DATA PREPROCESSING AND TRANSFORMATION

Group 5B|0801-DV Associate internship

INTRODUCTION

- Data preprocessing and transformation are crucial steps in the data analysis and machine learning workflow. These processes involve cleaning, organizing, and structuring raw data to make it suitable for analysis or training machine learning models. Proper data preprocessing can significantly impact the performance and reliability of the models.

Data preprocessing is an important step in the data mining process that involves cleaning and transforming raw data to make it suitable for analysis. Some common steps in data preprocessing include:

Data Cleaning: This involves identifying and correcting errors or inconsistencies in the data, such as missing values, outliers, and duplicates. Various techniques can be used for data cleaning, such as imputation, removal, and transformation.

Data Integration: This involves combining data from multiple sources to create a unified dataset. Data integration can be challenging as it requires handling data with different formats, structures, and semantics. Techniques such as record linkage and data fusion can be used for data integration.

USER DATA

The User data which includes every user that has ever created an account on the Excelerate platform involves datasets with 8 column/column headings; Preferred sponsors of the user, gender of the user, country of residence during signup, degree or academic level of user, signup date and time of the user, city of residence, zip or postal code and the last column showing whether the user got the information through social media or not. The data has a total of 27,563 rows which is imperative to the same number of users with an account on Excelerate.

OPPORTUNITY WISE DATA

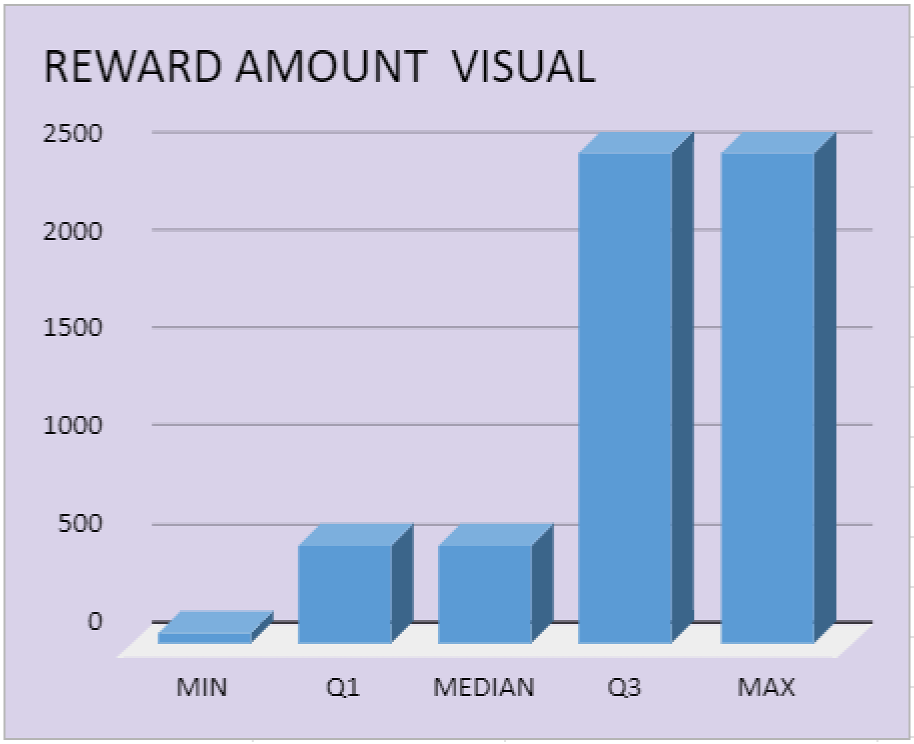
The Opportunity Wise Data comprises 17 different columns and 20323 rows. The rows were later reduced to 11482 after duplicates were removed. The profile ID column was used to remove the duplication because it is the most unique field among other fields.

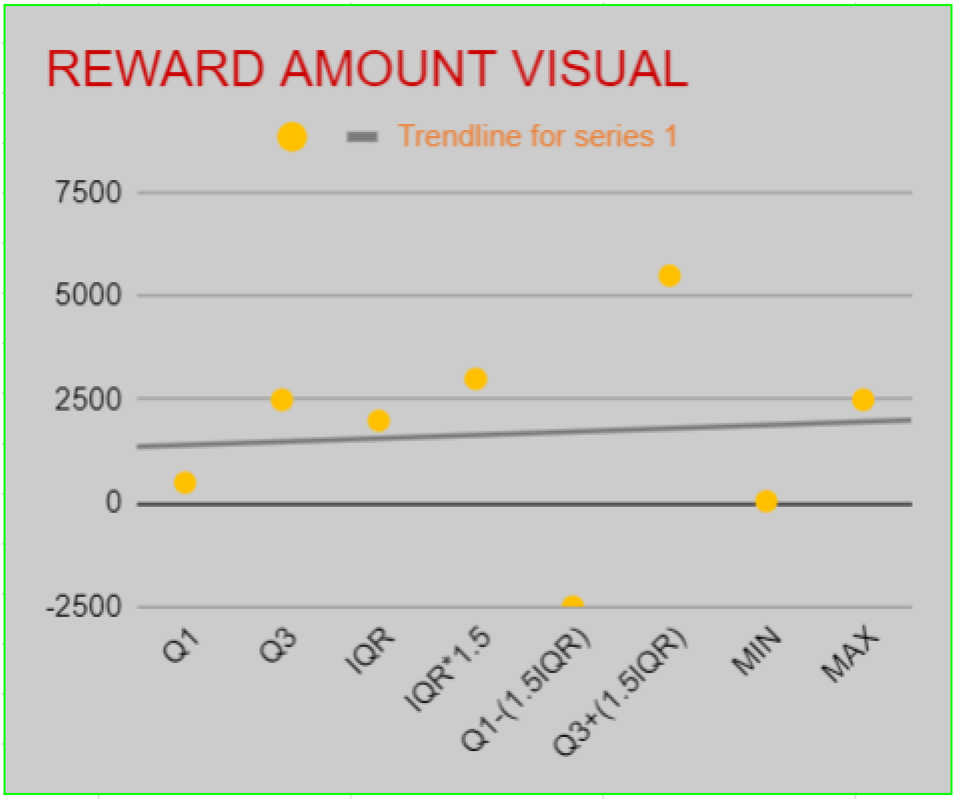
PREPROCESS THE DATASETS

1. Handling Outliers and Anomalies

Opportunity Sign Up and Completion Data:

1. select the rewards amount column
2. copy and paste selected data into a new sheet and sorted from A-Z from smallest to highest with 50 being the lowest and 2500 and null values(0) following suit.
3. use Interquartile function to select cell A1:A:1449
discover an outlier is any data values that is
1.Less than First Quartile(Q1) -1.5*IQR
2.Greater than third quartile +1.5*IQR
Interquartile Range (IQR) = Third Quartile(Q3) - First Quartile(Q1)
And also manually check or glance through the figures of rewards point which were as follows :$2500,$1000,$500,$250,$150,$120,$100,$80,$50,$0 with majority being null values.


REWARD AMOUNT VISUAL
2500
2000
1500
1000
500
0
MIN
Q1
MEDIAN
Q3
MAX


REWARD AMOUNT VISUAL
● Trendline for series 1
7500
5000
2500
0
-2500
Q1
Q3
IQR
IQR*1.5
Q1-(1.5IQR)
Q3+(1.5IQR)
MIN
MAX

2. Normalize or Scale Relevant Features:

USER DATA

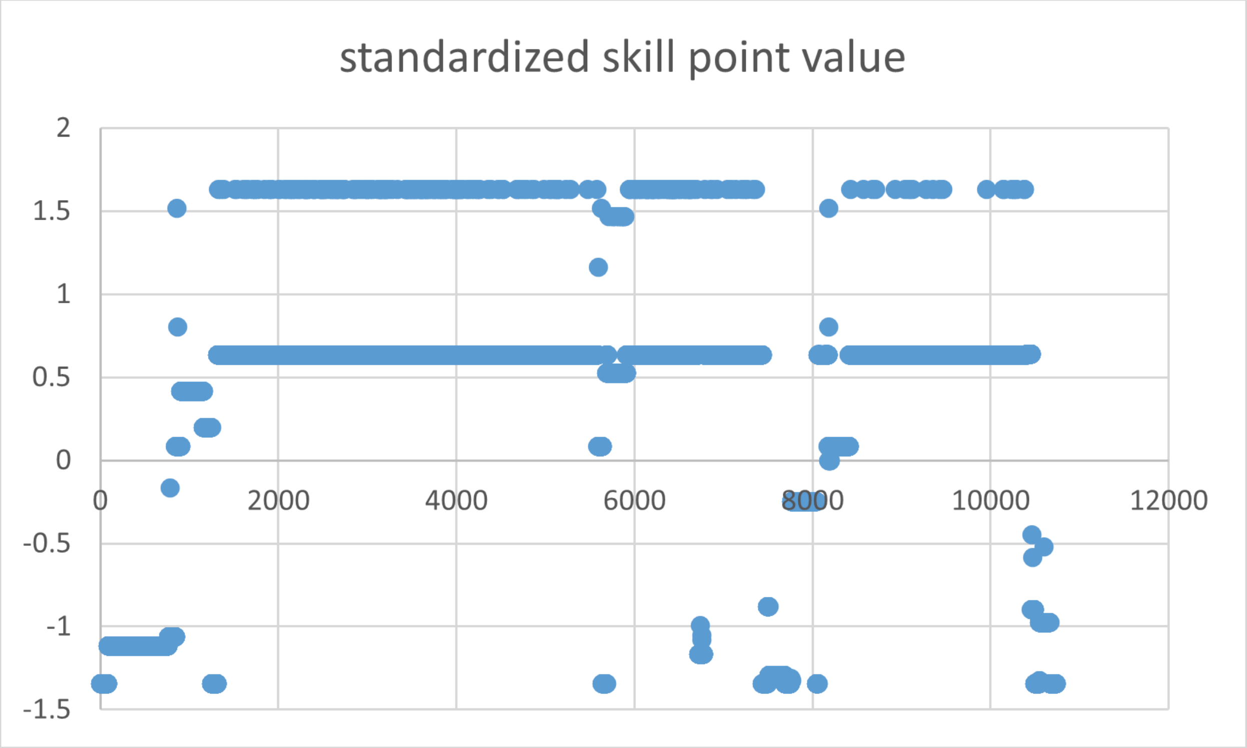
The null cells in the gender column were filled with the modal gender i.e the gender with the highest frequency which is the "male"because of the data type; (gender) which is a nominal data. The columns were filled up to ensure consistency and reduced discrepancies.

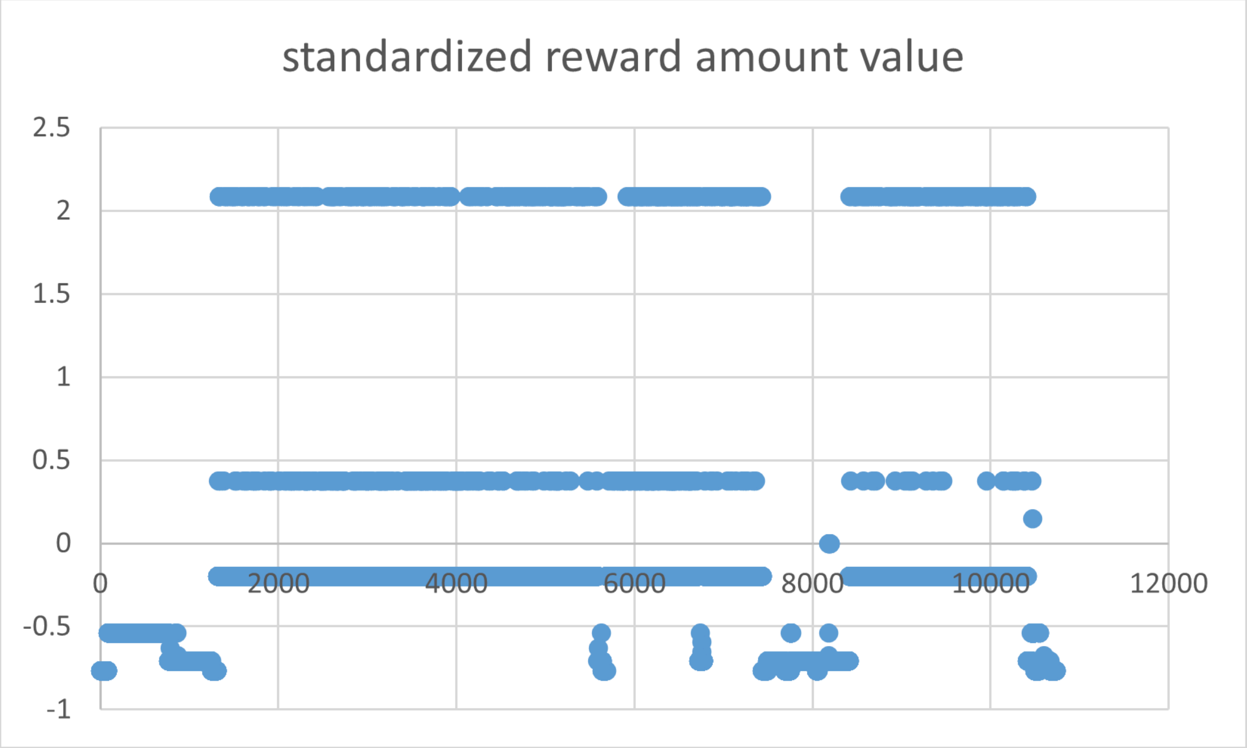
Entire rows containing null cells in the "Current student status" were removed completely as the larger percentage of the rows with null entries in the column has null entries for the majority of the columns. Keeping these cells blank or null might affect data analysis or give skewed results if filled using statistical methods because null entries showed a very high frequency.

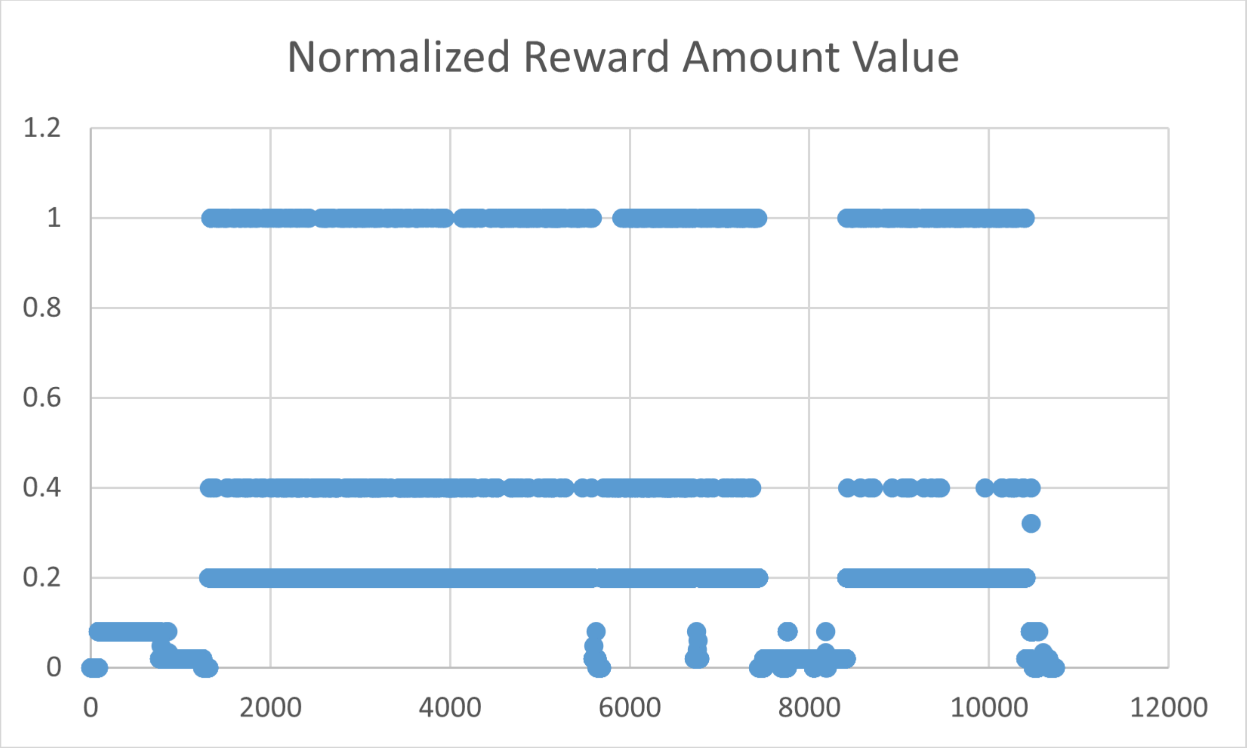
The "City" column alphabetical case was adjusted as some were in uppercase while some were in lower case. All null entries have been removed following the deletion of rows containing null current student status.

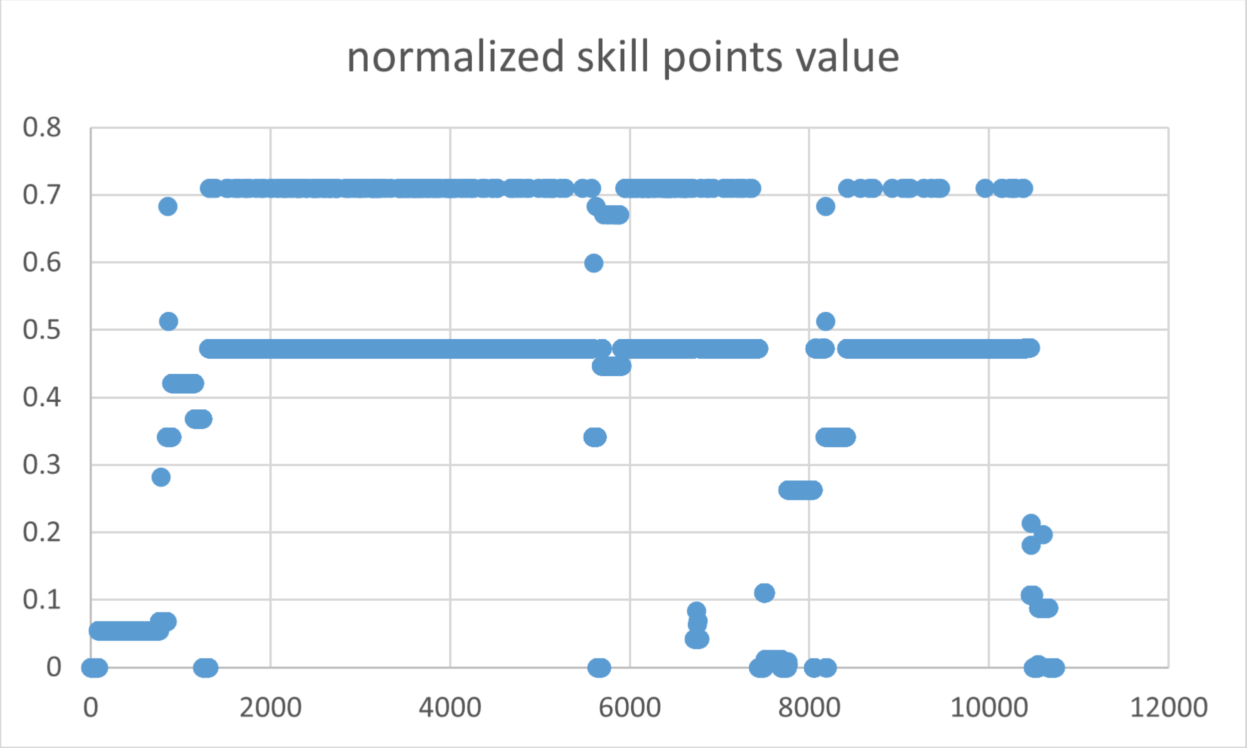
OPPORTUNITY WISE DATA

Duplicate entries were cleaned. In order to normalize and standardize the rewards amount and skills point numerical column, the column for status description was cleared of entries that are "rejected" or "withdrawn". The missing or null entries for reward amount and skill points were filled accordingly with the modal value of filled entries for each opportunity category type. Also, using the badge name column, the modal value also corresponds with the lowest possible points and reward amount for participation in each opportunity category type using the reward amount and skill point of cells with "completed" in the status description for each category type as reference. Categorical type of opportunities with no "completed" status in all entries were filled with 0 for the skill points and reward amount.


standardized skill point value
2
1.5
1
0.5
0
-0.5
-1
-1.5
0
2000
4000
6000
8000
10000
12000


standardized reward amount value
2.5
2
1.5
1
0.5
0
-0.5
-1
0
2000
4000
6000
8000
10000
12000


Normalized Reward Amount Value
1.2
1
0.8
0.6
0.4
0.2
0
0
2000
4000
6000
8000
10000
12000


normalized skill points value
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
2000
4000
6000
8000
10000
12000

3. Addressing Data Quality Issues:

USER DATA

HANDLING NULLS

The null cells in gender column was filled with the modal gender i.e the gender with the highest frequency frequency which is the "male"because of the data type; (gender) which is a nominal data. The columns were filled up to ensure consistency and reduced discrepancies.

Entire rows containing null cells in the "Current student status" were removed completely as the larger percentage of the rows with null entries in the column has null entries for majority of the columns. Keeping this cells blank or null might affect data analysis or give a skewed results if filled using statistical method because null entries showed a very high frequency.

The "City" column alphabetical case was adjusted as some were in uppercase while some were in lower case. All null entries has been removed following the deletion of rows containing null current student status.

OPPORTUNITY WISE DATA

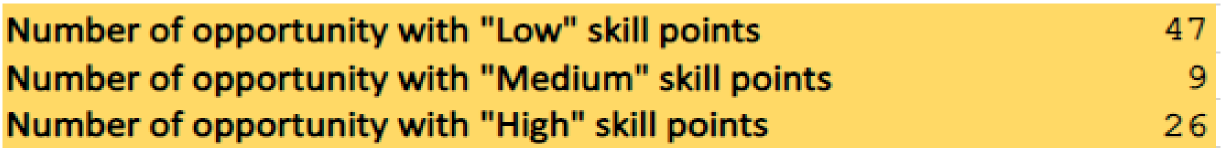
HANDLING NULL VALUES

Duplicate entries were cleaned. The column for status description was cleared of entries that are "rejected" or "withdrawn". The missing or null entries for reward amount and skill points was filled accordingly with the modal value of filled entries(completed opportunities) for each opportunity category type. The modal value also corresponds with the lowest possible points and reward amount for participation in each opportunity category type using the reward amount and skill point of cells with "completed" in the status description for each category type as reference. Categorical type of opportunities with no "completed" status and no rewards awarded in all available entries were filled with 0 for the skill points and reward amount consecutively.

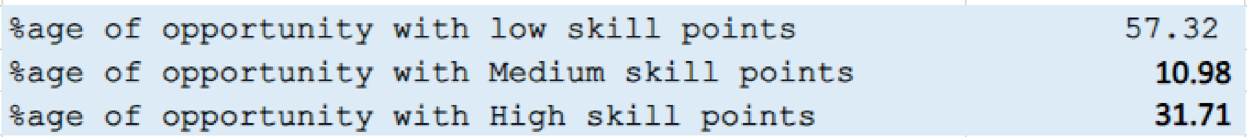
4. Feature Engineering:

Data feature engineering is the process of leveraging on data to create or manipulate new variables that are not in the training set

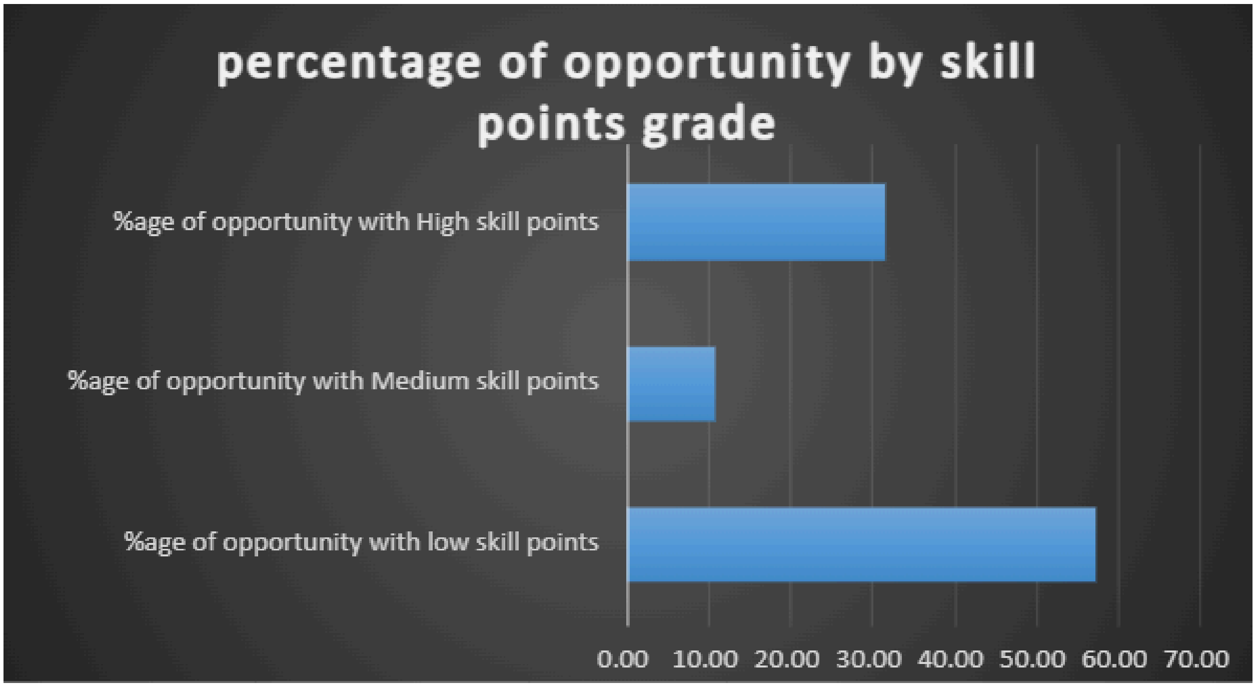
* Highlighted and copy out the columns opportunity name, skills point and reward amount.
*Then use the sort and replace function to filter out the opportunity names having null skill points and null reward...thus, set the null valué to zero.
* Then sort and filter unique values this cleaned the rows from 10737 to 4749.....then start analysis
*Then use the count If formula to count each occurrences of each unique opportunity,
* Use the Average If formula to determine the average skills for each opportunity earned and the average reward for opportunity as well.
*And divide reward by skill points to get the ratio of reward to skill points
 *Then used the IF function to grade opportunity categorization based on skill points and used se function for opportunity categorization based on reward amount
 *Use the SUM IF function to calculate the total points for each opportunity and the total reward for each opportunity
 *Then do the percentage analysis of opportunity by skills point grade using the COUNTA function



Number of opportunity with "Low" skill points	47
Number of opportunity with "Medium" skill points	9
Number of opportunity with "High" skill points	26



%age of opportunity with low skill points	57.32
%age of opportunity with Medium skill points	10.98
%age of opportunity with High skill points	31.71



5. One Hot Encoding:

One-hot encoding is a technique used in machine learning and natural language processing to represent categorical variables as binary vectors. In this encoding scheme, each category or class is represented by a unique binary value, and all values are mutually exclusive.

Here's how one-hot encoding works:

Identification of Categories*:* Identify all the unique categories or classes in the categorical variable.

Assigning Binary Values: Assign a unique binary value to each category. Typically, these binary values are 0 or 1.

Creating Binary Vectors: Represent each data point by a binary vector of length equal to the number of unique categories. Each position in the vector corresponds to a category, and only one position will have the value 1, indicating the presence of that category.

Process : Datasheet 1

- Performed one-hot encoding for the **"Gender"** column and created separate columns for **"Male"** and **"Female,"** and created a new column indicating whether "True" or "False" is present in another column used a similar approach.

- To create one-hot encoding columns for "Male" and "Female" based on the given data structure in Sheets, the data starts from cell A1, we used the following formulas:

- The "Male" and "Female" columns start in column F, we used the following formulas:

- For the "Male" column ("Male" is the Nth column, starting in cell F2):

```
=IF(F2="Male", 1, 0)
```

For the "Female" column ("Female" is the Oth column, starting in cell F2):

```
=IF(F2="Female", 1, 0)
```

- To create one-hot encoding for the **“IsFromSocialMedia”** and created columns for **"TRUE"** and **"FALSE"** based on the given data structure in Sheets, the data starts from cell A1, we used the following formulas:

The "TRUE" and "FALSE" columns start in column M, we can use the following formulas:

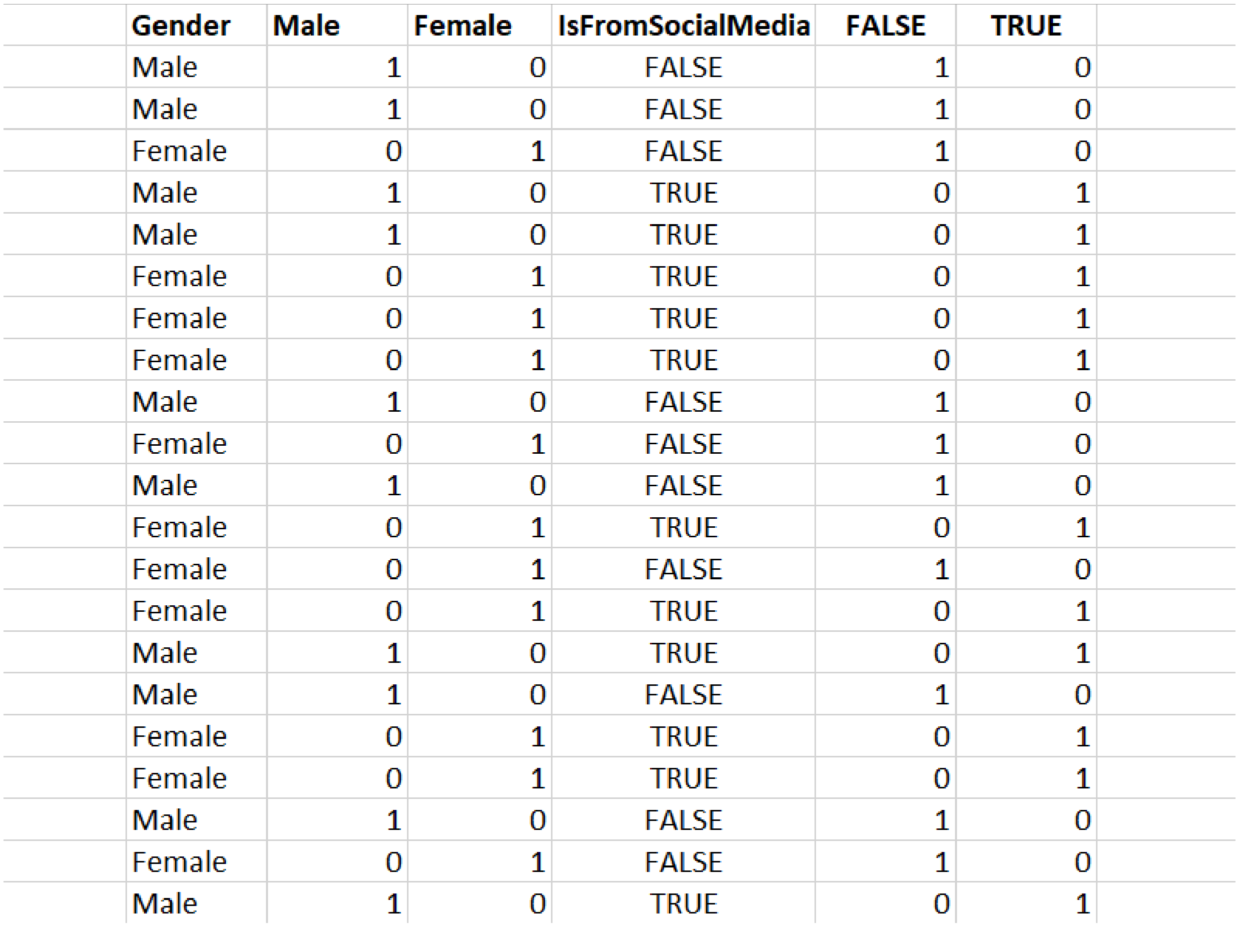
For the "TRUE" column ("TRUE" is the Pth column, starting in cell M2):

```
=IF(M2="TRUE", 1, 0)
```

For the "Female" column (assuming "Female" is the Qth column, starting in cell M2):

```
=IF(M2="FALSE", 1, 0)
```

FINAL OUTPUT :



Gender	Male	Female	IsFromSocialMedia	FALSE	TRUE
Male	1	0	FALSE	1	0
Male	1	0	FALSE	1	0
Female	0	1	FALSE	1	0
Male	1	0	TRUE	0	1
Male	1	0	TRUE	0	1
Female	0	1	TRUE	0	1
Female	0	1	TRUE	0	1
Female	0	1	TRUE	0	1
Male	1	0	FALSE	1	0
Female	0	1	FALSE	1	0
Male	1	0	FALSE	1	0
Female	0	1	TRUE	0	1
Female	0	1	FALSE	1	0
Female	0	1	TRUE	0	1
Male	1	0	TRUE	0	1
Male	1	0	FALSE	1	0
Female	0	1	TRUE	0	1
Female	0	1	TRUE	0	1
Male	1	0	FALSE	1	0
Female	0	1	FALSE	1	0
Male	1	0	TRUE	0	1

Process : Datasheet 2

-- Performed one-hot encoding for the **"Gender"** column and created separate columns for **"Male"** and **"Female"**.

-- To create one-hot encoding columns for "Male" and "Female"

For the "Male" column ("Male" is the Kth column, starting in cell B2):

```
=IF(B2="Male", 1, 0)
```

For the "Female" column ("Female" is the Lth column, starting in cell B2):

```
=IF(B2="Female", 1, 0)
```

-- Performed one-hot encoding for the **"Opportunity Category"** column and created separate columns for 5 different categories : **Internship, Event, Course, Competition, Engagement.**

-- For the "Internship" column ("Internship" is the Mth column, starting in cell H2):

```
=IF(H2="Internship", 1, 0)
```

-- For the "Event" column ("Event" is the Nth column, starting in cell H2):

```
=IF(H2="Event", 1, 0)
```

-- For the "Course" column ("Course" is the Oth column, starting in cell H2):

```
=IF(H2="Course", 1, 0)
```

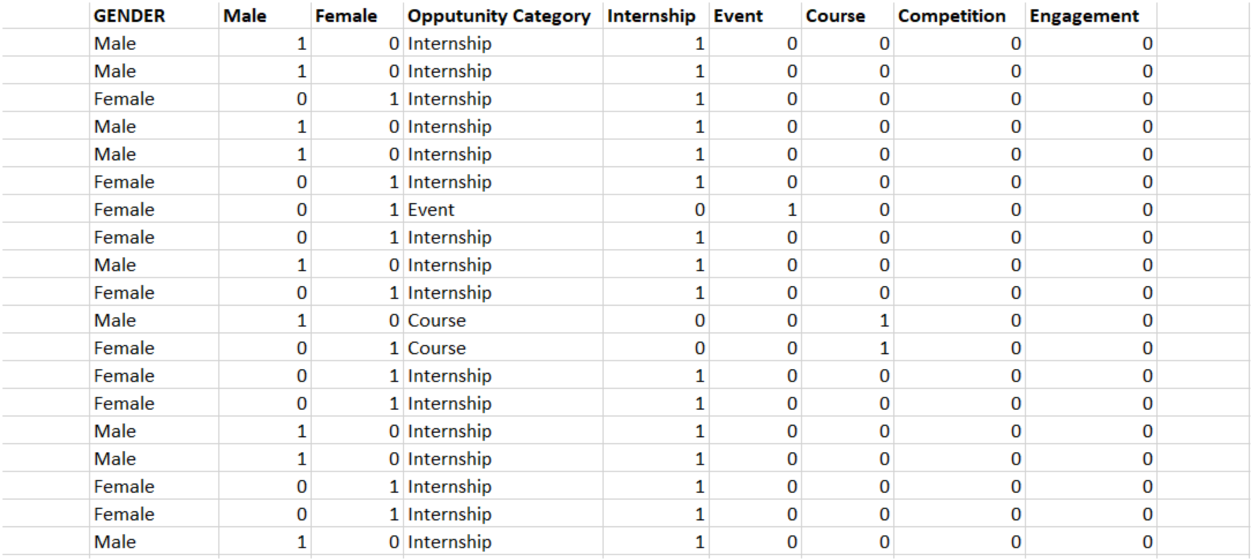
-- For the "Competition" column ("Competition" is the Pth column, starting in cell H2):

```
=IF(H2="Competition", 1, 0)
```

-- For the "Engagement" column ("Engagement" is the Qth column, starting in cell H2):

```
=IF(H2="Engagement", 1, 0)
```

FINAL OUTPUT :



GENDER	Male	Female	Opputunity Category	Internship	Event	Course	Competition	Engagement
Male	1	0	Internship	1	0	0	0	0
Male	1	0	Internship	1	0	0	0	0
Female	0	1	Internship	1	0	0	0	0
Male	1	0	Internship	1	0	0	0	0
Male	1	0	Internship	1	0	0	0	0
Female	0	1	Internship	1	0	0	0	0
Female	0	1	Event	0	1	0	0	0
Female	0	1	Internship	1	0	0	0	0
Male	1	0	Internship	1	0	0	0	0
Female	0	1	Internship	1	0	0	0	0
Male	1	0	Course	0	0	1	0	0
Female	0	1	Course	0	0	1	0	0
Female	0	1	Internship	1	0	0	0	0
Female	0	1	Internship	1	0	0	0	0
Male	1	0	Internship	1	0	0	0	0
Male	1	0	Internship	1	0	0	0	0
Female	0	1	Internship	1	0	0	0	0
Female	0	1	Internship	1	0	0	0	0
Male	1	0	Internship	1	0	0	0	0

6. Documentation:

1.	Handling Outliers and Anomalies - Identify outliers and anomalies	- Outliers can distort analysis and negatively affect model performance. Identifying and handling them ensures a more accurate representation of the data.
2.	Normalize or Scale Relevant Features - Normalize or scale numerical features	- Features with different scales can have varying impacts on model training. Normalizing or scaling ensures consistency and improves model convergence.
3.	Addressing Data Quality Issues - Identify and address missing values	- Missing values can lead to biased or inaccurate results. Addressing data quality issues ensures the reliability of the analysis.
4.	Feature Engineering - Create new features	- Feature engineering introduces new information to enhance the dataset, potentially improving model performance.
5.	Data Transformation	- Data transformations, such as log

	- Perform additional transformations - One-hot Coding	transformations or encoding, help meet model assumptions, handle skewed distributions, and capture non-linear relationships. Transformations contribute to improved model fit and capturing complex patterns. -Many machine learning algorithms require | numerical input. One-hot encoding is a technique to convert categorical variables into a format suitable for numerical analysis. - Transform categorical variables into a binary format, creating binary columns for each category. This enables the algorithm to consider each category independently.

-Handling Outliers and Anomalies:

Outliers in sales data might distort the overall trend .
Identifying anomalies helps ensure the accuracy of customer demographics analysis (Q2).
Modified Rationale:
Handling outliers and anomalies is crucial to maintain the integrity of the data, ensuring that the overall sales trend and customer demographics insights are not skewed by extreme values.

-Normalize or Scale Relevant Features:

Scaling features is essential for accurate analysis of different product categories' contributions .
Modified Rationale:
Scaling relevant features ensures that the contributions of different product categories are comparable, aiding in the analysis of their impact on overall sales.

-Addressing Data Quality Issues:

Addressing data quality issues ensures the reliability of insights related to factors influencing sales .
Modified Rationale:
Ensuring data quality is critical to reliably identify and analyze factors like seasonality or promotional events that might influence sales.

-Feature Engineering:

Creating new features can enhance the dataset for better predictions of sales trends .
Modified Rationale:
Feature engineering contributes to a more nuanced understanding of the factors contributing to the overall sales performance trend.

-Data Transformation (One-Hot Encoding):

One-hot encoding enables the analysis of customer demographics, aligning with .
Modified Rationale:
The one-hot encoding of categorical variables, such as customer demographics, facilitates a detailed analysis of patterns and insights that may affect sales.

CONDUCT INITIAL ANALYSIS

Trends and Comparative Analysis

Trend Analysis

Trend analysis involves examining data over time to identify patterns, tendencies, or movements that may indicate a consistent direction or tendency in a particular variable. In the context of a sales performance dashboard, trend analysis is crucial for understanding how sales have been evolving over time.

Trend analysis is a quantitative review of what happens over a period of time. It entails the collection of data from multiple time periods and plotting the information on a line graph for further analysis. There are three types of trend analysis:geographic, temporal, and intuitive.

1) Trend Analysis > Using User Data

a) User Growth Overtime: Utilized timestamp information to visualize user sign-ups and identify period of Growth.

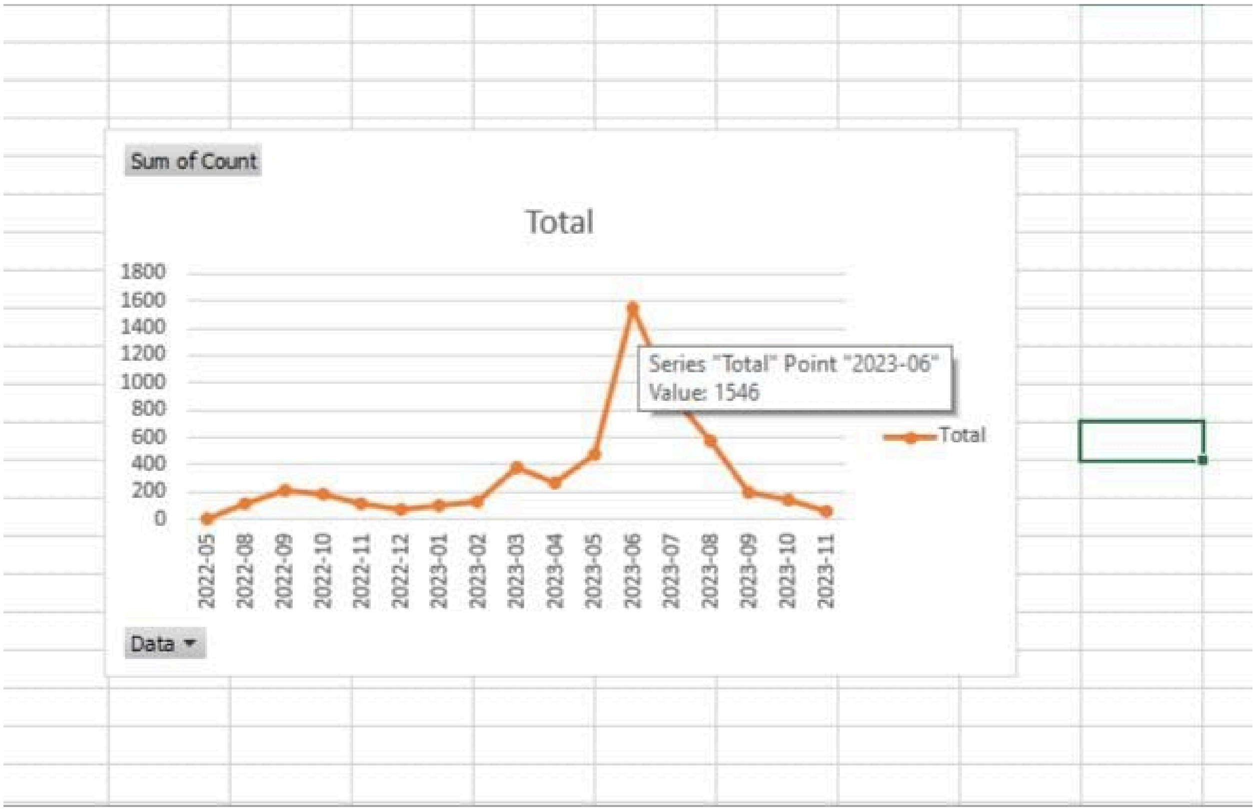
Outcome:

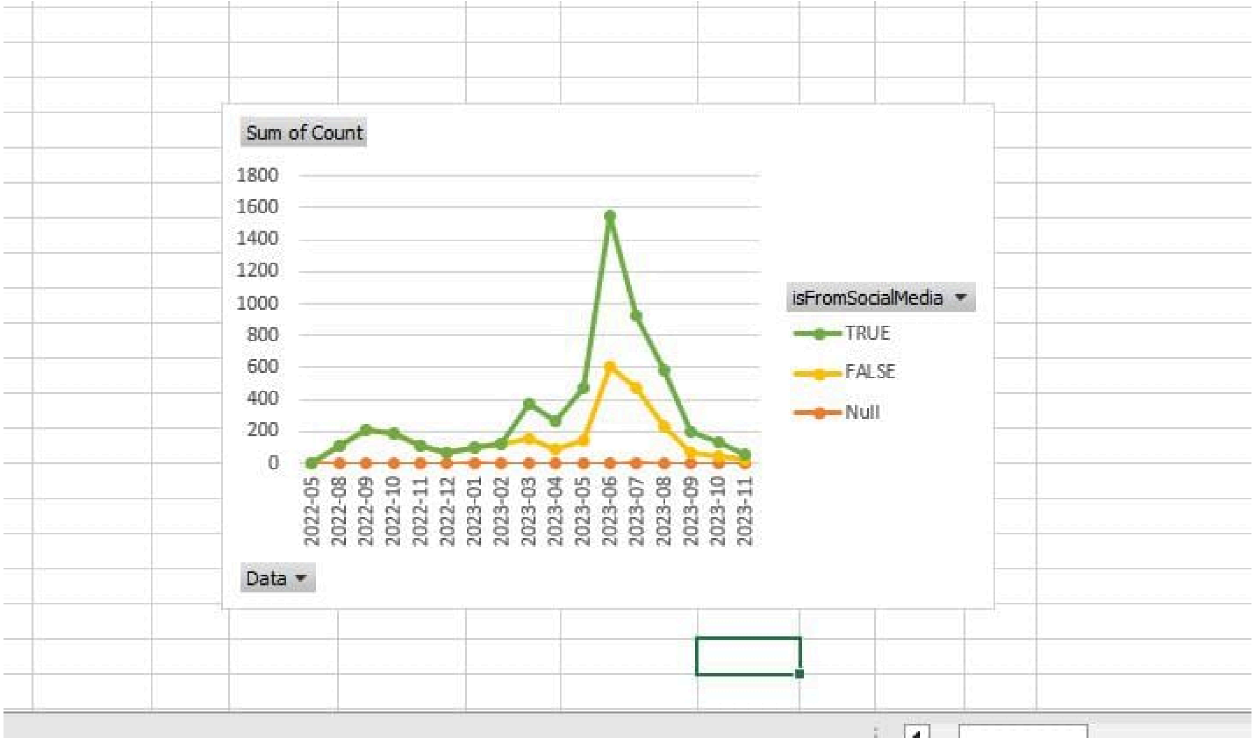
- The period of Growth started on January 2023 where the highest Growth in signup Is in July 2023
- The period of decline in signup is from July 2023 - November 2023

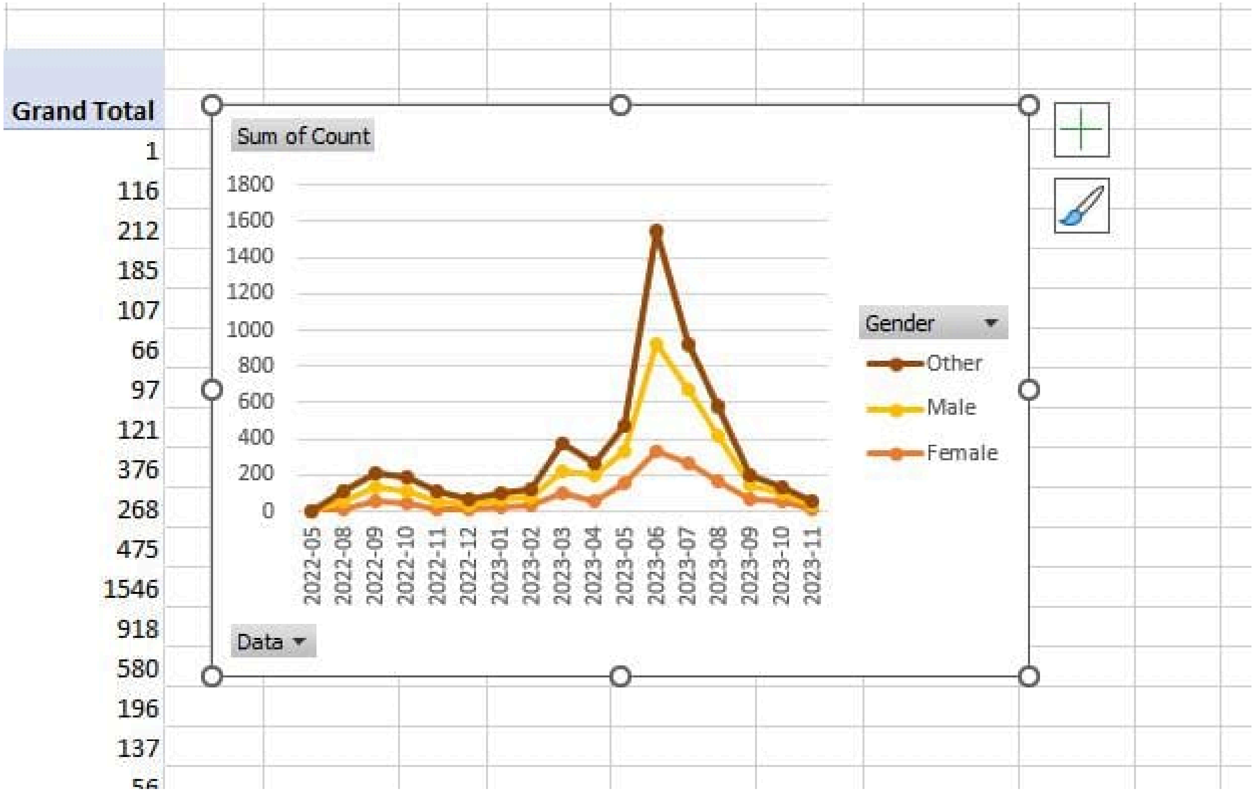
b) Demographic Shift: Using the categorical variables (gender, IsFromSocailMedia) to observe the changes over Time.

Outcome:

- Users who indicated there Gender as "other" has the highest signup, followed by "Male"
- Majority of users sign up using Social media platforms.


Sum of Count
Total
1800
1600
1400
1200
1000
800
600
400
200
0
2022-05
2022-08
2022-09
2022-10
2022-11
2022-12
2023-01
2023-02
2023-03
2023-04
2023-05
2023-06
2023-07
2023-08
2023-09
2023-10
2023-11
Series "Total" Point "2023-06"
Value: 1546
Total
Data


Sum of Count
1800
1600
1400
1200
1000
800
600
400
200
0
2022-05
2022-08
2022-09
2022-10
2022-11
2022-12
2023-01
2023-02
2023-03
2023-04
2023-05
2023-06
2023-07
2023-08
2023-09
2023-10
2023-11
isFromSocialMedia
TRUE
FALSE
Null
Data



Grand Total
1
116
212
185
107
66
97
121
376
268
475
1546
918
580
196
137
56

2) Trend Analysis > Using Opportunity Dataset

a) Opportunity participation Trend: Analyze the trend (growth or decline) in the number learners signing up for Opportunity over time

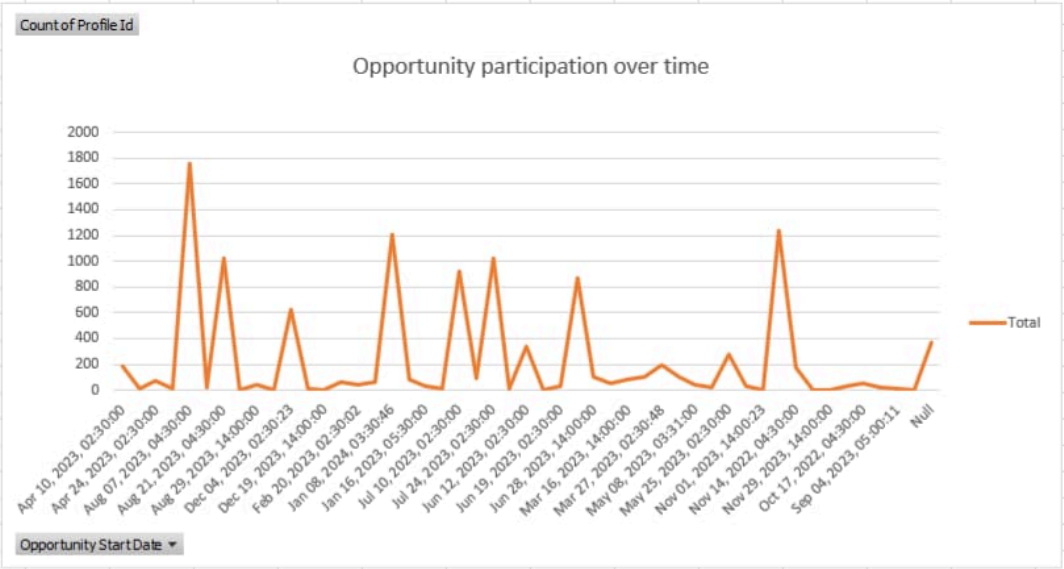
Outcome :

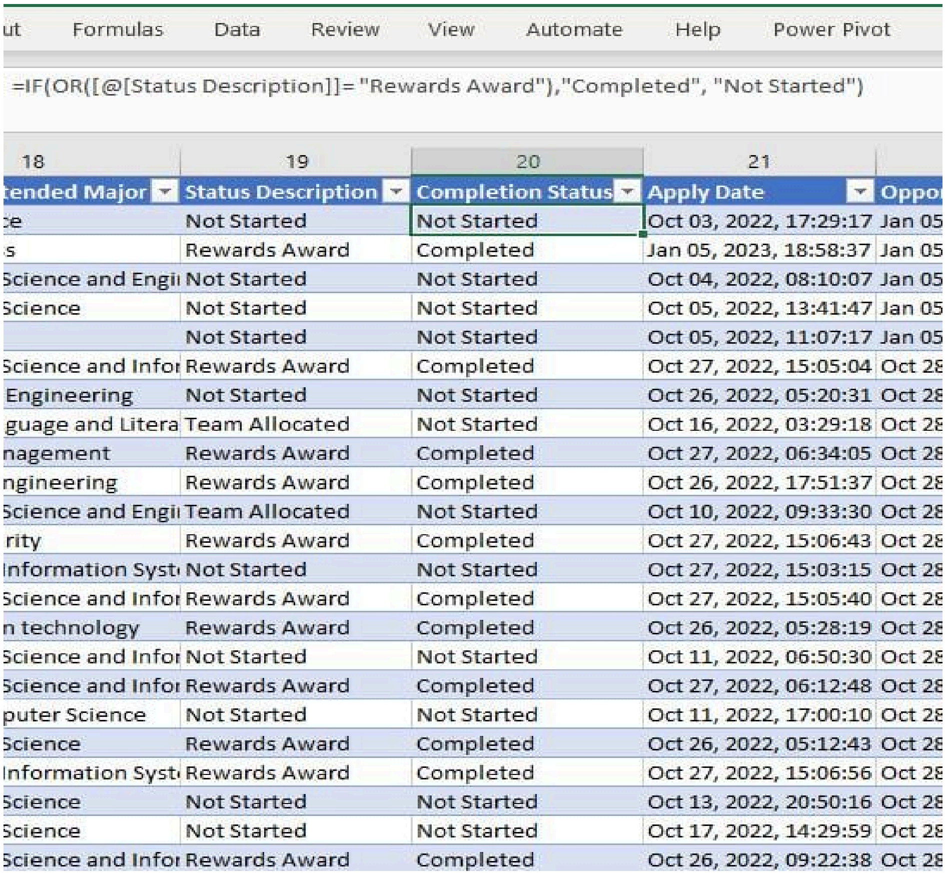
- The highest participation is in August 7 2023 over time.

b) Completion Rate: Calculate and analyze the trend in Completion rate of various opportunities(to identify which opportunities consistently show high Completion rate over time)

Outcome:

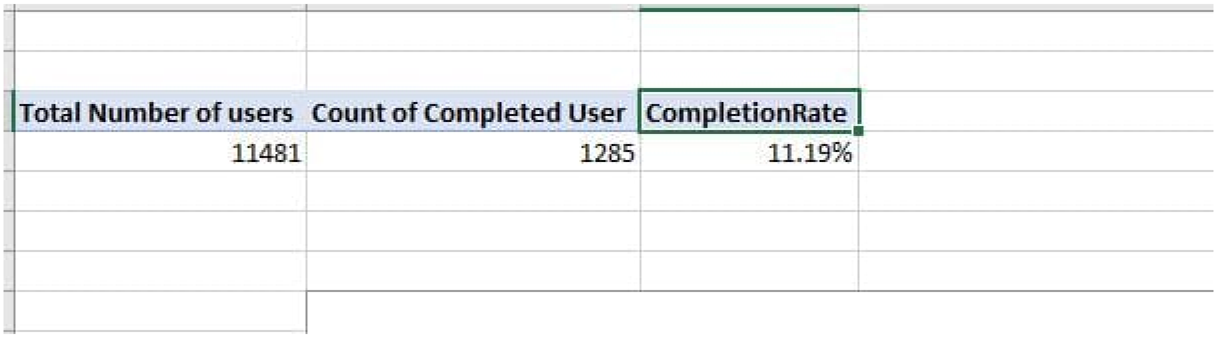
- Created a new column from the status description, as "Completion Status) using the the IF Formula (where "Reward Awards" = Completed else Not Completed). After which we calculated the Completion rate = Count of completed user/ Total number of User (1285 ÷ 11481 = 11.19%)
- Internship has the highest Completion rate over time. In July 13th 2022 the internship opportunity has 100% Completion.



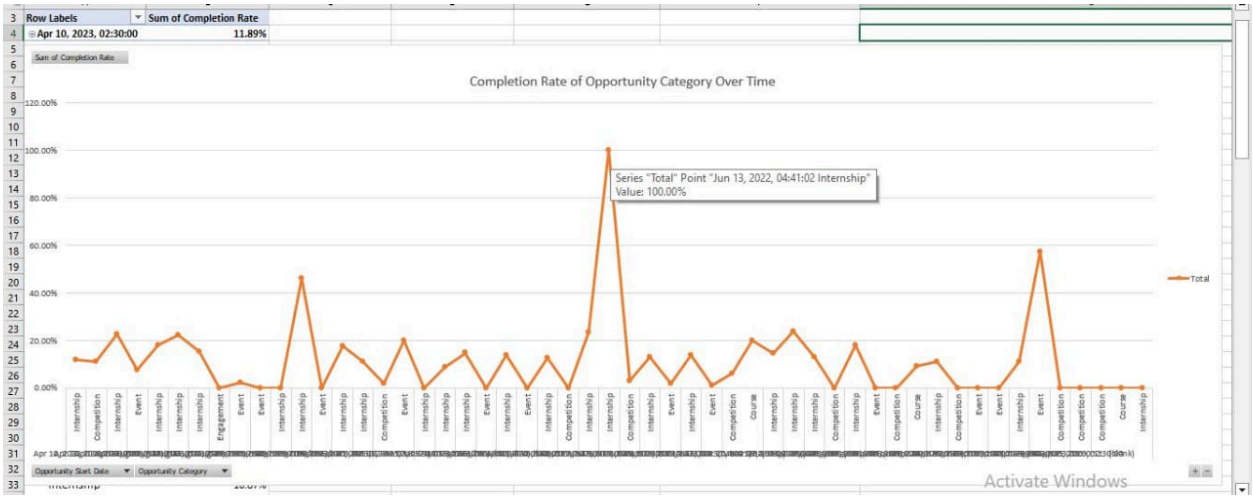


=IF(OR([@[Status Description]]= "Rewards Award"),"Completed", "Not Started")

18	19	20	21	
tended Major	Status Description	Completion Status	Apply Date	Oppo
ce	Not Started	Not Started	Oct 03, 2022, 17:29:17	Jan 05
s	Rewards Award	Completed	Jan 05, 2023, 18:58:37	Jan 05
Science and Engi	Not Started	Not Started	Oct 04, 2022, 08:10:07	Jan 05
Science	Not Started	Not Started	Oct 05, 2022, 13:41:47	Jan 05
	Not Started	Not Started	Oct 05, 2022, 11:07:17	Jan 05
Science and Infor	Rewards Award	Completed	Oct 27, 2022, 15:05:04	Oct 28
Engineering	Not Started	Not Started	Oct 26, 2022, 05:20:31	Oct 28
guage and Litera	Team Allocated	Not Started	Oct 16, 2022, 03:29:18	Oct 28
nagement	Rewards Award	Completed	Oct 27, 2022, 06:34:05	Oct 28
ngineering	Rewards Award	Completed	Oct 26, 2022, 17:51:37	Oct 28
Science and Engi	Team Allocated	Not Started	Oct 10, 2022, 09:33:30	Oct 28
rity	Rewards Award	Completed	Oct 27, 2022, 15:06:43	Oct 28
Information Syst	Not Started	Not Started	Oct 27, 2022, 15:03:15	Oct 28
Science and Infor	Rewards Award	Completed	Oct 27, 2022, 15:05:40	Oct 28
n technology	Rewards Award	Completed	Oct 26, 2022, 05:28:19	Oct 28
Science and Infor	Not Started	Not Started	Oct 11, 2022, 06:50:30	Oct 28
Science and Infor	Rewards Award	Completed	Oct 27, 2022, 06:12:48	Oct 28
puter Science	Not Started	Not Started	Oct 11, 2022, 17:00:10	Oct 28
Science	Rewards Award	Completed	Oct 26, 2022, 05:12:43	Oct 28
Information Syst	Rewards Award	Completed	Oct 27, 2022, 15:06:56	Oct 28
Science	Not Started	Not Started	Oct 13, 2022, 20:50:16	Oct 28
Science	Not Started	Not Started	Oct 17, 2022, 14:29:59	Oct 28
Science and Infor	Rewards Award	Completed	Oct 26, 2022, 09:22:38	Oct 28



Total Number of users	Count of Completed User	CompletionRate
11481	1285	11.19%



Row Labels	Sum of Completion Rate
⊟Apr 10, 2023, 02:30:00	11.89%

Series "Total" Point "Jun 13, 2022, 04:41:02 Internship"
Value: 100.00%

Demographic comparative analysis

Comparative analysis was carried out using statistical chart representation for visualization to understand demographic differences among user groups. The distribution of student statuses according to regions and their completion rates. The demographic distribution of users spans across 170 countries from all continent. Chart 1 shows the top 10 countries with the highest frequency of users, from India to Nepal and chart 2 showing the map distribution

CHART 1

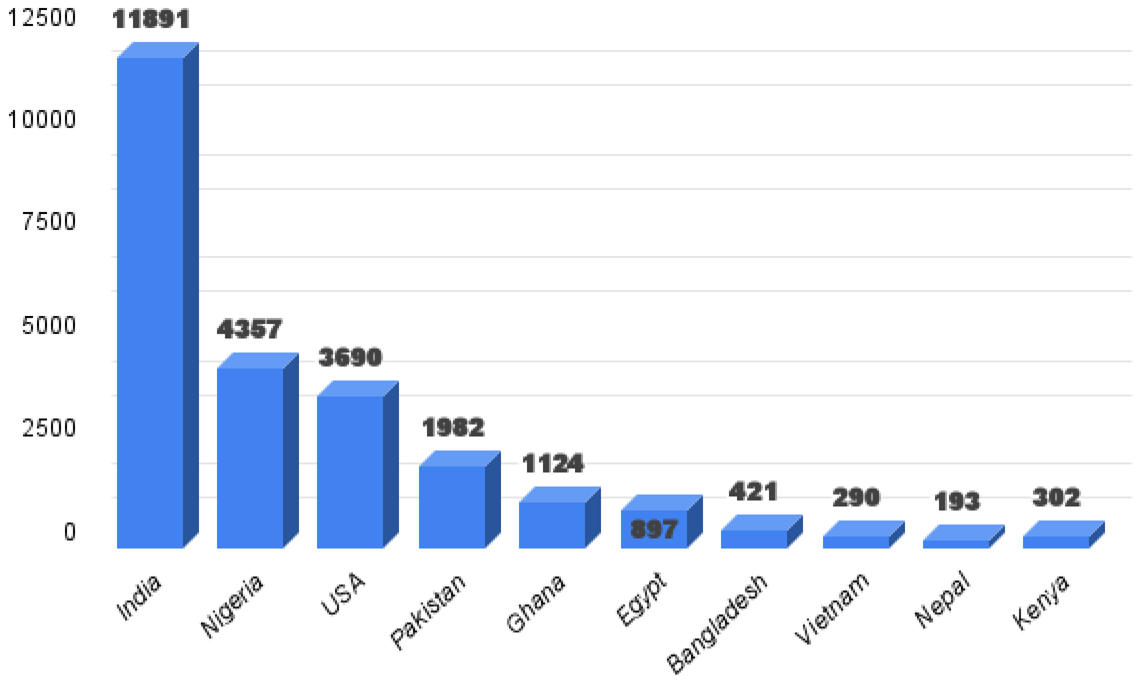
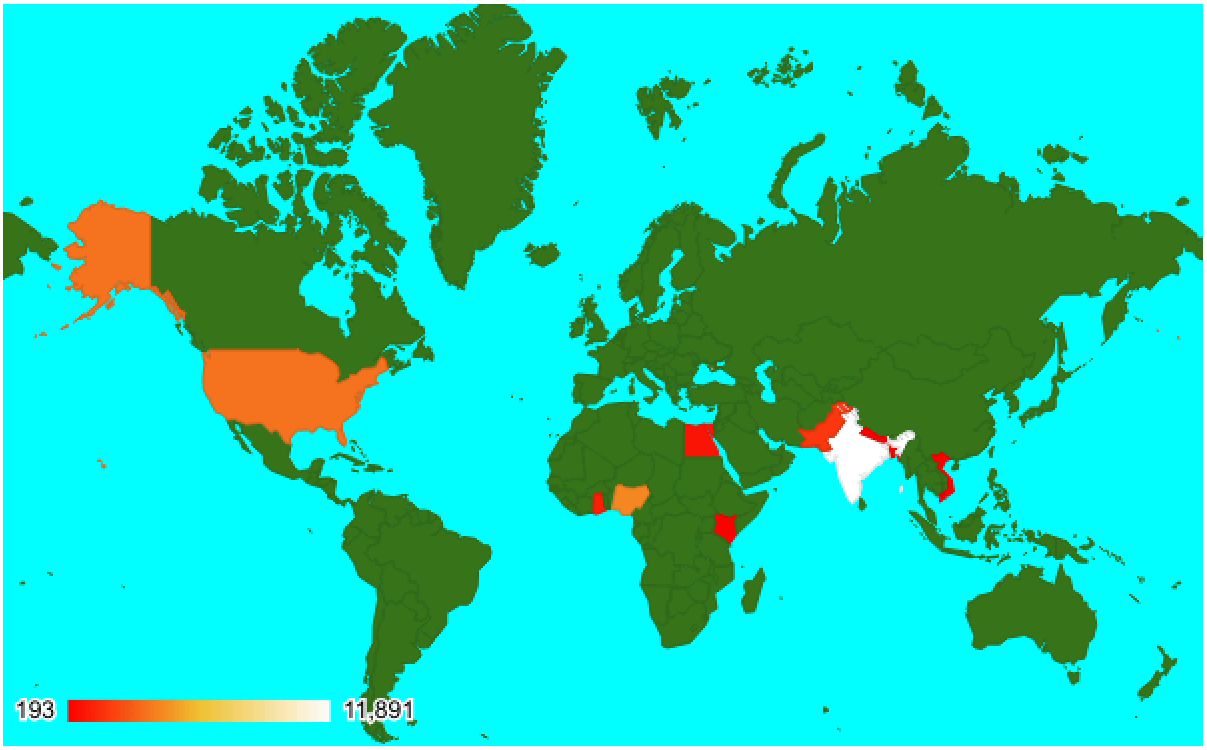
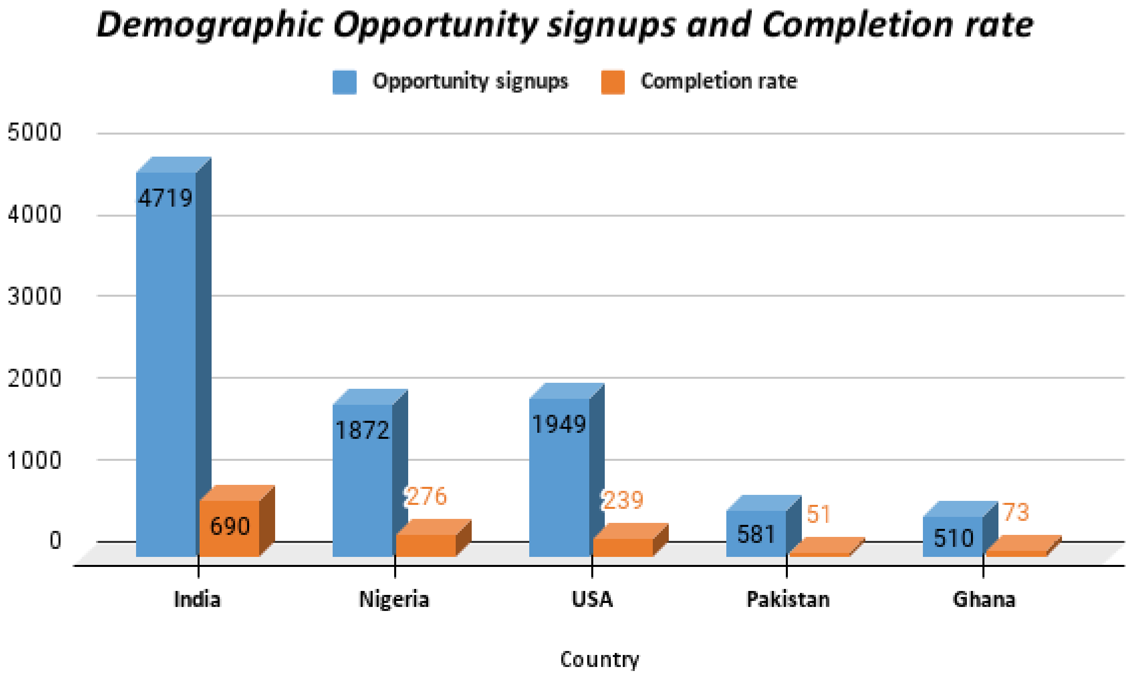


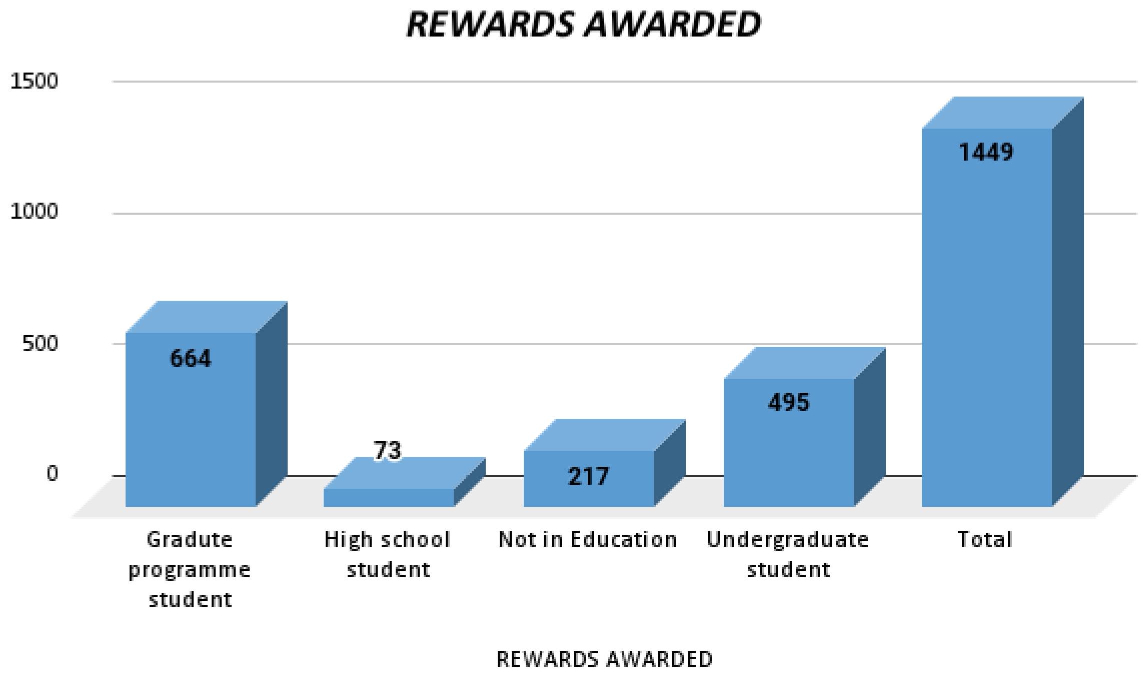
CHART 2



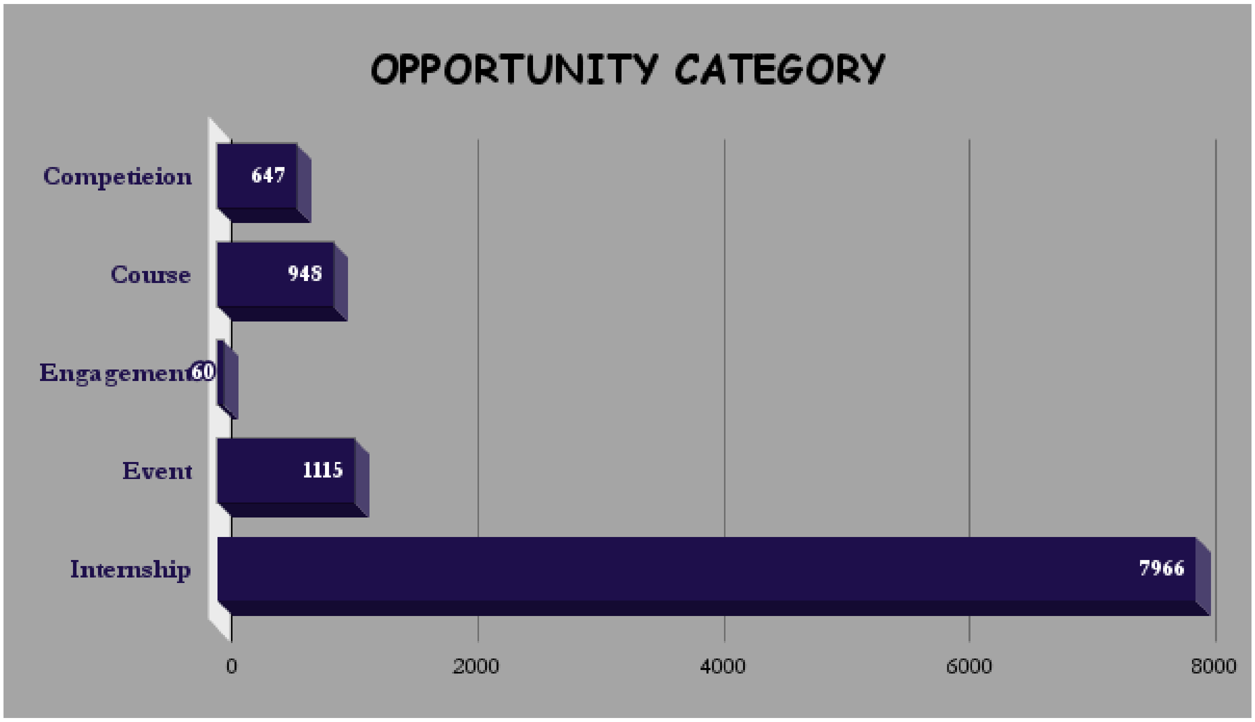
The chart below shows the demographic distribution of opportunity signups of the top five countries including India, which is the highest, Nigeria, USA, Pakistan and Ghana and also the completion rates per region.

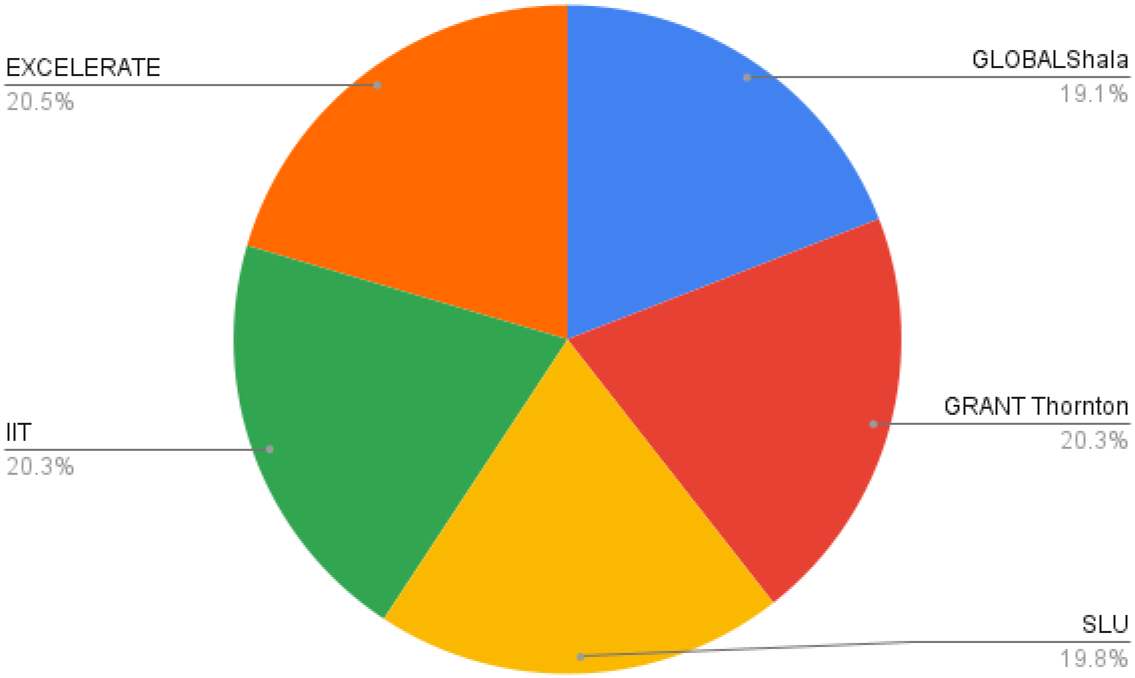


The rewards awarded chart below shows student statuses for completed opportunities which are also with their rewards awarded. With 1449 as the total number of completed opportunities, the graduate programme student showed the highest value with the high school students in the low with just 73 opportunities completed.



Opportunity category chart shows the most preferred opportunity type using opportunity signups data. Internship opportunities showed the highest frequency by far with 7966 entries and Engagement with the lowest having 60 entries. The pie chart below it shows the percentage of users preferred sponsors for each sponsor.


OPPORTUNITY CATEGORY
Competieion
647
Course
948
Engagement
60
Event
1115
Internship
7966
0
2000
4000
6000
8000


EXCELERATE
20.5%
GLOBALShala
19.1%
IIT
20.3%
GRANT Thornton
20.3%
SLU
19.8%

CROSS DATA SET ANALYSIS

A major challenge was faced in combining both dataset for combined analysis using different tools. Some were due to contrast in the number of rows and so on. The observation made using charts from both dataset however follows:

- The user data shows that there are 27,563 users with an account while about just below average of the figure proceeded to sign up for opportunities(11482).
- The demographic signup follows the same trend with the same top five countries for both dataset. India, USA, Pakistan, Ghana and Nigeria.
- The current student status also showed a level of consistency with the graduate programme students having the highest population for both dataset.
- The male gender has the highest level of gender for both datasets after the null entries were handled.