For the purpose of this project, I will utilize a proprietary dataset retrieved from our Human Resources Information System (HRIS) platform, ADP. This comprehensive dataset includes complete records of payroll transactions from the period of January 2021 through May 2023. The structure of this dataset is organized, with rows representing individual employees, and columns denoting various categories such as payroll dates, amounts, and the respective companies the employees were affiliated with at the time of payroll issuance. As noted in the data dictionary below.

My primary objective is to analyze this data by employing statistical methods and data analysis techniques. I will thoroughly cleanse and preprocess the data to ensure its optimal state for the subsequent predictive modeling.

Based on the insights drawn from the initial analysis, I will proceed to apply the most suitable machine learning model that aligns best with my objective - forecasting future payroll expenses. The intent is to develop a robust model that is capable of predicting payroll outflows, thereby assisting the organization in making more informed financial planning decisions.

In [24]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
import warnings
warnings.filterwarnings("ignore")
```

Data Dictionary

Column Name	Description
Company	The name or identifier of the company that the employee belongs to.
Employee ID	A unique identifier for each employee in the company.
Unique ID	Another unique identifier, used for specific purposes within the dataset.
Title	The job title or position of the employee within the company.
Job Class	The job classification or category of the employee's position.
Address State	The state where the employee's address is located.
Hire Date	The date when the employee was hired by the company.
Tenure	The length of time (in years) the employee has been working in the company.
Gender	The gender of the employee.
Department At Payroll Process	The department to which the employee belongs at the time of payroll processing.
Payroll Code	A code related to the employee's payroll transactions.
G L Account Number	The account number used in the company's General Ledger for financial payroll transactions.
G L Department	The department in the company associated with financial transactions.
Post Date	The date when a transaction or entry was posted.
Description	A description of the check date.
Dollars	The amount of money involved in the transaction.
Section Type	The type or category of the payroll code.
Month	The month in which a particular event or transaction occurred.
Year	The year in which a particular event or transaction occurred.

In [3]:
```
# Loading the data set and viewing dataframe.

df = pd.read_excel(r'C:\Users\mdyoung\OneDrive - Bankers Financial Corporation\Desktop\Bellevue\DCS630_T301_22
df
```

Out[3]:

	Company	Employee I D	Unique ID	Title	Job Class	Address State	Hire Date	Tenure	Gender	Department At Payroll Process	Payroll Code	Ac Nu
0	EBM	73730	EBM7373070199	401(k) / Benefits Specialist	Administrative Support Workers	Florida	2022-03-20	1.3	M	70199	CK1	10610
1	EBM	73730	EBM7373070199	401(k) / Benefits Specialist	Administrative Support Workers	Florida	2022-03-20	1.3	M	70199	EEFED	22040
2	EBM	73730	EBM7373070199	401(k) / Benefits Specialist	Administrative Support Workers	Florida	2022-03-20	1.3	M	70199	EEFICA	22042
3	EBM	73730	EBM7373070199	401(k) / Benefits Specialist	Administrative Support Workers	Florida	2022-03-20	1.3	M	70199	EEMEDICARE	22042
4	EBM	73730	EBM7373070199	401(k) / Benefits Specialist	Administrative Support Workers	Florida	2022-03-20	1.3	M	70199	ERFICAEXP	70120
...	...	...	...	...	...	...	...	...	...	...	...	...
477919	EBM	3874	EBM387450599	Workers Compensation Claims Manager	First/Mid-Level Officials and Managers	Florida	2015-02-23	8.3	M	50599	K	21200
477920	EBM	3874	EBM387450599	Workers Compensation Claims Manager	First/Mid-Level Officials and Managers	Florida	2015-02-23	8.3	M	50599	REG	70010
477921	EBM	3874	EBM387450599	Workers Compensation Claims Manager	First/Mid-Level Officials and Managers	Florida	2015-02-23	8.3	M	50599	SLF	70420
477922	EBM	3874	EBM387450599	Workers Compensation Claims Manager	First/Mid-Level Officials and Managers	Florida	2015-02-23	8.3	M	50599	STD	70420
477923	EBM	3874	EBM387450599	Workers Compensation Claims Manager	First/Mid-Level Officials and Managers	Florida	2015-02-23	8.3	M	50599	VLF	70420

477924 rows × 19 columns

In [4]:
```
# Summary of data.

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 477924 entries, 0 to 477923
Data columns (total 19 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   Company                        477924 non-null  object
 1   Employee I D                   477924 non-null  int64
 2   Unique ID                      477924 non-null  object
 3   Title                          477924 non-null  object
 4   Job Class                      477924 non-null  object
 5   Address State                  477924 non-null  object
 6   Hire Date                      477924 non-null  datetime64[ns]
 7   Tenure                         477924 non-null  float64
 8   Gender                         477924 non-null  object
 9   Department At Payroll Process  477924 non-null  int64
 10  Payroll Code                   477821 non-null  object
 11  G L Account Number             477924 non-null  int64
 12  G L Department                 477924 non-null  int64
 13  Post Date                      477924 non-null  int64
 14  Description                    477924 non-null  object
 15  Dollars                        477924 non-null  float64
 16  Section Type                   477902 non-null  object
 17  Month                          477924 non-null  int64
 18  Year                           477924 non-null  int64
dtypes: datetime64[ns](1), float64(2), int64(7), object(9)
memory usage: 69.3+ MB
```

- The data file has 477,924 rows and 19 columns.
- The data types contain both object and numerical vlaues.
- Will remove some of the object columns as they will not be needed for modeling. Such as Employee I D.

In [5]:
```
# Viewing stat summary for numerical columns.

df.describe()
```

Out[5]:

	Employee I D	Hire Date	Tenure	Department At Payroll Process	G L Account Number	G L Department	Post Date	Dollars	Mor
count	477924.000000	477924	477924.000000	477924.000000	4.779240e+05	4.779240e+05	4.779240e+05	477924.000000	477924.0000
mean	59330.341301	2015-03-19 14:26:38.654179584	8.291013	53093.500276	4.417767e+09	9.960172e+07	2.021816e+07	-0.000143	5.9086
min	54.000000	1968-06-10 00:00:00	0.200000	10308.000000	1.061000e+09	9.050000e+05	2.021012e+07	-320692.800000	1.0000
25%	3469.000000	2012-09-04 00:00:00	3.000000	24599.000000	2.204050e+09	9.050000e+05	2.021081e+07	-118.460000	3.0000
50%	7587.000000	2017-07-31 00:00:00	5.900000	50899.000000	2.204200e+09	9.050000e+05	2.022032e+07	-21.040000	5.0000
75%	8632.000000	2020-06-22 00:00:00	10.800000	80108.000000	7.013000e+09	7.002420e+07	2.022102e+07	5.790000	9.0000
max	999970.000000	2023-05-09 00:00:00	55.100000	98107.000000	7.952001e+09	6.077910e+08	2.023052e+07	429807.000000	12.0000
std	202932.132222	NaN	7.739738	28269.275908	2.511857e+09	1.718216e+08	7.094773e+03	2491.092212	3.5346

In [6]:
```
# Viewing stat summary for non-numerical columns.

df.describe(include = ['O'])
```

Out[6]:

	Company	Unique ID	Title	Job Class	Address State	Gender	Payroll Code	Description	Section Type
count	477924	477924	477924	477924	477924	477924	477821	477924	477902
unique	8	859	316	6	32	2	112	39	166
top	EBM	EBM771950599	Customer Experience Specialist I	Administrative Support Workers	Florida	F	EEMEDICARE	2021-12-31 00:00:00	Employer Medicare Tax
freq	124108	1603	18625	220532	389013	292263	30110	196430	58976

In [7]:
```
# Checking for missing values to ensure data completeness.

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

Out[7]:
```
Company                          0
Employee I D                     0
Unique ID                        0
Title                            0
Job Class                        0
Address State                    0
Hire Date                        0
Tenure                           0
Gender                           0
Department At Payroll Process    0
Payroll Code                   103
G L Account Number               0
G L Department                   0
Post Date                        0
Description                      0
Dollars                          0
Section Type                    22
Month                            0
Year                             0
dtype: int64
```

There are some missing values we will need to handle. In this case, I will drop the columns as they are redundant. First I will check account totals by year.

In [8]:
```
# Defining a function to format currency.
def format_currency(x):
    return "${:,.2f}".format(x)

# Create the pivot table
pivot_table = df.pivot_table(
    index='G L Account Number',
    columns='Year',
    values='Dollars',
    aggfunc=np.sum
)

# Apply the function to the pivot table
formatted_pivot_table = pivot_table.applymap(format_currency)

formatted_pivot_table
```

Out[8]:

Year	2021	2022	2023
G L Account Number			
1061000115	$-26,377,651.76	$-32,076,465.46	$nan
1201000101	$90,313.55	$212,258.78	$97,192.46
1204100000	$-3,023.06	$nan	$nan
1901200005	$nan	$nan	$-13,320,935.03
2120000504	$-12,254.00	$-13,895.40	$-5,597.50
2120000505	$-2,874,416.18	$-3,164,421.61	$-1,362,519.61
2120000506	$-24,433.19	$-39,153.41	$-17,176.56
2120000507	$-178,110.01	$-214,989.65	$-86,887.20
2120000514	$-273,285.92	$-355,178.62	$-170,079.86
2120000515	$-22,870.29	$-25,664.34	$-20,742.81
2120000528	$-95,577.80	$-70,171.22	$-14,491.60
2204050000	$-4,727,167.94	$-5,886,073.20	$-2,481,380.67
2204200000	$-4,929,422.70	$-5,854,547.54	$-2,648,116.31
6010000000	$1,056,294.26	$679,745.74	$558,830.41
7001000000	$31,578,399.41	$36,711,156.18	$13,980,699.43
7002000000	$247,511.61	$379,921.35	$168,650.84
7003000000	$3,048,482.15	$4,203,551.76	$3,178,580.64
7003000200	$nan	$65,000.00	$30,000.00
7004000000	$2,025,923.39	$2,605,684.88	$1,024,427.52
7006000000	$80,981.08	$948,038.01	$164,207.28
7012000000	$2,445,902.14	$2,900,753.96	$1,317,782.80
7013000000	$22,870.29	$25,664.34	$20,742.81
7014000000	$40,864.14	$44,488.09	$35,154.94
7042000011	$-922,447.00	$-941,411.50	$-412,947.03
7042000020	$-220,195.73	$-240,842.67	$-93,260.54
7042000030	$-31,554.00	$-34,659.93	$-12,831.84
7042000040	$-101,272.17	$-110,724.83	$-36,416.19
7042000041	$-23,138.25	$-18,182.97	$-11,397.50
7042000050	$-3,209.45	$-1,215.74	$-418.60
7042000070	$-10,856.40	$nan	$nan
7042500010	$27,453.83	$31,414.63	$574.24
7043000000	$17,927.66	$11,923.45	$1,146.00
7043510000	$61,500.00	$135,000.00	$76,000.00
7043520000	$14,500.00	$16,500.00	$10,500.00
7044000000	$22,136.68	$18,103.30	$6,393.52
7952001000	$49,757.32	$58,393.62	$24,315.96

In [12]:
```
# Define the desired G L Account Numbers
desired_gl_numbers = [7001000000, 7004000000, 6010000000]

# Filter the DataFrame to include only the desired G L Account Numbers
filtered_df = df[df['G L Account Number'].isin(desired_gl_numbers)]

# Group by 'Section Type' and 'G L Account Number' and sum the 'Dollars'
section_gl_sum = filtered_df.groupby(['G L Account Number',
                                       'Section Type'])['Dollars'].sum().reset_index(name='Total Dollars')

# Function to format currency
def format_currency(x):
    return "${:,.2f}".format(x)

# Apply the function to the 'Total Dollars' column
section_gl_sum['Total Dollars'] = section_gl_sum['Total Dollars'].apply(format_currency)

# Print the filtered table
print("Filtered Table - Section Type and G L Account Number with Total Dollars:")
section_gl_sum
```

Filtered Table - Section Type and G L Account Number with Total Dollars:

Out[12]:

	G L Account Number	Section Type	Total Dollars
0	6010000000	COMM BOND	$2,294,870.41
1	7001000000	ADJUST	$-2,773.08
2	7001000000	BEREAVMNT	$34,273.20
3	7001000000	Earnings (PYT)	$59,303.63
4	7001000000	FLOAT HOL	$64,690.96
5	7001000000	FMLA	$35,157.77
6	7001000000	HOLIDAY	$660,417.39
7	7001000000	Inclmnt Wthr	$11,210.35
8	7001000000	JURY DUTY	$4,589.18
9	7001000000	Miscellaneous	$171.60
10	7001000000	PAID TIME OFF	$944,282.43
11	7001000000	PD TIME OFF	$432,249.97
12	7001000000	PTO Payout	$37,914.63
13	7001000000	Paid Fam Lve	$101,076.11
14	7001000000	RETRO PAY	$46,423.17
15	7001000000	Regular Earnings	$79,772,451.87
16	7001000000	RetirBon	$30,400.00
17	7001000000	Retire Bonus	$2,000.00
18	7001000000	RetireBon	$600.00
19	7001000000	SCK	$9,942.16
20	7001000000	Spiff Bonus	$8,500.00
21	7001000000	VOLUNTEER	$17,373.68
22	7004000000	COMMISSION	$5,585,484.30
23	7004000000	OTHER	$31,991.49
24	7004000000	TIPS	$38,560.00

- Given the information in the above pivot table, I can see that I only want to use the GL Accounts 6010000000 and 7001000000 though 7004000000 as these are the base earnings code accounts from our data dictionary for commissions and regular base calculation wages.

In [13]:
```
# Dropping features that are redundant and unnessecary to analysis for earnings.

# Define the list of accounts to keep
accounts_to_keep = [6010000000, 7001000000, 7004000000]

# Drop features that are redundant and unnecessary for analysis for earnings
df_drop = df.drop(['Employee I D','Company', 'Payroll Code', 'Description', 'Unique ID',
                   'Section Type','Post Date',
                   'G L Department','Hire Date'], axis=1)

# Filter the DataFrame to only include the specified accounts
df_drop = df_drop[df_drop['G L Account Number'].isin(accounts_to_keep)]

# Display the first 10 rows of the updated DataFrame
df_drop.head(10)
```

Out[13]:

	Title	Job Class	Address State	Tenure	Gender	Department At Payroll Process	G L Account Number	Dollars	Month	Year
12	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	1216.32	4	2022
13	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	810.88	4	2022
27	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	2027.20	4	2022
41	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	2027.20	5	2022
55	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	2027.20	5	2022
66	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	2027.20	6	2022
76	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	202.72	6	2022
78	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	1837.15	6	2022
89	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	2027.20	7	2022
99	401(k) / Benefits Specialist	Administrative Support Workers	Florida	1.3	M	70199	7001000000	202.72	7	2022

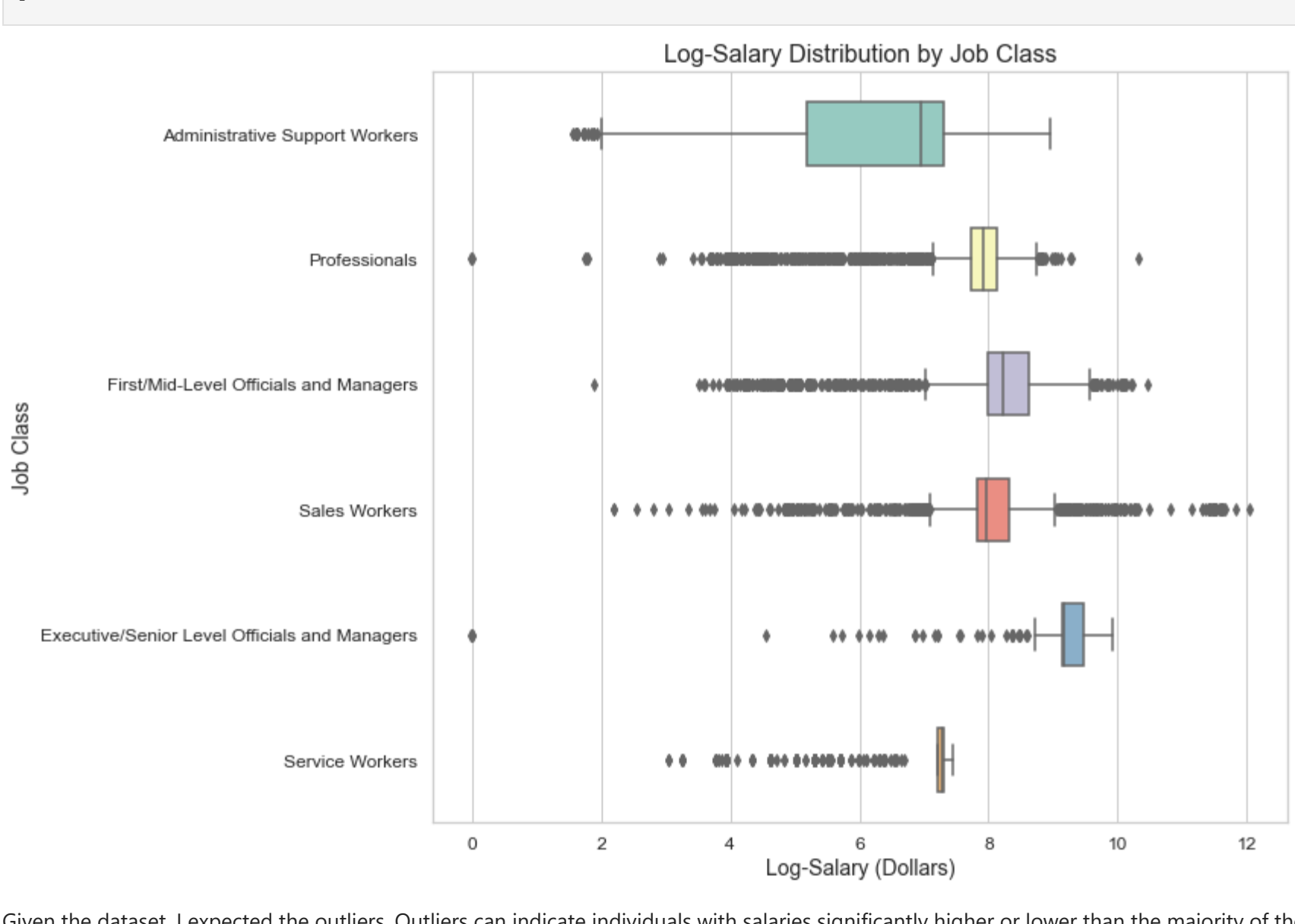
In [14]:
```
df_drop.shape
```

Out[14]: (39538, 10)

In [15]:
```
# Checking for missing values to ensure data completeness after droping rows and columns.

df_drop.isnull().sum()
```

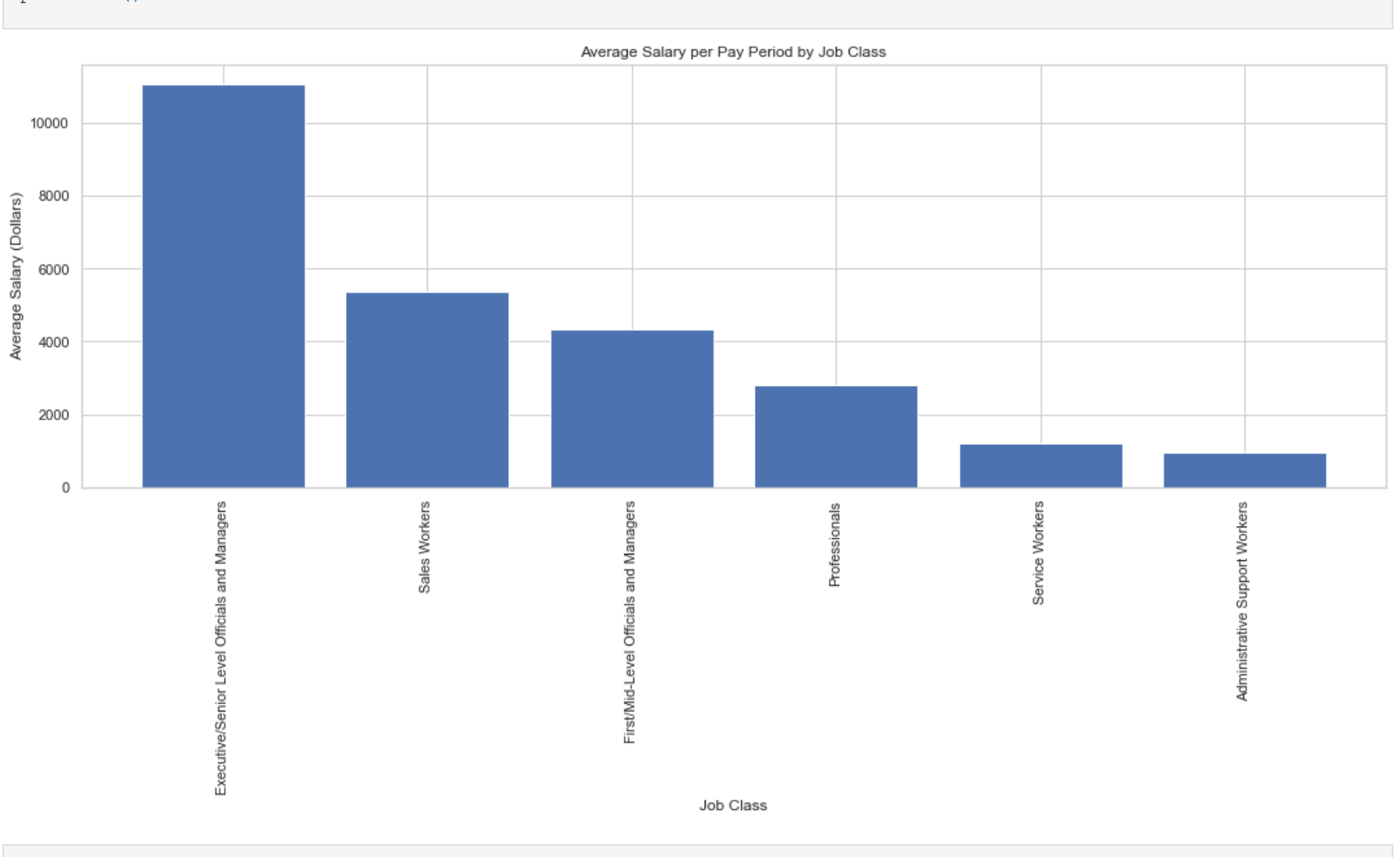
Out[15]:
```
Title                            0
Job Class                        0
Address State                    0
Tenure                           0
Gender                           0
Department At Payroll Process    0
G L Account Number               0
Dollars                          0
Month                            0
Year                             0
dtype: int64
```

In [20]:
```
# Apply logarithm transformation to the 'Dollars' column
df_drop['Log_Dollars'] = np.log1p(df_drop['Dollars'])

# Set the style for the plot
sns.set(style="whitegrid")

# Create a larger box plot with spread-out dots using the transformed data
plt.figure(figsize=(12, 8))
sns.boxplot(data=df_drop, x='Log_Dollars', y='Job Class', orient='h', palette="Set3", width=0.5)  # Adjust the

# Set the title and axis labels
plt.title('Log-Salary Distribution by Job Class', fontsize=16)
plt.xlabel('Log-Salary (Dollars)', fontsize=14)
plt.ylabel('Job Class', fontsize=14)

# Adjust tick label font size
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)

# Show the plot
plt.tight_layout()
plt.show()
```



Given the dataset, I expected the outliers. Outliers can indicate individuals with salaries significantly higher or lower than the majority of the job class, refelcting reality. They will remain in the dataset to genereate tailored approaches when needed or can be addressed at a later date for removal depending on model need. The spread of dots within each box represents the distribution of log-salaries within that job class. A wider spread implies more variability in log-salaries within that class.

In [21]:
```
data = df_drop

# Calculate average salary by job title
average_salary = data.groupby('Job Class')['Dollars'].mean().reset_index()

# Sort the data by average salary in descending order
average_salary = average_salary.sort_values('Dollars', ascending=False)

# Create a bar plot
plt.figure(figsize=(18, 6))
plt.bar(average_salary['Job Class'], average_salary['Dollars'])
plt.xlabel('Job Class')
plt.ylabel('Average Salary (Dollars)')
plt.title('Average Salary per Pay Period by Job Class')
plt.xticks(rotation=90)
plt.show()
```



In [22]:
```
from scipy.stats import chi2_contingency, pearsonr

# Assuming your DataFrame is named 'data'
data = df_drop

# Select the relevant columns for correlation analysis
categorical_features = ['Title', 'Job Class', 'Address State', 'Gender']
numeric_features = ['Tenure', 'G L Account Number', 'Month', 'Year',
                    'Department At Payroll Process']
target_variable = 'Dollars'

# Create an empty DataFrame to store the results
correlation_df = pd.DataFrame(columns=['Feature', 'Correlation Coefficient'])

# Compute the correlation for each categorical feature
for feature in categorical_features:
    contingency_table = pd.crosstab(data[feature], data[target_variable])
    chi2, p, _, _ = chi2_contingency(contingency_table)
    n = contingency_table.sum().sum()
    cramers_v = np.sqrt(chi2 / (n * min(contingency_table.shape) - 1))
    correlation_df = pd.concat([correlation_df, pd.DataFrame({'Feature':
                                                              [feature], 'Correlation Coefficient':
                                                              [cramers_v]})], ignore_index=True)

# Compute the correlation for each numeric feature
for feature in numeric_features:
    correlation_coef, _ = pearsonr(data[feature], data[target_variable])
    correlation_df = pd.concat([correlation_df, pd.DataFrame({'Feature': [feature],
                                                              'Correlation Coefficient':
                                                              [correlation_coef]})], ignore_index=True)

# Display the correlations
print(correlation_df)

# Sort the DataFrame by 'Correlation Coefficient' in descending order
correlation_df = correlation_df.sort_values(by='Correlation Coefficient', ascending=False)

# Create a bar plot
plt.figure(figsize=(10, 6))
plt.bar(range(len(correlation_df)), correlation_df['Correlation Coefficient'])
plt.xlabel('Feature')
plt.ylabel('Correlation Coefficient')
plt.title('Correlation with Dollars')
plt.xticks(range(len(correlation_df)), correlation_df['Feature'], rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

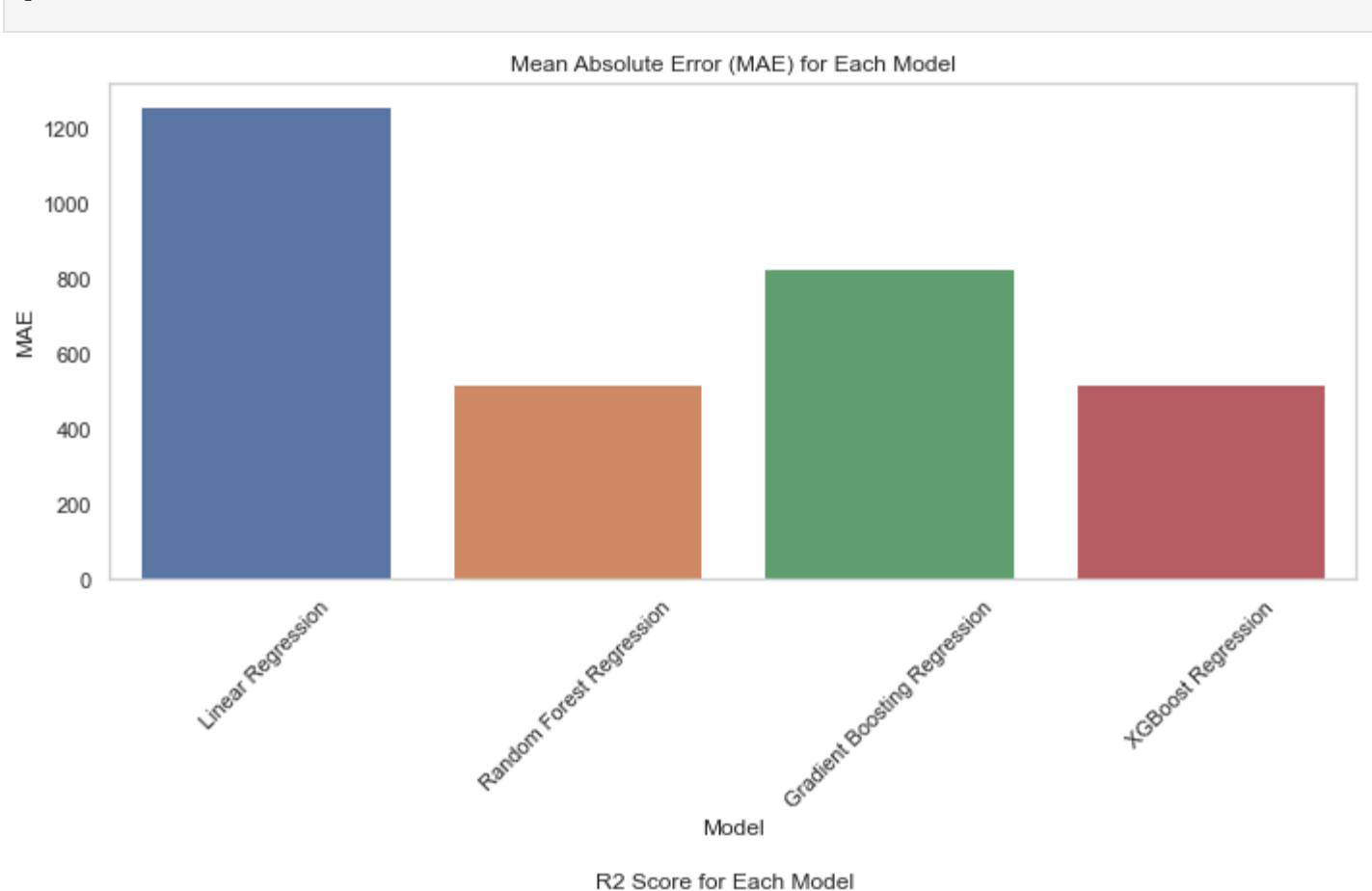
```
                         Feature  Correlation Coefficient
0                          Title                 0.840511
1                      Job Class                 0.843788
2                  Address State                 0.761201
3                         Gender                 0.591082
4                         Tenure                 0.169975
5             G L Account Number                -0.100014
6                          Month                -0.009227
7                           Year                 0.036250
8  Department At Payroll Process                -0.126170
```

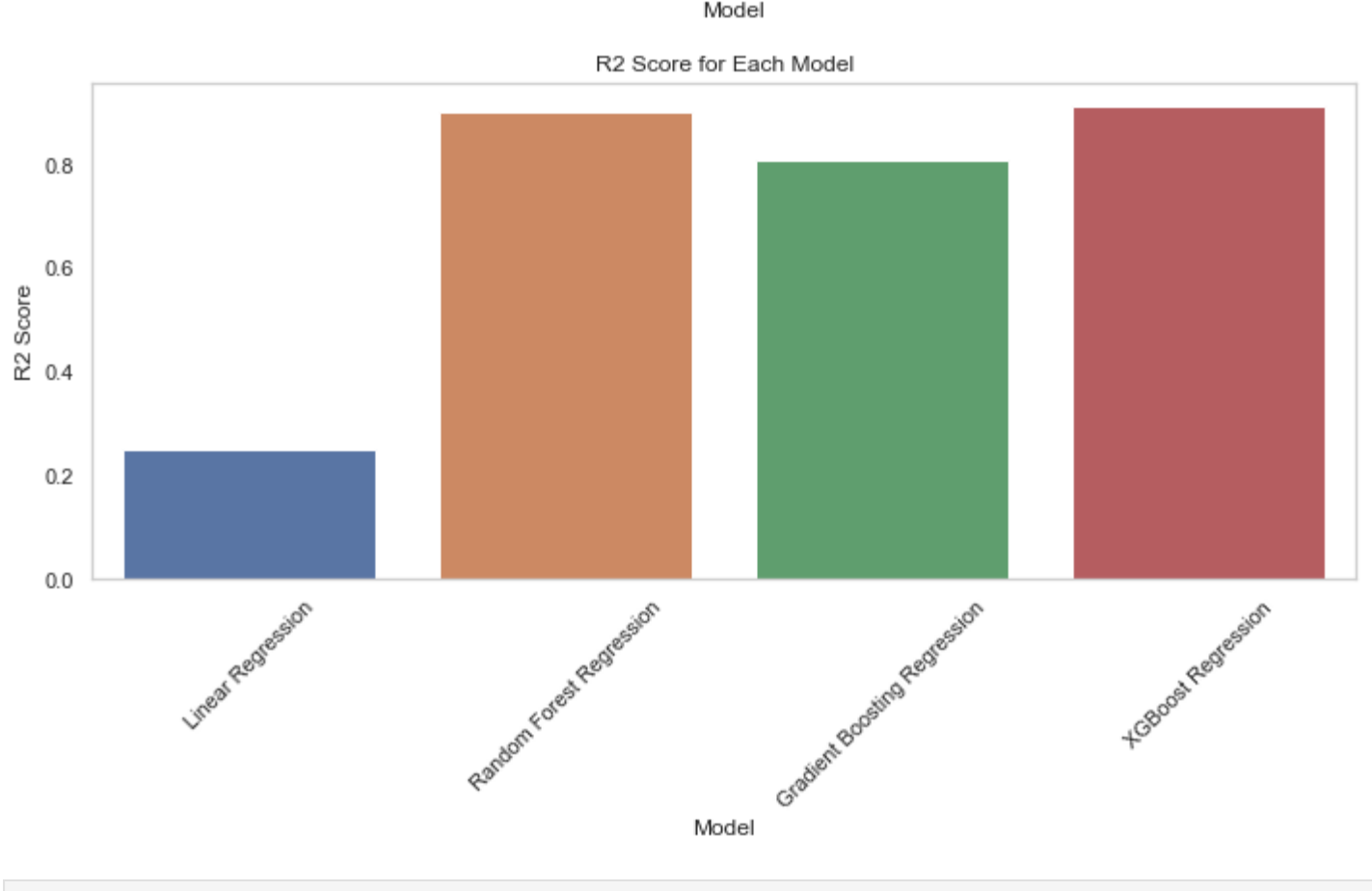
In this code, we iterate over each categorical feature and compute the Cramér's V value using the chi-square test and contingency tables. The Cramér's V values are then stored in a DataFrame called association_df. The resulting DataFrame displays the associations between each categorical feature and the "Dollars" variable.

In [30]:
```
# Load data and select features
data = df_drop
features = ['Title', 'Job Class', 'Address State', 'Tenure', 'Gender',
            'Department At Payroll Process', 'G L Account Number', 'Dollars', 'Month', 'Year']
data = data[features]

# Encode categorical variables
categorical_features = ['Title', 'Job Class', 'Address State', 'Gender',
                        'Department At Payroll Process',
                        'G L Account Number', 'Month', 'Year']

# Collect all unique values for each categorical feature
unique_values = {}
for feature in categorical_features:
    unique_values[feature] = data[feature].unique()

# Encode the categorical variables
for feature in categorical_features:
    encoder.classes_ = unique_values[feature]
    data[feature] = encoder.transform(data[feature])

# Split data into features (X) and target variable (y)
X = data.drop('Dollars', axis=1)
y = data['Dollars']

# Define models
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest Regression': RandomForestRegressor(random_state=42),
    'Gradient Boosting Regression': GradientBoostingRegressor(random_state=42),
    'XGBoost Regression': XGBRegressor(random_state=42)
}

# Initialize dictionaries to store results
mae_results = {}
r2_results = {}

# Train and evaluate models
for model_name, model in models.items():
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    mae_results[model_name] = mae
    r2_results[model_name] = r2

# Print MAE and R2 for each model
for model_name, mae in mae_results.items():
    print(f"{model_name} - MAE: {mae:.2f}")

for model_name, r2 in r2_results.items():
    print(f"{model_name} - R2 Score: {r2:.2f}")
```

```
Linear Regression - MAE: 1257.03
Random Forest Regression - MAE: 517.28
Gradient Boosting Regression - MAE: 825.75
XGBoost Regression - MAE: 519.31
Linear Regression - R2 Score: 0.25
Random Forest Regression - R2 Score: 0.90
Gradient Boosting Regression - R2 Score: 0.81
XGBoost Regression - R2 Score: 0.91
```

In [31]:
```
# Store MAE and R2 scores in dataframes
mae_df = pd.DataFrame.from_dict(mae_results, orient='index', columns=['MAE'])
r2_df = pd.DataFrame.from_dict(r2_results, orient='index', columns=['R2 Score'])

# Plot the MAE results on a bar chart
plt.figure(figsize=(10, 6))
sns.barplot(x=mae_df.index, y='MAE', data=mae_df)
plt.title('Mean Absolute Error (MAE) for Each Model')
plt.xlabel('Model')
plt.ylabel('MAE')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.tight_layout()
plt.show()

# Plot the R2 Score results on a bar chart
plt.figure(figsize=(10, 6))
sns.barplot(x=r2_df.index, y='R2 Score', data=r2_df)
plt.title('R2 Score for Each Model')
plt.xlabel('Model')
plt.ylabel('R2 Score')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```





In [32]:
```
# 6a. Model Deployment
# Saving the trained model and using it to predict salaries for new data
# Example: Predicting the salary for a new employee

new_employee = pd.DataFrame({'Title': ['Vice President'],
                             'Job Class': ['First/Mid-Level Officials and Managers'],
                             'Address State': ['Florida'],
                             'Tenure': [5],
                             'Gender': ['M'],
                             'Department At Payroll Process': ['28299'],
                             'G L Account Number': [7001000000],
                             'Month': [7],
                             'Year': [2023]
                             })

# Encode the categorical variables in the new employee data
for feature in categorical_features:
    encoder.classes_ = unique_values[feature]
    new_employee[feature] = encoder.transform(new_employee[feature])

# Making salary prediction for the new employee for month of July 2023
predicted_salary = model.predict(new_employee)

print("Predicted Annual Salary:","${:,.2f}".format(predicted_salary[0] * 26))
```

Predicted Annual Salary: $175,507.49

In [33]:
```
# 6b. Model Deployment
# Saving the trained model and using it to predict salaries for new data
# Example: Predicting the salary for a new employee

new_employee = pd.DataFrame({'Title': ['Vice President'],
                             'Job Class': ['First/Mid-Level Officials and Managers'],
                             'Address State': ['Florida'],
                             'Tenure': [5],
                             'Gender': ['F'],
                             'Department At Payroll Process': ['28299'],
                             'G L Account Number': [7001000000],
                             'Month': [7],
                             'Year': [2023]
                             })

# Encode the categorical variables in the new employee data
for feature in categorical_features:
    encoder.classes_ = unique_values[feature]
    new_employee[feature] = encoder.transform(new_employee[feature])

# Making salary prediction for the new employee for month of July 2023
predicted_salary = model.predict(new_employee)

print("Predicted Annual Salary:","${:,.2f}".format(predicted_salary[0] * 26))
```

Predicted Annual Salary: $173,161.40

Keeping the gender in the features could be cause for bias, I wanted to test for gender pay equality. As we can see, with our dataset, pay seems to equivalent for test performed above.

In [34]:

```python
# 6c. Model Deployment
# Saving the trained model and using it to predict salaries for new data
# Example: Predicting monthly salaries for dataset

from sklearn.preprocessing import LabelEncoder

# Create a copy of the DataFrame to avoid modifying the original data
data_filtered = df_drop.copy()

# Filter the data to include only the rows with Month = 5 and Year = 2023 for most recent actuals
data_filtered = data_filtered[(data_filtered['Month'] == 5) & (data_filtered['Year'] == 2023)]

# Extract the relevant columns for analysis
features = ['Title', 'Job Class', 'Address State', 'Tenure', 'Gender',
            'Department At Payroll Process',
            'G L Account Number', 'Dollars', 'Month', 'Year']
data_filtered = data_filtered[features]

# Encode categorical variables using LabelEncoder
categorical_features = ['Title', 'Job Class', 'Address State', 'Gender',
                        'Department At Payroll Process',
                        'G L Account Number', 'Month', 'Year']
encoder = LabelEncoder()

# Collect all unique values for each categorical feature
unique_values = {}
for feature in categorical_features:
    unique_values[feature] = data_filtered[feature].unique()

# Encode the categorical variables in the filtered data
for feature in categorical_features:
    encoder.classes_ = unique_values[feature]
    data_filtered[feature] = encoder.transform(data_filtered[feature])

# Split the filtered data into features (X) and target variable (y)
X_filtered = data_filtered.drop('Dollars', axis=1)
y_filtered = data_filtered['Dollars']

# Predict the salaries for the filtered data
predicted_salaries = model.predict(X_filtered)

# Calculate the total monthly salary for those paid within the specified month and year
total_monthly_salary = predicted_salaries.sum()

print("Total Predicted Monthly Salary based upon May 2023:", "${:,.2f}".format(total_monthly_salary))
print("Total Predicted Annual Salary based upon May 2023:", "${:,.2f}".format(total_monthly_salary*12))
```

```
Total Predicted Monthly Salary based upon May 2023: $2,637,237.50
Total Predicted Annual Salary based upon May 2023: $31,646,850.00
```