721	334.803571	340.134715
	Term3	336.314286	344.913978	334.899083	346.395349	346.589286	337.401554
2023	Term1	345.219048	348.623656	345.463303	344.779070	345.473214	345.054404
	Term2	338.923810	348.430108	345.522936	345.220930	340.794643	346.759067
	Term3	346.466667	340.322581	341.711009	344.279070	337.901786	341.787565

(Column header "Region" sits above the region names.)

In [89]:

```
# Plot Average Scores per Region, Year, and Term

df_plot = region_term_year_avg.reset_index().melt(id_vars=['Year', 'Term'], var_nam

# Plot Average Scores per Region, Year, and Term

import seaborn as sns
import matplotlib.pyplot as plt

# Create a combined column for sequential x-axis labels
df_plot['Year_Term'] = df_plot['Year'].astype(str) + '-' + df_plot['Term']

# To preserve the correct order on the x-axis
df_plot['Year_Term'] = pd.Categorical(df_plot['Year_Term'],
    categories=sorted(df_plot['Year_Term'].unique(), key=lambda x: (x.split('-')[0]
    ordered=True
)

# Plot

plt.figure(figsize=(16, 8))
sns.lineplot(data=df_plot, x='Year_Term', y='Average_Score', hue='Region', marker='

plt.title('Regional Performance Trends (Average Total Student Score per Year & Term
```

```python
plt.xlabel('Year-Term')
plt.ylabel('Average Total Score')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.legend(title='Region', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



Key Observations

- There was consistent growth across all regions
- All six regions show a steady increase in average performance from 2019 to 2023.
- The rise is particularly notable between 2020 and 2021, suggesting either curriculum changes, improved teaching strategies, or better student outcomes post-2020 disruptions.
- **Top Performing Regions**
    - Myrelia and Sunderal consistently lead across most terms, especially from 2021 onward.
    - By 2023, Myrelia achieves the highest scores across Terms 1 and 2.
- **Notable Improvements**
    - Cresthaven showed a major jump in scores between 2020 and 2021, maintaining steady growth afterward.
    - Zerador displayed a significant leap in performance in 2021, catching up with other regions.
- **Variations Across Terms**

- Term 1 often has slightly higher scores compared to Terms 2 and 3.
- This may suggest stronger performance earlier in the year, possibly influenced by student motivation or curriculum pacing.

- **Closing Gaps**
    - The performance gap between top and lower-performing regions narrows over time, indicating a trend toward equity in education quality across regions.

8.3 Boarding Status Performance Analysis

In [90]:
```
# Step 1: Total score per student per boarding_status, year and term
student_boarding_total = (
    df_merged_performance.groupby(['Student_ID', 'BoardingStatus', 'Year', 'Term'])
    .sum()
    .reset_index(name='total_score')
)

# Step 2: Average total_score across students per boarding_status, year and term
boarding_term_year_avg = (
    student_boarding_total.groupby(['BoardingStatus', 'Year', 'Term'])['total_score
    .mean()
    .reset_index()
    .pivot_table(index=['Year', 'Term'], columns='BoardingStatus', values='total_sc
    .sort_index()
)

boarding_term_year_avg
```

Out[90]:

Year	Term	Boarding	Day
2019	Term1	286.897351	292.497475
	Term2	287.264901	293.767677
	Term3	288.849338	289.989899
2020	Term1	290.215232	292.378788
	Term2	289.846026	291.005051
	Term3	292.000000	290.593434
2021	Term1	328.629139	326.911616
	Term2	327.163907	328.297980
	Term3	326.922185	326.989899
2022	Term1	335.903974	335.810606
	Term2	337.758278	337.542929
	Term3	337.629139	341.704545
2023	Term1	345.299669	345.845960
	Term2	343.834437	346.833333
	Term3	342.622517	340.810606

Key Observations:

- **2019–2020 (Pre-COVID and COVID Onset):**
  - Day schools had higher average scores than boarding schools in most terms, possibly due to closer family support during disruptions.
  - The performance gap was narrow but consistent, with Day students outperforming Boarding students in 5 out of 6 terms.
- **2021 (Post-COVID Rebound):**
  - Scores between both groups nearly converged, with Boarding students slightly outperforming in Term 1, while Day students led in Term 2.
  - Indicates equal recovery across school types after pandemic-related challenges.
- **2022 (Stabilization Period):**
  - A very tight race in Term 1 and Term 2 shows strong parity.

- However, Day schools surpassed Boarding schools notably in Term 3 (Day: 341.70 vs. Boarding: 337.63), suggesting better academic momentum heading into exam periods.

- **2023 (Recent Trends):**
  - Performance flipped between terms:
  - Term 1: Day schools slightly outperformed Boarding.
  - Term 2: Day schools clearly led by ~3 points.
  - Term 3: Boarding reclaimed the lead with ~2-point advantage.

- **Insights & Interpretation:**
  - Over the five-year period, Day schools consistently performed at par or better than Boarding schools.
  - This defies traditional assumptions that Boarding environments always produce stronger academic outcomes, highlighting the importance of home-based support, community involvement, or better teacher-to-student ratios in Day schools.

8.4 Gender & Subject trends over time

In [91]:

```
# Step 1: Total score per student per term
student_term_score = (
    df_merged_performance.groupby(['Student_ID', 'Year', 'Term', 'Gender'])['Score'
    .sum()
    .reset_index(name='term_total')
)

# Step 2: Total annual score per student (sum of all 3 terms)
student_year_score = (
    student_term_score.groupby(['Student_ID', 'Year', 'Gender'])['term_total']
    .sum()
    .reset_index(name='annual_total_score')
)

# Step 3: Divide by 3 to get average per term
student_year_score['avg_per_term'] = student_year_score['annual_total_score'] / 3

# Step 4: Average score per gender per year
gender_year_avg = (
    student_year_score.groupby(['Year', 'Gender'])['avg_per_term']
    .mean()
    .reset_index()
    .pivot(index='Year', columns='Gender', values='avg_per_term')
    .sort_index()
)
```

```
gender_year_avg
```

Out[91]:

Gender	F	M
Year		
2019	289.496188	289.346821
2020	290.633403	291.224149
2021	328.273735	326.789981
2022	337.316701	337.851638
2023	344.011088	344.274245

In [92]:

```
# Step 5: Average score per gender per year per Subject
gender_subject_avg = (
    df_merged_performance.groupby(['Year', 'Gender', 'Subject'])['Score']
    .mean()
    .reset_index()
)
gender_subject_avg
```

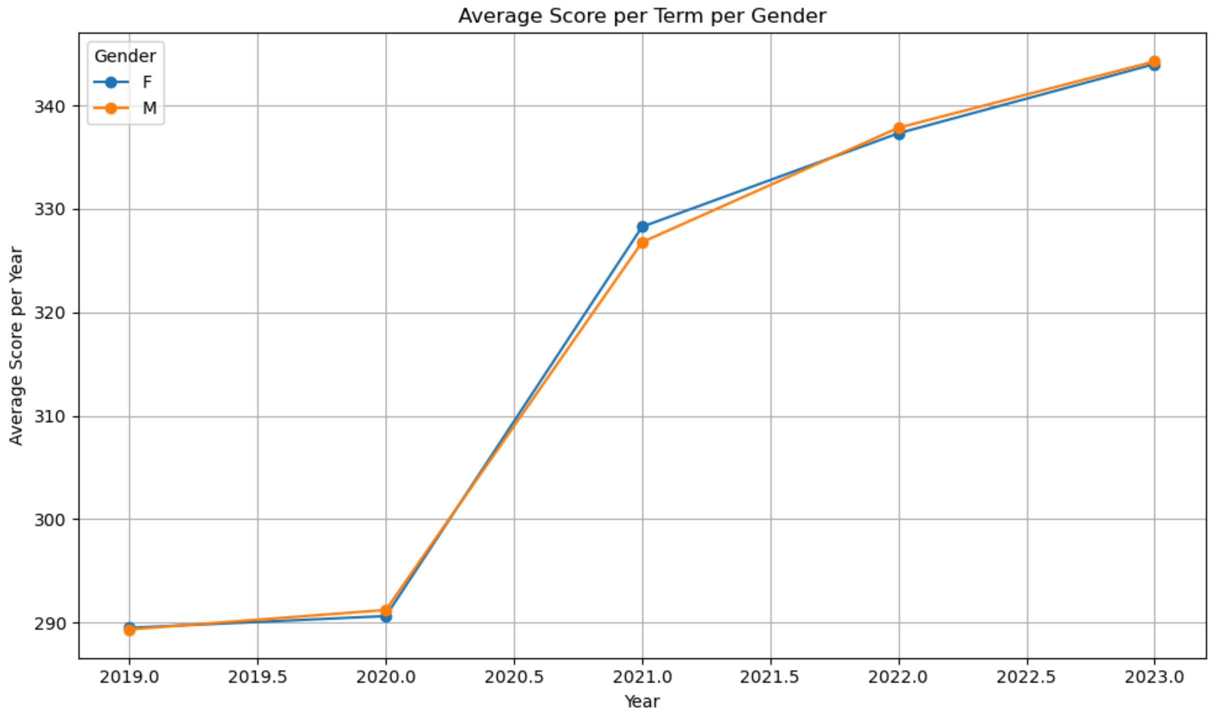
Out[92]:

	Year	Gender	Subject	Score
0	2019	F	English	63.781705
1	2019	F	ICT	69.463617
2	2019	F	Math	49.736660
3	2019	F	Science	48.661816
4	2019	F	Social Studies	57.852391
5	2019	M	English	63.817598
6	2019	M	ICT	68.401413
7	2019	M	Math	50.858703
8	2019	M	Science	48.897881
9	2019	M	Social Studies	57.371227
10	2020	F	English	58.596674
11	2020	F	ICT	61.620236
12	2020	F	Math	55.982675
13	2020	F	Science	56.872488
14	2020	F	Social Studies	57.561331
15	2020	M	English	58.569043
16	2020	M	ICT	62.129094
17	2020	M	Math	55.344252
18	2020	M	Science	56.989082
19	2020	M	Social Studies	58.192678
20	2021	F	English	56.839224
21	2021	F	ICT	59.282051
22	2021	F	Math	71.455994
23	2021	F	Science	70.734581
24	2021	F	Social Studies	69.961885
25	2021	M	English	56.614644
26	2021	M	ICT	59.242775
27	2021	M	Math	71.781631
28	2021	M	Science	69.478484
29	2021	M	Social Studies	69.672447

	Year	Gender	Subject	Score
30	2022	F	English	71.125433
31	2022	F	ICT	69.939016
32	2022	F	Math	71.030492
33	2022	F	Science	69.364518
34	2022	F	Social Studies	55.857242
35	2022	M	English	70.361593
36	2022	M	ICT	71.192678
37	2022	M	Math	71.100193
38	2022	M	Science	69.527296
39	2022	M	Social Studies	55.669878
40	2023	F	English	73.777547
41	2023	F	ICT	70.971587
42	2023	F	Math	72.152460
43	2023	F	Science	70.783091
44	2023	F	Social Studies	56.326403
45	2023	M	English	72.885035
46	2023	M	ICT	71.588953
47	2023	M	Math	72.979448
48	2023	M	Science	70.935132
49	2023	M	Social Studies	55.885678

In [93]:

```
# Plot of average score per gender by year using a line chart for clear trend compa

import matplotlib.pyplot as plt

# Plotting
gender_year_avg.plot(kind='line', marker='o', figsize=(10, 6))

plt.title('Average Score per Term per Gender')
plt.xlabel('Year')
plt.ylabel('Average Score per Year')
plt.legend(title='Gender')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Gender & Subject Trends

- **Overall Summary:**
  - Both male and female students have shown steady improvement in average scores from 2019 to 2023. Performance has remained competitive with no consistent dominance by either gender.
- **Key Highlights:**
  - 2019–2020: Scores were fairly balanced. Females had a slight lead in 2019, while males edged ahead in 2020.
  - 2021: Marked improvement for both genders. Females led slightly.
  - 2022: Males had a marginal lead.
  - 2023: Near tie with males averaging just 0.26 points higher.
- **Subject-Level Trends:**
  - English & ICT: Both genders improved consistently. Females excelled in English, males in ICT.
  - Math & Science: Steady rise in scores, with males slightly outperforming in recent years.
  - Social Studies: Females led in earlier years, but scores leveled out by 2023.
- **Conclusion:**

- The gender gap has narrowed significantly. Both groups have benefited from systemic improvements in teaching and curriculum.

8.5 Parental Education Impact on Student Scores

- This analysis explores how the level of parental education correlates with average student scores over the years 2019 to 2023.

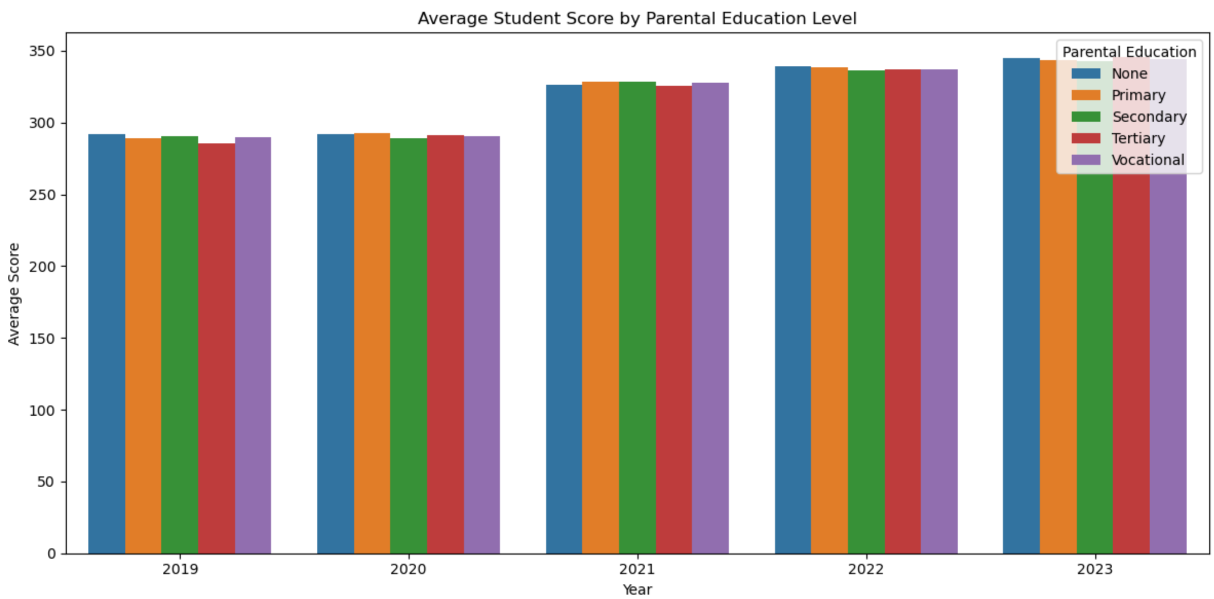
In [94]:
```
# Step 1: Total score per student per term
student_term_score = (
    df_merged_performance.groupby(['Student_ID', 'Year', 'Term', 'Parent_Education'
    .sum()
    .reset_index(name='term_total')
)

# Step 2: Total annual score per student (sum of all 3 terms)
student_year_score = (
    student_term_score.groupby(['Student_ID', 'Year', 'Parent_Education'])['term_to
    .sum()
    .reset_index(name='annual_total_score')
)

# Step 3: Divide by 3 to get average per term
student_year_score['avg_score'] = student_year_score['annual_total_score'] / 3

# Step 4: Average score per Parent_Education per year
pedu_year_avg = (
    student_year_score.groupby(['Year', 'Parent_Education'])['avg_score']
    .mean()
    .reset_index()
    .pivot(index='Year', columns='Parent_Education', values='avg_score')
    .sort_index()
)

pedu_year_avg
```

Out[94]:

Parent_Education	None	Primary	Secondary	Tertiary	Vocational
Year					
2019	291.626214	289.371528	290.297209	285.731183	289.708920
2020	291.731392	292.598958	289.356322	290.876344	290.244131
2021	326.590615	328.711806	328.333333	325.849462	327.951487
2022	339.187702	338.112847	336.339901	336.921147	337.369327
2023	344.666667	343.720486	342.940887	345.301075	344.173709

In [95]:
```
# Plot of average score per parent_education by year

import matplotlib.pyplot as plt
```

```python
import seaborn as sns
import pandas as pd

# Melt pedu_year_avg to long format
pedu_melted = pedu_year_avg.reset_index().melt(id_vars='Year', var_name='Parent_Edu

# Plotting
plt.figure(figsize=(12, 6))
sns.barplot(x='Year', y='avg_score', hue='Parent_Education', data=pedu_melted)
plt.title('Average Student Score by Parental Education Level')
plt.ylabel('Average Score')
plt.legend(title='Parental Education')
plt.tight_layout()
plt.show()
```



Key Observations: Parental Education and Student Performance

- **2019–2020**
  - Differences in average scores across parental education levels were minimal.
  - Students whose parents had no formal education slightly outperformed others, although the variation remained under 2 points across all groups.
- **2021**
  - A notable overall increase in scores was observed.
  - Students whose parents attained Primary or Vocational education showed slightly higher averages.
  - However, the gap among education levels remained narrow (around 3 points).
- **2022–2023**

  Scores continued to improve across all categories.
  In 2023:

- Students with Tertiary-educated parents had the highest average scores (**345.30**).
- Closely followed by students whose parents had no formal education (**344.67**).
- Overall, the performance gap across education levels remained consistently small (typically less than 3 points).

Conclusion:

While average student scores have increased significantly from 2019 to 2023, parental education level appears to have a minimal impact on overall student performance.
The differences between groups are minor, suggesting that other factors - such as school quality, teacher effectiveness, or community support—may play a stronger role in shaping academic outcomes.

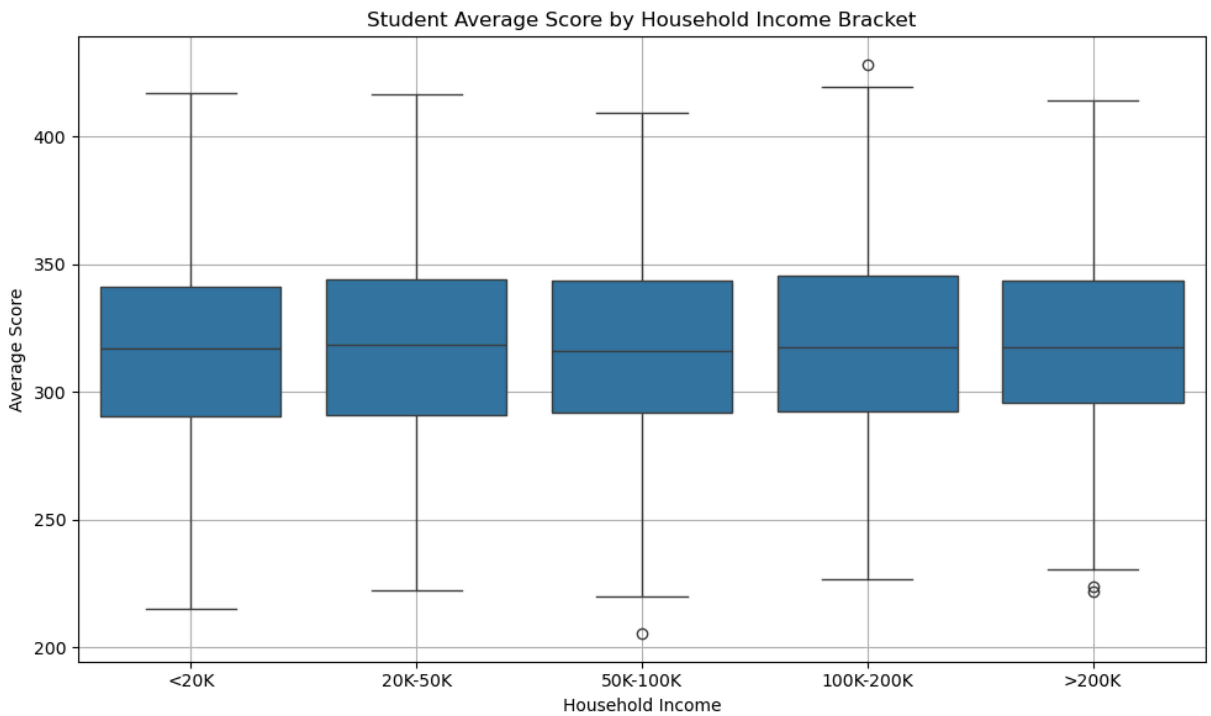
8.6 Household Income Correlation

In [96]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Define the order and midpoint values for each income category
income_order = ["<20K", "20K-50K", "50K-100K", "100K-200K", ">200K"]
income_mapping = {
    "<20K": 10000,
    "20K-50K": 35000,
    "50K-100K": 75000,
    "100K-200K": 150000,
    ">200K": 250000
}

# Step 1: Total score per student per term
student_term_score = (
    df_merged_performance.groupby(['Student_ID', 'Year', 'Term', 'Household_Income'
    .sum()
    .reset_index(name='term_total')
)

# Step 2: Total annual score per student (sum of all 3 terms)
student_year_score = (
    student_term_score.groupby(['Student_ID', 'Year', 'Household_Income'])['term_to
    .sum()
    .reset_index(name='annual_total_score')
)

# Step 3: Divide by 3 to get average per term
student_year_score['avg_score'] = student_year_score['annual_total_score'] / 3

# Step 4: Replace income category with midpoint numeric value for correlation
student_year_score['Income_Midpoint'] = student_year_score['Household_Income'].map(

# Drop rows with missing values (if any)
```

```
student_year_score.dropna(subset=['Income_Midpoint', 'avg_score'], inplace=True)

# Step 5: Calculate correlation
correlation = student_year_score['Income_Midpoint'].corr(student_year_score['avg_sc
print(f"Correlation between Household Income and Student Score: {correlation:.4f}")

# Step 6: Plot the relationship
plt.figure(figsize=(10, 6))
sns.boxplot(data=student_year_score, x='Household_Income', y='avg_score', order=inc
plt.title('Student Average Score by Household Income Bracket')
plt.xlabel('Household Income')
plt.ylabel('Average Score')
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Correlation between Household Income and Student Score: 0.0140
```



Key Findings

- **Weak Positive Correlation:**

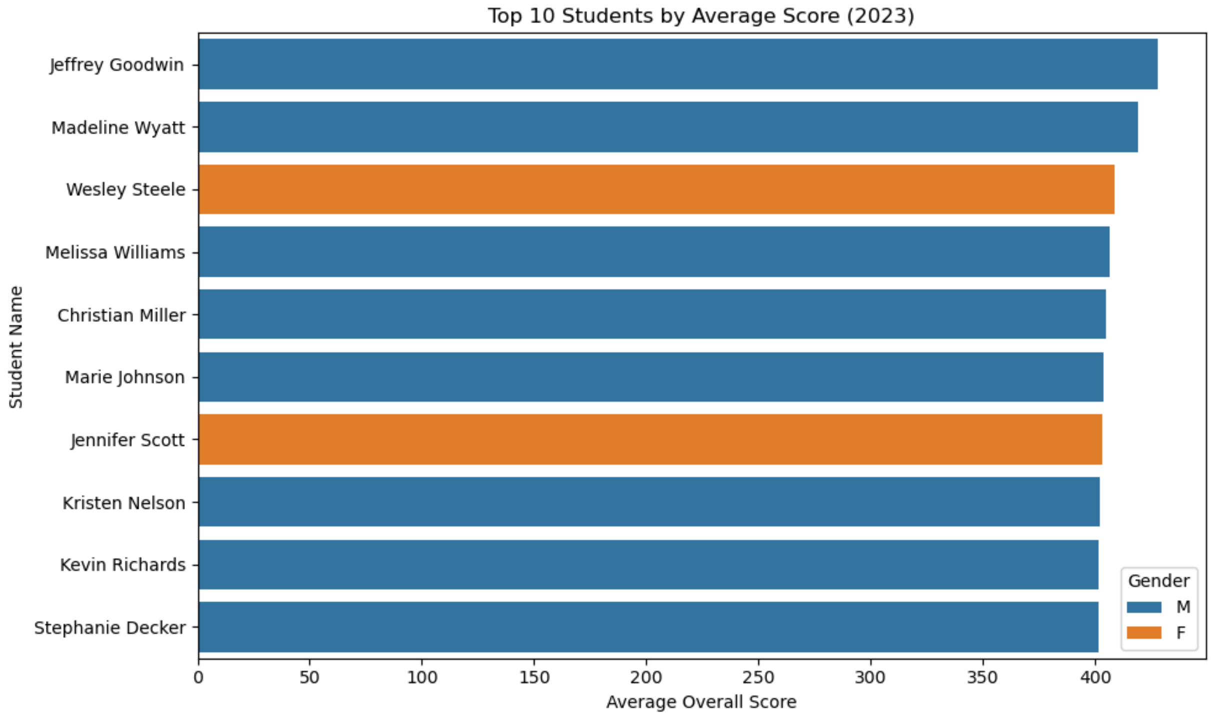
The correlation coefficient between household income and student average score is 0.0140, indicating a very weak positive relationship. This suggests that household income has minimal impact on student performance across all years.

Additional Analysis

- **Top 10 Performing Students Overall for year 2023**

In [97]:
```
# Step 1: Filter year 2023
df_2023 = df_merged_performance[df_merged_performance['Year'] == 2023]
print("Step 1: Filtered 2023 data:", df_2023.shape)

# Step 2: Total score per student per term
df_term_totals = df_2023.groupby(['Student_ID', 'Term'])['Score'].sum().reset_index
print("Step 2: Score per student per term:", df_term_totals.shape)

# Step 3: Average total score across terms
df_student_avg = df_term_totals.groupby('Student_ID')['Term_Total_Score'].mean().re
print("Step 3: Average across terms:", df_student_avg.shape)

# Step 4: Join back student details (student name, gender & School)
student_details = df_merged_performance[['Student_ID', 'Student_Name', 'Gender', 'S
df_top_students = df_student_avg.merge(student_details, on='Student_ID', how='left'

# Step 5: Sort and display top 10
df_top_10 = df_top_students.sort_values(by='Avg_Overall_Score', ascending=False).he
df_top_10['Avg_Overall_Score'] = df_top_10['Avg_Overall_Score'].round(2)

# Step 6: Visualize top 10 students

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
sns.barplot(data=df_top_10, x='Avg_Overall_Score', y='Student_Name', hue='Gender',
plt.title("Top 10 Students by Average Score (2023)")
plt.xlabel("Average Overall Score")
plt.ylabel("Student Name")
plt.tight_layout()
plt.show()
```

```
Step 1: Filtered 2023 data: (15000, 16)
Step 2: Score per student per term: (3000, 3)
Step 3: Average across terms: (1000, 2)
```



- **Proportion (%) of students from each Country within each Gender.**

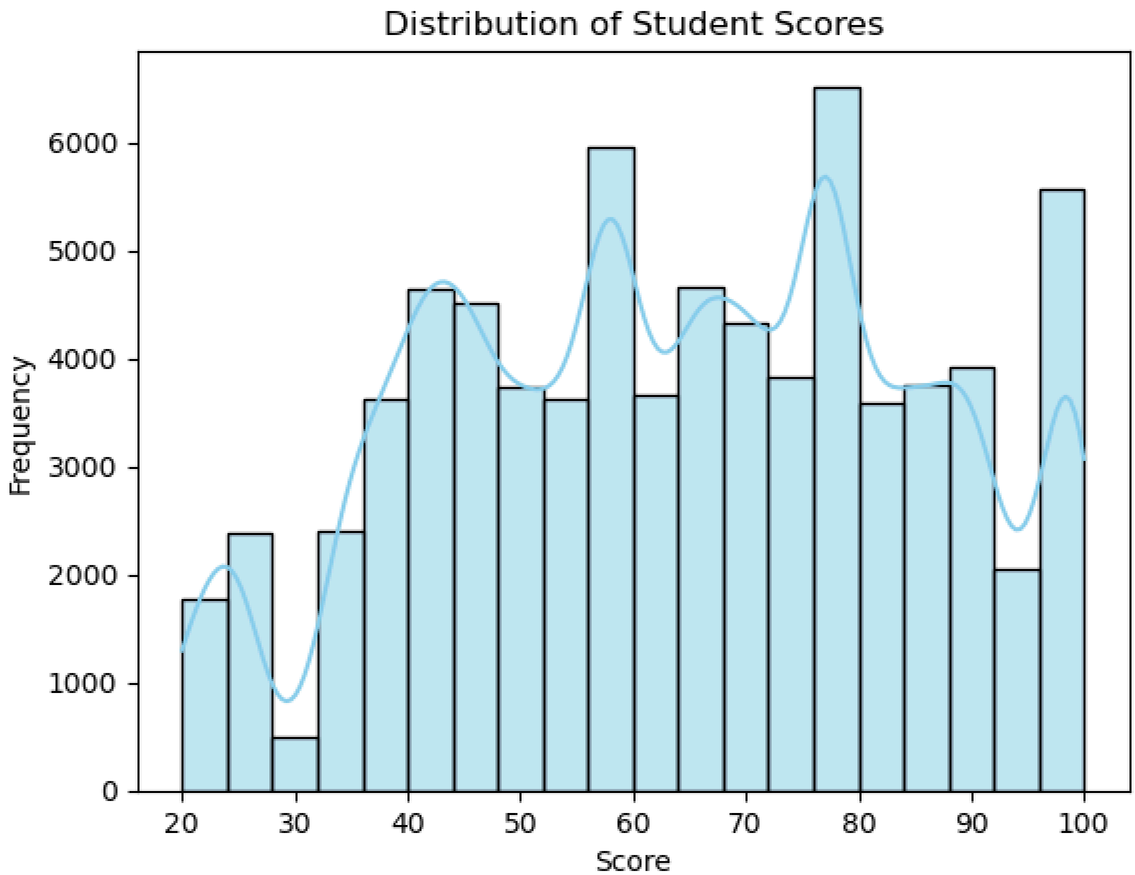
In [98]:
```
pd.crosstab(df_merged_performance['Gender'], df_merged_performance['Country'], norm
```

Out[98]:

Country Gender	Montalei	Utopia	Val Verde	Wakanda
F	0.334719	0.214137	0.081081	0.370062
M	0.292871	0.183044	0.102119	0.421965

- **Distribution of student scores**

In [99]:
```
sns.histplot(df_merged_performance['Score'], kde=True, bins=20, color='skyblue')
plt.title('Distribution of Student Scores')
plt.xlabel('Score')
plt.ylabel('Frequency')
plt.show()
```



9. Final Conclusion and Recommendations

Conclusion

The EduPulse data analysis from 2019–2023 has uncovered insightful trends related to academic performance, demographics, and school dynamics:

1. **COVID-19 Impact**
   - Performance was steady through 2019–2020, with a notable post-pandemic improvement in 2021. This may reflect recovery measures such as enhanced teaching strategies, revised assessments, or digital interventions.
2. **Regional and School Type Trends**
   - Myrelia and Cresthaven consistently outperformed other regions.
   - Day schools have slightly outpaced boarding schools since 2022, especially during pandemic recovery, suggesting that home support may have contributed to learning continuity.
3. **Gender and Subject Performance**
   - Performance between male and female students remained close, with no sustained gender gaps.

- Female students showed stronger gains in Math and Science between 2021–2023, narrowing the historical gender divide.

4. **Parental Education Influence**

   - While average student scores have increased significantly from 2019 to 2023, parental education level appears to have a minimal impact on overall student performance.
   - The differences between groups are minor, suggesting that other factors may play a stronger role in shaping academic outcomes.

5. **Household Income Correlation**

   - The correlation between income and academic performance was very weak (r = 0.014).
   - This suggests that income alone does not predict success — school environment and support systems may be more influential.

Recommendations

1. **Target Underperforming Regions**
   Direct investments toward regions like Zerador and Sunderal through better teacher training, infrastructure, and regional performance monitoring.

2. **Enhance Math and Science Instruction**
   Sustain the gains in STEM subjects by adopting adaptive learning tools and investing in teacher upskilling.

3. **Revitalize Boarding Schools**
   Re-evaluate boarding school strategies—especially in student engagement, pastoral care, and academic rigor — to close the emerging gap with day schools.

4. **Focus on Equity Beyond Income**
   Prioritize interventions that address learning needs and school quality, regardless of a student's income bracket, to promote equal opportunity for all learners.

The EduPulse Dashboard serves as a blueprint for using data to drive actionable insights and improve educational outcomes across diverse demographics.

```
Prepared By Ann Kandie
```

In [ ]: