



# *All Tools Data Analysis Project*

During our training at

*National Telecommunication Insitute And ITIDA*

Full Data Analysis Process with Python

Full Data Analysis Process with SQL

Full Data Analysis Process with Excel



# *Our Dataset Talk About*

**This dataset provides a comprehensive overview of global student migration patterns, capturing the educational and professional journeys of 5,000 international students. Each record represents an individual student and includes detailed information about their academic background, mobility decisions, and career outcomes.**

***Key dimensions covered in the dataset include:***

- **Demographics of Movement:** Origin and destination countries/cities of students.
- **Academic Pathways:** University name, course of study, field of specialization, year of enrollment, graduation year, and academic performance (GPA/score).
- **Motivations and Support:** Reasons for enrollment abroad (e.g., higher rankings, scholarships, job opportunities, quality of life, political stability) and whether financial scholarships were received.
- **Language and Visa Information:** Language proficiency tests and scores, visa status during study, and post-graduation visa types.
- **Career Outcomes:** Placement status upon graduation, placement country, employing company, and starting salary in USD.

# Our Full Data Analysis Process with Python

We carried out a comprehensive *end-to-end data analysis using Python* , transforming raw student migration records into clear insights and recommendations.

## Process Overview:

### 1. Data Loading & Initial Inspection

- Imported essential Python libraries: pandas, numpy, matplotlib, seaborn.
- Uploaded and read the dataset (5,000 student records across 20 variables).
- Performed initial checks: structure, data types, summary statistics.

### 2. Data Cleaning

- Removed duplicates and standardized inconsistent categorical entries.
- Handled missing values logically:
  - Students marked “Not Placed” → placement company & country set to NaN, starting salary corrected to NaN instead of zero.
  - Language proficiency missing → test score also marked as NaN.
- Normalized text fields (title case, no extra spaces).
- Replaced unknown categories with “Unknown” for clarity.

### 3. Feature Engineering

- Added scholarship\_flag and placement\_flag for easier filtering and analysis.
- Created new analytical dimensions such as average salary by scholarship status, placement rates by language test, etc.

```
[ ] # Replace "None" or empty strings with NaN
df = df.replace(["None", ""], np.nan)
```

```
[ ] # Handle students who are not placed
mask_not_placed = df["placement_status"].str.lower() == "not placed"
df.loc[mask_not_placed, ["placement_country", "placement_company"] =
```

```
[ ] # Replace starting salary 0 with NaN for not placed students
df.loc[(df["placement_status"].str.lower() == "not placed") &
       (df["starting_salary_usd"] == 0), "starting_salary_usd"] =
```

```
[ ] # Replace test_score 0 with NaN if no language test
df.loc[(df["language_proficiency_test"].isna()) &
       (df["test_score"] == 0), "test_score"] = np.nan
```

## ▼ Insights

```
[ ] insights = []

if placement_rate < 70:
    insights.append(f"Placement rate is relatively low ({placement_rate}%)")

if salary_difference > 0:
    insights.append("Students with scholarships have higher average salary")

if placement_by_language.max() - placement_by_language.min() > 10:
    insights.append("Language proficiency test results strongly influence placement")

print("Insights:")
```

# Our Full Data Analysis Process with Python

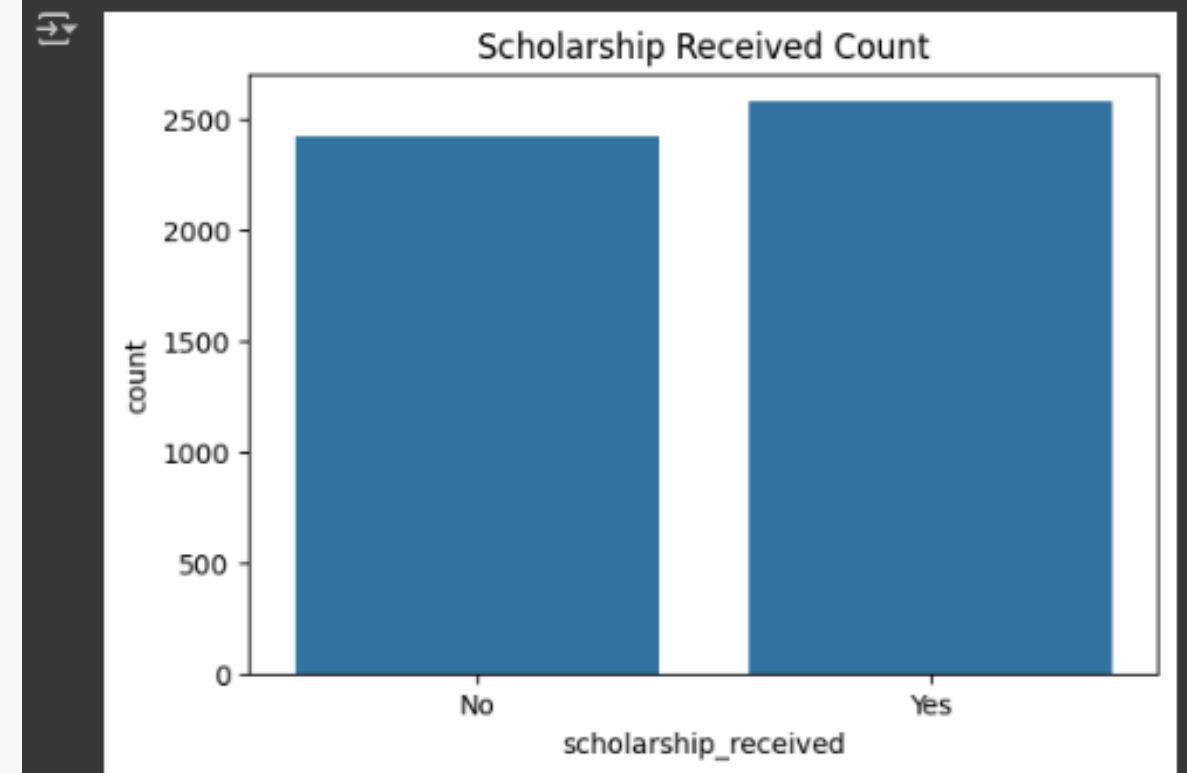
## 4-Exploratory Data Analysis (EDA)

- Identified top destination countries and most popular fields of study.
- Compared scholarship vs. non-scholarship students in terms of GPA, salary, and placement success.
- Investigated salary distributions, GPA performance, and graduation trends.
- Detected correlations between GPA, test scores, and starting salaries.

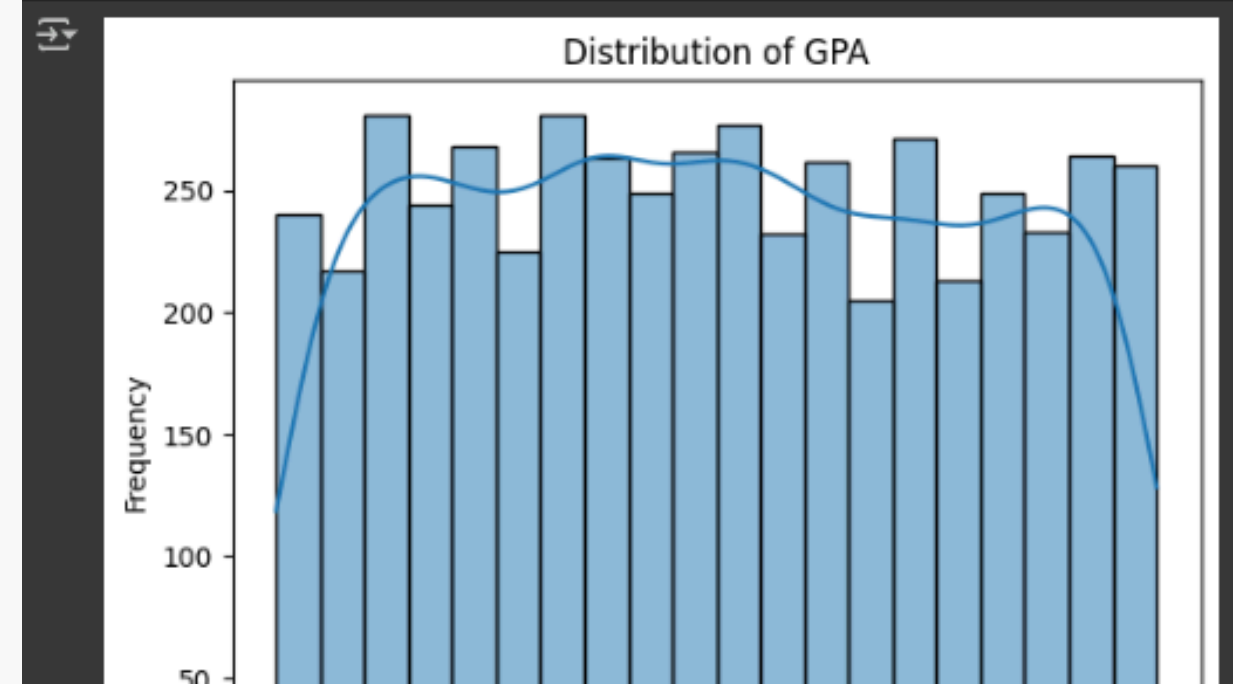
## 5-Data Visualization

- Bar charts and pie charts for scholarships, placements, and destination countries.
- Histograms and boxplots to explore GPA and salary distributions.
- Correlation heatmap to highlight relationships between academic and employment factors.
- Line graphs showing enrollment growth and migration patterns over time.

```
plt.figure(figsize=(6, 4))
sns.countplot(x="scholarship_received", data=df)
plt.title("Scholarship Received Count")
plt.show()
```



```
[ ] # Plot a histogram of the 'gpa_or_score'
sns.histplot(df['gpa_or_score'], bins=20, kde=True)
plt.title("Distribution of GPA")
plt.xlabel('GPA')
plt.ylabel('Frequency')
plt.show()
```





# Our Full Data Analysis Process with Python

## 6-Key Performance Indicators (KPIs)

- **Placement Rate (% of students employed after graduation).**
- **Average Starting Salary (overall, with scholarship, without scholarship).**
- **Placement Success by Language Test (TOEFL, IELTS, PTE, etc.).**
- **Salary difference between scholarship holders and non-holders.**

## 7-Insights & Recommendations

- **Scholarships are strongly linked to higher placement rates and better salaries.**
- **Language proficiency significantly impacts job opportunities in destination countries.**
- **Certain fields of study (e.g., Engineering, Data Science) consistently yield higher starting salaries.**
- **Employers like Microsoft, Google, Apple, and IBM are among the top recruiters, highlighting strong industry connections.**
- **Recommended actions: expand scholarships, strengthen partnerships with employers, and support students with language training programs.**

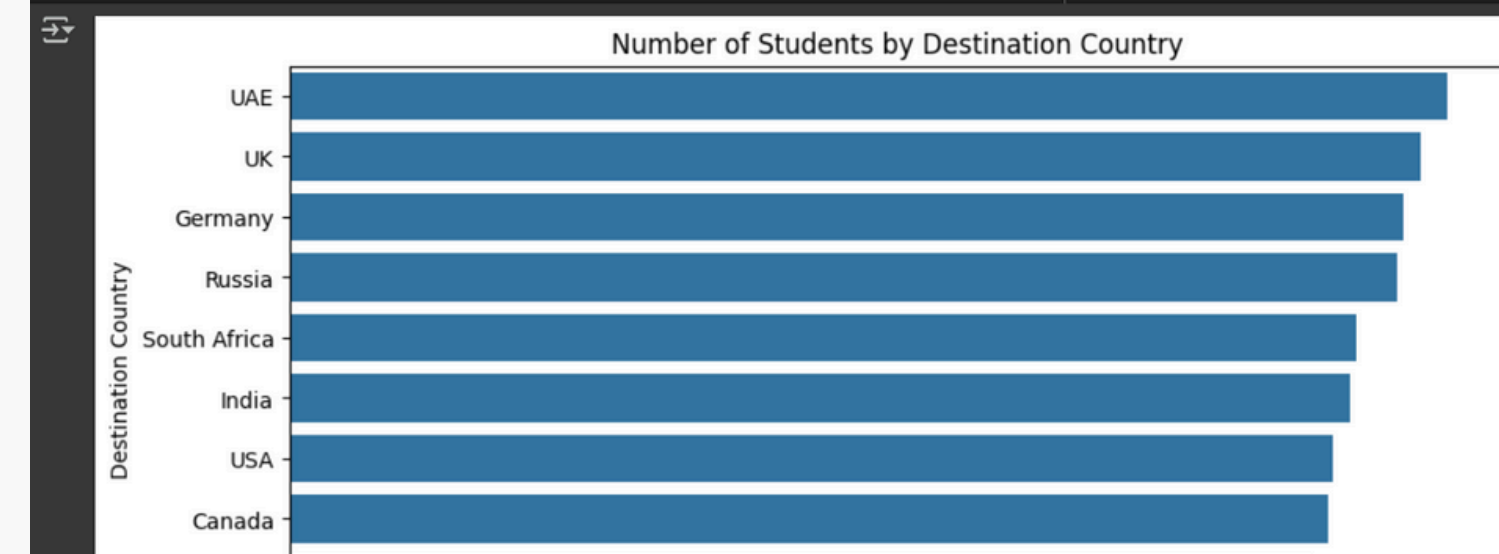
### ✓ KPIs

```
# Calculate some key metrics for student placement and salaries
placement_rate = df['placed_flag'].mean() * 100
average_salary = df['starting_salary_usd'].mean()
average_salary_scholarship = df[df['scholarship_flag']]['starting_salary_usd'].mean()
average_salary_no_scholarship = df[~df['scholarship_flag']]['starting_salary_usd'].mean()
salary_difference = average_salary_scholarship - average_salary_no_scholarship

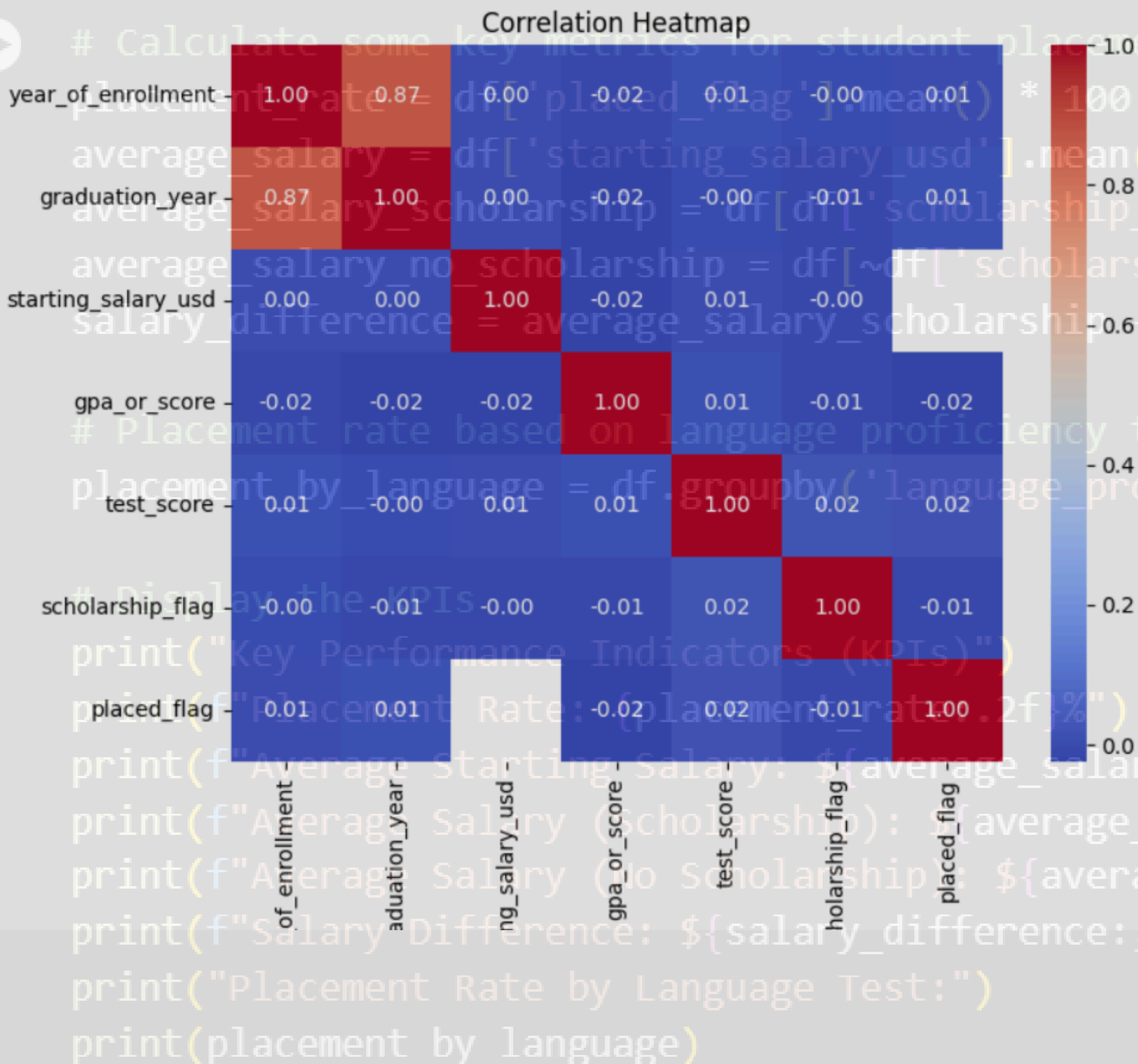
# Placement rate based on language proficiency test
placement_by_language = df.groupby('language_proficiency_test')['placed_flag'].mean()

# Display the KPIs
print("Key Performance Indicators (KPIs)")
print(f"Placement Rate: {placement_rate:.2f}%")
print(f"Average Starting Salary: ${average_salary:,.2f}")
print(f"Average Salary (Scholarship): ${average_salary_scholarship:,.2f}")
print(f"Average Salary (No Scholarship): ${average_salary_no_scholarship:,.2f}")
print(f"Salary Difference: ${salary_difference:,.2f}")
print("Placement Rate by Language Test:")
print(pd.Series(placement_by_language))
```

```
[ ] # Bar chart: Number of students by destination country
plt.figure(figsize=(10,5))
sns.countplot(y='destination_country', data=df, order=df['destination_country'].value_counts().index)
plt.title("Number of Students by Destination Country")
plt.xlabel("Count")
plt.ylabel("Destination Country")
plt.show()
```



# KPIs



## Extract key insights

```
[ ] # Top 5 countries receiving most students
top_destinations = df['destination_country'].value_counts().head(5)
print("Top 5 Destination Countries:\n", top_destinations)
```

```
Top 5 Destination Countries:
destination_country
UAE                538
UK                 526
Germany            518
Russia             515
South Africa       496
Name: count, dtype: int64
```

```
[ ] # Average starting salary by field of study
avg_salary_by_field = df.groupby('field_of_study')['starting_salary_usd'].mean().sort_values(ascending=False)
print("\nAverage Starting Salary by Field of Study:\n", avg_salary_by_field)
```

```
Average Starting Salary by Field of Study:
field_of_study
Medicine          92317.744526
Business          91072.245098
Law               90966.996865
Social Sciences   88660.177177
Engineering       87801.701149
Computer Science  87459.235484
Arts              87277.836066
Natural Sciences  85255.031847
Name: starting_salary_usd, dtype: float64
```

## Recommendations

```
[ ] recommendations = []

if placement_rate < 70:
    recommendations.append("Expand job partnerships to improve placement rate.")
if salary_difference > 0:
    recommendations.append("Increase the number of scholarships to boost salary outcomes.")
if placement_by_language.max() - placement_by_language.min() > 10:
    recommendations.append("Offer language training programs to improve placement opportunities.")

print("Recommendations:")
for r in recommendations:
    print(f"- {r}")
```

```
Recommendations:
Expand job partnerships to improve placement rate
Increase the number of scholarships to boost salary outcomes
Offer language training programs to improve placement opportunities
```

# Our Full Data Analysis Process with SQL

We also performed a complete data analysis process using *SQL* to ensure robust validation, efficient querying, and powerful insights from the global student migration dataset.

## Steps We Followed:

### 1. Data Quality & Cleaning with SQL

- **Missing Data Check:** Used aggregate queries (COUNT, SUM CASE) to detect missing values in key columns (student ID, origin, destination, university, field of study, placement status, etc.).
- **Duplicates Check:** Grouped by student\_id to identify students with duplicate entries.
- **Data Standardization:** For example, we updated records where destination\_country was listed as “UK”, “Britain”, or “England” into a unified format: “United Kingdom”.
- **Validation of GPA & Scores:** Ensured GPA and test scores were positive values and checked their min, max, and average.

```
cast(sum(case when placement_status = 'placed' then 1 else 0 end) *
avg(starting_salary_usd) as avg_salary
from global_student_migration
where starting_salary_usd > 0
group by case when field_of_study in ('computer science', 'engineering',
then 'stem' else 'non-stem' end;
-----
select
destination_country,
language_proficiency_test,
count(*) as test_count,
cast(count(*) * 100.0 / sum(count(*)) over (partition by destination
from global_student_migration
where language_proficiency_test <> 'none'
and destination_country in ('united kingdom', 'usa'))
group by destination_country, language_proficiency_test
order by destination_country, test_count desc;
-----
select
avg(case when placement_status = 'placed' then gpa_or_score end) as
avg(case when placement_status = 'not placed' then gpa_or_score end)
avg(case when placement_status = 'placed' then test_score end) as av
avg(case when placement_status = 'not placed' then test_score end) a
from global_student_migration
where gpa_or_score > 0 and test_score > 0;
-----
select
university_name,
count(*) as total,
sum(case when placement_status = 'placed' then 1 else 0 end) as plac
cast(sum(case when placement_status = 'placed' then 1 else 0 end) *
from global_student_migration
group by university_name
having count(*) > 5
```



# *Our Full Data Analysis Process with SQL*

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## **2-Exploratory Data Analysis (EDA) with SQL**

wrote multiple SQL queries to explore the dataset from different perspectives:

- **Placement Analysis:** Counted students by placement status (Placed vs. Not Placed) and calculated placement percentages.
- **Enrollment Trends:** Measured reasons for enrollment, enrollment growth by year, and study duration from enrollment to graduation.
- **Origin vs. Destination:** Aggregated student counts by origin countries, destination countries, and their flows.
- **Universities & Fields of Study:** Identified the top universities, most popular fields of study, and calculated placement rates per field.

## **3-Key Insights & Business Intelligence with SQL**

- **Scholarships & Outcomes:** Compared scholarship holders vs. non-holders in terms of placement success and salaries.
  - **Placement Companies:** Extracted the top hiring companies (e.g., Microsoft, Google, Apple, IBM) and calculated their average salaries offered.
  - **Field Performance:** Ranked fields of study by GPA, placement rate, and starting salary.
  - **Visa Impact:** Measured how different post-graduation visa types affected placement success.
  - **Language Proficiency:** Compared TOEFL, IELTS, PTE, etc. and found that higher test scores correlated with higher placement rates.
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# Our Full Data Analysis Process with SQL

## 4-KPI Calculations with SQL

Using SQL, we directly computed key metrics:

- **Placement Rate (%) = (Placed ÷ Total Students) × 100.**
- **Average Starting Salary (by field, university, company, country).**
- **Scholarship Impact on placement success and salary.**
- **STEM vs. Non-STEM Analysis showing higher placement rates and salaries in STEM fields.**
- **High Achievers Check (students with GPA ≥ 3.95) and their placement outcomes.**

## 5-Advanced Comparative Analysis with SQL

- **Tracked outbound vs. inbound flows for specific countries (e.g., UAE).**
- **Compared India vs. Germany or India vs. Russia in terms of destination preferences.**
- **Analyzed how enrollment reasons and graduation years influenced student outcomes.**
- **Evaluated university-level performance (placement success, average salaries).**

```
select
    count(*) as total_records,
    sum(case when student_id is null then 1 else 0 end) as null_student_id,
    sum(case when origin_country is null then 1 else 0 end) as null_origin_country,
    sum(case when destination_country is null then 1 else 0 end) as null_destination_country,
    sum(case when university_name is null then 1 else 0 end) as null_university_name,
    sum(case when field_of_study is null then 1 else 0 end) as null_field_of_study,
    sum(case when year_of_enrollment is null then 1 else 0 end) as null_year_of_enrollment,
    sum(case when placement_status is null then 1 else 0 end) as null_placement_status
from global_student_migration;

-----

select student_id, count(*) as count
from global_student_migration
group by student_id
having count(*) > 1;

-----

update global_student_migration
set destination_country = 'united kingdom'
where destination_country in ('uk', 'england', 'britain');

-----

select min(gpa_or_score) as min_gpa, max(gpa_or_score) as max_gpa
from global_student_migration
where gpa_or_score > 0;

-----

select
    placement_status,
    count(*) as count,
    cast(count(*) * 100.0 / (select count(*) from global_student_migration) as float) as percentage
from global_student_migration
group by placement_status;

-----

select
    enrollment_reason,
    count(*) as count,
    cast(count(*) * 100.0 / (select count(*) from global_student_migration) as float) as percentage
from global_student_migration
group by enrollment_reason
order by count desc;
```

```

cast(sum(case when placement_status = 'placed' then 1 else 0 end) * 100.0 / count(*) as
from global_student_migration
where test_score > 0
group by case when test_score >= 7.5 then 'high score' else 'lower score' end;
-----

select
    field_of_study,
    destination_country,
    count(*) as student_count
from global_student_migration
where field_of_study in ('computer science', 'business')
group by field_of_study, destination_country
order by field_of_study, student_count desc;
-----

select
    origin_country,
    field_of_study,
    destination_country,
    count(*) as student_count
from global_student_migration
where origin_country in ('india', 'russia')
    and field_of_study in ('computer science', 'business')
group by origin_country, field_of_study, destination_country
order by origin_country, field_of_study, student_count desc;
-----

t
ost_graduation_visa,
vg(starting_salary_usd) as avg_salary
global_student_migration
placement_status = 'placed' and starting_salary_usd > 0
by post_graduation_visa
by avg_salary desc;
-----

t
raduation_year,
vg(starting_salary_usd) as avg_salary
global_student_migration
placement_status = 'placed' and starting_salary_usd > 0
by graduation_year
by graduation_year;
-----

t
ase when field_of_study in ('computer science', 'engineering', 'medicine', 'natural sciences')
then 'stem' else 'non-stem' end as field_category,
ount(*) as total,

```

```

destination_country,
language_proficiency_test,
count(*) as test_count,
cast(count(*) * 100.0 / sum(count(*)) over (partition by desti
from global_student_migration
where language_proficiency_test <> 'none'
    and destination_country in ('united kingdom', 'usa')
group by destination_country, language_proficiency_test
order by destination_country, test_count desc;
-----

select
    avg(case when placement_status = 'placed' then gpa_or_score en
    avg(case when placement_status = 'not placed' then gpa_or_scor
    avg(case when placement_status = 'placed' then test_score end)
    avg(case when placement_status = 'not placed' then test_score
from global_student_migration
where gpa_or_score > 0 and test_score > 0;
-----
    avg(case when placement_status = 'not placed' then test_score end, as avg_test_not_plac
from global_student_migration
where gpa_or_score > 0 and test_score > 0;
-----

select
    university_name,
    count(*) as total,
    sum(case when placement_status = 'placed' then 1 else 0 end) as placed,
    cast(sum(case when placement_status = 'placed' then 1 else 0 end) * 100.0 / count(*) as
from global_student_migration
group by university_name
having count(*) > 5
order by placement_rate desc;
-----

select count(*) as high_achievers
from global_student_migration
where gpa_or_score >= 3.95 and placement_status = 'placed';
-----

select *
from global_student_migration
where gpa_or_score > 3.8 and placement_status = 'not placed';
-----

```

# *Our Full Data Analysis Process with Excel*

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We also performed a complete data analysis process using Excel, leveraging pivot tables, slicers, and dashboards to ensure data cleaning, interactive exploration, and clear visualization of insights from the global student migration dataset.

## *Steps We Followed:*

### **1-Data Cleaning & Preparation**

- **Removed duplicates and standardized values.**
- **Cleaned missing fields: salaries, GPA, test scores, visa status.**
- **Converted numeric fields into proper types.**
- **Standardized placement status.**
- **Created structured tables ready for Pivot Tables & Dashboard.**

**Result: A clean dataset ready for analysis.**

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# *Our Full Data Analysis Process with Excel*

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We also performed a complete data analysis process using Excel, leveraging pivot tables, slicers, and dashboards to ensure data cleaning, interactive exploration, and clear visualization of insights from the global student migration dataset.

## **2-Pivot Tables & Slicers**

- **Pivot Tables Built For:**
    - **Scholarships by field of study.**
    - **Student distribution by country & city.**
    - **Placement outcomes by company.**
    - **Student numbers trend (2019–2023).**
  - **Slicers Added:**
    - **Year of enrollment**
    - **Field of study**
    - **Placement country**
-

# *Our Full Data Analysis Process with Excel*

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We also performed a complete data analysis process using Excel, leveraging pivot tables, slicers, and dashboards to ensure data cleaning, interactive exploration, and clear visualization of insights from the global student migration dataset.

## **3-Dashboard KPIs**

At the top of the dashboard, we displayed Key Performance Indicators:

- **Average Starting Salary → \$88,618**
- **Scholarship Rate → 52%**
- **Average GPA/Score → 3.24**
- **Placement Rate → 50.18% placed, 49.82% not placed**

KPIs give a quick summary of overall student outcomes.

## **4-Dashboard Visuals**

The dashboard includes:

- **Placements by City (area chart).**
- **Student Numbers Trend (line chart showing growth 2019–2023).**
- **Scholarships by Field (bar chart).**
- **Student Distribution by Country (bar chart).**
- **Enrollment Reasons by City (clustered bar).**
- **Company-wise Student Distribution (bar chart of top recruiters).**

Each visual shows a different perspective: fields, cities, countries, companies.

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# *Our Full Data Analysis Process with Excel*

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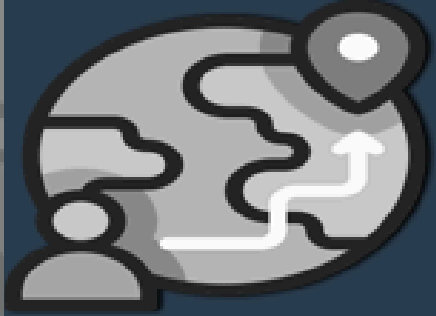
We also performed a complete data analysis process using Excel, leveraging pivot tables, slicers, and dashboards to ensure data cleaning, interactive exploration, and clear visualization of insights from the global student migration dataset.

## **5 – Insights & Key Findings**

- **Top Sending Countries → Russia, Canada, South Africa.**
  - **Top Cities for Enrollment → Dubai, Moscow, London (due to job opportunities & stability).**
  - **Scholarships are evenly spread (~600–645 per field).**
  - **Top Companies Hiring → Microsoft, Apple, Amazon, Deloitte.**
  - **Student Numbers remained stable with a peak in 2022 (1027 students).**
  - **Placements → Half of students successfully placed; tech and business students domina**
-



# Global Student Migration



year\_of\_enrollment

2019

2020

2021

2022

2023

field\_of\_study

Arts

Business

Computer Science

Engineering

Law

Medicine

Natural Sciences

Social Sciences

placement\_country

Canada

Finland

Germany

India

Ireland

N/A

Russia

South Africa

UAE

UK

USA

Average of starting salary  
\$88,618

% of scholarship recieved  
52%

Average of gpa or score  
3.24

Placed Students %  
50.18%

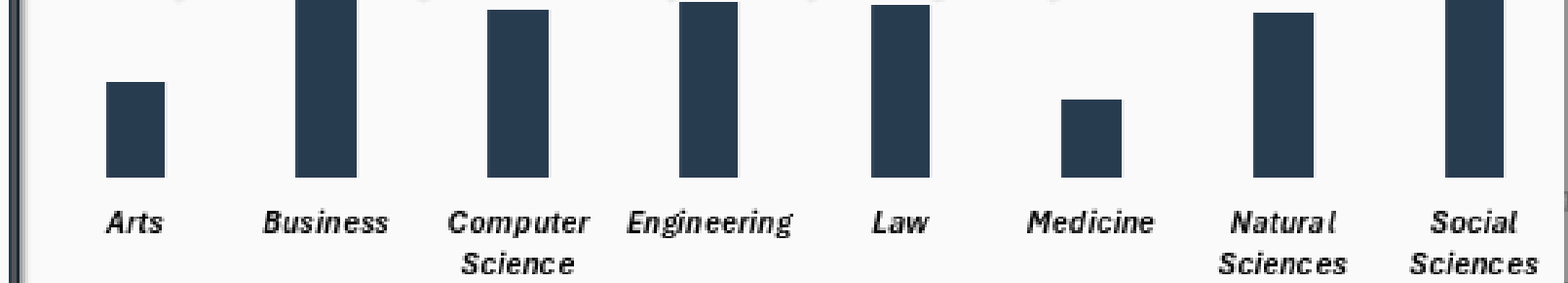


Not Placed Students %  
49.82%

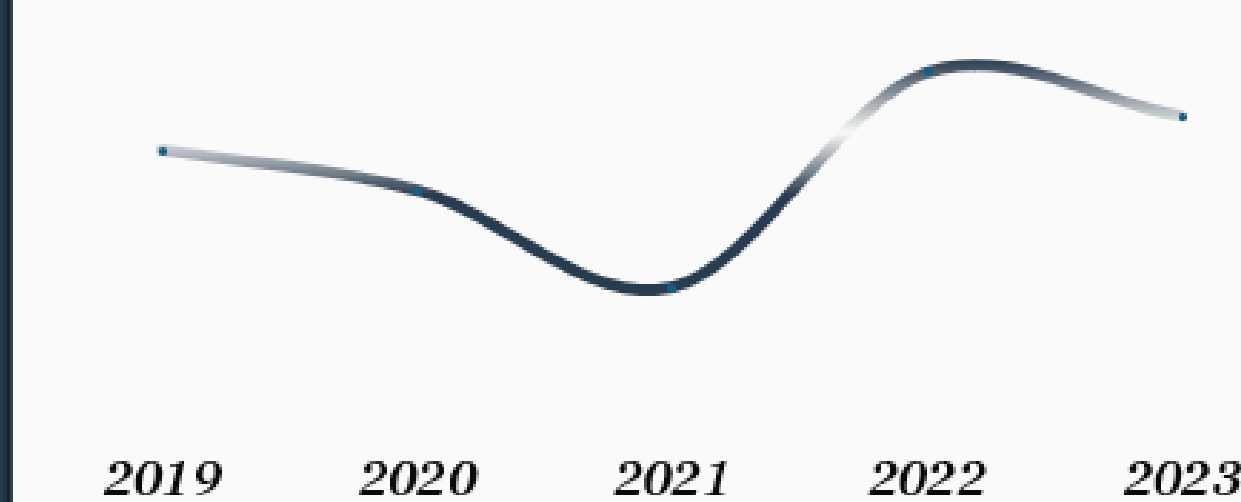
Placements by City



count of scholarship\_received by each field of study



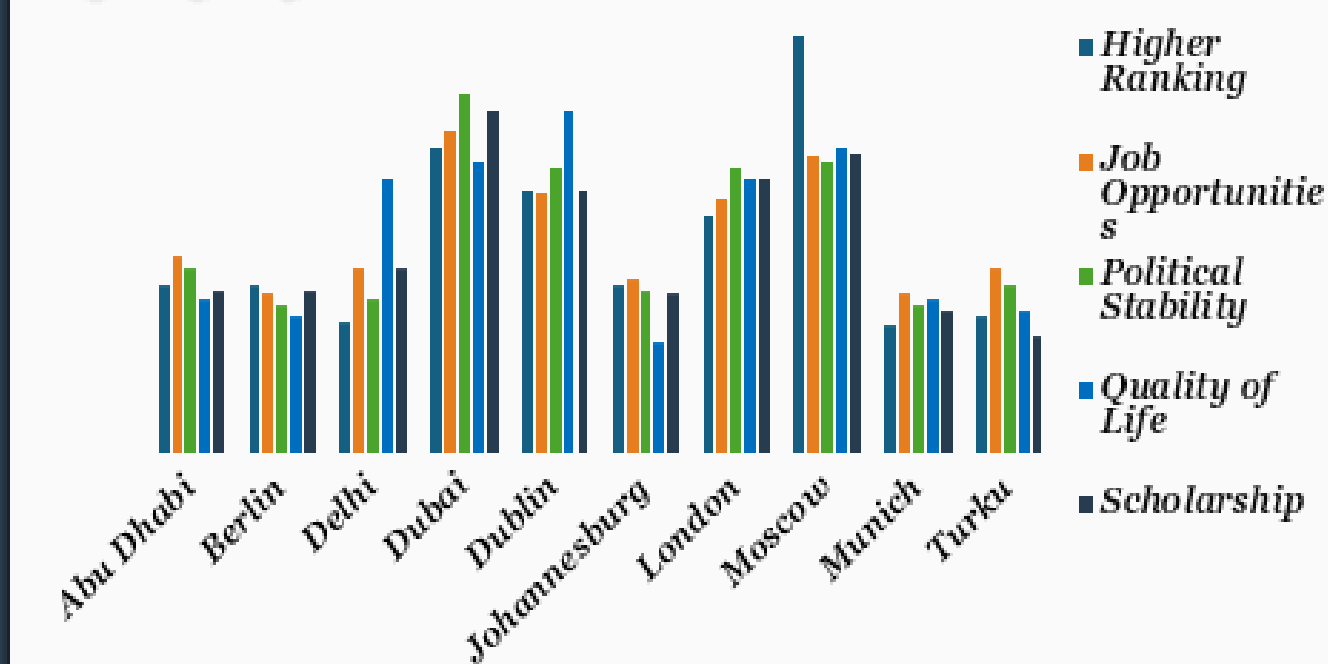
Student Numbers Trend Over the Years



Students Distribution by Country of Origin



Top cities by enrollments and the reason



Company-wise Student Distribution



# Conclusion



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*“Data is not just about charts and numbers; it’s about making things clearer, easier, and more meaningful. I hope this presentation didn’t just share insights, but also helped you see how data can actually support decisions in a practical and simple way. Because when data is understood, it truly becomes power.”*

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*“I’ll be happy to answer any  
questions you may have?”*



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*Thank you*

