Introduction:
The Aspiring Minds Employment Outcome (AMEO) 2015 dataset captures the employment results of engineering graduates across India, offering a deep dive into how different skills and demographics affect career outcomes.

Problem Statement:
The primary goal is to analyze the factors influencing the employment outcomes of engineering graduates based on their cognitive, technical, and personality skills, as well as demographic factors. By studying these variables, we aim to determine key predictors for job titles, job locations, and salary, thereby providing insights into how skills and demographics impact career success in the engineering field.

Data Description:

- **Data Points:** 4000 records
- **Variables:** 40 independent variables (continuous and categorical)
- **Key Variables:** Cognitive, technical, and personality skills, demographic details, and employment outcomes (Salary, Job Titles, Job Locations)

Objective:
To analyze and identify the influence of various skills and demographic factors on the employment outcomes of engineering graduates, focusing on salary, job roles, and job locations.

Importing the dataset

```
import pandas as pd
df = pd.read_excel(r"C:\Users\Srikanth\Downloads\data.xlsx")
df
```

```
     Unnamed: 0      ID   Salary        DOJ                  DOL  \
0         train  203097   420000 2012-06-01              present
1         train  579905   500000 2013-09-01              present
2         train  810601   325000 2014-06-01              present
3         train  267447  1100000 2011-07-01              present
4         train  343523   200000 2014-03-01  2015-03-01 00:00:00
...         ...     ...      ...        ...                  ...
3993      train   47916   280000 2011-10-01  2012-10-01 00:00:00
3994      train  752781   100000 2013-07-01  2013-07-01 00:00:00
3995      train  355888   320000 2013-07-01              present
3996      train  947111   200000 2014-07-01  2015-01-01 00:00:00
3997      train  324966   400000 2013-02-01              present

                      Designation           JobCity Gender        DOB
\
```

```
0         senior quality engineer         Bangalore      f 1990-02-19

1               assistant manager            Indore      m 1989-10-04

2                systems engineer           Chennai      f 1992-08-03

3        senior software engineer           Gurgaon      m 1989-12-05

4                             get           Manesar      m 1991-02-27

...                           ...               ...    ...        ...

3993            software engineer        New Delhi       m 1987-04-15

3994             technical writer         Hyderabad      f 1992-08-27

3995  associate software engineer         Bangalore      m 1991-07-03

3996           software developer  Asifabadbanglore      f 1992-03-20

3997      senior systems engineer           Chennai      f 1991-02-26


      10percentage  ... ComputerScience  MechanicalEngg
ElectricalEngg  \
0            84.30  ...              -1              -1               -
1
1            85.40  ...              -1              -1               -
1
2            85.00  ...              -1              -1               -
1
3            85.60  ...              -1              -1               -
1
4            78.00  ...              -1              -1               -
1
...            ...  ...             ...             ...              ..
.
3993         52.09  ...              -1              -1               -
1
3994         90.00  ...              -1              -1               -
1
3995         81.86  ...              -1              -1               -
1
3996         78.72  ...             438              -1               -
1
3997         70.60  ...              -1              -1               -
1

     TelecomEngg  CivilEngg  conscientiousness agreeableness
extraversion  \
```

```
0               -1          -1                0.9737        0.8128
0.5269
1               -1          -1               -0.7335        0.3789
1.2396
2               -1          -1                0.2718        1.7109
0.1637
3               -1          -1                0.0464        0.3448       -
0.3440
4               -1          -1               -0.8810       -0.2793       -
1.0697
...            ...         ...                   ...           ...
...
3993            -1          -1               -0.1082        0.3448
0.2366
3994            -1          -1               -0.3027        0.8784
0.9322
3995            -1          -1               -1.5765       -1.5273       -
1.5051
3996            -1          -1               -0.1590        0.0459       -
0.4511
3997            -1          -1               -1.1128       -0.2793       -
0.6343

      nueroticism  openess_to_experience
0         1.35490                -0.4455
1        -0.10760                 0.8637
2        -0.86820                 0.6721
3        -0.40780                -0.9194
4         0.09163                -0.1295
...           ...                    ...
3993      0.64980                -0.9194
3994      0.77980                -0.0943
3995     -1.31840                -0.7615
3996     -0.36120                -0.0943
3997      1.32553                -0.6035

[3998 rows x 39 columns]
```

```
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
```

```
df.isnull().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
```

```python
df.duplicated().sum()
```

```
0
```

```python
df.dtypes
```

```
Unnamed: 0                        object
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
```

```
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')
```

```
df.describe()
```

```
                 ID        Salary                           DOJ  \
count  3.998000e+03  3.998000e+03                          3998
```

```
mean   6.637945e+05  3.076998e+05  2013-07-02 11:04:10.325162496
min    1.124400e+04  3.500000e+04            1991-06-01 00:00:00
25%    3.342842e+05  1.800000e+05            2012-10-01 00:00:00
50%    6.396000e+05  3.000000e+05            2013-11-01 00:00:00
75%    9.904800e+05  3.700000e+05            2014-07-01 00:00:00
max    1.298275e+06  4.000000e+06            2015-12-01 00:00:00
std    3.632182e+05  2.127375e+05                            NaN

                                 DOB  10percentage  12graduation  \
count                           3998   3998.000000   3998.000000
mean   1990-12-06 06:01:15.637819008     77.925443   2008.087544
min              1977-10-30 00:00:00     43.000000   1995.000000
25%              1989-11-16 06:00:00     71.680000   2007.000000
50%              1991-03-07 12:00:00     79.150000   2008.000000
75%              1992-03-13 18:00:00     85.670000   2009.000000
max              1997-05-27 00:00:00     97.760000   2013.000000
std                              NaN      9.850162      1.653599

       12percentage     CollegeID  CollegeTier   collegeGPA  ...  \
count   3998.000000   3998.000000  3998.000000  3998.000000  ...
mean      74.466366   5156.851426     1.925713    71.486171  ...
min       40.000000      2.000000     1.000000     6.450000  ...
25%       66.000000    494.000000     2.000000    66.407500  ...
50%       74.400000   3879.000000     2.000000    71.720000  ...
75%       82.600000   8818.000000     2.000000    76.327500  ...
max       98.700000  18409.000000     2.000000    99.930000  ...
std       10.999933   4802.261482     0.262270     8.167338  ...

       ComputerScience  MechanicalEngg  ElectricalEngg  TelecomEngg  \
count      3998.000000     3998.000000     3998.000000  3998.000000
mean         90.742371       22.974737       16.478739    31.851176
min          -1.000000       -1.000000       -1.000000    -1.000000
25%          -1.000000       -1.000000       -1.000000    -1.000000
50%          -1.000000       -1.000000       -1.000000    -1.000000
75%          -1.000000       -1.000000       -1.000000    -1.000000
max         715.000000      623.000000      676.000000   548.000000
std         175.273083       98.123311       87.585634   104.852845

         CivilEngg  conscientiousness  agreeableness  extraversion  \
count  3998.000000        3998.000000    3998.000000   3998.000000
mean      2.683842          -0.037831       0.146496      0.002763
min      -1.000000          -4.126700      -5.781600     -4.600900
25%      -1.000000          -0.713525      -0.287100     -0.604800
50%      -1.000000           0.046400       0.212400      0.091400
75%      -1.000000           0.702700       0.812800      0.672000
max     516.000000           1.995300       1.904800      2.535400
std      36.658505           1.028666       0.941782      0.951471

       nueroticism  openess_to_experience
count  3998.000000            3998.000000
```

```
mean     -0.169033              -0.138110
min      -2.643000              -7.375700
25%      -0.868200              -0.669200
50%      -0.234400              -0.094300
75%       0.526200               0.502400
max       3.352500               1.822400
std       1.007580               1.008075

[8 rows x 29 columns]
```

```
df.describe(include='object')
```

```
       Unnamed: 0      DOL         Designation    JobCity Gender
10board  \
count        3998     3998                3998       3998   3998
3998
unique          1       67                 419        339      2
275
top         train  present  software engineer  Bangalore      m
cbse
freq         3998     1875                 539        627   3041
1395

       12board       Degree                              Specialization
\
count     3998         3998                                        3998

unique     340            4                                          46

top       cbse  B.Tech/B.E.  electronics and communication engineering

freq      1400         3700                                         880


         CollegeState
count            3998
unique             26
top     Uttar Pradesh
freq              915
```

```
df.head()
```

```
  Unnamed: 0      ID   Salary        DOJ                  DOL  \
0      train  203097   420000 2012-06-01              present
1      train  579905   500000 2013-09-01              present
2      train  810601   325000 2014-06-01              present
3      train  267447  1100000 2011-07-01              present
4      train  343523   200000 2014-03-01  2015-03-01 00:00:00

                Designation    JobCity Gender        DOB  10percentage
...  \
```

```
0   senior quality engineer  Bangalore      f 1990-02-19          84.3
...
1         assistant manager     Indore      m 1989-10-04          85.4
...
2          systems engineer    Chennai      f 1992-08-03          85.0
...
3  senior software engineer    Gurgaon      m 1989-12-05          85.6
...
4                       get    Manesar      m 1991-02-27          78.0
...

  ComputerScience  MechanicalEngg  ElectricalEngg TelecomEngg
CivilEngg  \
0              -1              -1              -1          -1
-1
1              -1              -1              -1          -1
-1
2              -1              -1              -1          -1
-1
3              -1              -1              -1          -1
-1
4              -1              -1              -1          -1
-1

   conscientiousness agreeableness extraversion  nueroticism  \
0             0.9737        0.8128       0.5269      1.35490
1            -0.7335        0.3789       1.2396     -0.10760
2             0.2718        1.7109       0.1637     -0.86820
3             0.0464        0.3448      -0.3440     -0.40780
4            -0.8810       -0.2793      -1.0697      0.09163

   openess_to_experience
0                -0.4455
1                 0.8637
2                 0.6721
3                -0.9194
4                -0.1295

[5 rows x 39 columns]
```

```
df.shape
```

```
(3998, 39)
```

```
df.size
```

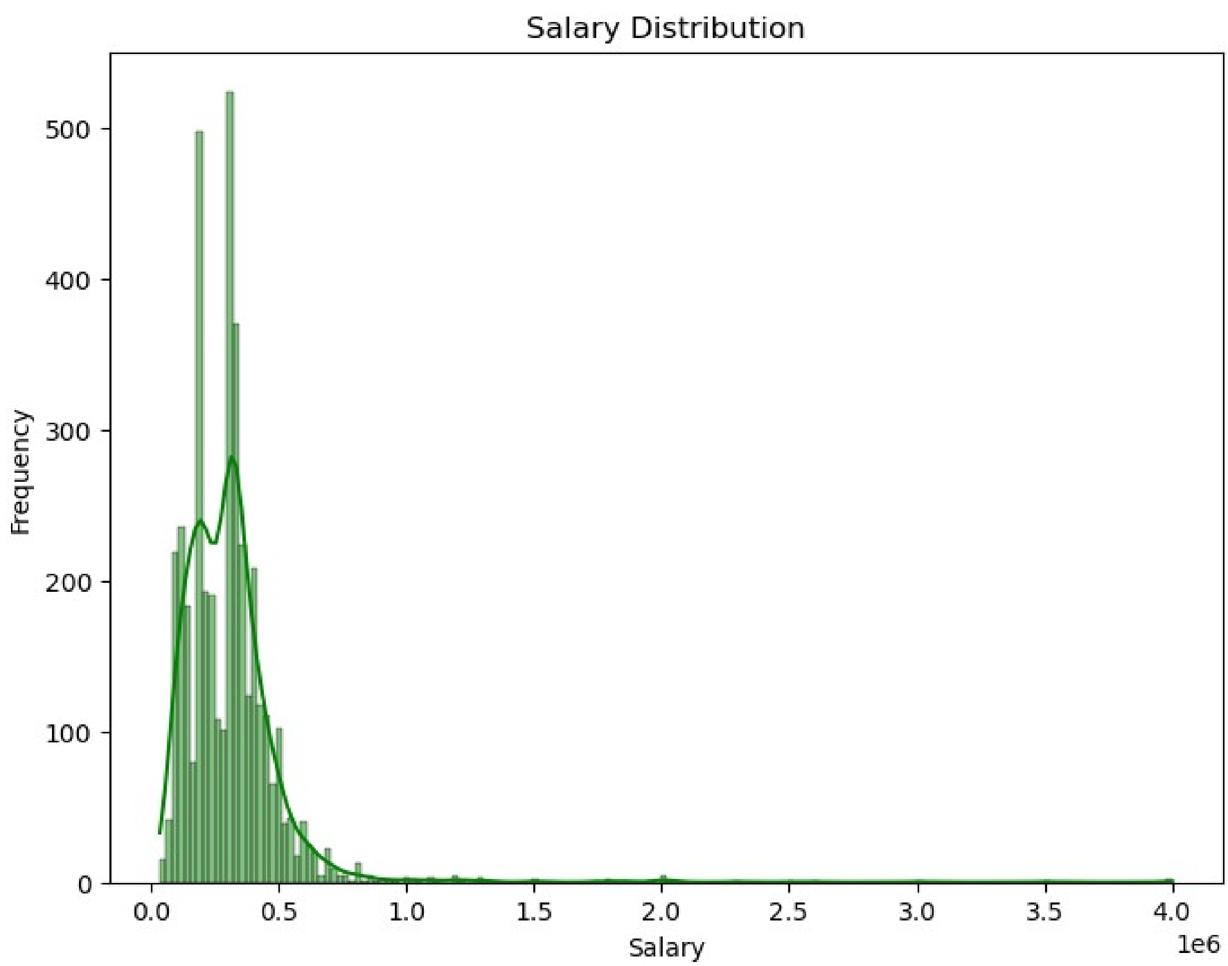
```
155922
```

Univariate Analysis: Numerical Variables

1. Salary Distribution

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

plt.figure(figsize=(8,6))
sns.histplot(df['Salary'],kde=True,color='green')
plt.title('Salary Distribution')
plt.xlabel('Salary')
plt.ylabel('Frequency')
plt.show()
```

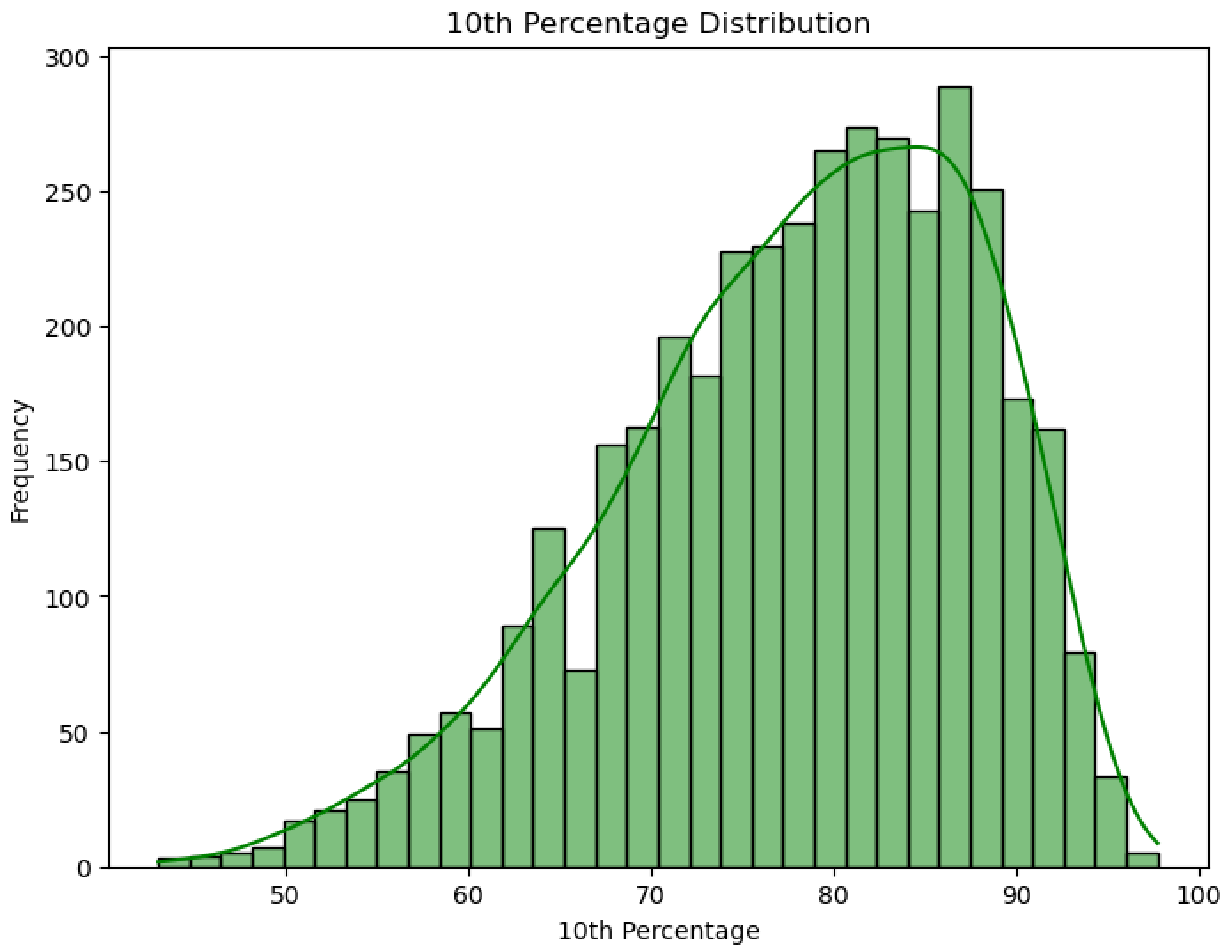


Observation:

The salary distribution is skewed to the right, meaning most of the engineers are earning a salary below the mean, while a few are earning much higher salaries.

2. 10th Percentage Distribution

```
plt.figure(figsize=(8, 6))
sns.histplot(df['10percentage'], kde=True, color='green')
plt.title('10th Percentage Distribution')
plt.xlabel('10th Percentage')
plt.ylabel('Frequency')
plt.show()
```



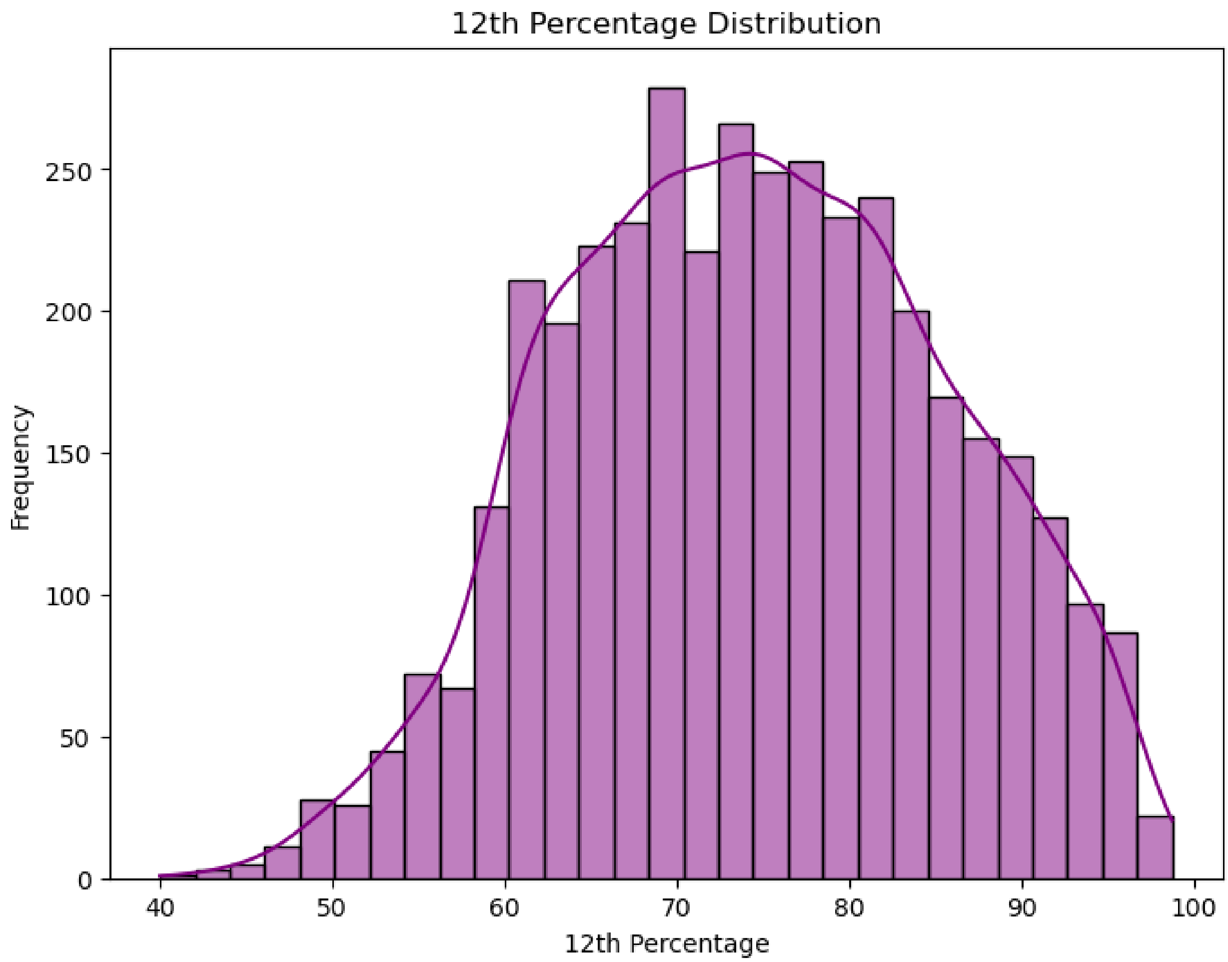
Observation:

Most students scored between 60% and 80% in their 10th-grade exams, with a small number of students achieving higher or lower percentages.

3. 12th Percentage Distribution

```
plt.figure(figsize=(8, 6))
sns.histplot(df['12percentage'], kde=True, color='purple')
plt.title('12th Percentage Distribution')
```

```
plt.xlabel('12th Percentage')
plt.ylabel('Frequency')
plt.show()
```

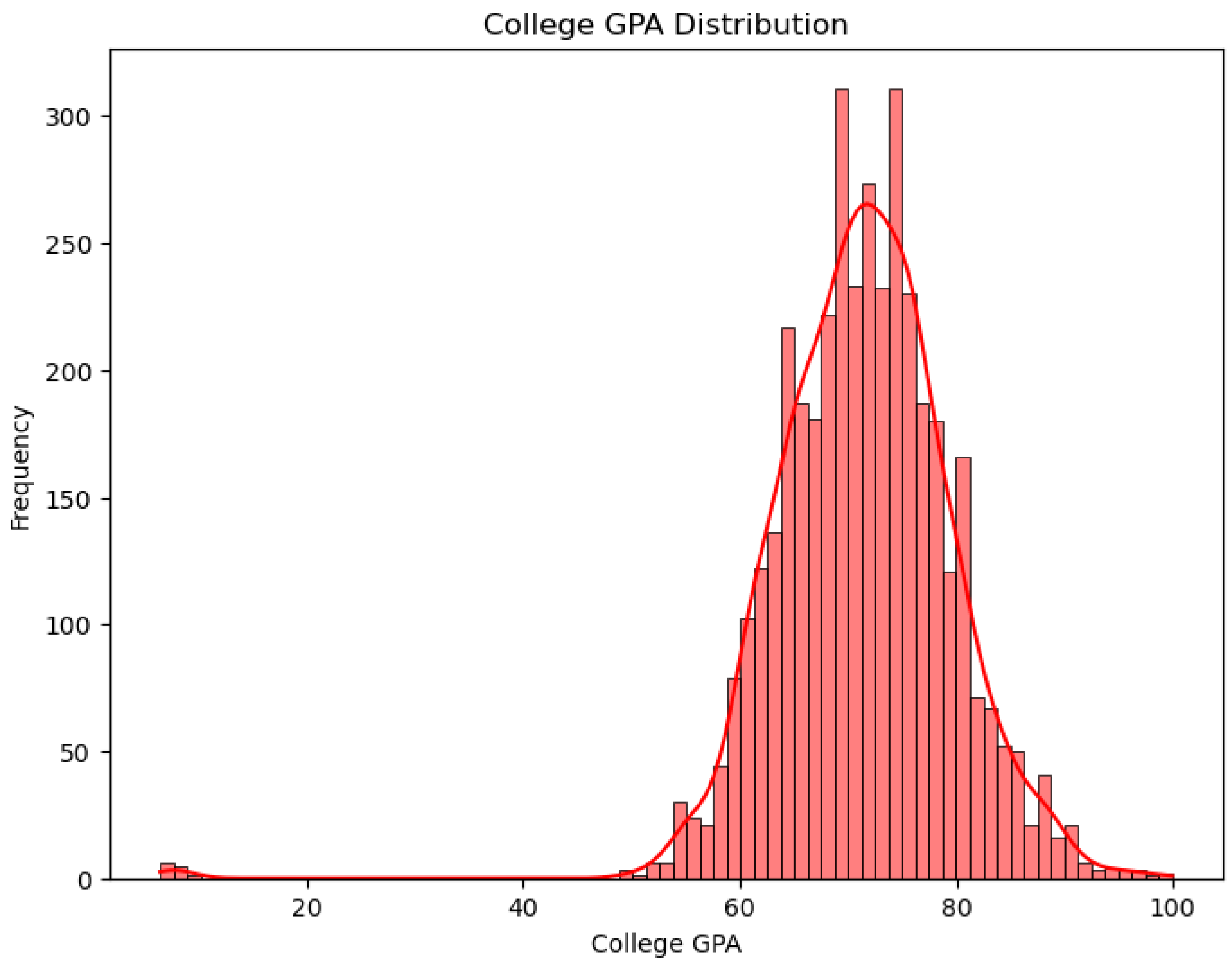


Observation:

The distribution of 12th-grade percentages follows a similar trend to the 10th percentage, with the majority of students scoring between 60% and 80%.

4. College GPA Distribution

```
plt.figure(figsize=(8, 6))
sns.histplot(df['collegeGPA'], kde=True, color='red')
plt.title('College GPA Distribution')
plt.xlabel('College GPA')
plt.ylabel('Frequency')
plt.show()
```

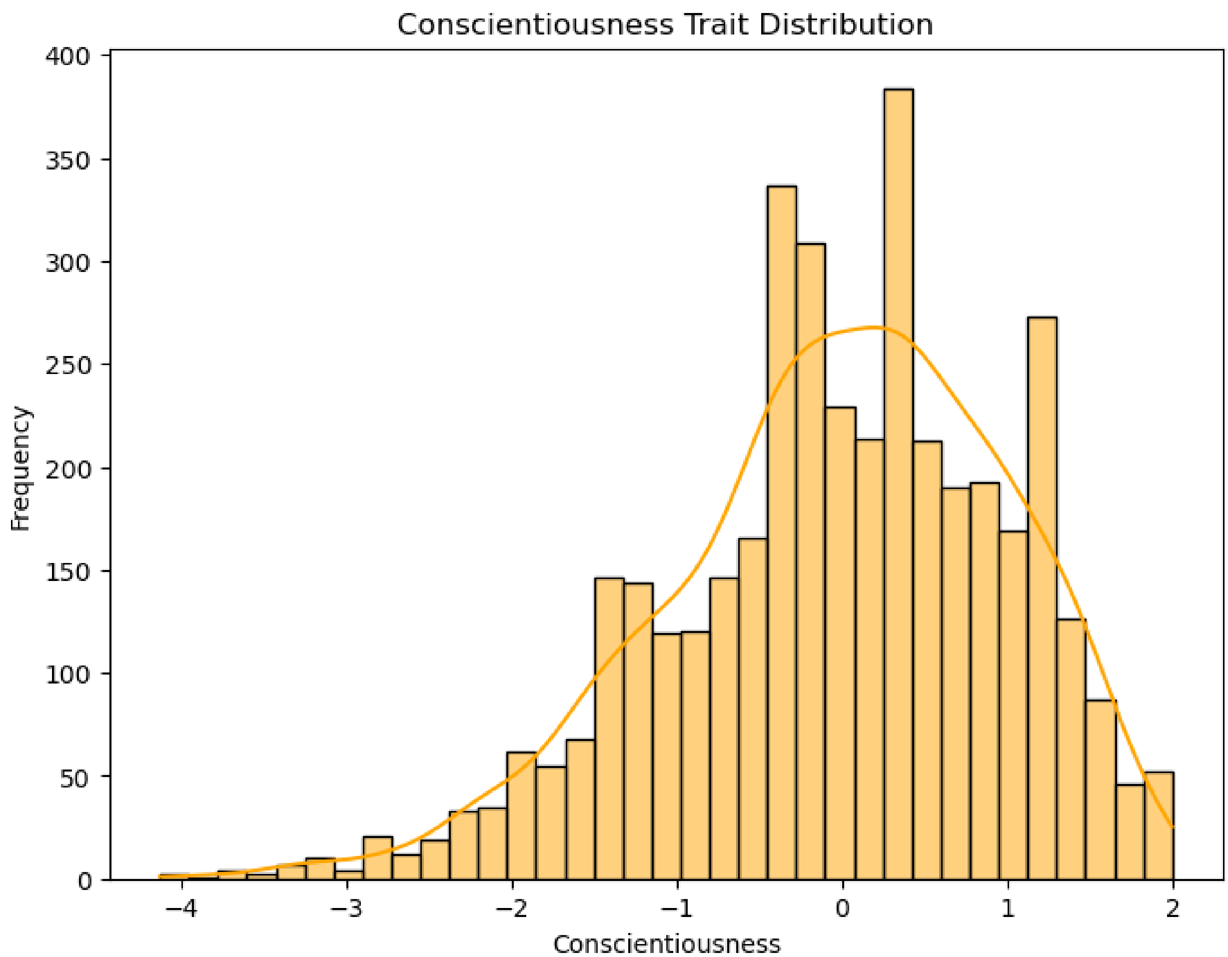


Observation:

College GPA is mostly concentrated between 6.0 and 8.0, indicating that the majority of students have decent academic performance during their college years.

5. Personality Traits: Conscientiousness

```
plt.figure(figsize=(8, 6))
sns.histplot(df['conscientiousness'], kde=True, color='orange')
plt.title('Conscientiousness Trait Distribution')
plt.xlabel('Conscientiousness')
plt.ylabel('Frequency')
plt.show()
```



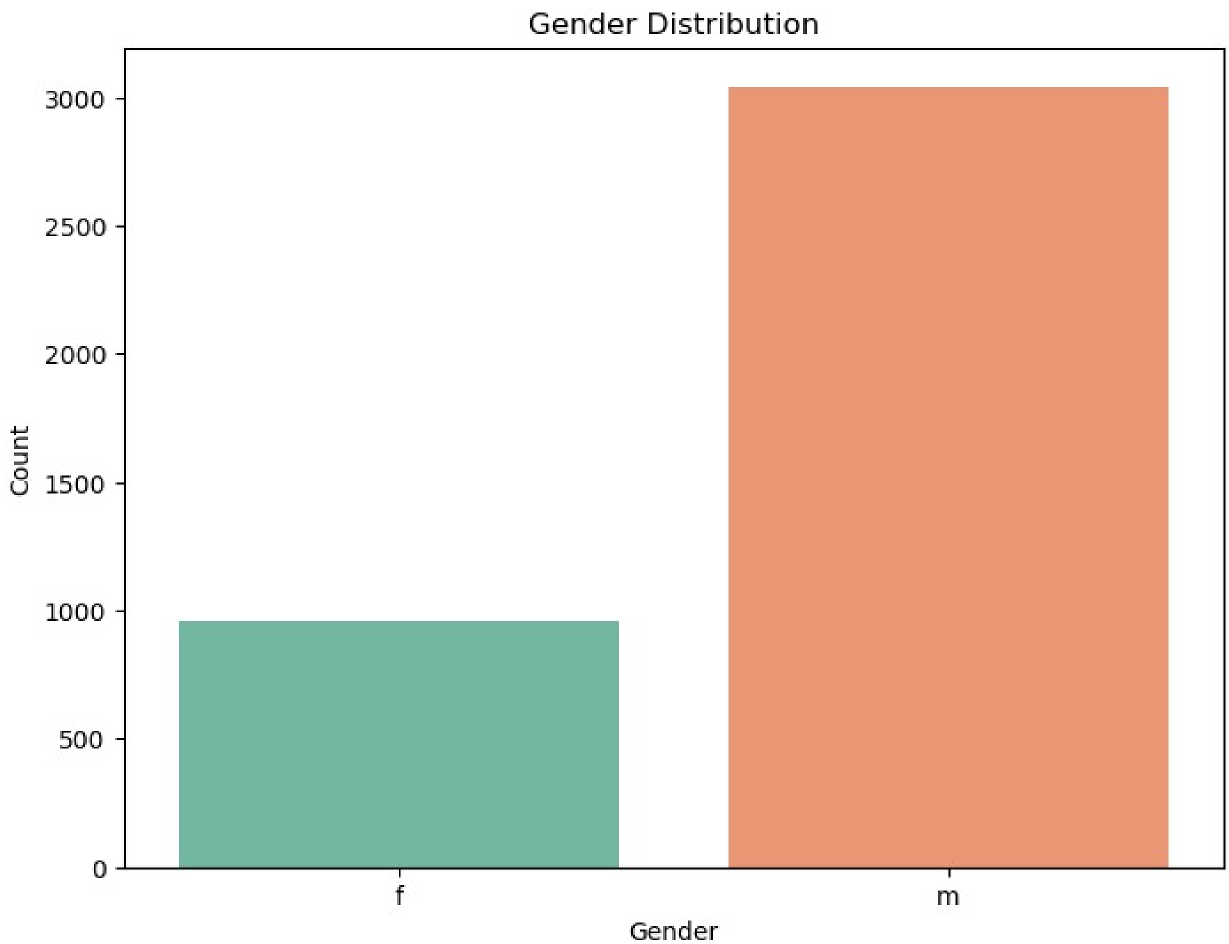
Observation:

The conscientiousness trait is fairly normally distributed, with most students scoring around the mid-level for this personality trait

Univariate Analysis: Categorical Variables

6. Gender Distribution

```
plt.figure(figsize=(8, 6))
sns.countplot(x='Gender', data=df, palette='Set2')
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```

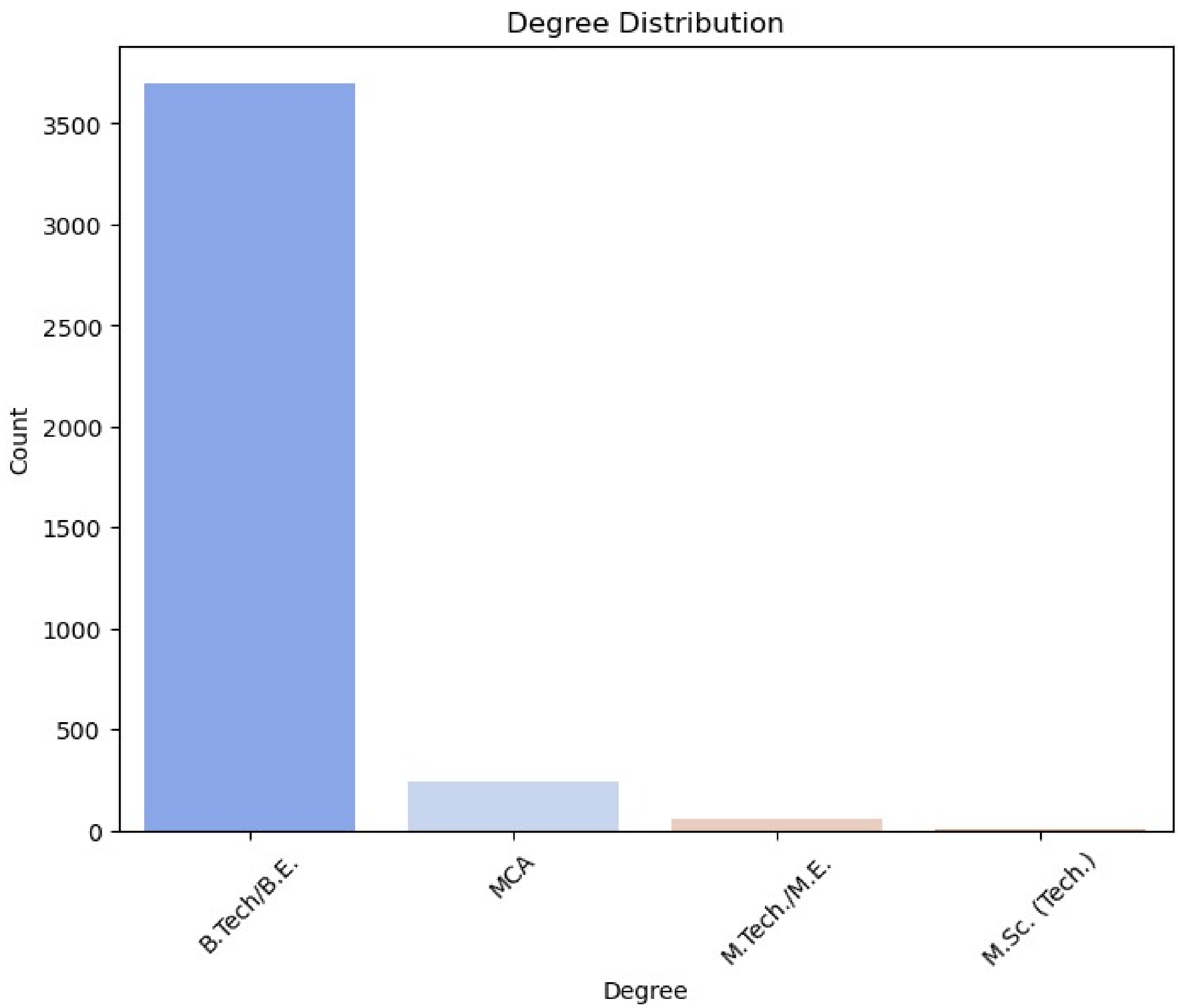


Observation:

There are more male students than female students in the dataset, indicating a gender imbalance in engineering disciplines.

7. Degree Distribution

```
plt.figure(figsize=(8, 6))
sns.countplot(x='Degree', data=df, palette='coolwarm')
plt.title('Degree Distribution')
plt.xticks(rotation=45)
plt.xlabel('Degree')
plt.ylabel('Count')
plt.show()
```

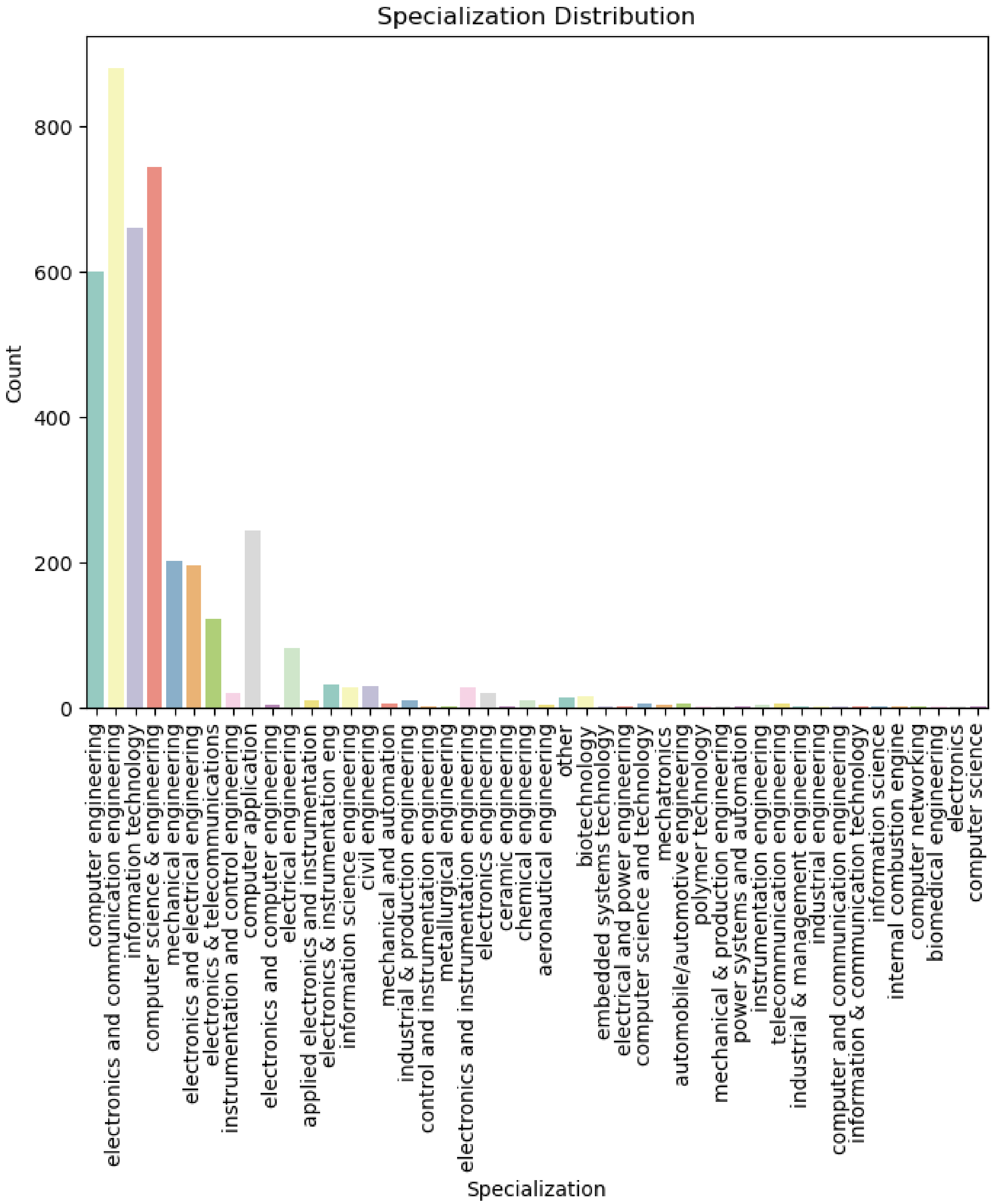


Observation:

B.Tech (Bachelor of Technology) is the most common degree among the students in the dataset.

8. Specialization Distribution

```
plt.figure(figsize=(8, 6))
sns.countplot(x='Specialization', data=df, palette='Set3')
plt.title('Specialization Distribution')
plt.xticks(rotation=90)
plt.xlabel('Specialization')
plt.ylabel('Count')
plt.show()
```



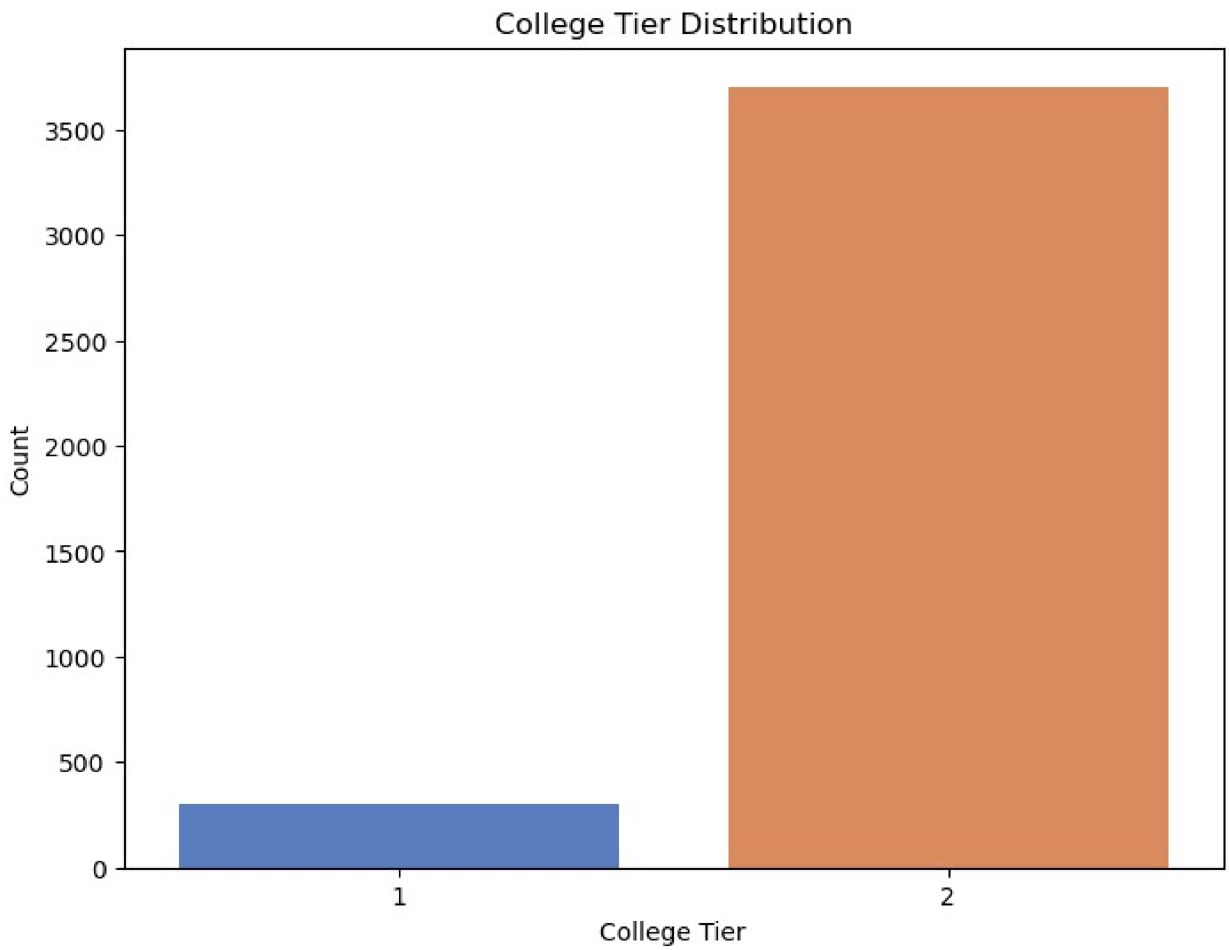
Observation:

Computer Science Engineering (CSE) is the most popular specialization, followed by Mechanical Engineering and Electronics and Communication Engineering.

Univariate Analysis: Other Variables

9. College Tier Distribution

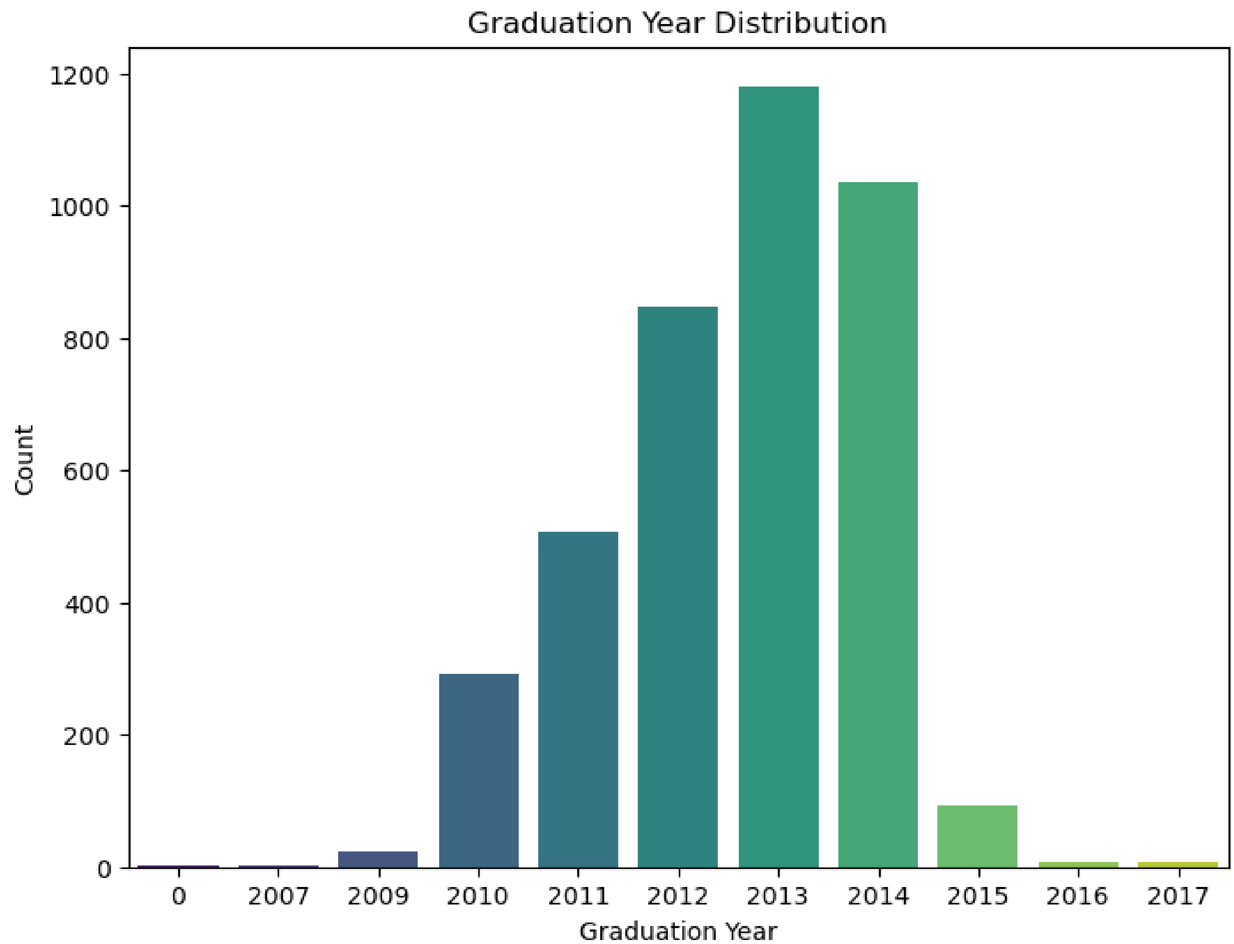
```
plt.figure(figsize=(8, 6))
sns.countplot(x='CollegeTier', data=df, palette='muted')
plt.title('College Tier Distribution')
plt.xlabel('College Tier')
plt.ylabel('Count')
plt.show()
```



10. Graduation Year Distribution

```
plt.figure(figsize=(8, 6))
sns.countplot(x='GraduationYear', data=df, palette='viridis')
plt.title('Graduation Year Distribution')
```

```
plt.xlabel('Graduation Year')
plt.ylabel('Count')
plt.show()
```



Observation:

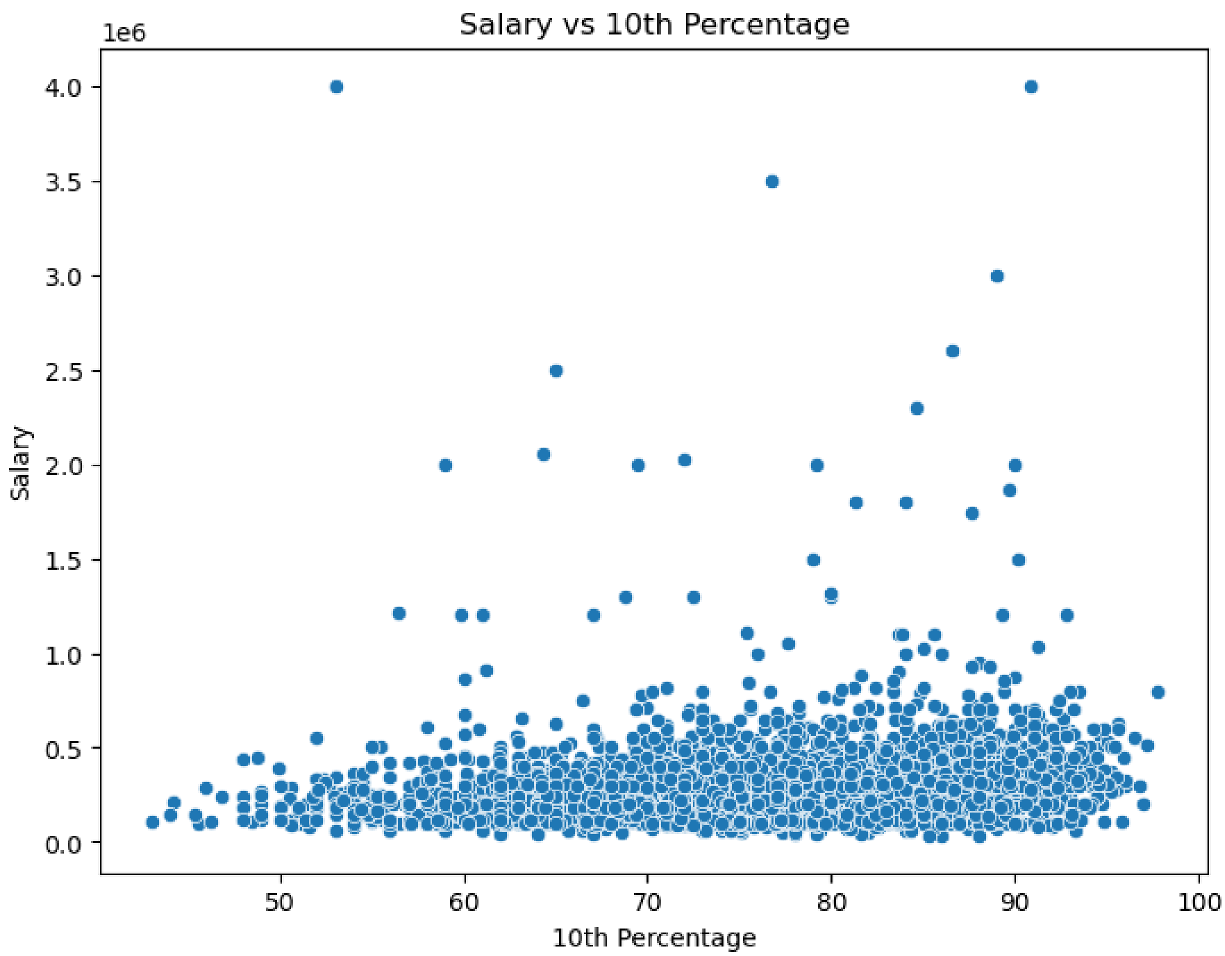
The majority of students in the dataset graduated in recent years, which could reflect a trend of increased engineering enrollments.

Bivariate Analysis: Numerical vs Numerical

1. Salary vs 10th Percentage

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='10percentage', y='Salary', data=df)
```

```
plt.title('Salary vs 10th Percentage')
plt.xlabel('10th Percentage')
plt.ylabel('Salary')
plt.show()
```

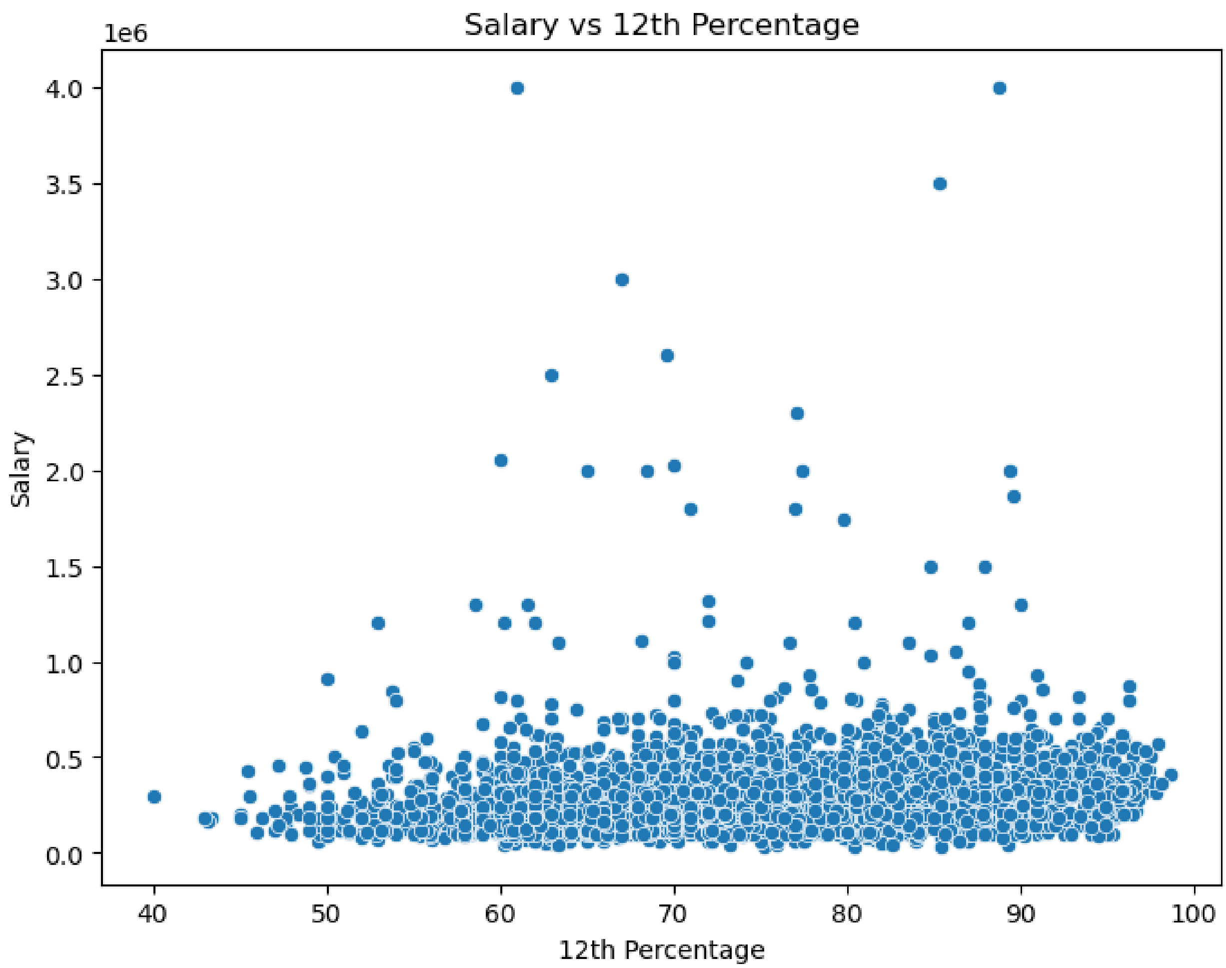


Observation:

There is no clear linear relationship between 10th-grade percentage and salary. Some students with lower percentages in 10th grade seem to earn higher salaries, indicating that early academic performance might not be strongly correlated with job outcomes.

2. Salary vs 12th Percentage

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='12percentage', y='Salary', data=df)
plt.title('Salary vs 12th Percentage')
plt.xlabel('12th Percentage')
plt.ylabel('Salary')
plt.show()
```

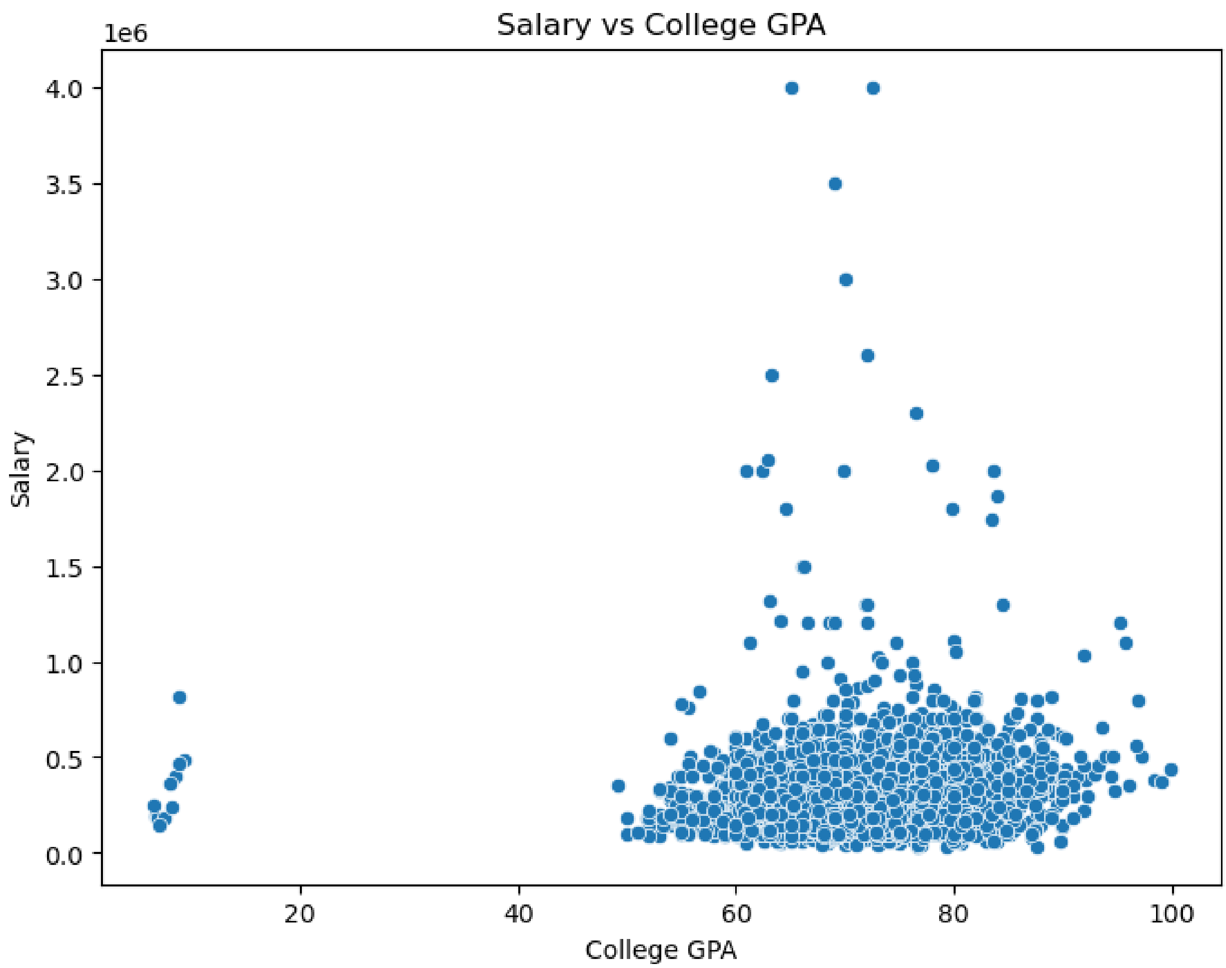


Observation:

Similar to the previous observation, the salary does not appear to be strongly correlated with the 12th-grade percentage. This suggests that high school academic performance may not have a direct influence on salary outcomes.

3. Salary vs College GPA

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='collegeGPA', y='Salary', data=df)
plt.title('Salary vs College GPA')
plt.xlabel('College GPA')
plt.ylabel('Salary')
plt.show()
```



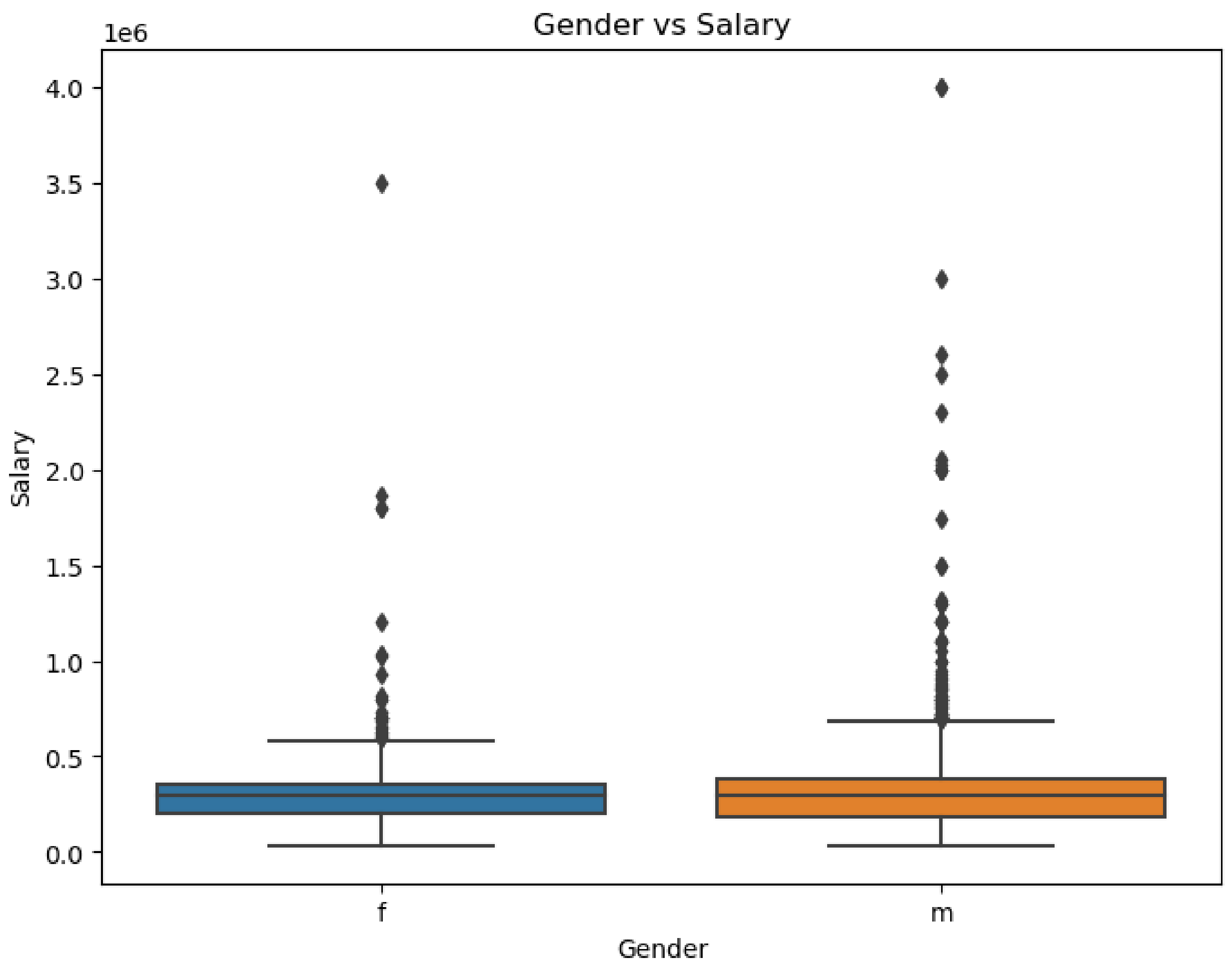
Observation:

There is a slight positive trend between college GPA and salary. Higher GPAs seem to lead to slightly higher salaries, though this relationship is not very strong.

Bivariate Analysis: Categorical vs Numerical

4. Gender vs Salary

```
plt.figure(figsize=(8, 6))
sns.boxplot(x='Gender', y='Salary', data=df)
plt.title('Gender vs Salary')
plt.xlabel('Gender')
plt.ylabel('Salary')
plt.show()
```

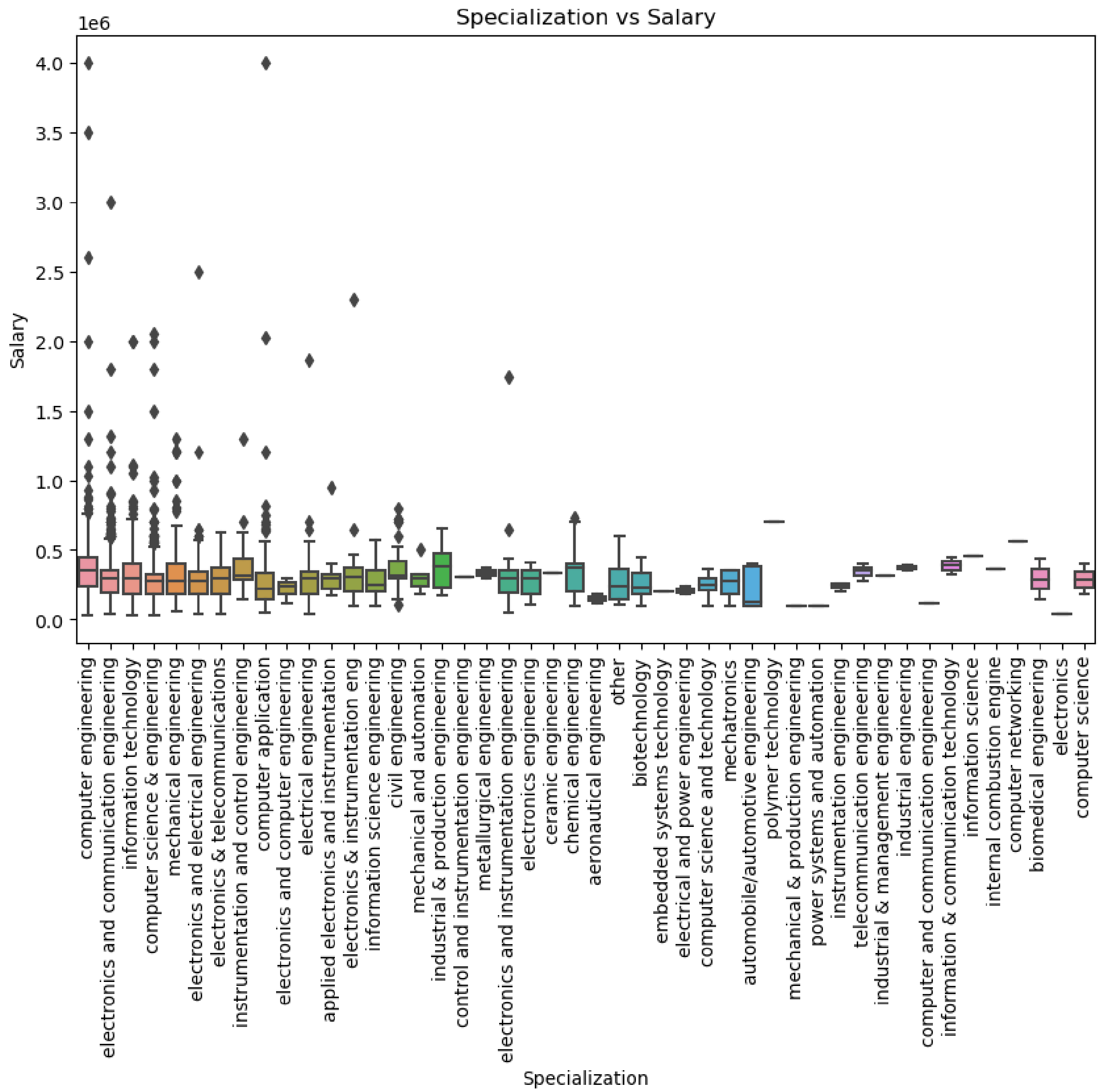


Observation:

There is a noticeable difference in salary distribution between genders. On average, males earn higher salaries than females, though there are outliers in both categories.

5. Specialization vs Salary

```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Specialization', y='Salary', data=df)
plt.xticks(rotation=90)
plt.title('Specialization vs Salary')
plt.xlabel('Specialization')
plt.ylabel('Salary')
plt.show()
```



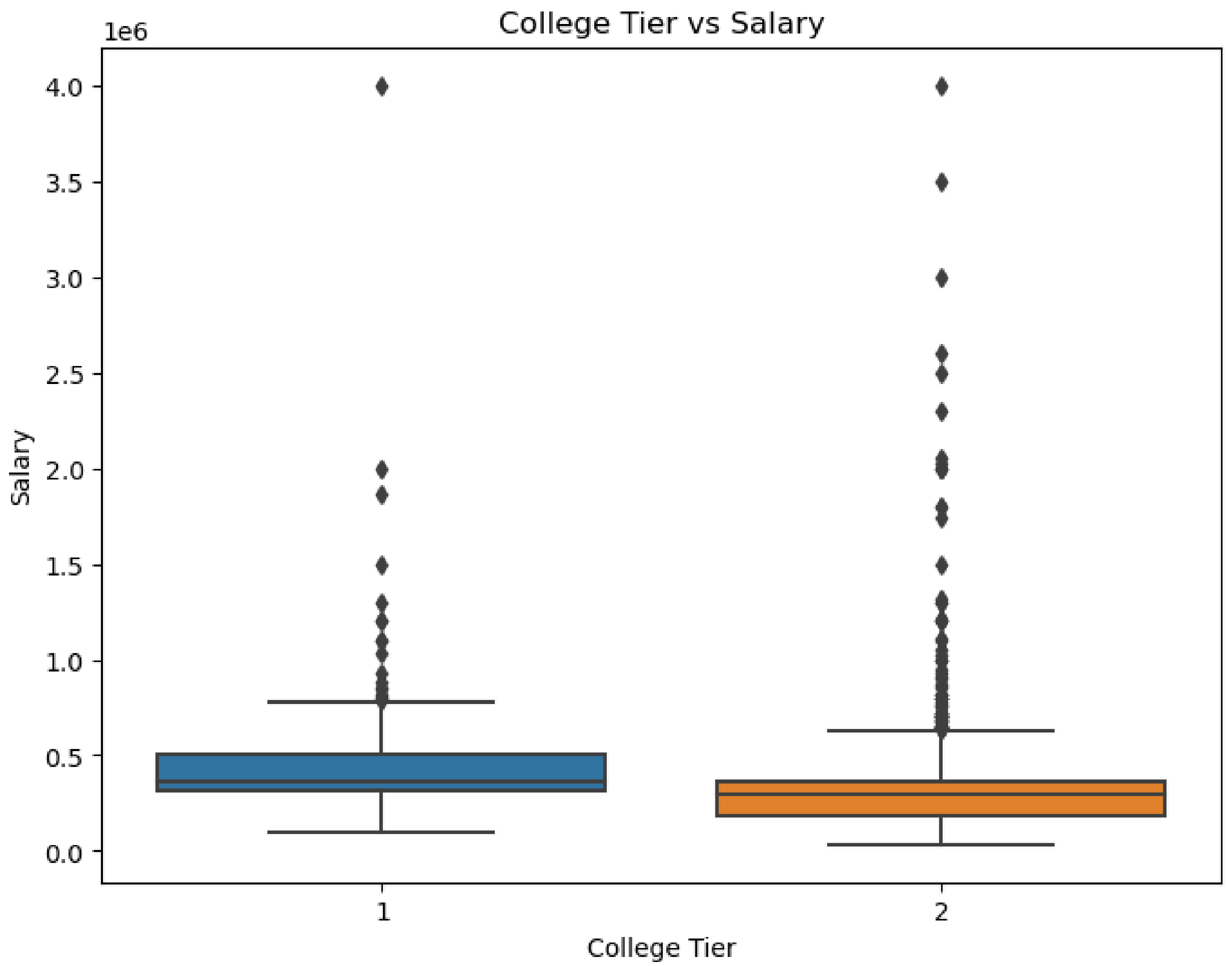
Observation:

Students with specializations in Computer Science and Electronics generally earn higher salaries compared to students in Civil or Mechanical Engineering. There are some high-salary outliers in the Computer Science specialization.

6. College Tier vs Salary

```
plt.figure(figsize=(8, 6))
sns.boxplot(x='CollegeTier', y='Salary', data=df)
plt.title('College Tier vs Salary')
plt.xlabel('College Tier')
```

```
plt.ylabel('Salary')
plt.show()
```



Observation:

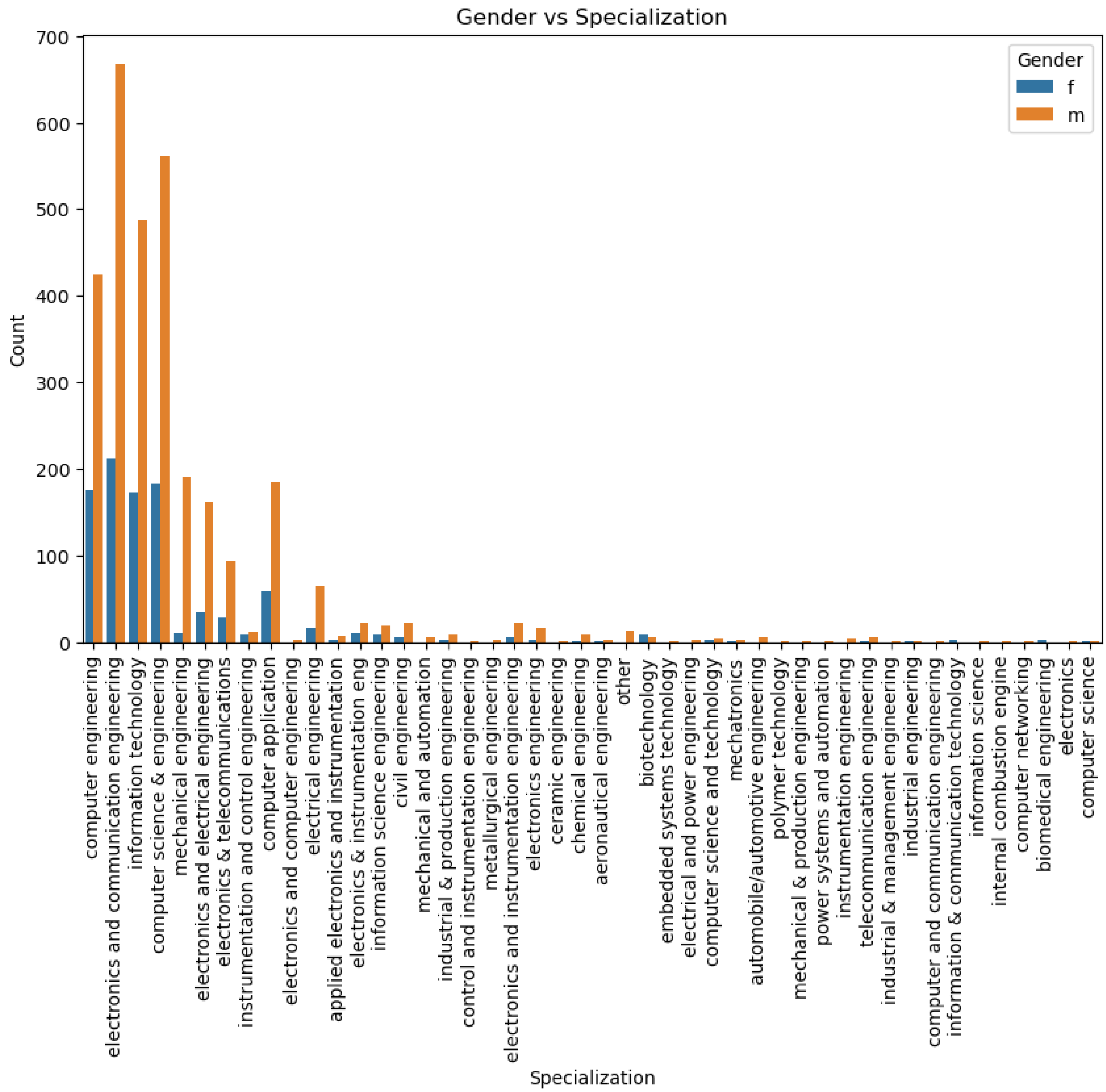
Students from tier 1 colleges tend to have higher salaries compared to those from tier 2 and tier 3 colleges. This suggests that college reputation or tier might have an impact on salary outcomes.

Bivariate Analysis: Categorical vs Categorical

7. Gender vs Specialization

```
plt.figure(figsize=(10, 6))
sns.countplot(x='Specialization', hue='Gender', data=df)
plt.xticks(rotation=90)
```

```
plt.title('Gender vs Specialization')
plt.xlabel('Specialization')
plt.ylabel('Count')
plt.show()
```

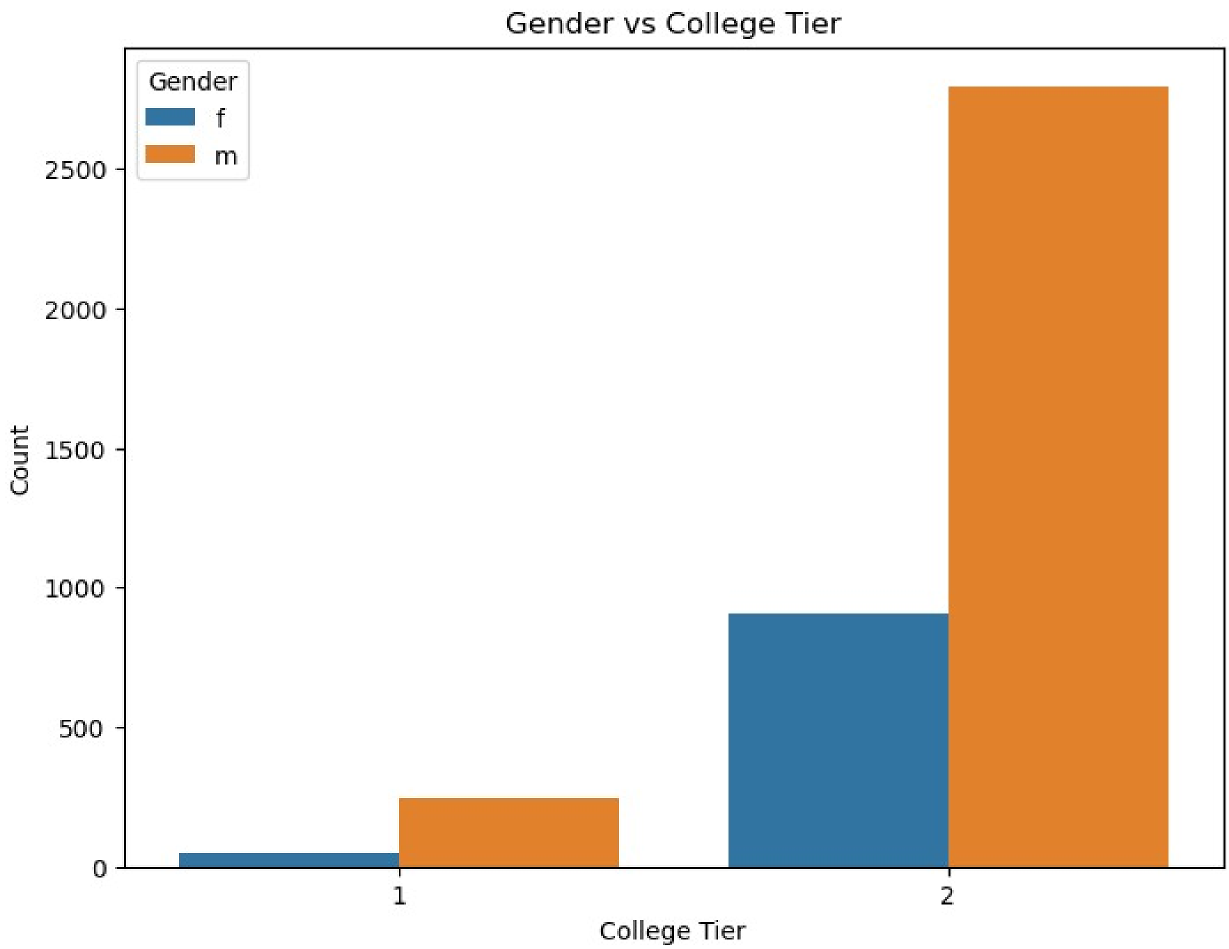


Observation:

In most specializations, males outnumber females. However, in some fields such as Computer Science, there is a more balanced distribution between genders compared to Mechanical and Electrical Engineering, where males dominate.

8. College Tier vs Gender

```
plt.figure(figsize=(8, 6))
sns.countplot(x='CollegeTier', hue='Gender', data=df)
plt.title('Gender vs College Tier')
plt.xlabel('College Tier')
plt.ylabel('Count')
plt.show()
```



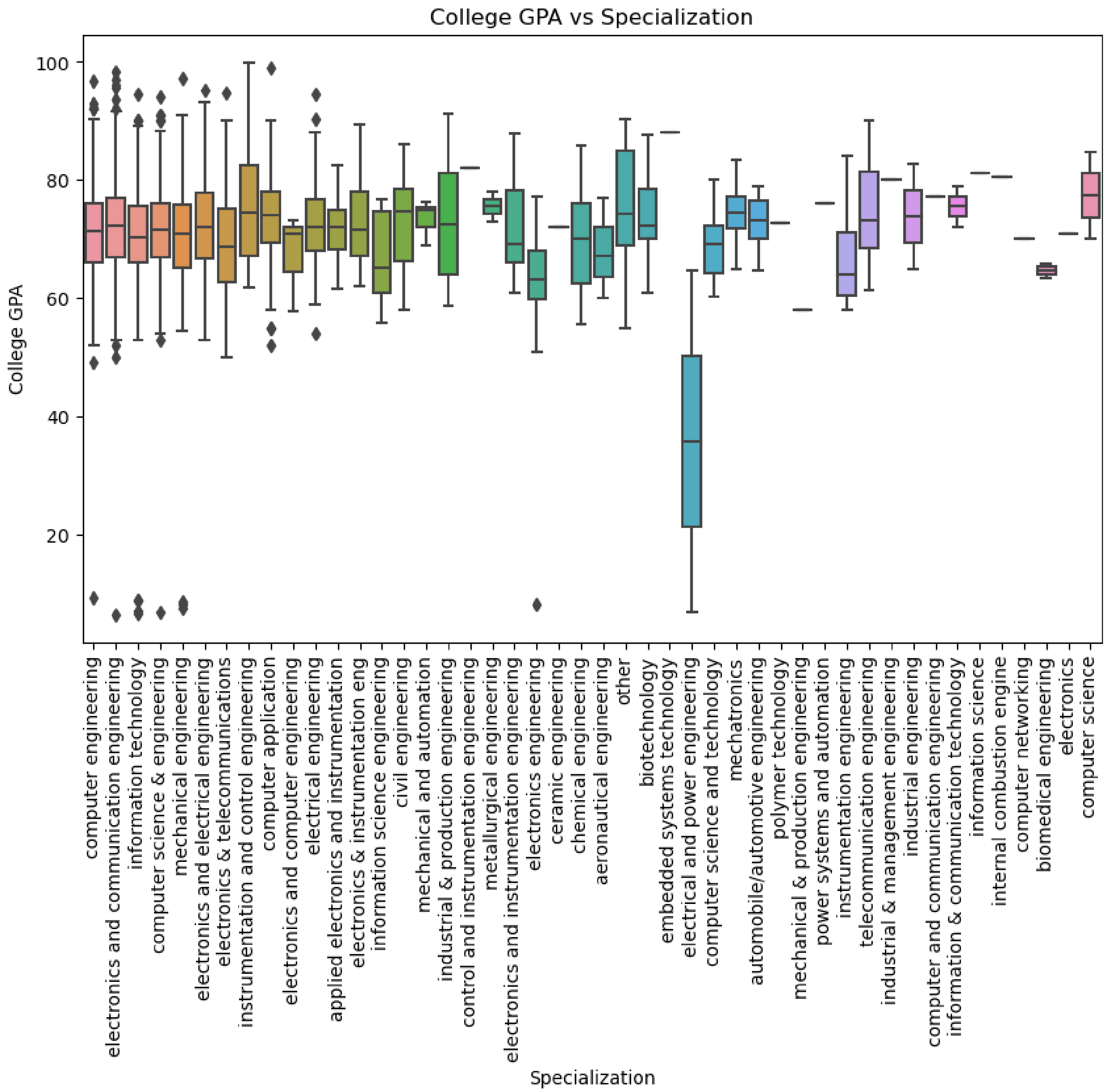
Observation:

Males are more prevalent across all college tiers, but the distribution is relatively consistent across different college tiers. Bivariate Analysis: Numerical vs Categorical

9. College GPA vs Specialization

```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Specialization', y='collegeGPA', data=df)
plt.xticks(rotation=90)
```

```
plt.title('College GPA vs Specialization')
plt.xlabel('Specialization')
plt.ylabel('College GPA')
plt.show()
```



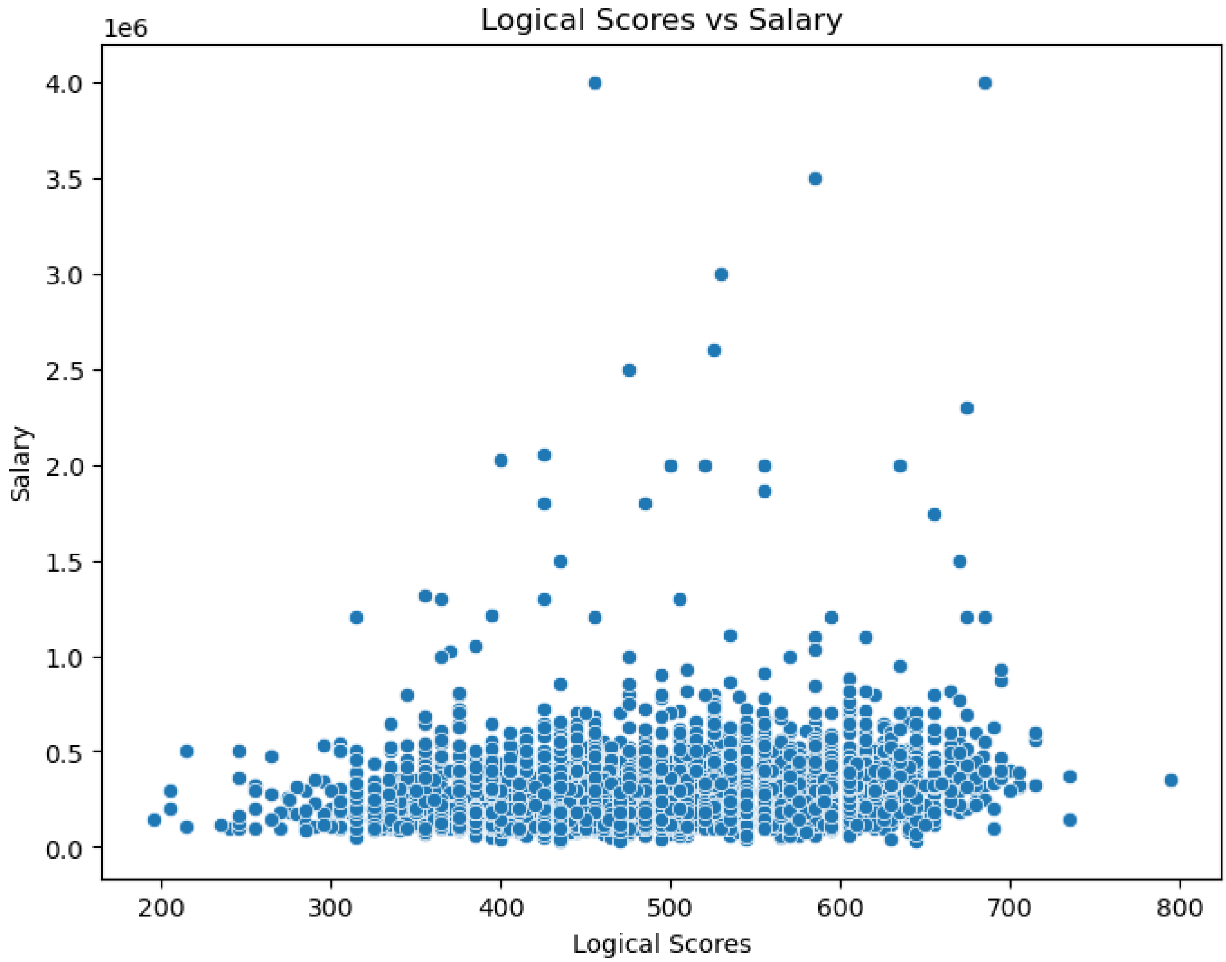
Observation:

College GPA tends to be higher for students in Computer Science and Electronics compared to Mechanical, Electrical, and Civil Engineering. There is less variation in GPA for students specializing in Mechanical and Civil Engineering.

Bivariate Analysis: Cognitive Skills vs Salary

10. Logical Scores vs Salary

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Logical', y='Salary', data=df)
plt.title('Logical Scores vs Salary')
plt.xlabel('Logical Scores')
plt.ylabel('Salary')
plt.show()
```

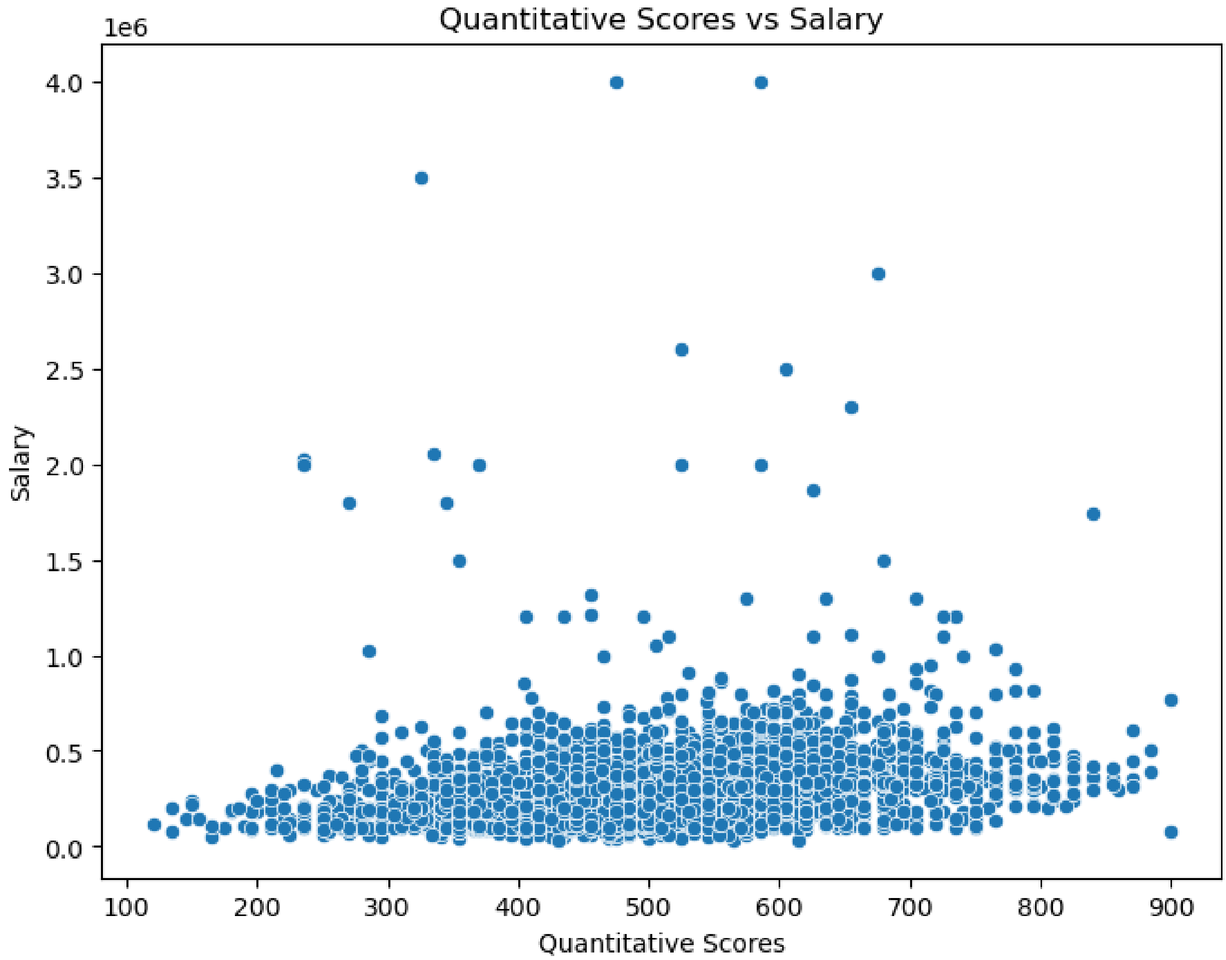


Observation:

There is no strong relationship between logical reasoning scores and salary. This indicates that cognitive skills alone may not significantly influence salary outcomes.

11. Quantitative Scores vs Salary

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Quant', y='Salary', data=df)
plt.title('Quantitative Scores vs Salary')
plt.xlabel('Quantitative Scores')
plt.ylabel('Salary')
plt.show()
```



Observation:

Similar to logical scores, there is no clear correlation between quantitative scores and salary. High scores in this category do not necessarily lead to higher salaries.

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3998 entries, 0 to 3997
Data columns (total 41 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
 39  DOJ_Year                3998 non-null   int32
 40  DOB_Year                3998 non-null   int32
dtypes: datetime64[ns](2), float64(9), int32(2), int64(18), object(10)
memory usage: 1.2+ MB
```

1. Testing the Claim from Times of India

```
cs_graduates = df[df['Specialization'] == 'computer science']
cs_graduates
```

```
     Unnamed: 0       ID  Salary        DOJ                  DOL  \
3256      train  1250504  400000 2014-09-01  2015-02-01 00:00:00
3505      train   455860  180000 2013-04-01  2013-07-01 00:00:00

                  Designation    JobCity Gender        DOB
10percentage  ...  \
3256  associate software engg  Hyderabad      m 1990-02-25
69.5  ...
3505               programmer   Phagwara      f 1989-12-27
73.0  ...

     ElectricalEngg  TelecomEngg  CivilEngg conscientiousness
agreeableness  \
3256             -1           -1         -1            0.9900         -
0.2871
3505             -1           -1         -1           -0.0696
0.5008

      extraversion nueroticism openess_to_experience  DOJ_Year
DOB_Year
3256        0.7785     -1.6289               -0.8608      2014
1990
3505        0.8171      0.4442                0.0284      2013
1989

[2 rows x 41 columns]
```

```
cs_graduates_roles =
cs_graduates[cs_graduates['Designation'].isin(['programmer', 'software
engineer', 'hardware engineer', 'associate software engg'])]
cs_graduates_roles
```

```
     Unnamed: 0       ID  Salary        DOJ                  DOL  \
3256      train  1250504  400000 2014-09-01  2015-02-01 00:00:00
3505      train   455860  180000 2013-04-01  2013-07-01 00:00:00

                  Designation    JobCity Gender        DOB
10percentage  ...  \
3256  associate software engg  Hyderabad      m 1990-02-25
69.5  ...
3505               programmer   Phagwara      f 1989-12-27
73.0  ...

     ElectricalEngg  TelecomEngg  CivilEngg conscientiousness
agreeableness  \
```

```
3256                -1            -1          -1             0.9900        -
0.2871
3505                -1            -1          -1            -0.0696
0.5008

      extraversion nueroticism openess_to_experience  DOJ_Year
DOB_Year
3256        0.7785     -1.6289                -0.8608      2014
1990
3505        0.8171      0.4442                 0.0284      2013
1989

[2 rows x 41 columns]
```

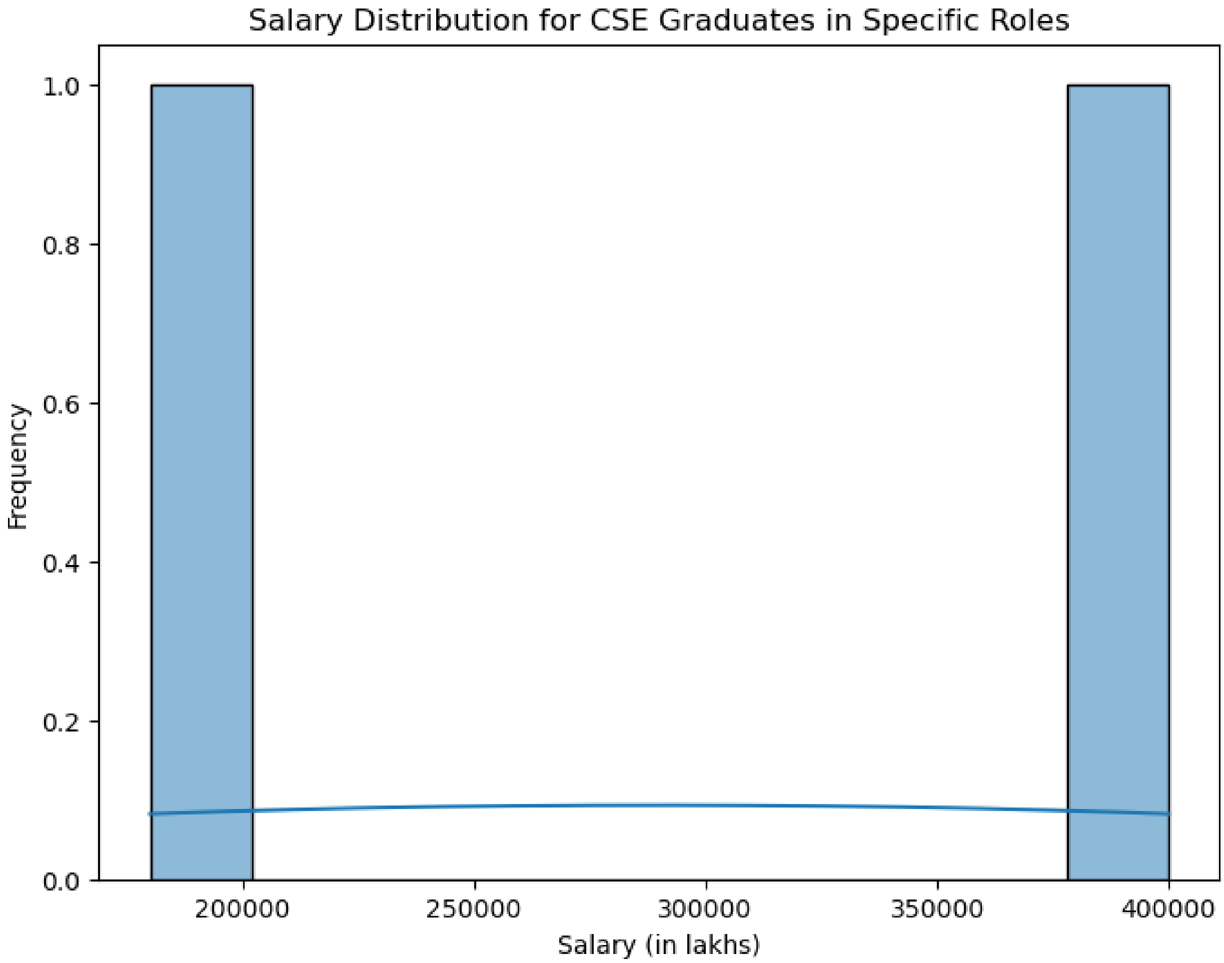
```
cs_graduates_roles_salary = cs_graduates_roles['Salary']
cs_graduates_roles_salary
```

```
3256    400000
3505    180000
Name: Salary, dtype: int64
```

```
cs_graduates_roles_salary.describe()
```

```
count         2.000000
mean     290000.000000
std      155563.491861
min      180000.000000
25%      235000.000000
50%      290000.000000
75%      345000.000000
max      400000.000000
Name: Salary, dtype: float64
```

```
plt.figure(figsize=(8, 6))
sns.histplot(cs_graduates_roles_salary, bins=10, kde=True)
plt.title('Salary Distribution for CSE Graduates in Specific Roles')
plt.xlabel('Salary (in lakhs)')
plt.ylabel('Frequency')
plt.show()
```



Observation:

The summary statistics (mean, median) will show whether the average salary of graduates in these roles falls within the range of 2 to 4 lakhs, as mentioned in the article. The histogram will help visually assess the salary distribution for these roles.

2. The relationship between gender and specialization.

```
contingency_table = pd.crosstab(df['Gender'], df['Specialization'])
contingency_table
```

```
Specialization  aeronautical engineering  \
Gender
f                                       1
m                                       2

Specialization  applied electronics and instrumentation  \
```

```
Gender
f                                                      2
m                                                      7

Specialization  automobile/automotive engineering  biomedical
engineering  \
Gender

f                                                0
2
m                                                5
0

Specialization  biotechnology  ceramic engineering  chemical
engineering  \
Gender

f                            9                    0
1
m                            6                    1
8

Specialization  civil engineering  computer and communication
engineering  \
Gender

f                                 6
0
m                                23
1

Specialization  computer application  ...  internal combustion engine
\
Gender                                ...

f                                   59  ...                           0

m                                  185  ...                           1


Specialization  mechanical & production engineering  \
Gender
f                                                  0
m                                                  1

Specialization  mechanical and automation  mechanical engineering  \
Gender
f                                       0                      10
m                                       5                     191
```

```
Specialization  mechatronics  metallurgical engineering  other  \
Gender
f                          1                          0      0
m                          3                          2     13

Specialization  polymer technology  power systems and automation  \
Gender
f                                0                             0
m                                1                             1

Specialization  telecommunication engineering
Gender
f                                           1
m                                           5

[2 rows x 46 columns]
```

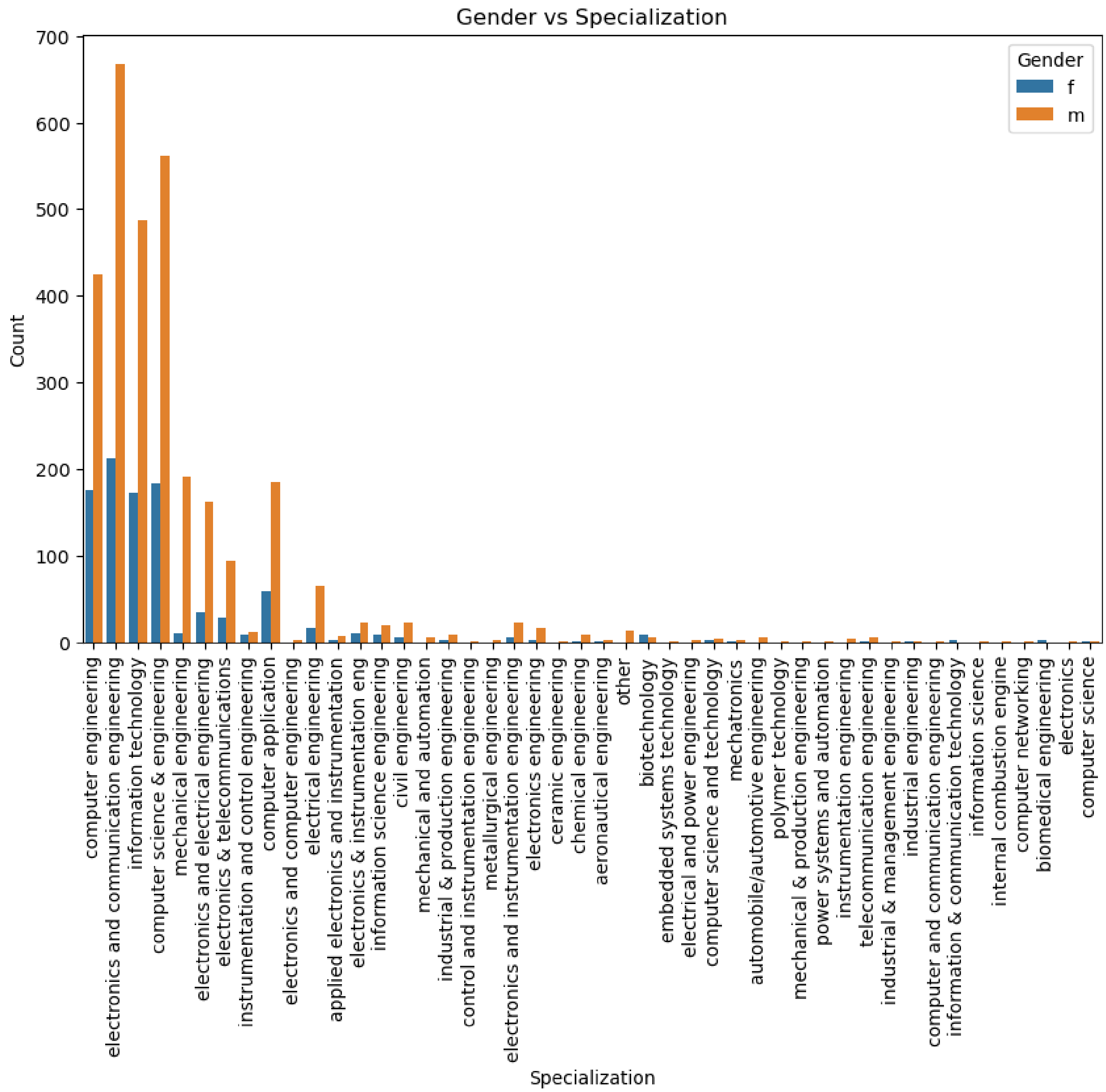
```python
from scipy.stats import chi2_contingency

chi2, p_value, dof, expected = chi2_contingency(contingency_table)

print(f"Chi-square statistic: {chi2}")
print(f"P-value: {p_value}")
```

```
Chi-square statistic: 104.46891913608455
P-value: 1.2453868176976918e-06
```

```python
plt.figure(figsize=(10, 6))
sns.countplot(x='Specialization', hue='Gender', data=df)
plt.xticks(rotation=90)
plt.title('Gender vs Specialization')
plt.xlabel('Specialization')
plt.ylabel('Count')
plt.show()
```



Observation: If the p-value is less than 0.05, we can reject the null hypothesis and conclude that there is a relationship between gender and specialization. If the p-value is greater than 0.05, we fail to reject the null hypothesis and conclude that gender does not have a significant impact on the choice of specialization.

Conclusion:

The dataset provides valuable insights into the employment outcomes of engineering graduates, revealing a diverse range of salaries, job locations, and specializations. While technical and cognitive skills play a significant role in determining job outcomes, the analysis also highlights that demographic factors like gender and specialization are not strongly related. This suggests that job opportunities in engineering are largely merit-based, with skills and qualifications being the key determinants for career progression.