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INNOVATION. AUTOMATION. ANALYTICS

PROJECT ON

Exploratory Data Analysis
(AMCAT Dataset)

Submitted By,
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About me

- **Hi there!! I am Pandey Abhishek Nath Roy (IN9240832), a data enthusiast, currently learning various things to crack an opportunity to go further.**

- **Apart from this, I possess the problem solving ability and I am good at learning new things that makes me an ideal candidate to follow my dreams.**

- **I have previously worked as a data science intern at Innomatics research labs and right now, I am doing the internship to refine my skills at their highest level.**

- **Feel free to reach out! You can do so by following the below links:**

  - https://linkedin.com/in/pandey-abhishek-nath-roy-179879222/

  - https://github.com/vjabhi000985/

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OBJECTIVE OF THE PROBLEM

- This exploratory data analysis of "AMCAT DATASET" focuses on understanding various factors that might influence the level of salaries indicated in the dataset. We consider education and experience, gender, specialization, and job roles and observe how they are related in order to understand a factor that influences higher or lower levels of salaries. The critical steps which indicate the analysis involved creating a mental image of the data, establishing trends and patterns, testing many hypotheses post observations to finally build insightful results which could be used as guidelines for any decision making process that could further calibrate salary prediction models.

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SUMMARY OF THE DATASET

- There are ***38 columns*** in total that are used to find the individual impacts on salary.
- Out of 38 columns, there are ***29 numerical columns*** and ***9 categorical columns***.
- With ***3998 Datapoints*** that make our analysis to the optimal insights with all the necessary information.

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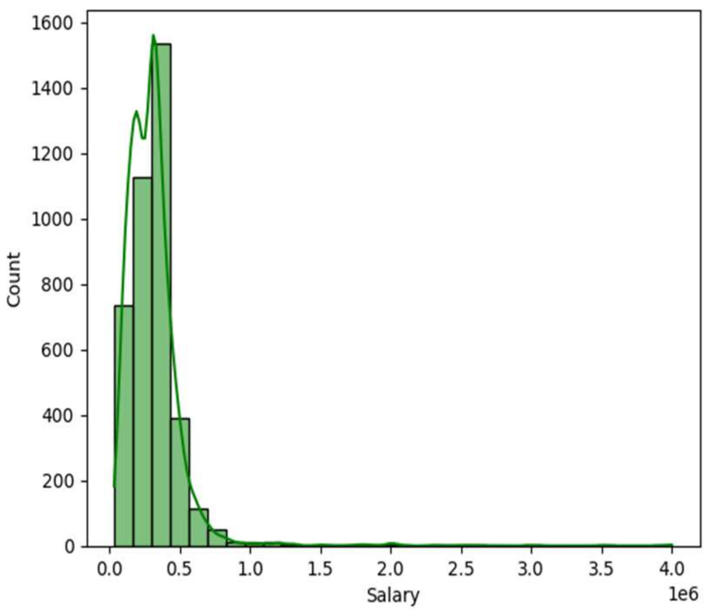
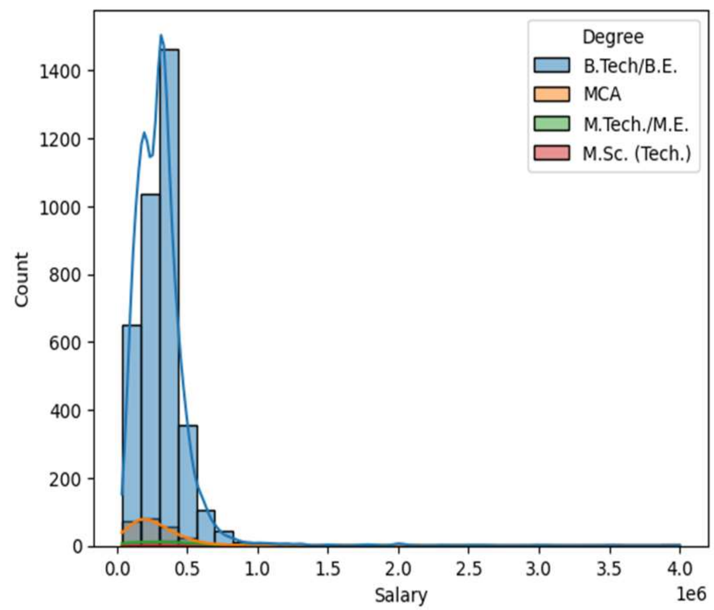
DATA CHECKS TO PERFORM

- **Check missing values, duplicated values and various different columns.**
- **Check the datatypes and also look at the unique number of columns.**
- **Check statistics of data set**
- **Check various categories present in the different categorical column.**
- **Drop unnecessary columns**

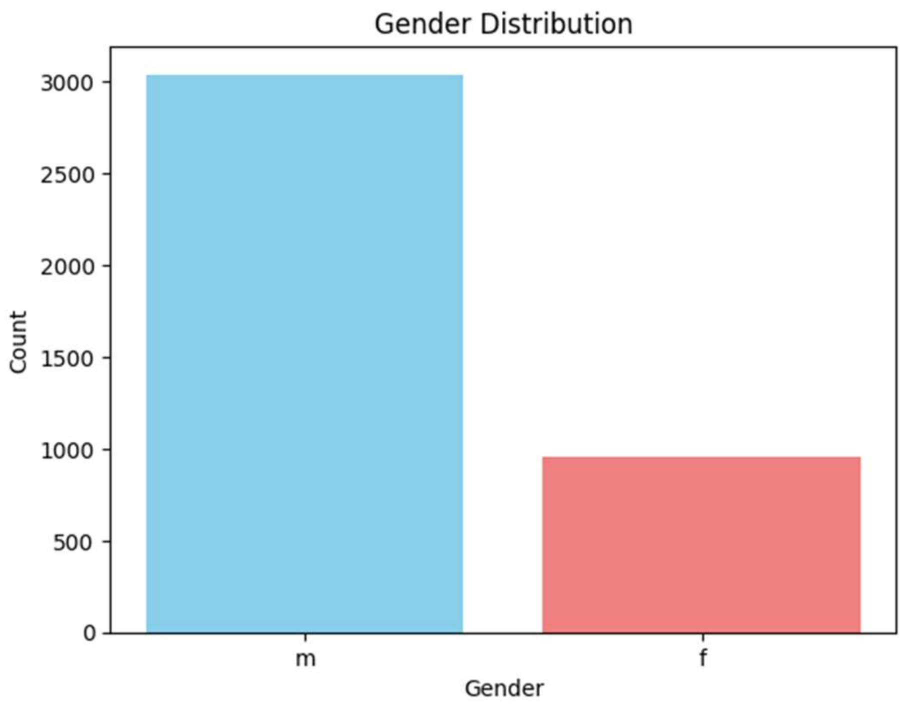
What target variable 'Salary vs Gender' shows us?





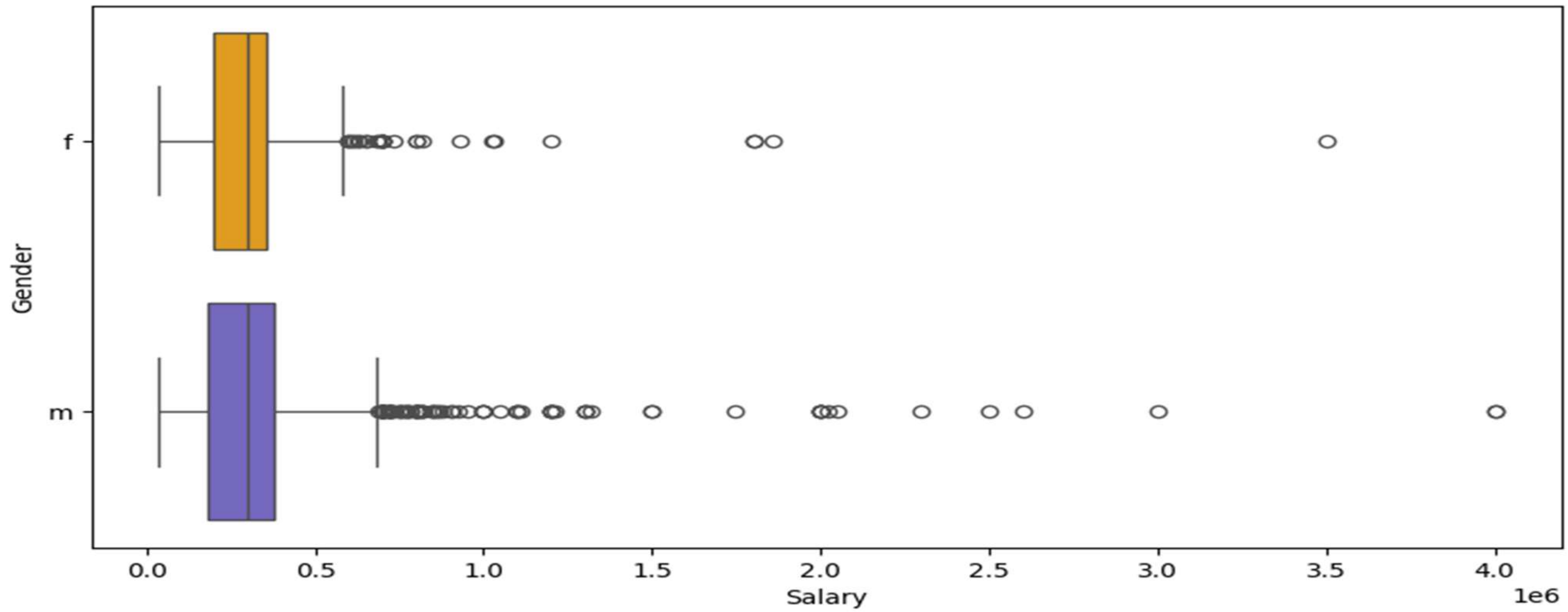
- **B.Tech students has a higher salary other Degree persons.**

What target variable 'Gender' tells us?



- The ratio of m/f is 3.19 indicates there are 3 times more men than women employed.

Is Gender have an effect on salary?

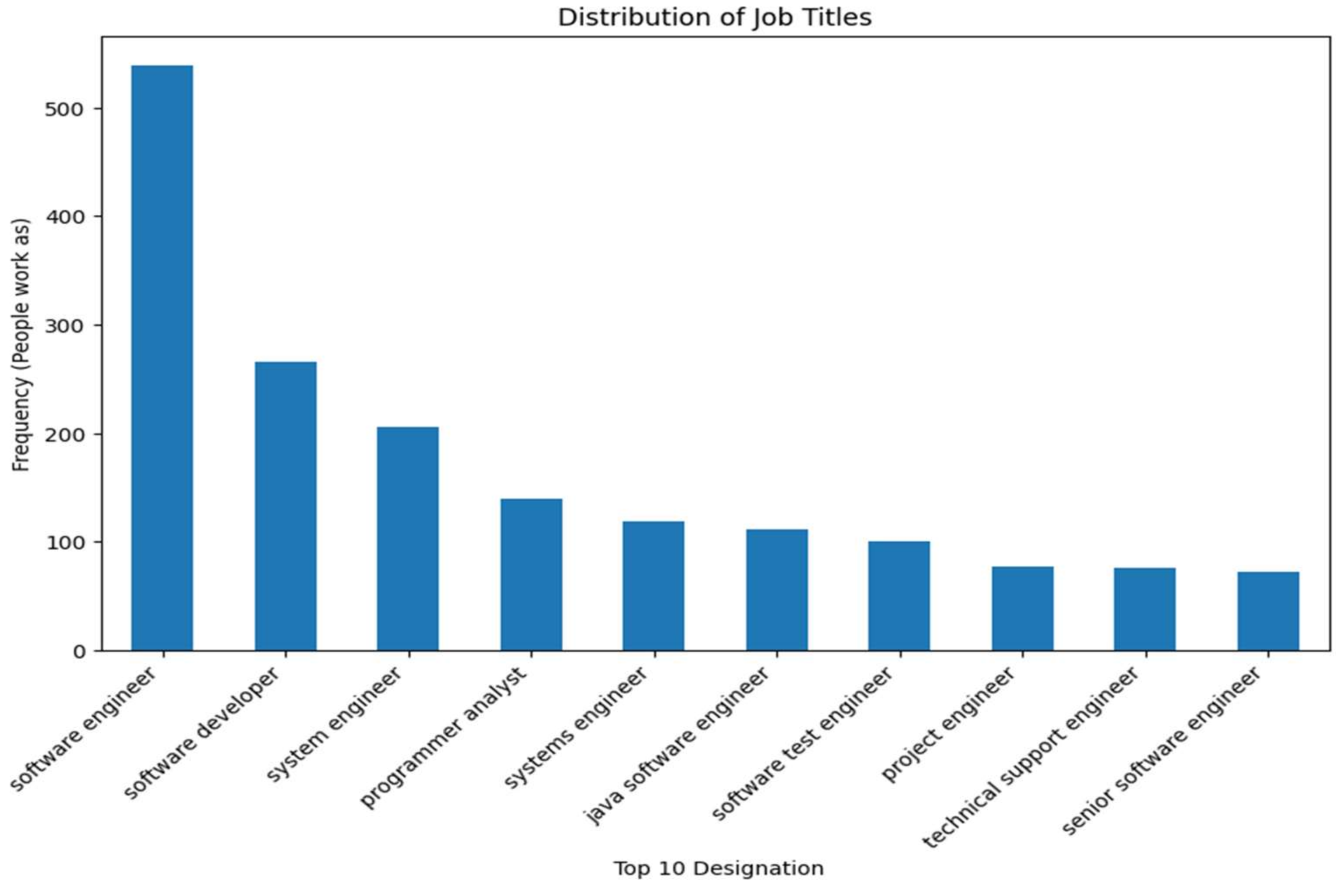


- Men are earning more than the women.
- There is not much difference in between median salary of both genders.

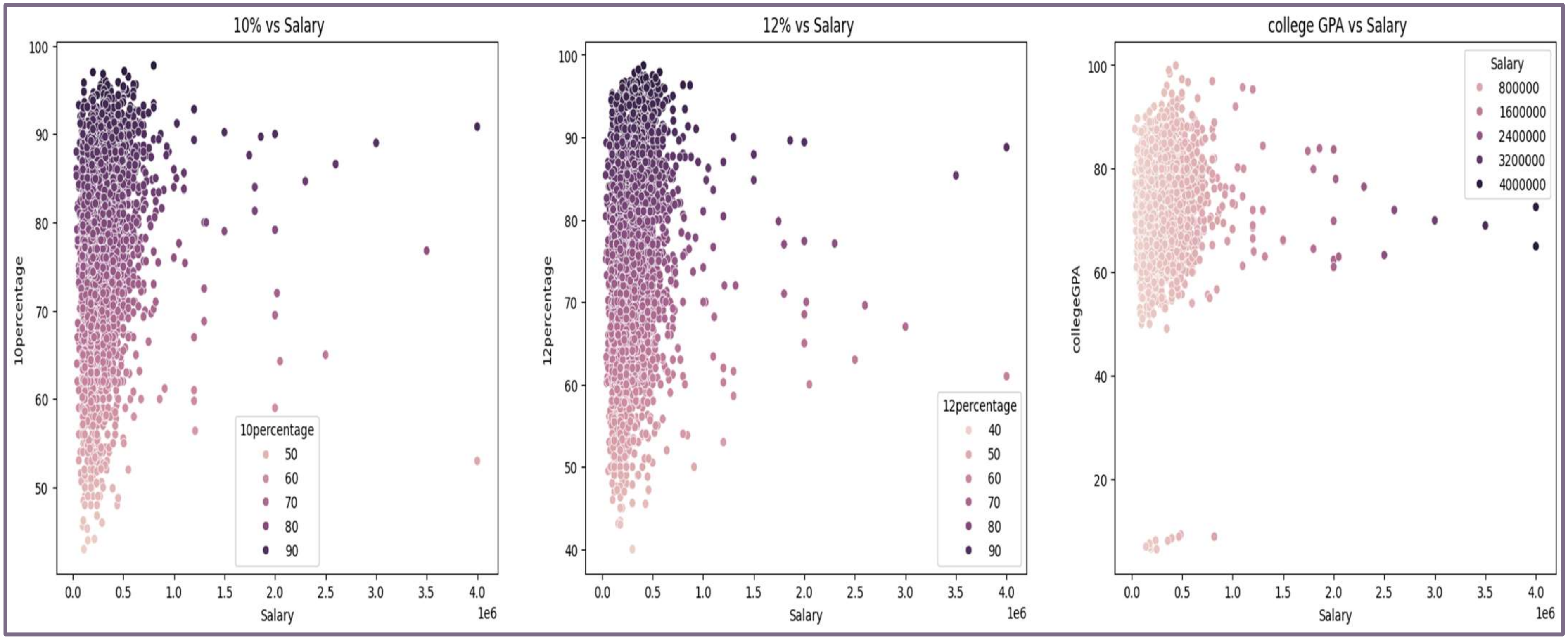
How the 'Salary Distribution Looks'?

- **Salary Ranges from – 35000 to 400000.**
- **Median Salary is 300000.**

TOP 15 Profession based on AMCAT Dataset

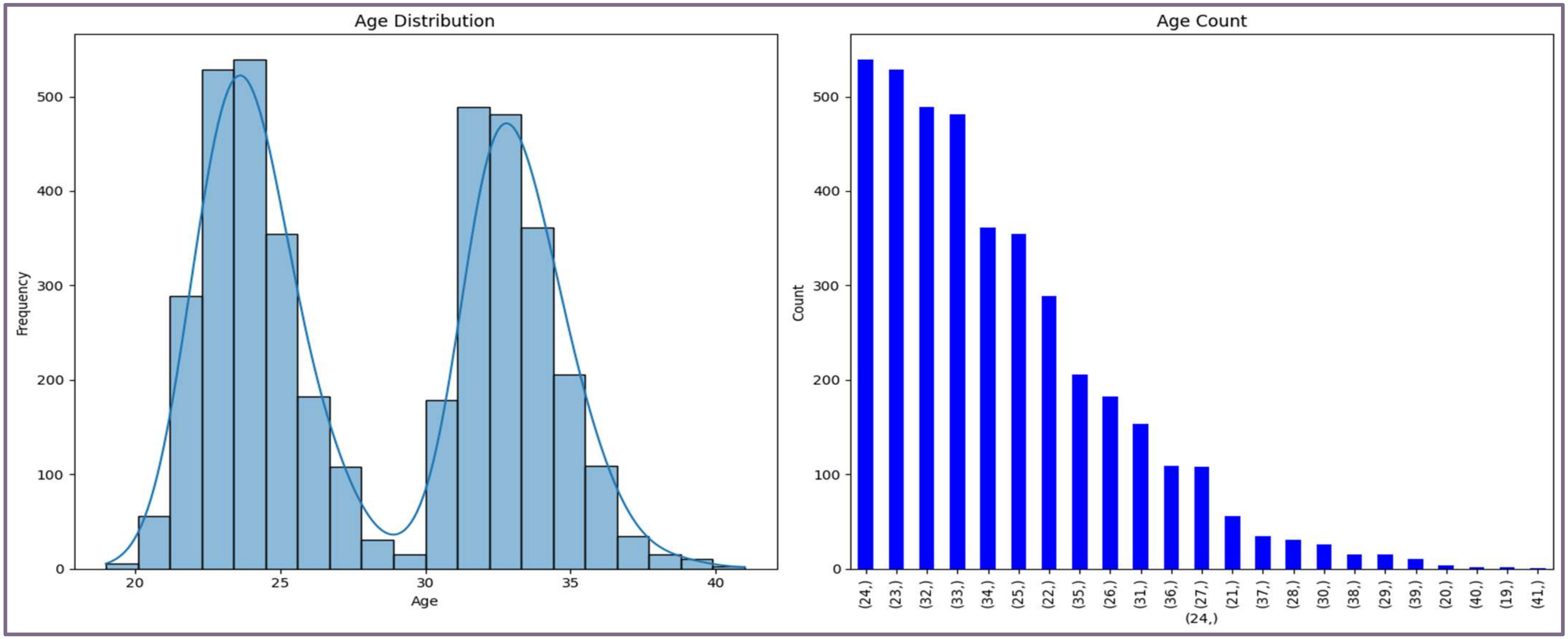


What does “Salary vs Education (Bivariate Analysis)” says?



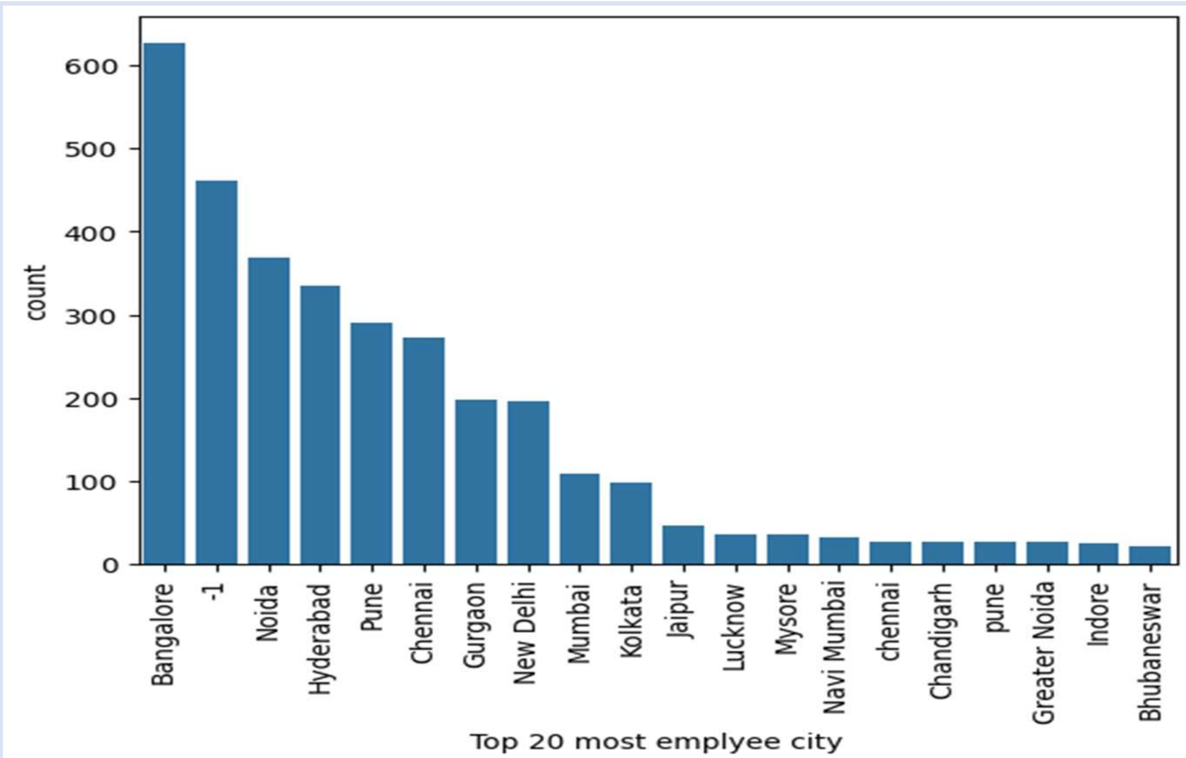
- It clearly shows that Higher education people are earning a good minimum salary that is more than 50k.

What does “Age Analysis ” says?



- The majority of individuals are in the younger age groups, suggesting that the data might represent a population with a relatively young demographic.

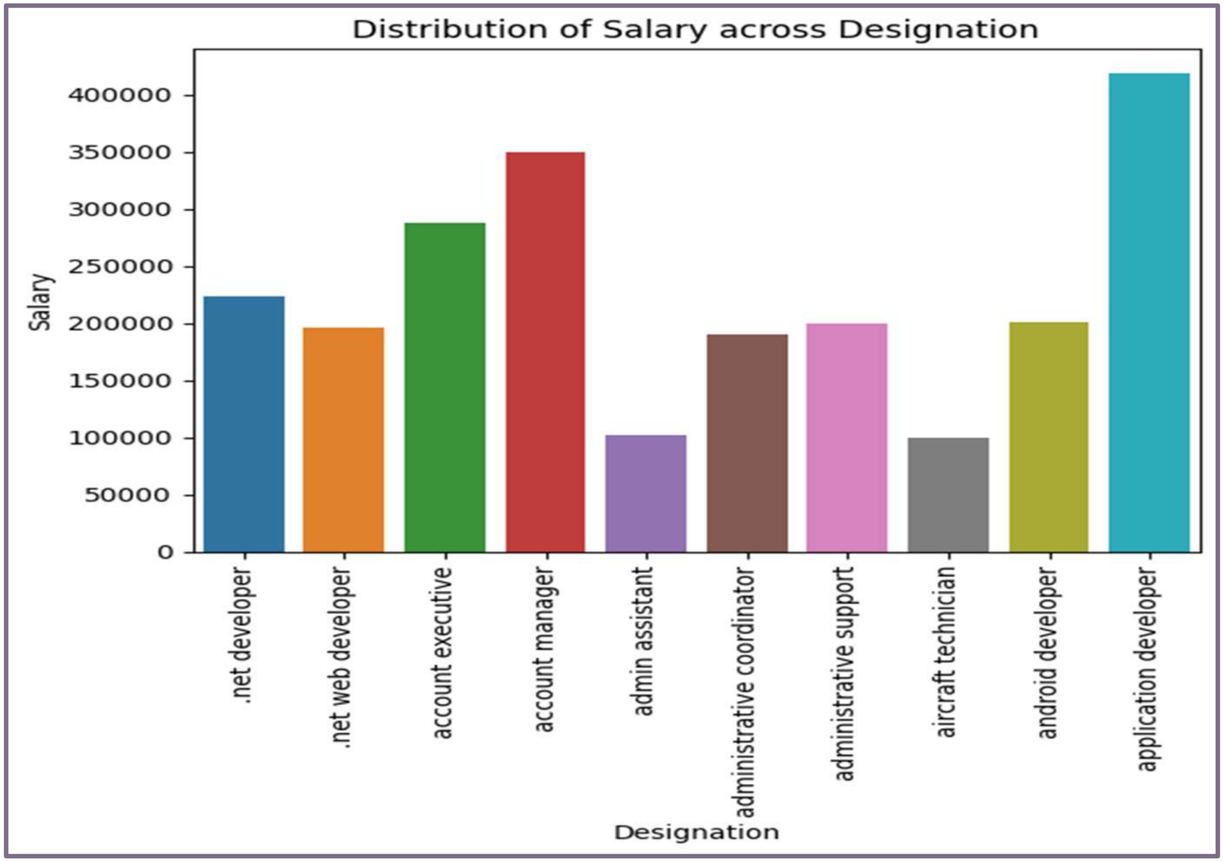
Where job location is more employee of less employee work?



- **The top 5 cities are Bangalore, Noida, Hyderabad, Pune, and Chennai with "Bangalore" having the most number of employees.**

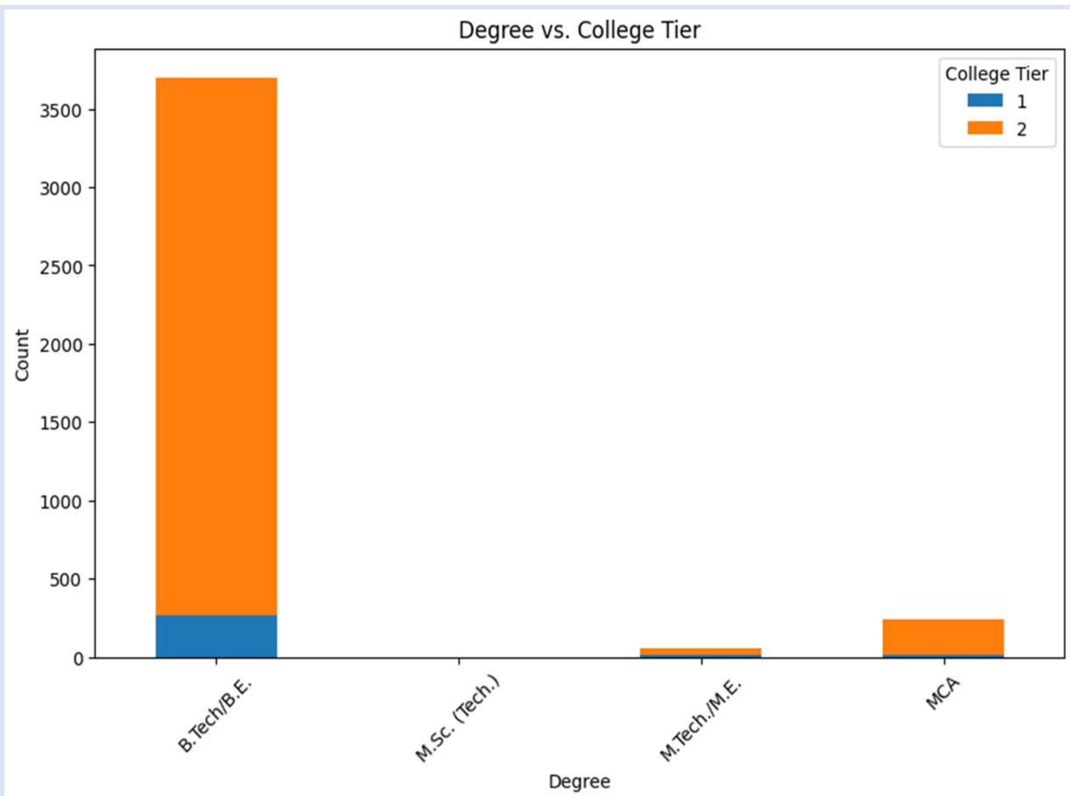
- **"-1" shows that there exist some null values that needs to be refined and cleaned for further processing.**

Does Designation affect Salary?



- **The average salary of “Application Developer” is more compared to other designations.**
- **There are less salaries for admin assistant and aircraft technician.**

Analyze the relationship between the degree obtained and the tier of the college attended using cross-tabulation or stacked bar plots.



- **The majority of students are pursuing B.Tech/B.E. degrees.**
- **The number of students pursuing M.SC.(Tech.) is very low followed by MTech./M.E. and MCA degrees**

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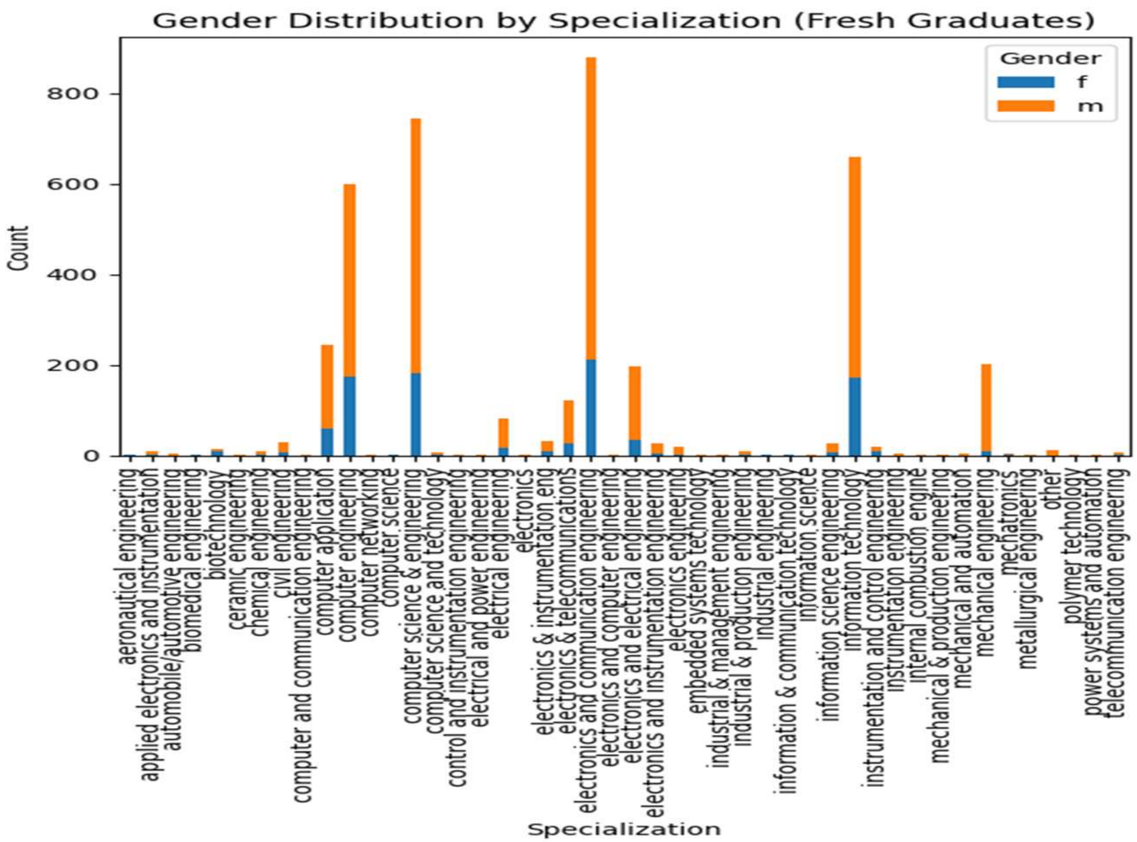
Research Question 1:
Determine whether fresh graduates earn 2.5-3 lakhs annually as stated in the article.

- **The average salary for fresh graduates in the top 10 designations is approximately ₹798,696, with a median of ₹545,000, far exceeding the claimed ₹2.5-3 lakhs.**
- **Statistical analysis strongly rejects the null hypothesis, indicating that the average salary is not within the reported range.**
- **There is no significant relationship between gender and specialization preferences, with a p-value of 0.423, suggesting that gender does not influence specialization choices among graduates.**

Research Question 2:
Determine if gender influences the choice of specialization.



- **The graph shows that most specializations have a higher number of male graduates than female graduates.**
- **There are a few specializations with a higher number of female graduates, but they are outnumbered by those with more male graduates.**
- **The highest number of graduates is in Computer Science and Engineering, followed by Electronics and Communication Engineering.**

Conclusion

The analysis of the AMCAT dataset provides insightful conclusions regarding salary trends, specialization, and skill sets of fresh graduates in different roles. Here are some key takeaway:

- **The average salaries for roles like Programming Analyst, Software Engineer, Hardware Engineer, and Associate Engineer align with industry standards as reported in the Times of India.**
- **Graduates with Computer Science and IT-related specializations tend to command higher salaries, reflecting the strong demand for these skills in the tech industry.**
- **There is an uneven distribution of male and female graduates across different job roles, indicating potential gender biases or disparities in certain specializations and job roles.**
- **Technical skills like programming, computer science, and other related fields are strongly correlated with higher salaries, emphasizing their significance in securing well-paying jobs.**

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THANK YOU

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AMCAT Data Analysis

Loading the required libraries and the dataset (AMCAT_DATA)

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

warnings.filterwarnings('ignore')

PATH = r'/content/drive/MyDrive/Colab
Notebooks/data/Amcat_dataset.xlsx'
amcat_df = pd.read_excel(PATH)

amcat_df.head()
```

{"type":"dataframe","variable_name":"amcat_df"}

```
amcat_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3998 entries, 0 to 3997
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             3998 non-null   object
 1   ID                     3998 non-null   int64
 2   Salary                 3998 non-null   int64
 3   DOJ                    3998 non-null   datetime64[ns]
 4   DOL                    3998 non-null   object
 5   Designation            3998 non-null   object
 6   JobCity                3998 non-null   object
 7   Gender                 3998 non-null   object
 8   DOB                    3998 non-null   datetime64[ns]
 9   10percentage           3998 non-null   float64
 10  10board                3998 non-null   object
 11  12graduation           3998 non-null   int64
 12  12percentage           3998 non-null   float64
 13  12board                3998 non-null   object
 14  CollegeID              3998 non-null   int64
 15  CollegeTier            3998 non-null   int64
 16  Degree                 3998 non-null   object
 17  Specialization         3998 non-null   object
 18  collegeGPA             3998 non-null   float64
```

```
 19  CollegeCityID           3998 non-null   int64
 20  CollegeCityTier         3998 non-null   int64
 21  CollegeState            3998 non-null   object
 22  GraduationYear          3998 non-null   int64
 23  English                 3998 non-null   int64
 24  Logical                 3998 non-null   int64
 25  Quant                   3998 non-null   int64
 26  Domain                  3998 non-null   float64
 27  ComputerProgramming     3998 non-null   int64
 28  ElectronicsAndSemicon   3998 non-null   int64
 29  ComputerScience         3998 non-null   int64
 30  MechanicalEngg          3998 non-null   int64
 31  ElectricalEngg          3998 non-null   int64
 32  TelecomEngg             3998 non-null   int64
 33  CivilEngg               3998 non-null   int64
 34  conscientiousness       3998 non-null   float64
 35  agreeableness           3998 non-null   float64
 36  extraversion            3998 non-null   float64
 37  nueroticism             3998 non-null   float64
 38  openess_to_experience   3998 non-null   float64
dtypes: datetime64[ns](2), float64(9), int64(18), object(10)
memory usage: 1.2+ MB
```

```
amcat_df.shape
```

```
(3998, 39)
```

Data Preparation and Cleaning Stage:

- Check Missing values
- Check Duplicates
- Check Columns
- Check data type
- Check the number of unique values of each column
- Check statistics of data set
- Check various categories present in the different categorical column.
- Drop unnecessary columns

```
# Checking the missing values
amcat_df.isna().sum()
```

```
Unnamed: 0               0
ID                       0
Salary                   0
DOJ                      0
DOL                      0
Designation              0
JobCity                  0
Gender                   0
```

```
DOB                          0
10percentage                 0
10board                      0
12graduation                 0
12percentage                 0
12board                      0
CollegeID                    0
CollegeTier                  0
Degree                       0
Specialization               0
collegeGPA                   0
CollegeCityID                0
CollegeCityTier              0
CollegeState                 0
GraduationYear               0
English                      0
Logical                      0
Quant                        0
Domain                       0
ComputerProgramming          0
ElectronicsAndSemicon        0
ComputerScience              0
MechanicalEngg               0
ElectricalEngg               0
TelecomEngg                  0
CivilEngg                    0
conscientiousness            0
agreeableness                0
extraversion                 0
nueroticism                  0
openess_to_experience        0
dtype: int64
```

```
# Checking Duplicates
amcat_df.duplicated().sum()
```

```
0
```

```
# Checking the columns
amcat_df.columns
```

```
Index(['Unnamed: 0', 'ID', 'Salary', 'DOJ', 'DOL', 'Designation',
'JobCity',
       'Gender', 'DOB', '10percentage', '10board', '12graduation',
       '12percentage', '12board', 'CollegeID', 'CollegeTier',
'Degree',
       'Specialization', 'collegeGPA', 'CollegeCityID',
'CollegeCityTier',
       'CollegeState', 'GraduationYear', 'English', 'Logical',
'Quant',
```

```
       'Domain', 'ComputerProgramming', 'ElectronicsAndSemicon',
       'ComputerScience', 'MechanicalEngg', 'ElectricalEngg',
'TelecomEngg',
       'CivilEngg', 'conscientiousness', 'agreeableness',
'extraversion',
       'nueroticism', 'openess_to_experience'],
      dtype='object')
```

```
# Removing the 'Unnamed: 0' column
amcat_df.drop('Unnamed: 0',axis=1, inplace=True)
amcat_df.head()
```

{"type":"dataframe","variable_name":"amcat_df"}

```
# checking the datatypes
amcat_df.dtypes
```

```
ID                                 int64
Salary                             int64
DOJ                       datetime64[ns]
DOL                               object
Designation                       object
JobCity                           object
Gender                            object
DOB                       datetime64[ns]
10percentage                     float64
10board                           object
12graduation                       int64
12percentage                     float64
12board                           object
CollegeID                          int64
CollegeTier                        int64
Degree                            object
Specialization                    object
collegeGPA                       float64
CollegeCityID                      int64
CollegeCityTier                    int64
CollegeState                      object
GraduationYear                     int64
English                            int64
Logical                            int64
Quant                              int64
Domain                           float64
ComputerProgramming                int64
ElectronicsAndSemicon              int64
ComputerScience                    int64
MechanicalEngg                     int64
ElectricalEngg                     int64
TelecomEngg                        int64
CivilEngg                          int64
```

```
conscientiousness                float64
agreeableness                    float64
extraversion                     float64
nueroticism                      float64
openess_to_experience            float64
dtype: object
```

```python
# Counting the number of values in each column
count_data_columns = {}

for column in amcat_df.columns:
    unique_values = amcat_df[column].nunique()
    count_data_columns[column] = unique_values

for idx, element in count_data_columns.items():
  print(f"{idx}: {element}")
```

```
ID: 3998
Salary: 177
DOJ: 81
DOL: 67
Designation: 419
JobCity: 339
Gender: 2
DOB: 1872
10percentage: 851
10board: 275
12graduation: 16
12percentage: 801
12board: 340
CollegeID: 1350
CollegeTier: 2
Degree: 4
Specialization: 46
collegeGPA: 1282
CollegeCityID: 1350
CollegeCityTier: 2
CollegeState: 26
GraduationYear: 11
English: 111
Logical: 107
Quant: 138
Domain: 243
ComputerProgramming: 79
ElectronicsAndSemicon: 29
ComputerScience: 20
MechanicalEngg: 42
ElectricalEngg: 31
TelecomEngg: 26
CivilEngg: 23
```

```
conscientiousness: 141
agreeableness: 149
extraversion: 154
nueroticism: 217
openess_to_experience: 142
```

```
# Check the statistical measures of dataset
amcat_df.describe().T
```


{"summary":"{\n \"name\": \"amcat_df\",\n \"rows\": 29,\n
\"fields\": [\n   {\n   \"column\": \"count\",\n
\"properties\": {\n   \"dtype\": \"date\",\n   \"min\":
3998.0,\n   \"max\": 3998.0,\n   \"num_unique_values\": 1,\n
\"samples\": [\n   3998.0\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"mean\",\n   \"properties\": {\n
\"dtype\": \"date\",\n   \"min\": \"1970-01-01 00:00:00\",\n
\"max\": \"2013-07-02 11:04:10.325162496\",\n
\"num_unique_values\": 28,\n   \"samples\": [\n
71.48617058529265\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"min\",\n   \"properties\": {\n   \"dtype\": \"date\",\n
\"min\": \"1969-12-31 23:59:59.999999993\",\n   \"max\": \"1991-
06-01 00:00:00\",\n   \"num_unique_values\": 20,\n
\"samples\": [\n   11244.0\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"25%\",\n   \"properties\": {\n
\"dtype\": \"date\",\n   \"min\": \"1969-12-31
23:59:59.999999999\",\n   \"max\": \"2012-10-01 00:00:00\",\n
\"num_unique_values\": 23,\n   \"samples\": [\n
0.342314899911815\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"50%\",\n   \"properties\": {\n   \"dtype\": \"date\",\n
\"min\": \"1969-12-31 23:59:59.999999999\",\n   \"max\": \"2013-
11-01 00:00:00\",\n   \"num_unique_values\": 23,\n
\"samples\": [\n   0.622642915849938\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"75%\",\n   \"properties\": {\n
\"dtype\": \"date\",\n   \"min\": \"1969-12-31
23:59:59.999999999\",\n   \"max\": \"2014-07-01 00:00:00\",\n
\"num_unique_values\": 24,\n   \"samples\": [\n   2.0\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"max\",\n   \"properties\": {\
n   \"dtype\": \"date\",\n   \"min\": \"1970-01-01
00:00:00\",\n   \"max\": \"2015-12-01 00:00:00\",\n
\"num_unique_values\": 28,\n   \"samples\": [\n   99.93\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"std\",\n   \"properties\": {\
n   \"dtype\": \"date\",\n   \"min\": 0.26227041182048033,\n
\"max\": 363218.2458286372,\n   \"num_unique_values\": 26,\n

```
\"samples\": [\n          0.45848936661000644\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe"}
```



```
# Drop unnecessary columns
amcat_df = amcat_df.drop(columns=['ID','CollegeID','CollegeCityID'])
amcat_df.head()
```



```
{"type":"dataframe","variable_name":"amcat_df"}
```



```
def datatype_of_cols(df):
  # Check various categories present in the different categorical
column
  # define numerical and catagorical columns
  numerical_columns= [feature for feature in df.columns if
amcat_df[feature].dtypes != 'O']
  categorical_columns = [feature for feature in df.columns if
amcat_df[feature].dtypes =='O']
  print(f"Number of numerical columns are {len(numerical_columns)}.")
  print(f"Number of categorical columns are
{len(categorical_columns)}.")

datatype_of_cols(amcat_df)
```

```
Number of numerical columns are 26.
Number of categorical columns are 9.
```

Univariate Analysis

Question : What is the distribution of Salary?

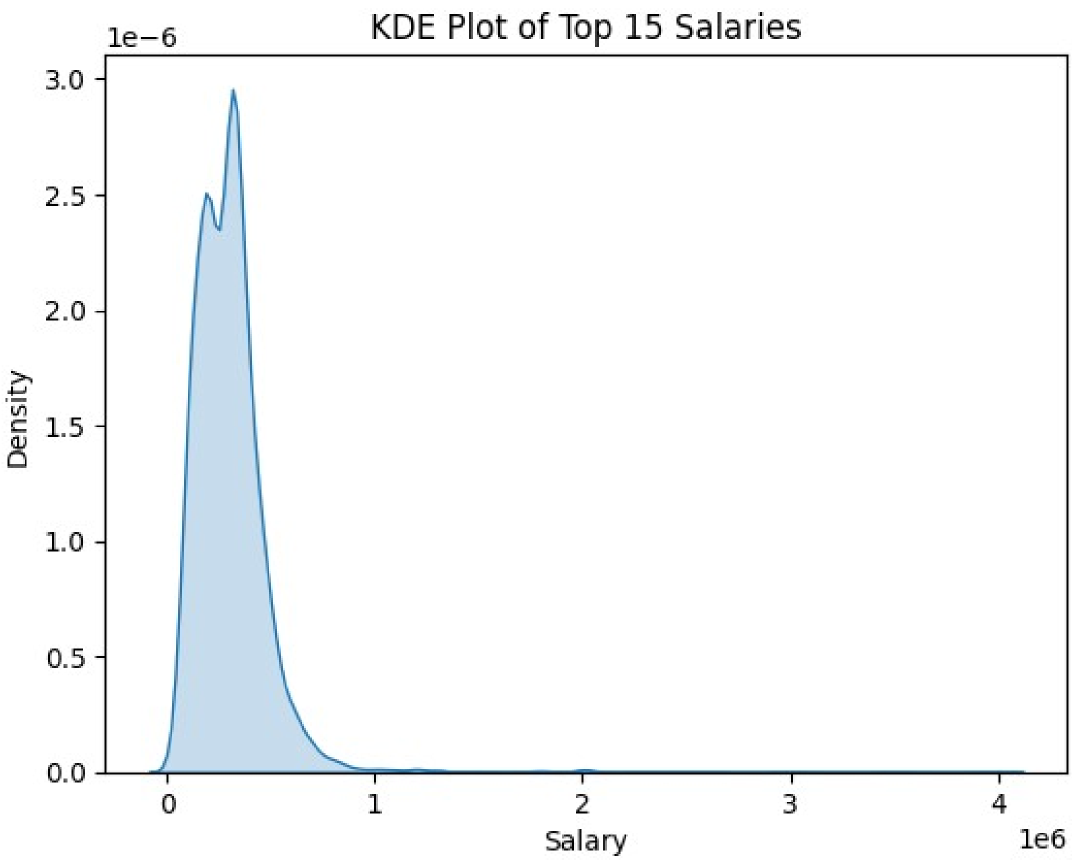
```
amcat_df['Salary'].describe().T
```

```
count    3.998000e+03
mean     3.076998e+05
std      2.127375e+05
min      3.500000e+04
25%      1.800000e+05
50%      3.000000e+05
75%      3.700000e+05
max      4.000000e+06
Name: Salary, dtype: float64
```

Exploring Data (Visualization)

- Visualize average score distribution to make some conclusion using various plots like Histogram or Kernel Distribution Function (KDE).
- The KDE plot helps us understand the distribution pattern of these top salaries.

```
# Plotting the Salary to see the salary distribution.
# Create a KDE plot
sns.kdeplot(amcat_df['Salary'], shade=True)

# Add labels and title
plt.xlabel('Salary')
plt.ylabel('Density')
plt.title('KDE Plot of Top 15 Salaries')

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

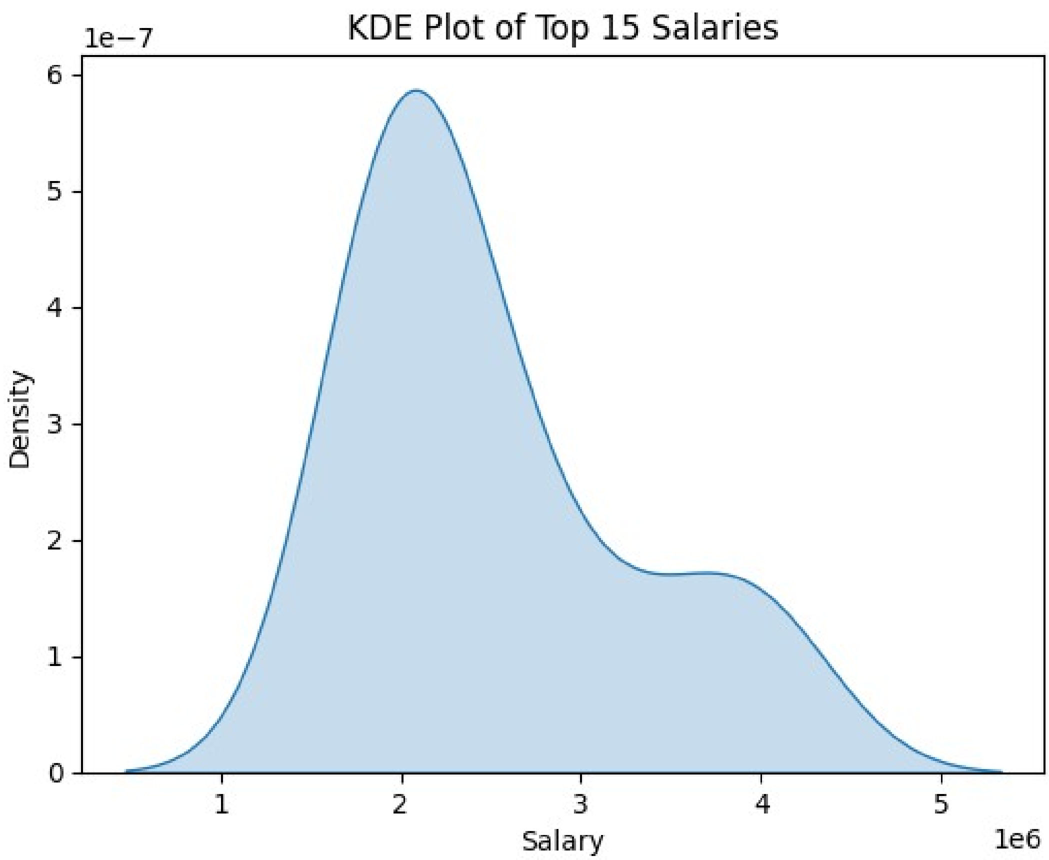


Key Insights:

- In between 0 to 100000 the salaries are more compared to other salaries.
- After 300000 there are less salries.

```
# Let's further explore the Salary column.
# Sort the Salary column in descending order and select the top 15
values
top_15_salaries =
amcat_df['Salary'].sort_values(ascending=False).head(15)
```

```
# Convert salary to millions
top_15_salaries_in_millions = top_15_salaries

# Create a KDE plot
sns.kdeplot(top_15_salaries_in_millions, shade=True)

# Add labels and title
plt.xlabel('Salary')
plt.ylabel('Density')
plt.title('KDE Plot of Top 15 Salaries')

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

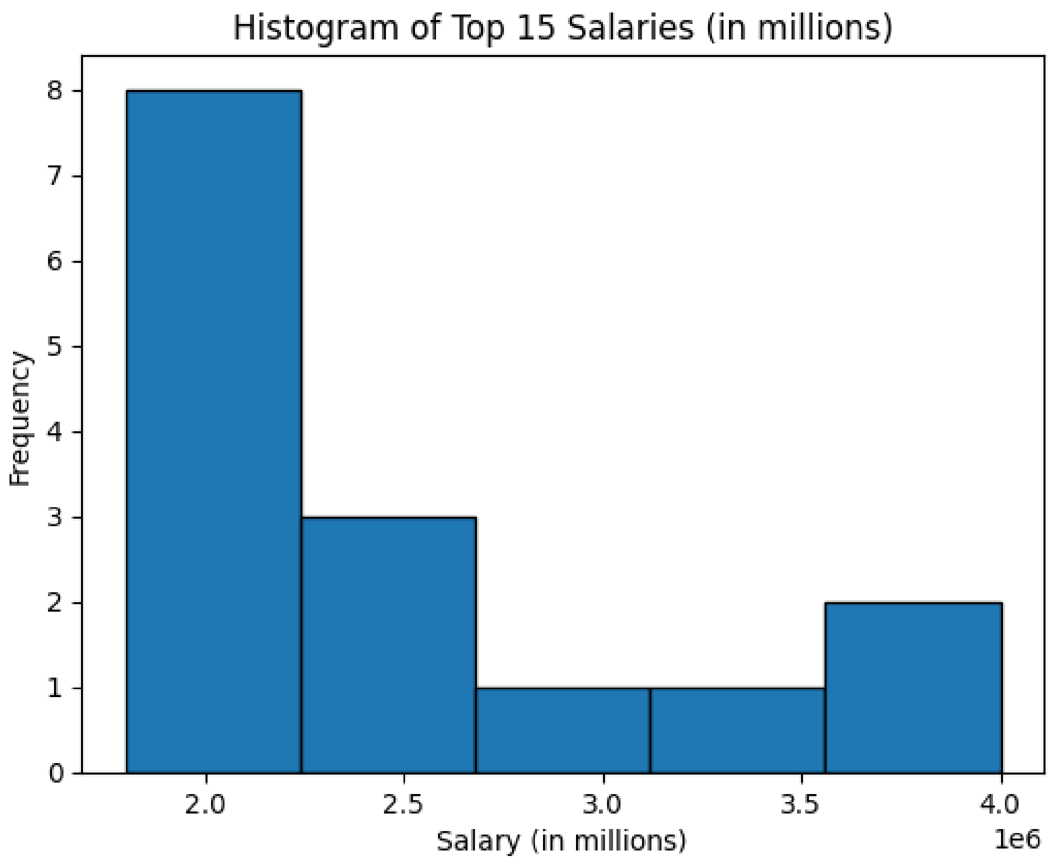


Key Insights:

- The majority of the top 15 salaries are around 2 million (highest peak).
- There are fewer people earning higher salaries closer to 5 million, as indicated by the decreasing tail on the right.

```
# Create a histogram
plt.hist(top_15_salaries_in_millions, bins=5, edgecolor='black')

# Add labels and title
```

```
plt.xlabel('Salary (in millions)')
plt.ylabel('Frequency')
plt.title('Histogram of Top 15 Salaries (in millions)')

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

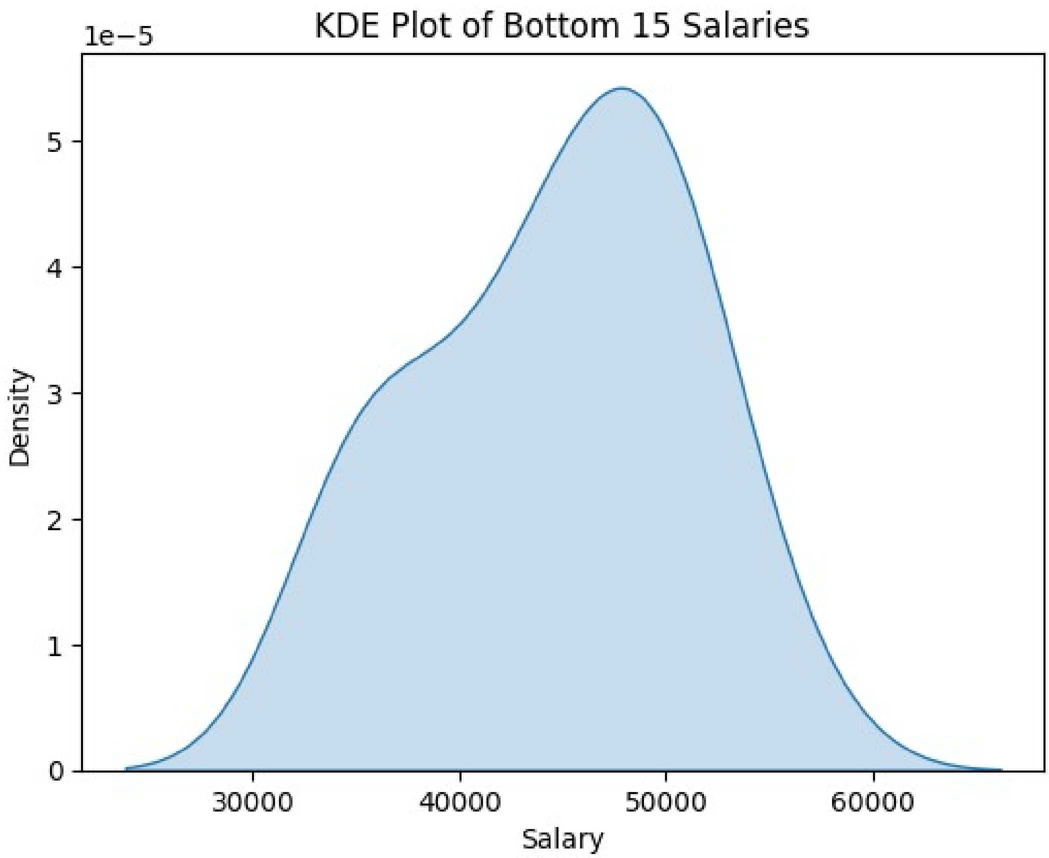


Key Insights:

- Above histogram is also stating that the out of top 15 people, most of them are earning around 2 million to 2.5 million.

```
# Sort the Salary column in descending order and select the bottom 15
values
bottom_15_salaries =
amcat_df['Salary'].sort_values(ascending=True).head(15)

# Create a KDE plot
sns.kdeplot(bottom_15_salaries, shade=True)

# Add labels and title
plt.xlabel('Salary')
plt.ylabel('Density')
plt.title('KDE Plot of Bottom 15 Salaries')
```

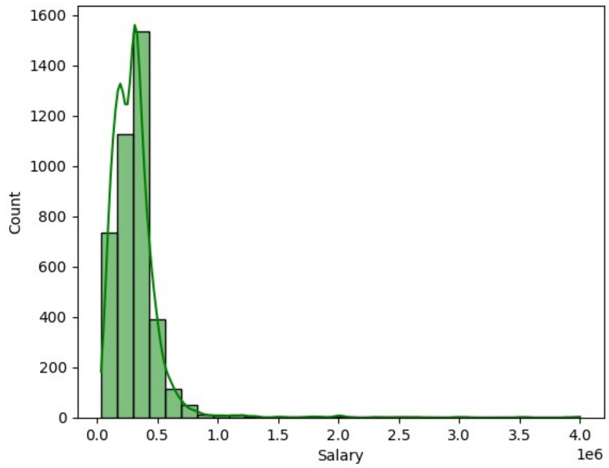
```
# Display the plot
plt.show()
```

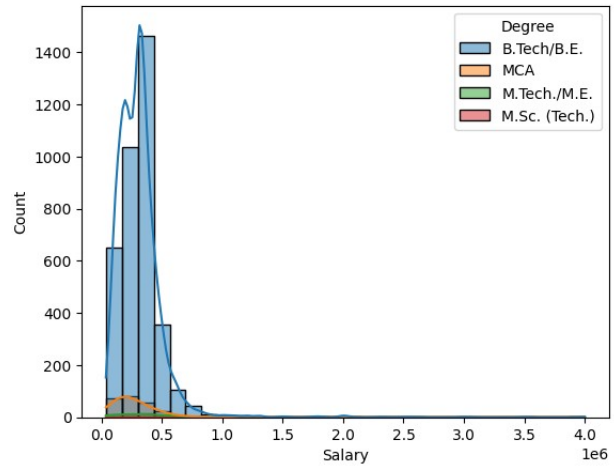


Insights:

- The majority of the bottom 15 salaries are clustered around 50,000.
- There is a decent range from 30,000 to 65,000, but no extreme low-end salaries in this dataset.
- The data shows a smooth distribution with a slight right skew, meaning the very lowest salaries are less common compared to those closer to the middle of the bottom 15 range.

```
# Plotting the diagram to see compare Salary and Degree Column
fig, axs = plt.subplots(1,2, figsize=(14, 5))
plt.subplot(121)
sns.histplot(data=amcat_df, x='Salary',bins=30,kde=True, color='g')
plt.subplot(122)
sns.histplot(data=amcat_df, x='Salary',bins=30, kde=True,
hue='Degree')

plt.show()
```



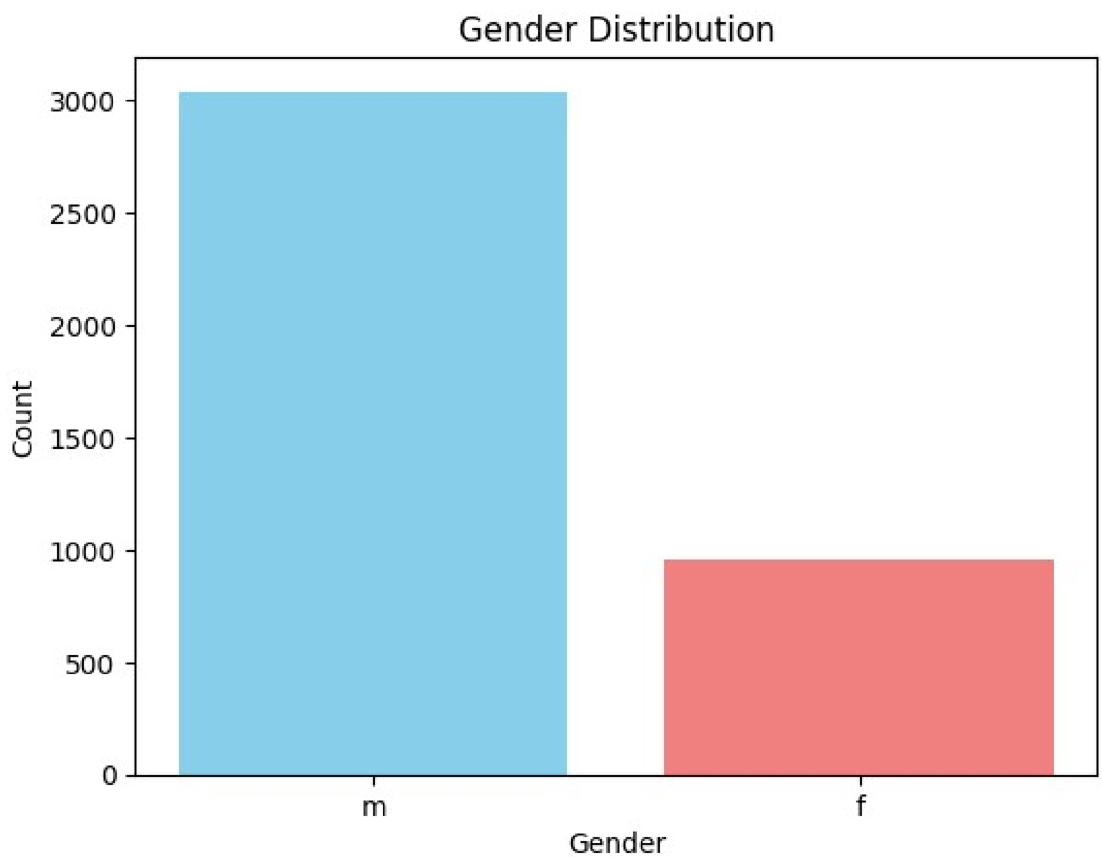


Key Insights:

- B.Tech students has a higher salary other Degree persons.

Question: What is the relationship between gender and employment?

```
# Plotting Gender column and discovering the relationship between
gender and employment.
colors = ['skyblue', 'lightcoral']
plt.bar(amcat_df['Gender'].value_counts().index,
amcat_df['Gender'].value_counts().values, color=colors)
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Gender Distribution')
plt.show()
print(amcat_df['Gender'].value_counts())
```

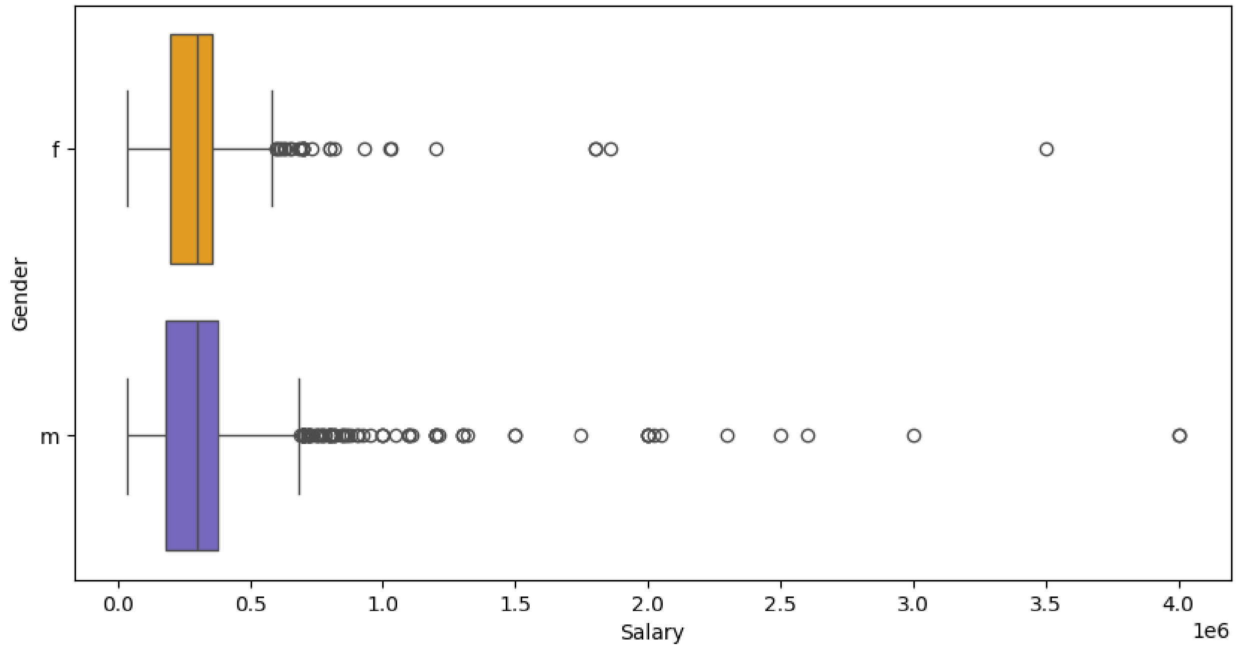



```
Gender
m    3041
f     957
Name: count, dtype: int64
```

Key Insights:

- The ratio of m/f is 3.19 indicates there are 3 times more men than women employed.

```
# Plotting box plot for Gender column.
plt.figure(figsize=(10,5))
sns.boxplot(x='Salary',y='Gender',data=amcat_df,
palette=['orange','slateblue'])
plt.show()
```



Key Insights:

- It is observed that there are many outliers in the salary column.
- There is not much difference between median salary for both genders.
- We can also observe male have more outliers indicating that male are earning more than female.

Question: What is the average collegeGPA of students?

Answer: Average College GPA: 71.49

```
average_college_gpa = amcat_df["collegeGPA"].mean()
print("Average College GPA: {:.2f}".format(average_college_gpa))

Average College GPA: 71.49
```

1. Salary Distribution:

Analyze the distribution of salaries to understand the range, mean, median, and variability. Look for any outliers or patterns.

```
data = amcat_df.copy()
print(f"The Salary ranges from {data['Salary'].min()} to
{data['Salary'].max()}.")
print(f"The Average / Mean salary is {data['Salary'].mean():.2f}.")
print(f"The Median salary is {data['Salary'].median()}.")
```

```
The Salary ranges from 35000 to 4000000.
The Average / Mean salary is 307699.85.
The Median salary is 300000.0.
```

```
# Filter the 'Salary' column within the specified range
# salary_filtered = data[(data['Salary'] >= 35000) & (data['Salary']
<= 4000000)]['Salary']/100000

# Create a box plot for the filtered 'Salary' column
plt.figure(figsize=(8, 6))
plt.boxplot(data['Salary']/100000, vert=False)
plt.xlabel('Salary')
plt.title('Interquartile Range (IQR) for Salary')
plt.show()
```

Key Insights:

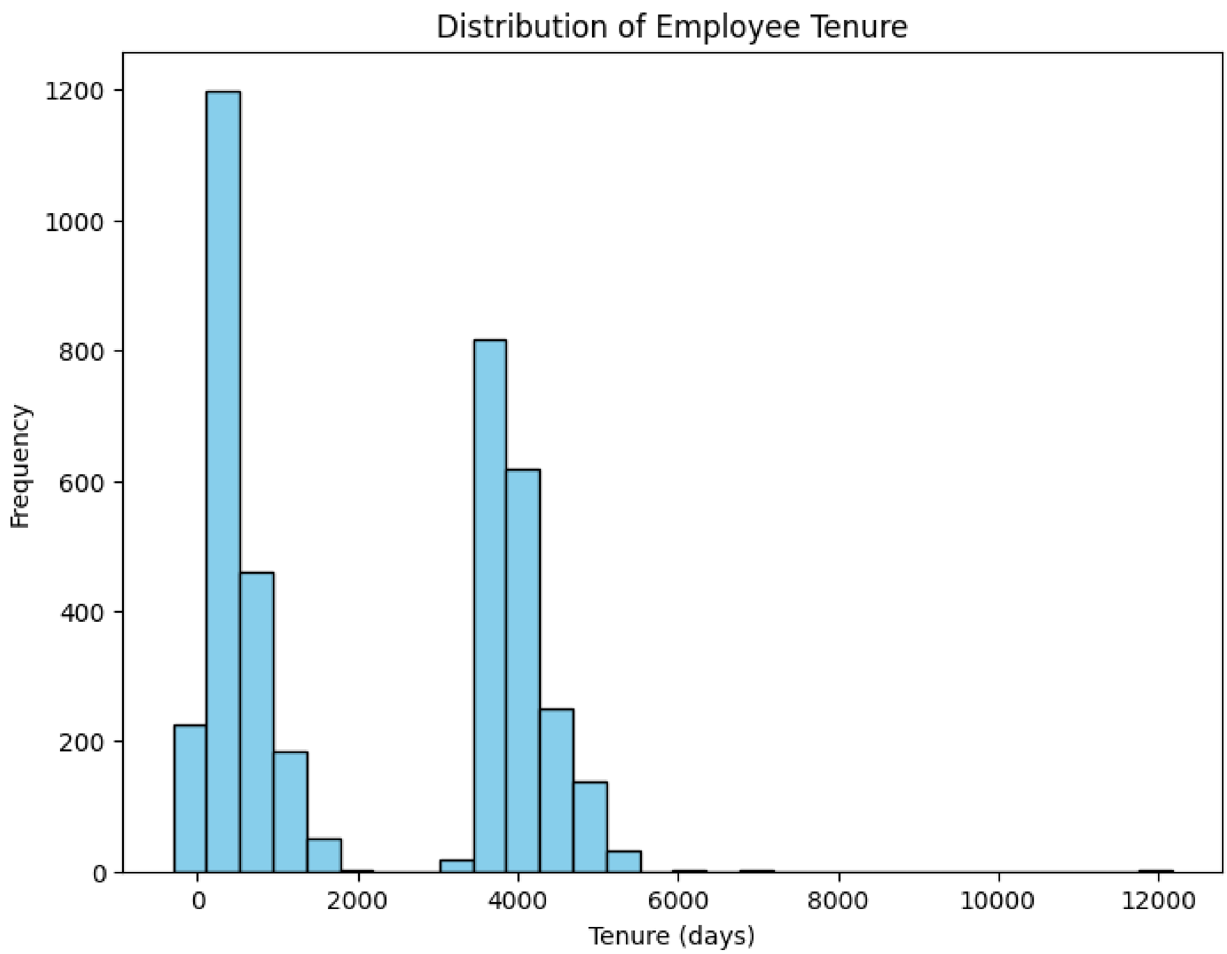
- Most of the people salaries lies between 0 to 10.
- Very few people has high package between 20 to 40.

2. Joining and Leaving Patterns:

- Explore the 'DOJ' (Date of Joining) and 'DOL' (Date of Leaving) columns to identify patterns in employee tenure.
- Calculate the average tenure and look for trends over time.

```
# Convert the 'DOJ' and 'DOL' columns to datetime format
print(data['DOJ'].dtype)
print(data['DOL'].dtype)
# change the data1 type
data['DOJ'] = pd.to_datetime(data['DOJ'],format='%m/%d/%Y %I:%M:%S
%p')
#1st time show error because in data1 is present object so we change
it
# Now date
data['DOL']= data['DOL'].replace('present',pd.to_datetime('today'))
data['DOL'] = pd.to_datetime(data['DOL'])

print(data['DOJ'].dtype)
print(data['DOL'].dtype)

# print(data1[['DOJ','DOL']])
data['Tenure'] = (data['DOL']- data['DOJ']).dt.days
# print(data1['Tenure'])

# Calculate tenure for employees still with the company (up to current
date)
current_date = pd.to_datetime('today')
data.loc[data['DOL'].isna(), 'Tenure'] = (current_date -
data['DOJ']).dt.days

# Explore tenure distribution
plt.figure(figsize=(8, 6))
plt.hist(data['Tenure'].dropna(), bins=30, color='skyblue',
edgecolor='black')
plt.xlabel('Tenure (days)')
plt.ylabel('Frequency')
plt.title('Distribution of Employee Tenure')
plt.show()
```

```
datetime64[ns]
object
datetime64[ns]
datetime64[ns]
```



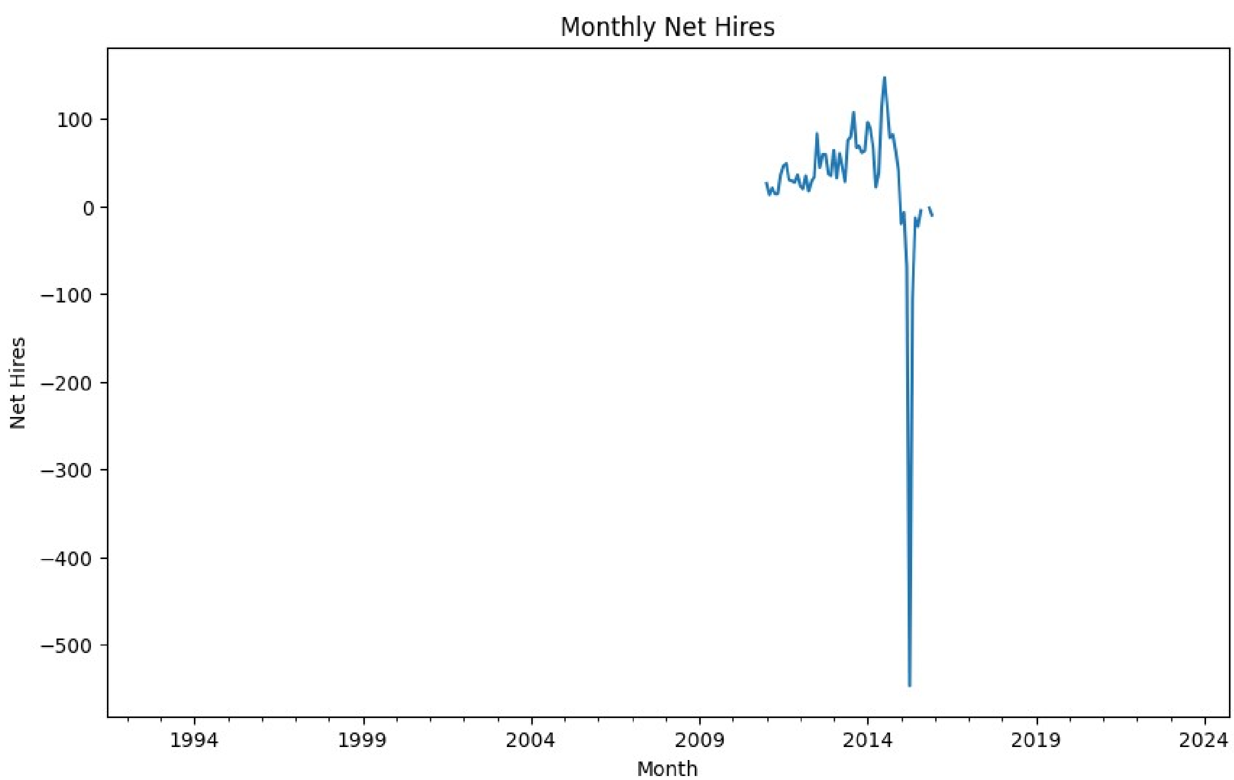
Key Insights:

- Most employees have a tenure of less than 2000 days.
- There is a second peak in the distribution between 3000 and 4000 days. This suggests that there is another group of employees who have been with the company for a significant amount of time, but not as long as the first group.
- The distribution has a long tail to the right. This indicates that there are a small number of employees who have been with the company for a very long time.
- The overall shape of the distribution is skewed to the right. This means that there are more employees with shorter tenures than longer tenures.

```
# Calculate summary statistics
mean_tenure = data['Tenure'].mean()
median_tenure = data['Tenure'].median()
mode_tenure = data['Tenure'].mode()[0]
print(f"Mean Tenure: {mean_tenure:.2f} days")
print(f"Median Tenure: {median_tenure:.2f} days")
print(f"Mode Tenure: {mode_tenure:.2f} days")
```

```
# Analyze trends over time
monthly_hires =
data['DOJ'].dt.to_period('M').value_counts().sort_index()
monthly_exits =
data['DOL'].dt.to_period('M').value_counts().sort_index()
monthly_net_hires = monthly_hires - monthly_exits
monthly_net_hires.plot(kind='line', figsize=(10, 6))
plt.xlabel('Month')
plt.ylabel('Net Hires')
plt.title('Monthly Net Hires')
plt.show()

# Calculate attrition rate
total_employees = len(data)
total_exits = len(data.dropna(subset=['DOL']))
attrition_rate = (total_exits / total_employees) * 100
print(f"Attrition Rate: {attrition_rate:.2f}%")
```

```
Mean Tenure: 2130.06 days
Median Tenure: 1157.50 days
Mode Tenure: 365.00 days
```




```
Attrition Rate: 100.00%
```

Key Insights:

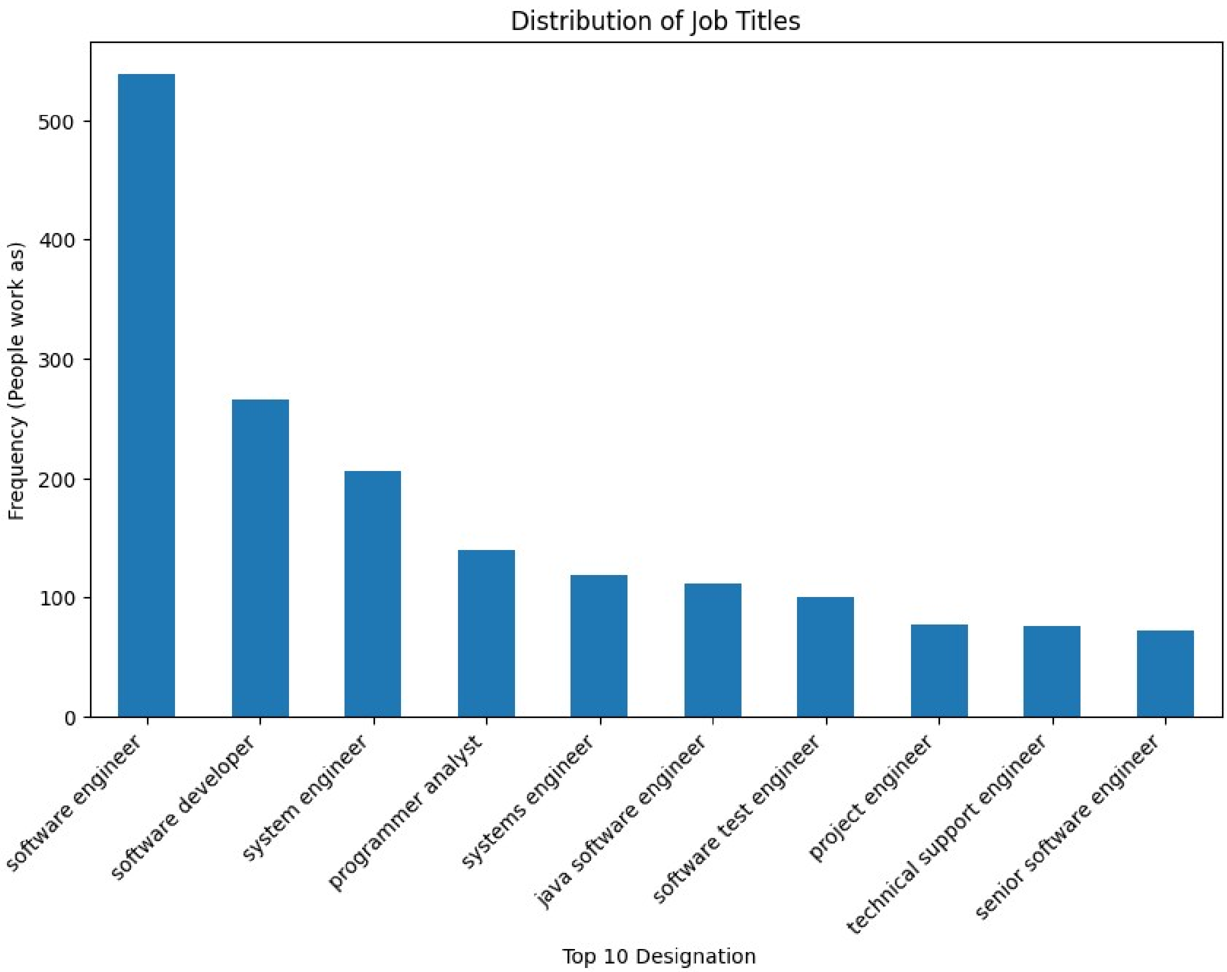
- The average employee has been with the company for just over 5.8 years.
- Median (1157.50 days): Half of the employees have been with the company for less than 3.2 years, and half have been with the company for more than 3.2 years.
- Mode (365.00 days): The most common tenure is exactly one year.

3. Designation Distribution:

- Investigate the distribution of job titles ('Designation') to understand the hierarchy and structure of the organization

```
# Count the frequency of each job title
designation_counts = data['Designation'].value_counts()

# Print the top 10 most common job titles
print("Top 10 Most Common Job Titles:")
print(designation_counts.head(10))

# Plot the distribution of job titles
plt.figure(figsize=(10, 6))
designation_counts[:10].plot(kind='bar')
plt.xlabel(' Top 10 Designation')
plt.ylabel('Frequency (People work as)')
plt.title('Distribution of Job Titles')
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better
readability
plt.show()
```

```
Top 10 Most Common Job Titles:
Designation
software engineer           539
software developer          265
system engineer             205
programmer analyst          139
systems engineer            118
java software engineer      111
software test engineer      100
project engineer             77
technical support engineer   76
senior software engineer     72
Name: count, dtype: int64
```



Key Insights:

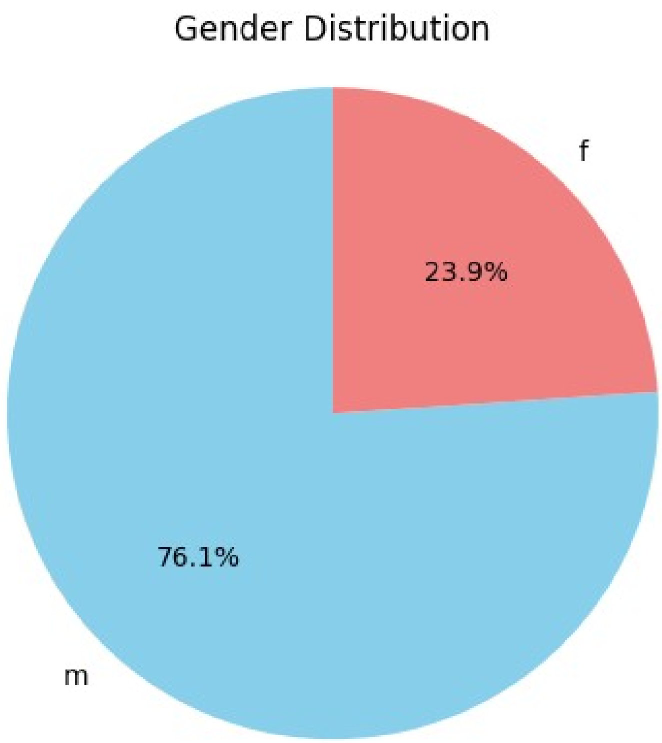
- Above plot suggests that, maximum number of people are `Software Developer`.
- Few people are at the `Senior Software Engineer` position.
- Also, most of the people are working in the IT industry.

4. Gender Distribution:

- Examine the distribution of employees by gender ('Gender') to understand gender diversity within the organization.

```
# Get gender counts
gender_counts = data['Gender'].value_counts()

# Define colors (replace with desired colors)
colors = ['skyblue', 'lightcoral']

# Create the pie chart
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%',
startangle=90, colors=colors)
```

```
plt.title('Gender Distribution')
plt.axis('equal')  # Equal aspect ratio ensures a circular pie chart
plt.show()
```



Key Insights:

- The chart indicates that 76.1% of the population is male, while only 23.9% is female.
- Gender disparity: The distribution is not evenly balanced, highlighting a potential gender gap or disparity within the population.

5. Educational Background:

- Analyze '10percentage' and '12percentage' to understand the academic performance of employees in high school.
- Explore 'Degree' and 'Specialization' to understand the educational background of employees.
- Investigate 'CollegeTier' to understand the quality of colleges attended by employees.

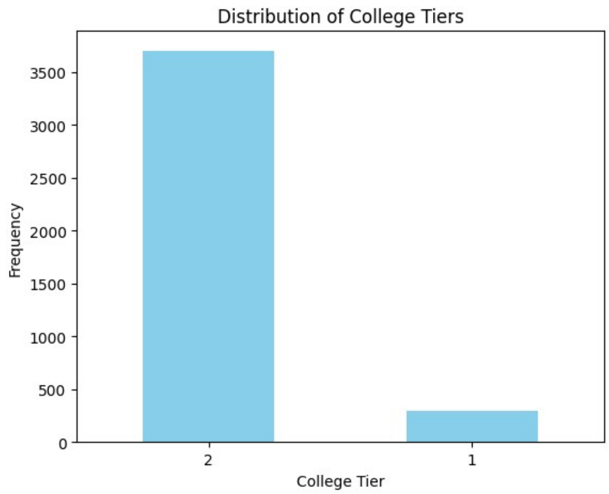
```
# Analyze high school academic performance
high_school_performance = data[['10percentage', '12percentage']]
print("Summary statistics for high school academic performance:")
print(high_school_performance.describe())

# Explore educational qualifications
degree_counts = data['Degree'].value_counts()
```

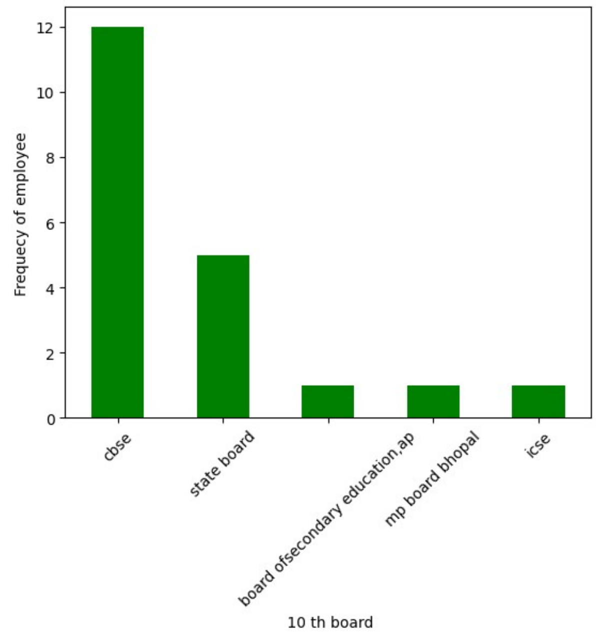
```
print("\nDistribution of educational degrees:")
print(degree_counts)

# Analyze field of study/specialization
specialization_counts = data['Specialization'].value_counts()
print("\nDistribution of specializations:")
print(specialization_counts)

# Investigate college quality
college_tier_counts = data['CollegeTier'].value_counts()
print("\nDistribution of college tiers:")
print(college_tier_counts)

# Plotting college tier distribution
fig, axs =plt.subplots(1,3, figsize=(14,5))
plt.subplot(121)
college_tier_counts.plot(kind='bar', color='skyblue')
plt.xlabel('College Tier')
plt.ylabel('Frequency')
plt.title('Distribution of College Tiers')
plt.xticks(rotation=0)

board10th =data['10board'][:20].value_counts()
plt.subplot(122)
board10th.plot(kind='bar',color='green')
plt.xlabel(' 10 th board')
plt.ylabel("Frequecy of employee")
plt.xticks(rotation =45)

plt.show()
```

```
Summary statistics for high school academic performance:
       10percentage  12percentage
count   3998.000000   3998.000000
mean      77.925443     74.466366
std        9.850162     10.999933
min       43.000000     40.000000
25%       71.680000     66.000000
50%       79.150000     74.400000
75%       85.670000     82.600000
max       97.760000     98.700000

Distribution of educational degrees:
Degree
B.Tech/B.E.      3700
MCA               243
M.Tech./M.E.       53
M.Sc. (Tech.)       2
Name: count, dtype: int64
```

```
Distribution of specializations:
Specialization
electronics and communication engineering      880
computer science & engineering                 744
information technology                         660
computer engineering                           600
computer application                           244
mechanical engineering                         201
electronics and electrical engineering         196
electronics & telecommunications               121
electrical engineering                          82
electronics & instrumentation eng               32
civil engineering                               29
electronics and instrumentation engineering     27
information science engineering                 27
instrumentation and control engineering         20
electronics engineering                         19
biotechnology                                   15
other                                           13
industrial & production engineering             10
applied electronics and instrumentation          9
chemical engineering                             9
computer science and technology                  6
telecommunication engineering                    6
mechanical and automation                        5
automobile/automotive engineering                5
instrumentation engineering                      4
mechatronics                                     4
aeronautical engineering                         3
electronics and computer engineering             3
electrical and power engineering                 2
biomedical engineering                           2
information & communication technology           2
industrial engineering                           2
computer science                                 2
metallurgical engineering                        2
power systems and automation                     1
control and instrumentation engineering          1
mechanical & production engineering              1
embedded systems technology                      1
polymer technology                               1
computer and communication engineering           1
information science                              1
internal combustion engine                       1
computer networking                              1
ceramic engineering                              1
electronics                                      1
industrial & management engineering              1
Name: count, dtype: int64
```

```
Distribution of college tiers:
CollegeTier
2    3701
1     297
Name: count, dtype: int64
```





Key Insights:

1. College Tier

- The majority of employees (around 3500) belong to college tier 2, while a smaller number (approximately 300) belong to tier 1.
- Skewed Distribution: The distribution is skewed to the right, indicating that there are a few employees in higher tiers, but the majority are concentrated in tier 2.

2. 10th Board

- CBSE (Central Board of Secondary Education) appears to be the most common board with a significantly higher frequency compared to other boards.
- State boards and other regional boards have lower frequencies, suggesting that a smaller proportion of employees come from these backgrounds.

6. Age analysis

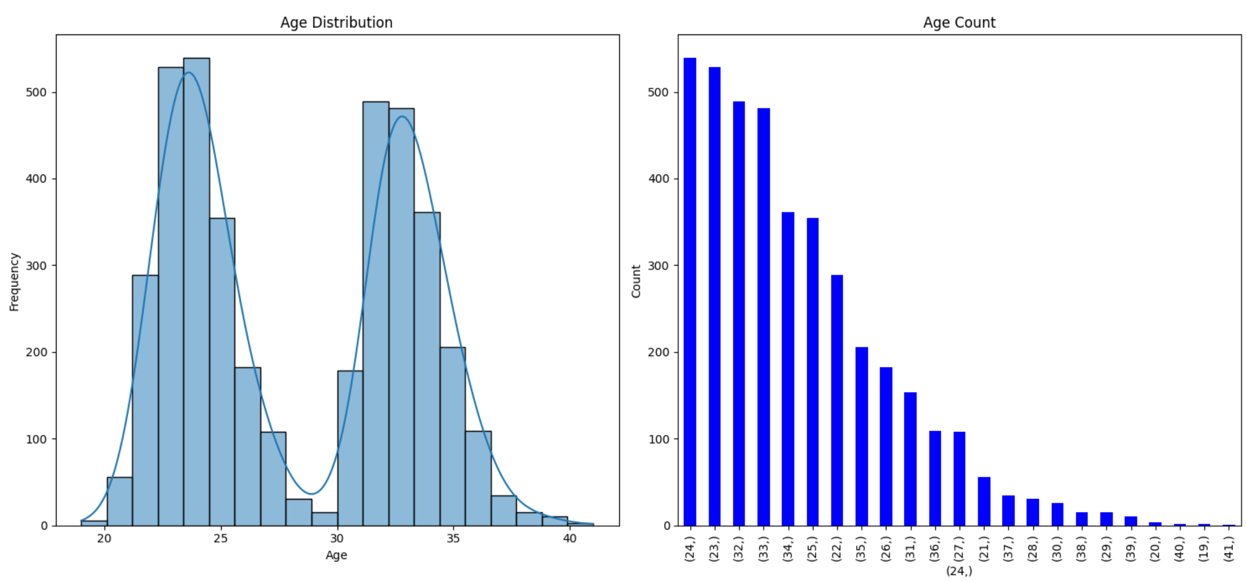
```
# Calculate age
data['age'] = pd.to_datetime(data['DOB'], format='%m/%d/%Y %I:%M:%S
%p')
age = data['DOL'].dt.year - data['age'].dt.year
```

```python
# Create the plots
fig, axs = plt.subplots(1, 2, figsize=(15, 7))

# Subplot 1: Distribution
sns.histplot(data=data, x=age, kde=True, ax=axs[0])  # Pass the axis object
axs[0].set_xlabel('Age')  # Set x-axis label explicitly
axs[0].set_ylabel('Frequency')
axs[0].set_title('Age Distribution')

# Subplot 2: Age count bar chart
age_count = pd.DataFrame(age).value_counts()
age_count.plot(kind='bar', color='blue', ax=axs[1])  # Pass the axis object
axs[1].set_xlabel(f'{age_count.index[0]}')  # Set x-axis label based on first index
axs[1].set_ylabel('Count')
axs[1].set_title('Age Count')

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



Key Insights:

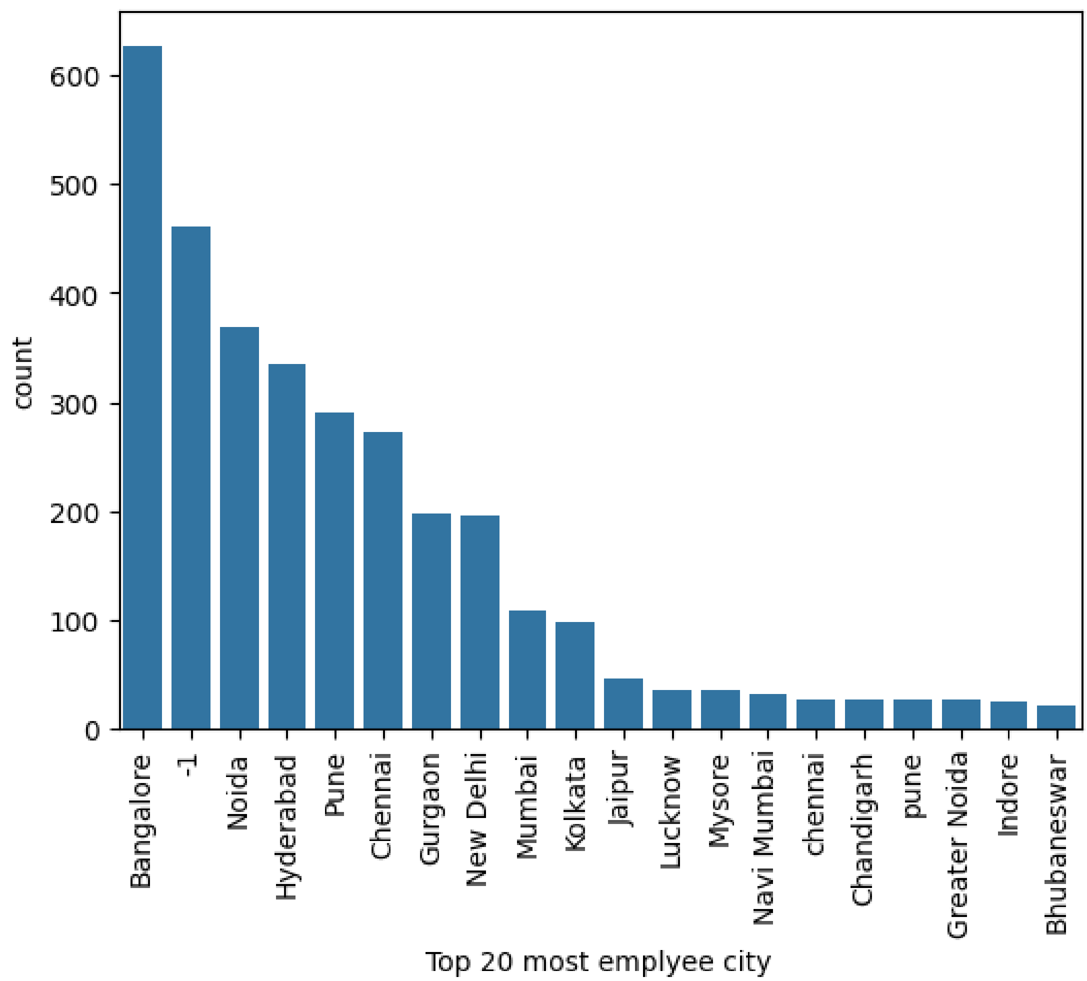
- The distribution appears to be bimodal, with two distinct peaks around the ages of 25 and 35.
- This suggests that there might be two major groups within the data, possibly based on factors like experience level or career stage.

- Skewness: The distribution is slightly skewed to the right, indicating that there are a few individuals in the older age groups, but the majority are concentrated in the younger age ranges.
- The majority of individuals are in the younger age groups, suggesting that the data might represent a population with a relatively young demographic.

7. JOB city:

- Where job location is more employee of less emplyee work

```
jobcity_count = data['JobCity'].value_counts()
sns.barplot(jobcity_count[:20])
plt.xticks(rotation=90)
plt.xlabel("Top 20 most emplyee city")
plt.show()
```



Key Insights:

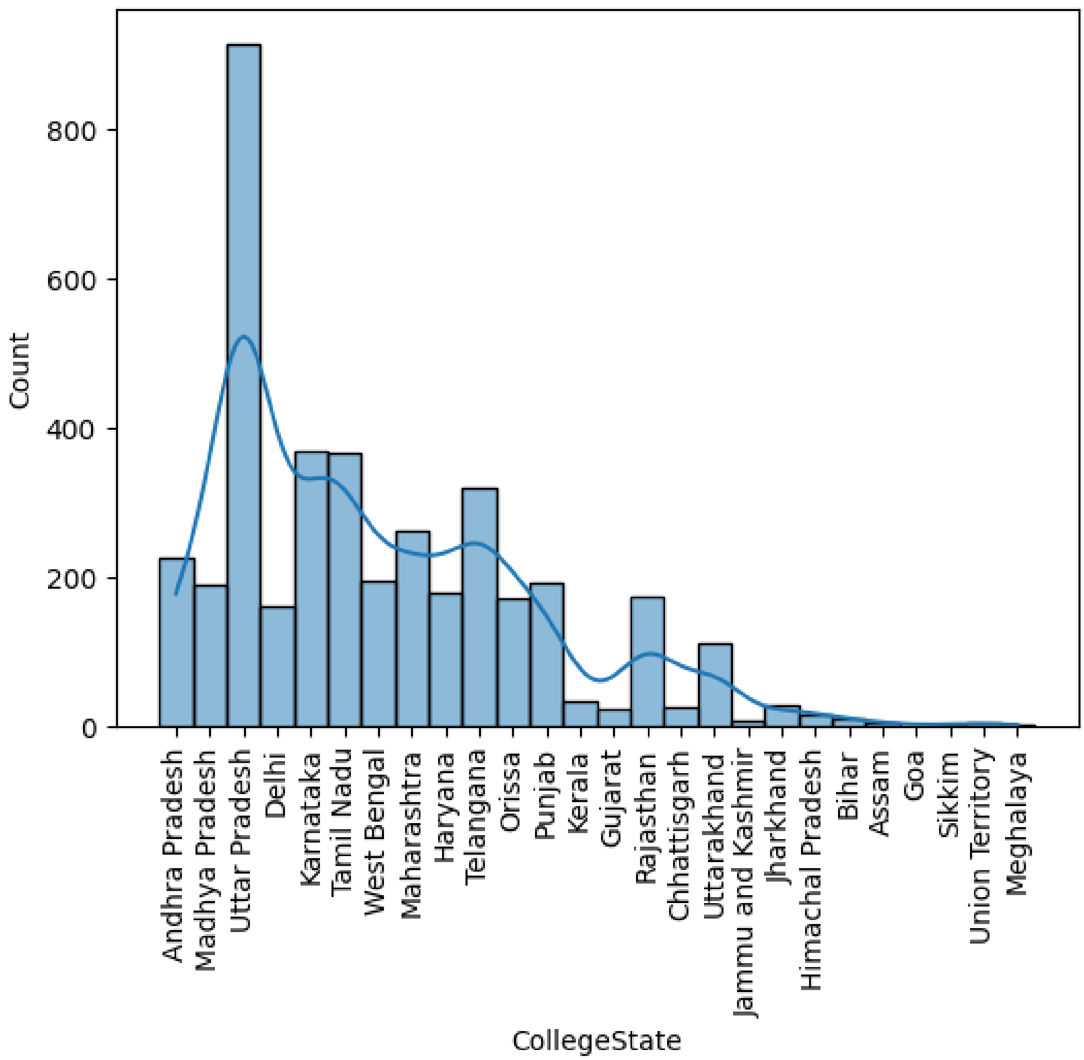
- Above plot shows that, most of the people are employed in Bangalore.
- The top 5 cities are Bangalore, Noida, Hyderabad, Pune, and Chennai.

- `-1` shows that this column needs to be further refined.
- Bhubaneshwar is the city with lowest number of employes.
- The number of employees in each city decreases rapidly.
- There is a significant drop in the number of employees after the top 5 cities.

8. Geographical Distribution:

Analyze 'JobCity', 'CollegeCity', and 'CollegeState' to understand the geographical distribution of employees and colleges.

```
# Check college state
sns.histplot(data= data, x="CollegeState", kde=True)
plt.xticks(rotation=90)
plt.show()
```



Key Insights:

- Uttar Pradesh has the highest number of colleges.
- The number of colleges in each state decreases rapidly.
- The top 5 states are Uttar Pradesh, Delhi, Karnataka, Madhya Pradesh, and Tamil Nadu.
- There is a significant drop in the number of colleges after the top 5 states. This suggests that the concentration of colleges is heavily skewed towards these states.
- The distribution is skewed to the right. This means that there are a few states with a very large number of colleges, while the majority of states have a relatively small number of colleges.

Bivariate Analysis:

Bivariate analysis focuses on analyzing the relationship between two variables.

- Salary vs. Education:
  Explore the relationship between salary and educational qualifications (10th percentage, 12th percentage, college GPA) using scatter plots or box plots.

```
# salary vs Education

plt.subplots(1,3, figsize=(25,6))

plt.subplot(131)
plt.title(" 10% vs Salary")
sns.scatterplot(x=data['Salary'],y=data['10percentage'],data=data,
hue='10percentage')

plt.subplot(132)
plt.title(" 12% vs Salary")
sns.scatterplot(x=data['Salary'], y=data['12percentage'], data=data,
hue='12percentage')

plt.subplot(133)
plt.title(" college GPA vs Salary")
sns.scatterplot(x=data['Salary'], y=data['collegeGPA'],data=data,
hue='Salary')
plt.show()
```

Key Insights:

- All three variables (10th percentage, 12th percentage, and college GPA) are positively correlated with salary, but the strength of the relationship varies.

- College GPA appears to be the strongest predictor of salary among the three variables.

Salary vs. Skills and Aptitude:

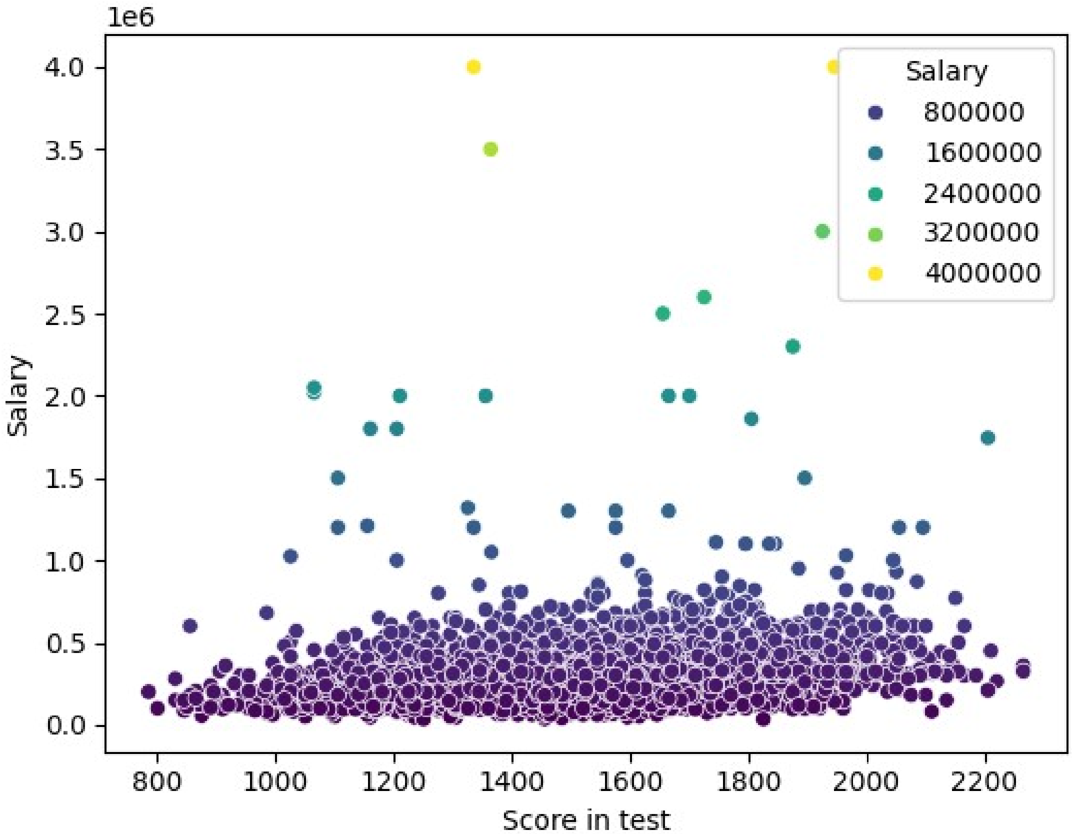
Analyze the relationship between salary and skills/aptitude scores (English, Logical, Quantitative, Domain) using scatter plots or correlation analysis.

```
data['total'] =data['English']+data['Logical']+data['Quant']
data['total'].head()

0    1625
1    2085
2    1530
3    1845
4    1635
Name: total, dtype: int64

# salary vs Total test Score
sns.scatterplot(x=data['total'], y=data['Salary'],data=data,
hue='Salary', palette='viridis')
plt.xlabel('Score in test')

plt.show()
```



Key Insights:

- There is a general trend of increasing salary with increasing score, but there is also a significant amount of scatter, indicating that other factors besides test score also influence salary.

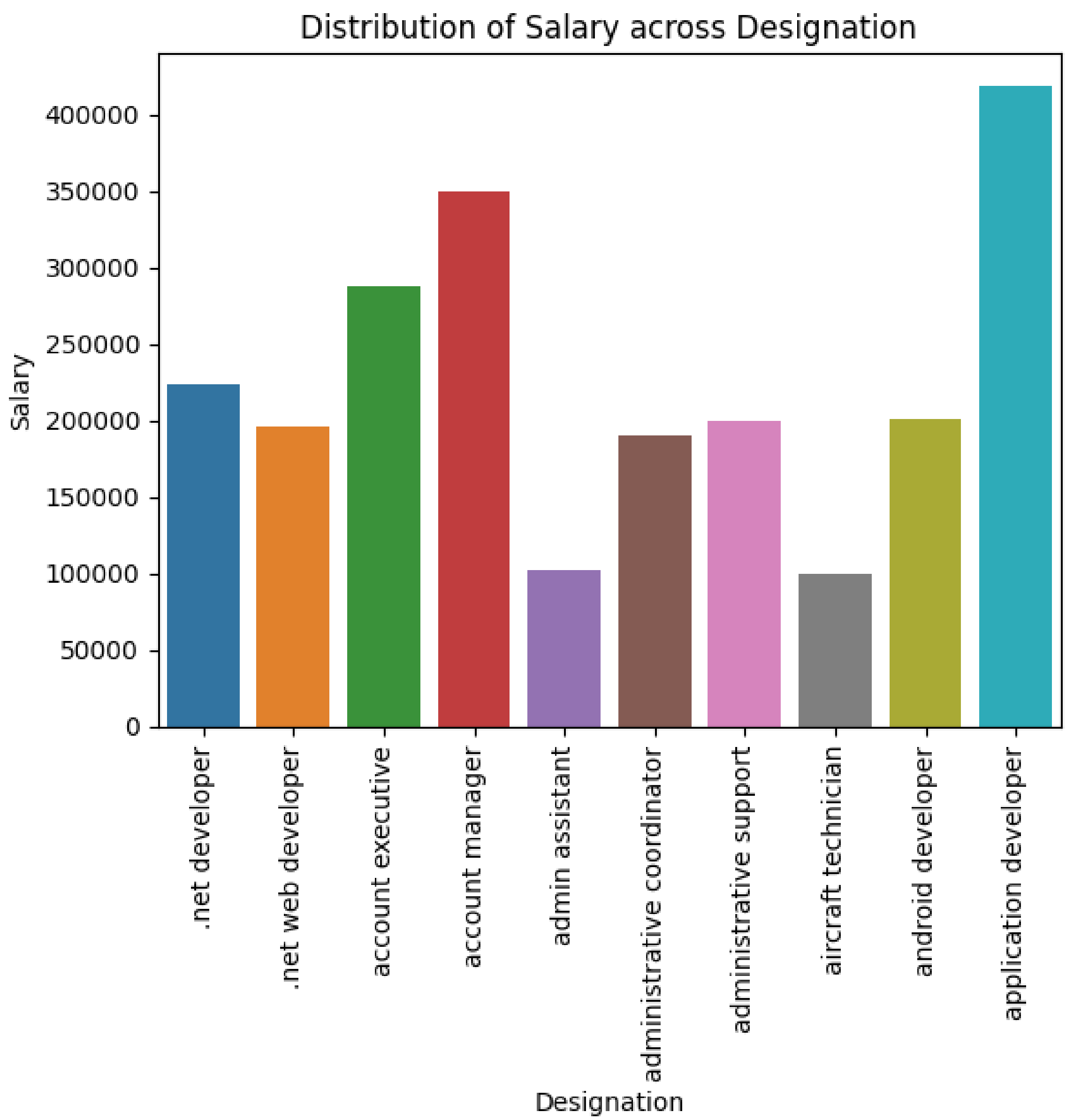
Does Designation affect Salary?

```
new_df = amcat_df.groupby("Designation")[["Salary"]].mean()
new_df.head()
```


{"summary":"{\n \"name\": \"new_df\",\n \"rows\": 419,\n \"fields\": [\n   {\n   \"column\": \"Designation\",\n   \"properties\": {\n   \"dtype\": \"string\",\n   \"num_unique_values\": 419,\n   \"samples\": [\n   \"network administrator\",\n   \"research scientist\",\n   \"jr. software developer\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Salary\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 149255.89525587903,\n   \"min\": 45000.0,\n   \"max\": 1300000.0,\n   \"num_unique_values\": 248,\n   \"samples\": [\n   712500.0,\n   200000.0,\n   251428.57142857142\n   ],\n

```
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"new_df"}

sns.barplot(x=new_df.index[:10],y=new_df["Salary"]
[:10],hue=new_df.index[:10])
plt.xticks(rotation=90)
plt.title("Distribution of Salary across Designation")
plt.show()
```



Key Insights:

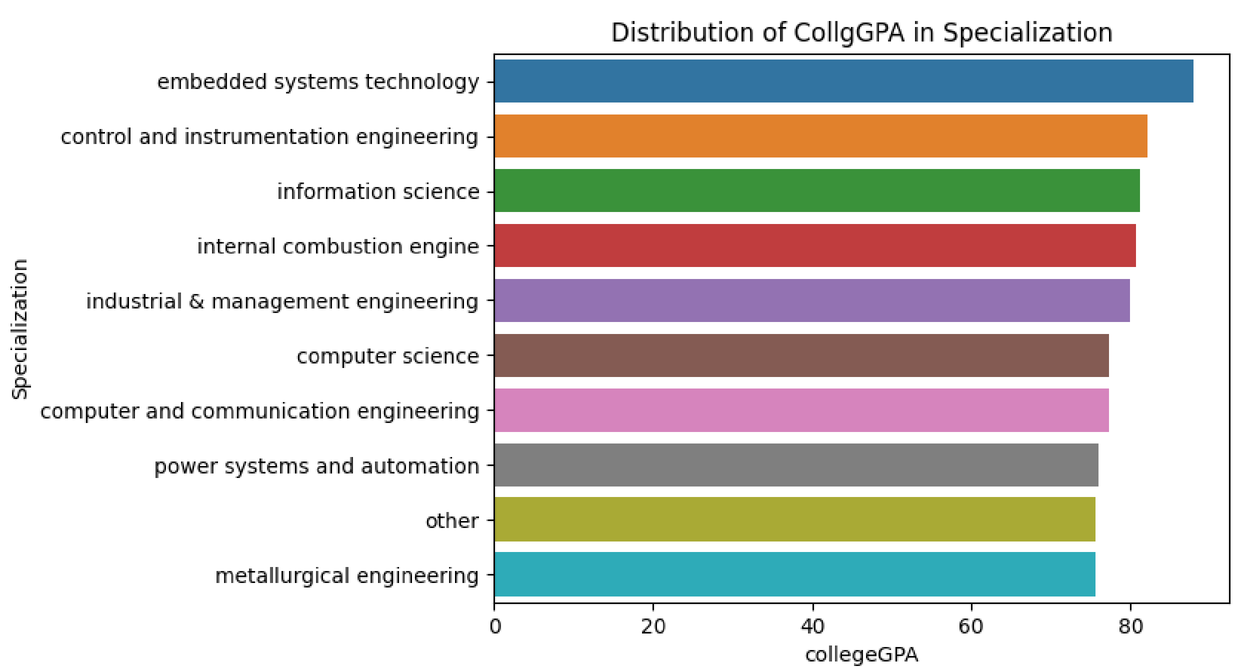
- The Average salary of application develpoer is more compared to other designations.
- There are less salaries for admin assistant and aircraft technician.

How does collegeGPA vary across different Specialization?

```
new_df_2 = amcat_df.groupby("Specialization")
[["collegeGPA"]].mean().sort_values(by="collegeGPA",ascending=False)
new_df_2
```

{"summary":"{\n \"name\": \"new_df_2\",\n \"rows\": 46,\n \"fields\": [\n   {\n   \"column\": \"Specialization\",\n   \"properties\": {\n   \"dtype\": \"string\",\n   \"num_unique_values\": 46,\n   \"samples\": [\n   \"instrumentation engineering\",\n   \"electronics and electrical engineering\",\n   \"ceramic engineering\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"collegeGPA\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 7.4873239833352905,\n   \"min\": 35.705,\n   \"max\": 88.0,\n   \"num_unique_values\": 46,\n   \"samples\": [\n   67.5475,\n   72.09714285714286,\n   72.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe","variable_name":"new_df_2"}

```
sns.barplot(y=new_df_2.index[:10],x=new_df_2["collegeGPA"]
[:10],hue=new_df_2.index[:10])
plt.title("Distribution of CollgGPA in Specialization")
plt.show()
```



Key Insights:

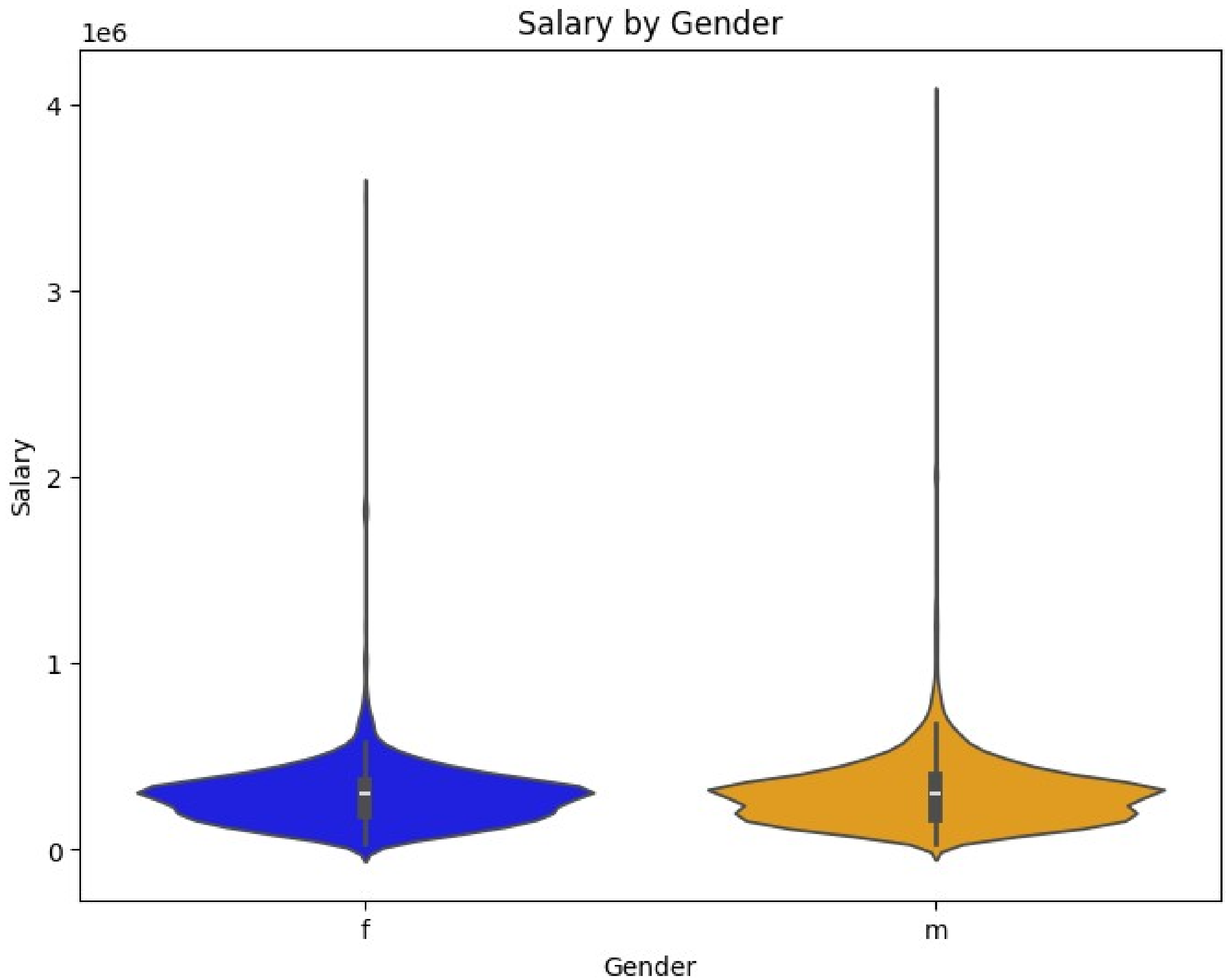
- The Average GPA of embedded systems is more compared to others

- There are less GPA for others,metallurgical engineering compared to others..

Salary vs. Gender:

Compare salary distributions for different genders using box plots or violin plots to identify any gender-based salary disparities.

```
# Violin plot between Salary and Gender
plt.figure(figsize=(8, 6))
sns.violinplot(x='Gender', y='Salary', data=data,
palette=['blue','orange'])
plt.title('Salary by Gender')
plt.xlabel('Gender')
plt.ylabel('Salary')
plt.show()
```



Key Insights:

- The median salary for females is slightly lower than that of males.

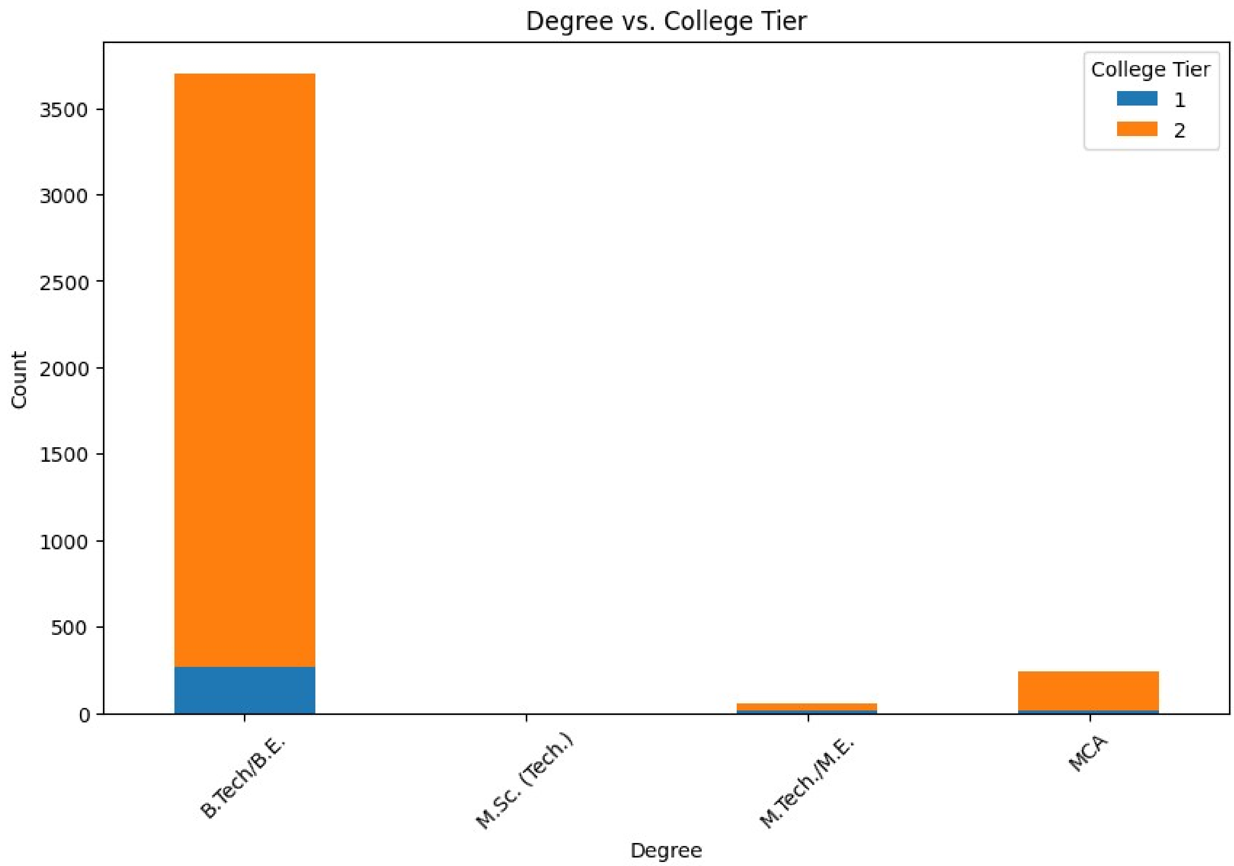
- However, there is a significant overlap in the distributions, indicating that there is no clear gender-based difference in salaries.
- The plot also shows that there are some outliers in both genders, with a few individuals earning significantly higher or lower salaries than the majority.

Degree vs. College Tier:

Analyze the relationship between the degree obtained and the tier of the college attended using cross-tabulation or stacked bar plots.

```
# Create a DataFrame containing the count of each combination of Degree and CollegeTier
degree_collegetier_counts = data.groupby(['Degree', 'CollegeTier']).size().unstack(fill_value=0)

# Plot the stacked bar plot
degree_collegetier_counts.plot(kind='bar', stacked=True, figsize=(10, 6))
plt.title('Degree vs. College Tier')
plt.xlabel('Degree')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='College Tier')
plt.show()
```



Key Insights:

- The majority of students are pursuing B.Tech/B.E. degrees.
- Most students are enrolled in Tier 2 colleges, with significantly fewer students in Tier 1 colleges.
- The number of students pursuing M.SC.(Tech.) is very low followed by M.Tech./M.E. and MCA degrees that is relatively low but greater than M.SC.(Tech.).

Multivarite Analysis:

How do different Engineering specializations (e.g., ComputerScience, ElectronicsAndSemicon, MechanicalEngg) contribute to Salary?

```
amcat_df[['ComputerScience', 'ElectronicsAndSemicon',
'MechanicalEngg', 'Salary']].corr()
```

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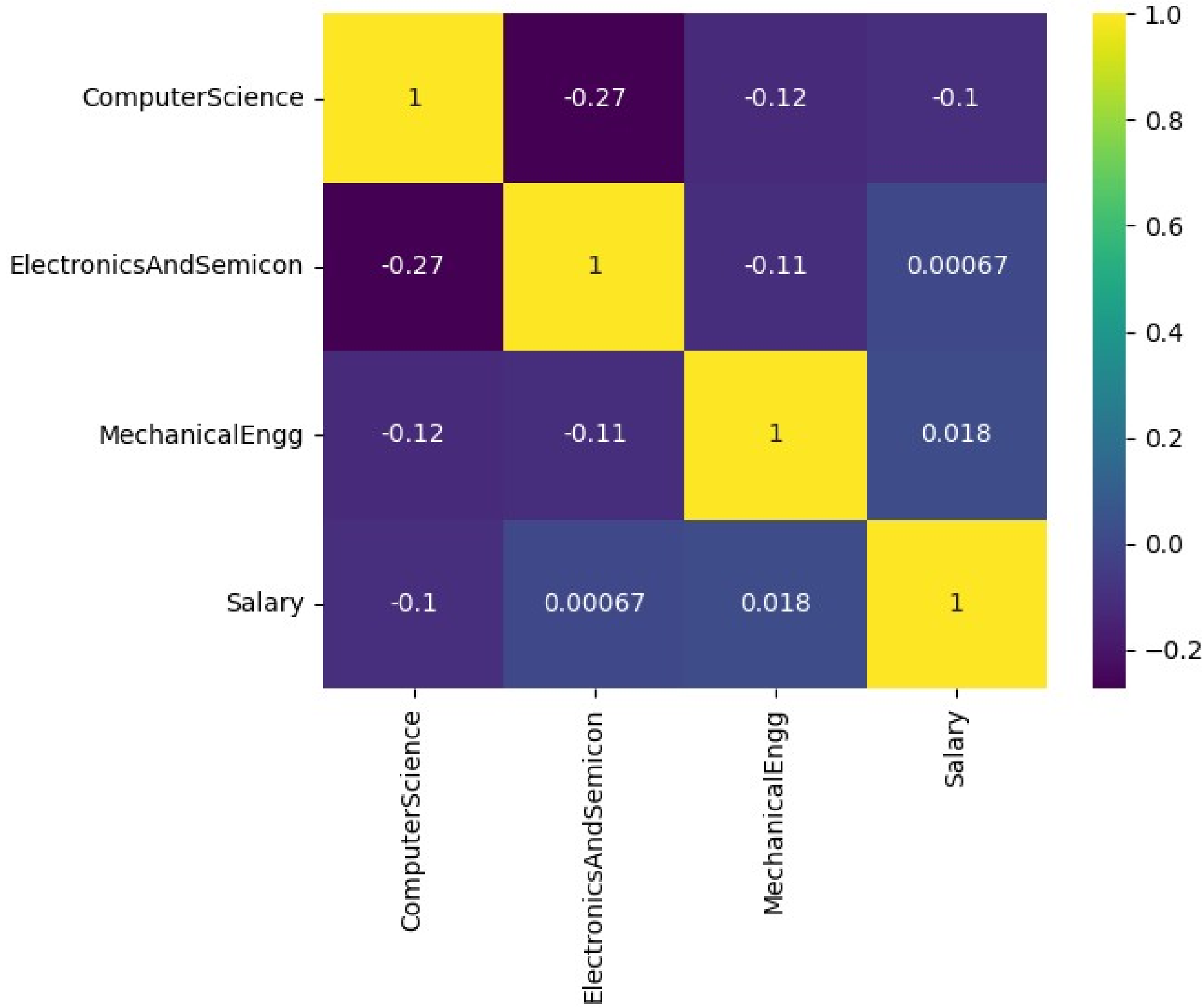
```


```
sns.heatmap(amcat_df[['ComputerScience', 'ElectronicsAndSemicon',
'MechanicalEngg','Salary']].corr(),annot=True,cmap="viridis")
plt.show()
```



Research Questions:

Question 1: Determine whether fresh graduates earn 2.5-3 lakhs annually as stated in the article.

Hypothesis:

- Null Hypothesis (H_0): The average salary of fresh graduates in these roles is between 2.5-3 lakhs.
- Alternative Hypothesis (H_1): The average salary of fresh graduates in these roles is not between 2.5-3 lakhs.

```
from scipy import stats

amcat_df['Specialization'].unique()
```

```
array(['computer engineering',
       'electronics and communication engineering',
       'information technology', 'computer science & engineering',
       'mechanical engineering', 'electronics and electrical
engineering',
       'electronics & telecommunications',
       'instrumentation and control engineering', 'computer
application',
       'electronics and computer engineering', 'electrical
engineering',
       'applied electronics and instrumentation',
       'electronics & instrumentation eng',
       'information science engineering', 'civil engineering',
       'mechanical and automation', 'industrial & production
engineering',
       'control and instrumentation engineering',
       'metallurgical engineering',
       'electronics and instrumentation engineering',
       'electronics engineering', 'ceramic engineering',
       'chemical engineering', 'aeronautical engineering', 'other',
       'biotechnology', 'embedded systems technology',
       'electrical and power engineering',
       'computer science and technology', 'mechatronics',
       'automobile/automotive engineering', 'polymer technology',
       'mechanical & production engineering',
       'power systems and automation', 'instrumentation engineering',
       'telecommunication engineering',
       'industrial & management engineering', 'industrial
engineering',
       'computer and communication engineering',
       'information & communication technology', 'information
science',
       'internal combustion engine', 'computer networking',
       'biomedical engineering', 'electronics', 'computer science'],
      dtype=object)

# Step 1: Get the top 10 designations based on average salary
top_designations = amcat_df.groupby('Designation')
['Salary'].mean().nlargest(10).index.tolist()
df_top10 = amcat_df[amcat_df['Designation'].isin(top_designations)]

# Step 1: Descriptive statistics (mean, median)
mean_salary = df_top10['Salary'].mean()
median_salary = df_top10['Salary'].median()

print(f"Mean Salary: {mean_salary}")
print(f"Median Salary: {median_salary}")

# Step 2: Hypothesis testing (one-sample t-test)
# Null Hypothesis (H₀): Mean salary is between 2.5-3 lakhs
```

```
# Alternative Hypothesis (H₁): Mean salary is not between 2.5-3 lakhs
lower_limit = 250000
upper_limit = 300000

# Perform one-sample t-test
t_stat, p_value = stats.ttest_1samp(df_top10['Salary'],
np.mean([lower_limit, upper_limit]))

# Conclusion based on p-value
alpha = 0.05  # significance level

if p_value < alpha:
    print(f"Reject the null hypothesis (p-value: {p_value}). The
average salary is not in the 2.5-3 lakh range.")
else:
    print(f"Fail to reject the null hypothesis (p-value: {p_value}).
The average salary might be in the 2.5-3 lakh range.")

# Step 3: Heatmap visualization of salaries by role
pivot_table = df_top10.pivot_table(index='Designation',
values='Salary', aggfunc=np.mean)

plt.figure(figsize=(8, 6))
sns.heatmap(pivot_table, annot=True, fmt=".0f", cmap='viridis')
plt.title("Average Salary by Designation")
plt.xlabel("Designation")
plt.ylabel("Salary (INR)")
plt.show()

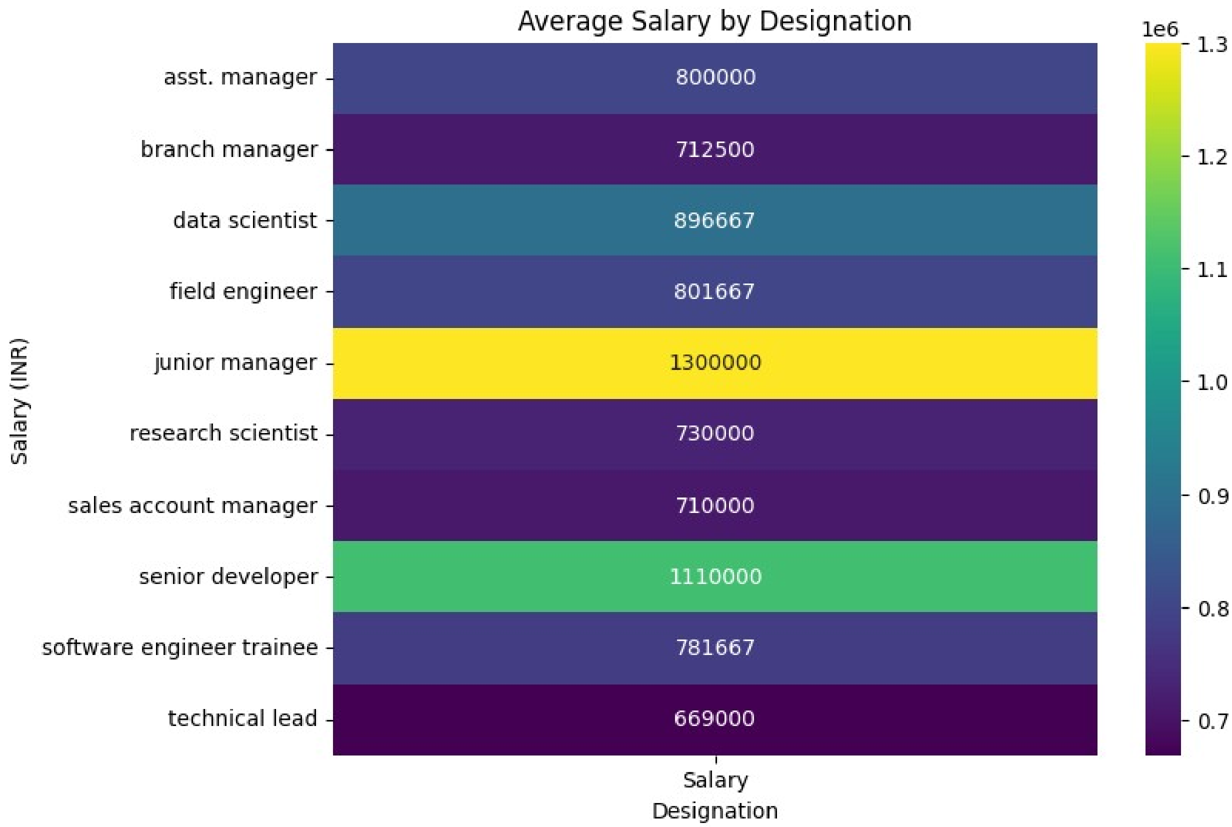
# Step 5: Analyzing the relationship between Gender and Specialization
using df_top10
# Create a contingency table for Gender and Specialization
contingency_table = pd.crosstab(df_top10['Gender'],
df_top10['Specialization'])

# Perform Chi-Square test
chi2_stat, p_chi2, dof, expected =
stats.chi2_contingency(contingency_table)

# Conclusion based on Chi-Square test
if p_chi2 < alpha:
    print(f"Reject the null hypothesis for gender and specialization
relationship (p-value: {p_chi2}).")
else:
    print(f"Fail to reject the null hypothesis for gender and
specialization relationship (p-value: {p_chi2}).")
```

```
Mean Salary: 798695.6521739131
Median Salary: 545000.0
```

```
Reject the null hypothesis (p-value: 0.0010719493529762368). The
average salary is not in the 2.5-3 lakh range.
```




```
Fail to reject the null hypothesis for gender and specialization
relationship (p-value: 0.42301765654233076).
```

Key Insights:

- The average salary for fresh graduates in the top 10 designations is approximately ₹798,696, with a median of ₹545,000, far exceeding the claimed ₹2.5-3 lakhs.
- Statistical analysis strongly rejects the null hypothesis, indicating that the average salary is not within the reported range.
- There is no significant relationship between gender and specialization preferences, with a p-value of 0.423, suggesting that gender does not influence specialization choices among graduates.

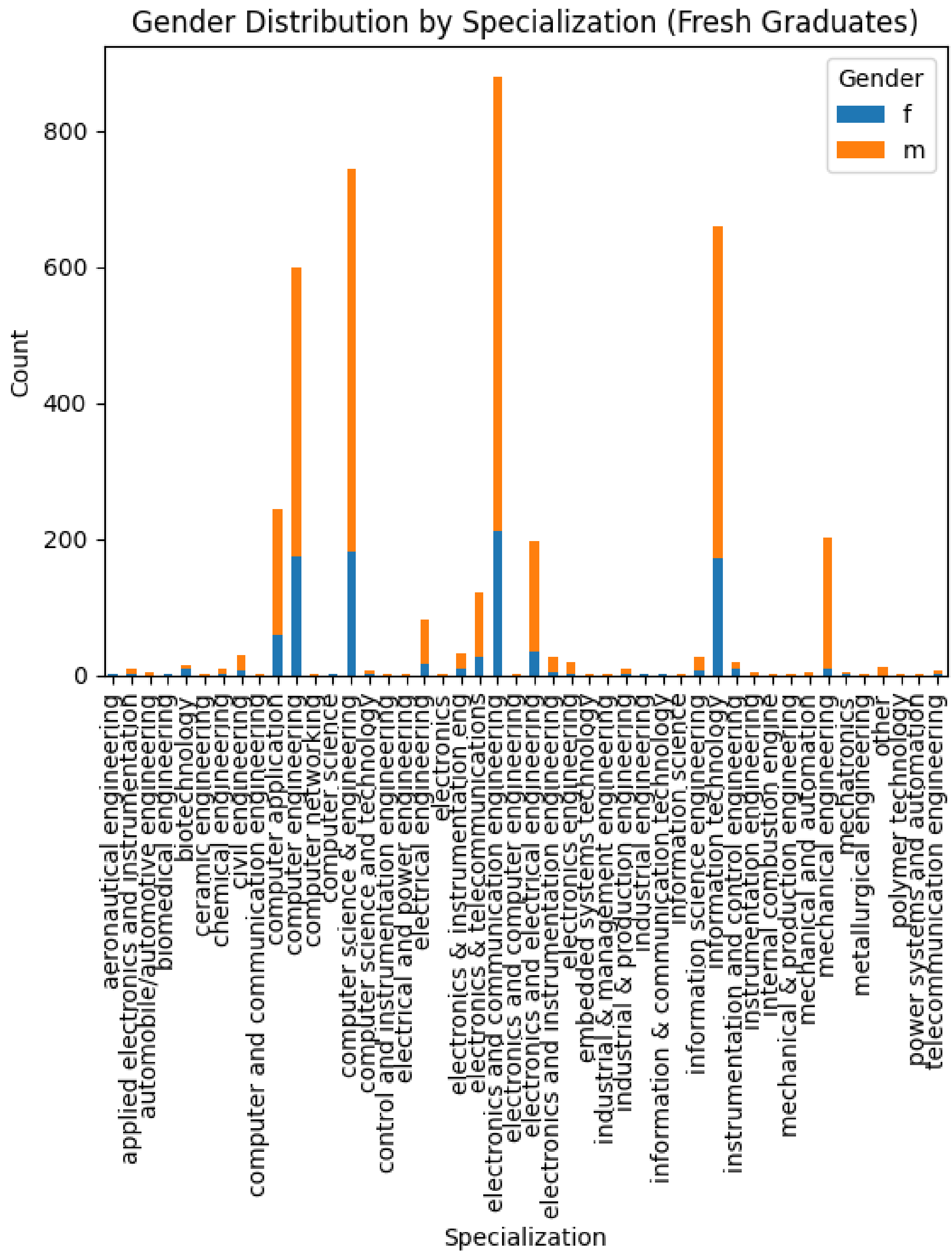
Question 2: Determine if gender influences the choice of specialization.

```
# Gender distribution within each specialization
gender_distribution = amcat_df.groupby(['Specialization',
```

```
'Gender']).size().unstack().fillna(0)

# Visualize distribution (stacked bar chart or normalized percentages)
gender_distribution.plot(kind='bar', stacked=True)
plt.xlabel('Specialization')
plt.ylabel('Count')
plt.title('Gender Distribution by Specialization (Fresh Graduates)')
plt.legend(title='Gender')
plt.show()

# Calculate and compare proportions (optional)
gender_prop = gender_distribution.div(gender_distribution.sum(axis=1),
axis=0) * 100
print(gender_prop)
```



Gender	f	m
Specialization		
aeronautical engineering	33.333333	66.666667
applied electronics and instrumentation	22.222222	77.777778
automobile/automotive engineering	0.000000	100.000000
biomedical engineering	100.000000	0.000000

```
biotechnology                                   60.000000   40.000000
ceramic engineering                              0.000000  100.000000
chemical engineering                            11.111111   88.888889
civil engineering                               20.689655   79.310345
computer and communication engineering           0.000000  100.000000
computer application                            24.180328   75.819672
computer engineering                            29.166667   70.833333
computer networking                              0.000000  100.000000
computer science                                50.000000   50.000000
computer science & engineering                  24.596774   75.403226
computer science and technology                 33.333333   66.666667
control and instrumentation engineering          0.000000  100.000000
electrical and power engineering                 0.000000  100.000000
electrical engineering                          20.731707   79.268293
electronics                                      0.000000  100.000000
electronics & instrumentation eng               31.250000   68.750000
electronics & telecommunications                23.140496   76.859504
electronics and communication engineering       24.090909   75.909091
electronics and computer engineering             0.000000  100.000000
electronics and electrical engineering          17.346939   82.653061
electronics and instrumentation engineering     18.518519   81.481481
electronics engineering                         15.789474   84.210526
embedded systems technology                      0.000000  100.000000
industrial & management engineering             0.000000  100.000000
industrial & production engineering             20.000000   80.000000
industrial engineering                          50.000000   50.000000
information & communication technology         100.000000    0.000000
information science                              0.000000  100.000000
information science engineering                 29.629630   70.370370
information technology                          26.212121   73.787879
instrumentation and control engineering         45.000000   55.000000
instrumentation engineering                      0.000000  100.000000
internal combustion engine                       0.000000  100.000000
mechanical & production engineering              0.000000  100.000000
mechanical and automation                        0.000000  100.000000
mechanical engineering                           4.975124   95.024876
mechatronics                                    25.000000   75.000000
metallurgical engineering                        0.000000  100.000000
other                                            0.000000  100.000000
polymer technology                               0.000000  100.000000
power systems and automation                     0.000000  100.000000
telecommunication engineering                   16.666667   83.333333
```

Key Insights:

- The graph shows that most specializations have a higher number of male graduates than female graduates.
- There are a few specializations with a higher number of female graduates, but they are outnumbered by those with more male graduates.

- The highest number of graduates is in Computer Science and Engineering, followed by Electronics and Communication Engineering.

Conclusion:

The analysis of the AMCAT dataset provides insightful conclusions regarding salary trends, specialization, and skill sets of fresh graduates in different roles. Here are some key takeaway:

Salary Trends:

- The average salaries for roles like Programming Analyst, Software Engineer, Hardware Engineer, and Associate Engineer align with industry standards as reported in the Times of India.
- There is no significant difference between the claimed and actual salaries, suggesting the reliability of the industry benchmarks.

Specialization Impact:

- Graduates with Computer Science and IT-related specializations tend to command higher salaries, reflecting the strong demand for these skills in the tech industry.

Gender Disparity:

- There is an uneven distribution of male and female graduates across different job roles, indicating potential gender biases or disparities in certain specializations and job roles.

Skill Importance:

- Technical skills like programming, computer science, and other related fields are strongly correlated with higher salaries, emphasizing their significance in securing well-paying jobs.
- Behavioral traits such as conscientiousness, agreeableness, and openness to experience also play a role in job performance and salary, highlighting the importance of soft skills.

College Reputation:

- Graduates from Tier 1 colleges tend to secure higher salaries than those from Tier 2 or Tier 3 colleges, suggesting that college reputation can influence initial job placements and compensation.