hr-employee-attrition

June 28, 2024

[67]:

```
# Import necessary libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
import warnings
```

[68]:

```
data = pd.read_csv('HR-Employee-Attrition.csv')
data.head()
```

[68]:

```
   Age Attrition     BusinessTravel  DailyRate              Department  \
0   41       Yes      Travel_Rarely       1102                   Sales
1   49        No  Travel_Frequently        279  Research & Development
2   37       Yes      Travel_Rarely       1373  Research & Development
3   33        No  Travel_Frequently       1392  Research & Development
4   27        No      Travel_Rarely        591  Research & Development

   DistanceFromHome  Education EducationField  EmployeeCount  EmployeeNumber  \
0                 1          2  Life Sciences              1               1
1                 8          1  Life Sciences              1               2
2                 2          2          Other              1               4
3                 3          4  Life Sciences              1               5
4                 2          1        Medical              1               7

   …  RelationshipSatisfaction StandardHours  StockOptionLevel  \
0  …                         1            80                 0
1  …                         4            80                 1
2  …                         2            80                 0
3  …                         3            80                 0
4  …                         4            80                 1

   TotalWorkingYears  TrainingTimesLastYear WorkLifeBalance  YearsAtCompany  \
0                  8                      0               1               6
1                 10                      3               3              10
2                  7                      3               3               0
3                  8                      3               3               8
4                  6                      3               3               2
```

```
  YearsInCurrentRole  YearsSinceLastPromotion  YearsWithCurrManager
0                  4                        0                     5
1                  7                        1                     7
2                  0                        0                     0
3                  7                        3                     0
4                  2                        2                     2

[5 rows x 35 columns]
```

0.1 Data Cleaning Steps

[69]:

```
# Deleting Redundant Columns
redundant_columns = ['EmployeeCount', 'Over18', 'StandardHours']
data.drop(columns=redundant_columns, inplace=True)

# Renaming Columns for Better Readability
# Define a dictionary for renaming columns
rename_columns = {
    'DailyRate': 'Daily_Rate', 'DistanceFromHome': 'Distance_From_Home',␣
  ↪'EducationField': 'Education_Field',
    'EmployeeNumber': 'Employee_Number', 'EnvironmentSatisfaction':␣
  ↪'Environment_Satisfaction',
    'JobInvolvement': 'Job_Involvement', 'JobLevel': 'Job_Level', 'JobRole':␣
  ↪'Job_Role',
    'JobSatisfaction': 'Job_Satisfaction', 'MaritalStatus': 'Marital_Status',
    'MonthlyIncome': 'Monthly_Income', 'MonthlyRate': 'Monthly_Rate',␣
  ↪'NumCompaniesWorked': 'Num_Companies_Worked',
    'OverTime': 'Over_Time', 'PercentSalaryHike': 'Percent_Salary_Hike',
    'PerformanceRating': 'Performance_Rating',
    'RelationshipSatisfaction': 'Relationship_Satisfaction',
    'StockOptionLevel': 'Stock_Option_Level', 'TotalWorkingYears':␣
  ↪'Total_Working_Years',
    'TrainingTimesLastYear': 'Training_Times_Last_Year', 'WorkLifeBalance':␣
  ↪'Work_Life_Balance',
    'YearsAtCompany': 'Years_At_Company', 'YearsInCurrentRole':␣
  ↪'Years_In_Current_Role',
    'YearsSinceLastPromotion': 'Years_Since_Last_Promotion',
    'YearsWithCurrManager': 'Years_With_Current_Manager'
}

data.rename(columns=rename_columns, inplace=True)

# Dropping Duplicates
data.drop_duplicates(inplace=True)
```

```
# Cleaning Individual Columns
data['Marital_Status'] = data['Marital_Status'].replace({'Married': 'Married',␣
 ↪'Single': 'Single', 'Divorced': 'Divorced'})

# Check for any outliers or invalid values in numerical columns (example: 'Age')
# Here we'll remove ages that are not within a realistic working age range
data = data[(data['Age'] >= 18) & (data['Age'] <= 65)]

# For 'Education' and other ordinal variables, ensure they fall within expected␣
 ↪categories
valid_education_levels = [1, 2, 3, 4, 5]  # Assuming 1 to 5 are valid levels
data = data[data['Education'].isin(valid_education_levels)]

# Drop rows with any NaN values
data.dropna(inplace=True)
```

[70]:

```
#Select the required columns for correlation analysis
selected_columns = [
    'Over_Time', 'Marital_Status', 'Job_Role', 'Gender', 'Education_Field',
    'Department', 'BusinessTravel', 'Age', 'Total_Working_Years',
    'Education', 'Num_Companies_Worked', 'Distance_From_Home'
]

# Subset the data with the selected columns
subset_data = data[selected_columns]
```

[71]:

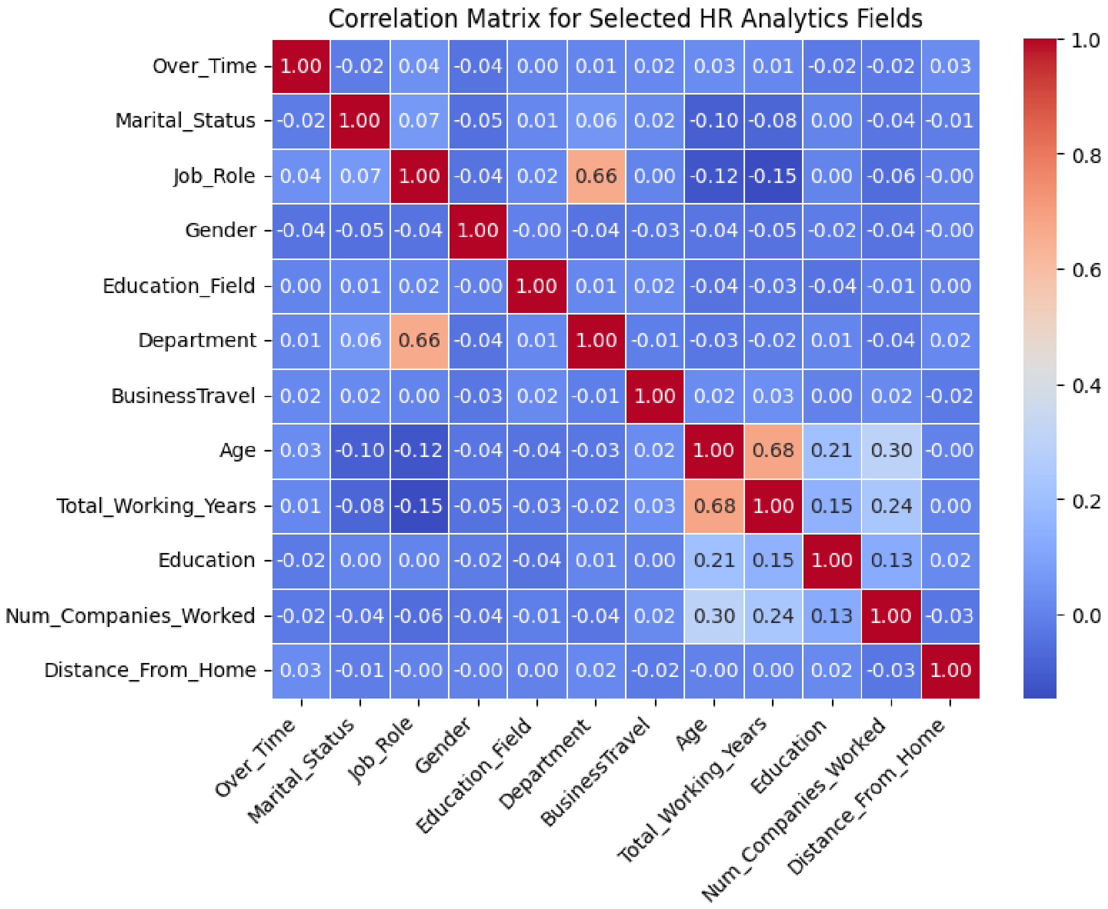
```
# Encode categorical variables into numeric form
label_encoders = {}
for column in ['Over_Time', 'Marital_Status', 'Job_Role', 'Gender',␣
 ↪'Education_Field',
    'Department', 'BusinessTravel', 'Age', 'Total_Working_Years',
    'Education', 'Num_Companies_Worked', 'Distance_From_Home']:
    le = LabelEncoder()
    subset_data[column] = le.fit_transform(subset_data[column])
    label_encoders[column] = le  # Store the label encoder for future use or␣
 ↪inverse transformation if needed
```

0.2 CORRELATION MATRIX

[72]:

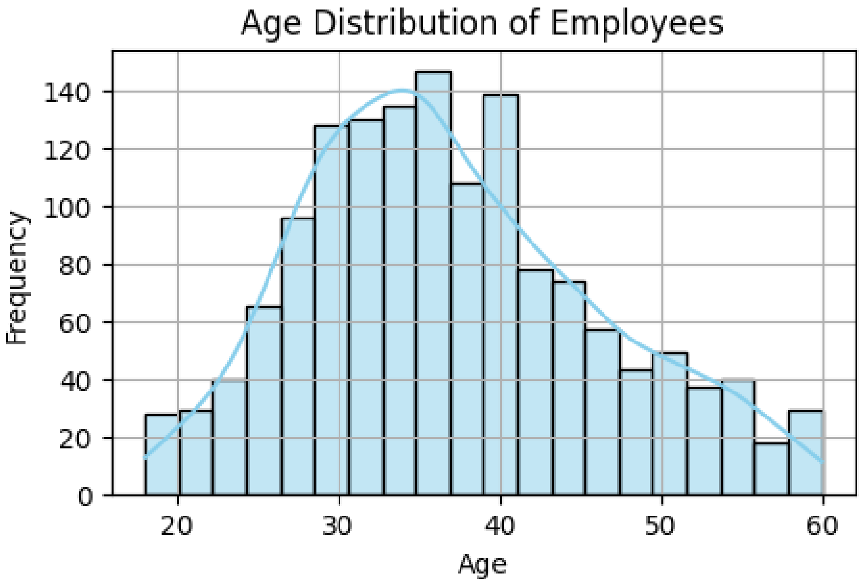
```
# Calculate the correlation matrix
correlation_matrix = subset_data.corr()

# Plot the correlation matrix using a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5,␣
 ↪fmt=".2f")
```

```
plt.title('Correlation Matrix for Selected HR Analytics Fields')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.show()
```



0.2.1 Age distribution of employees

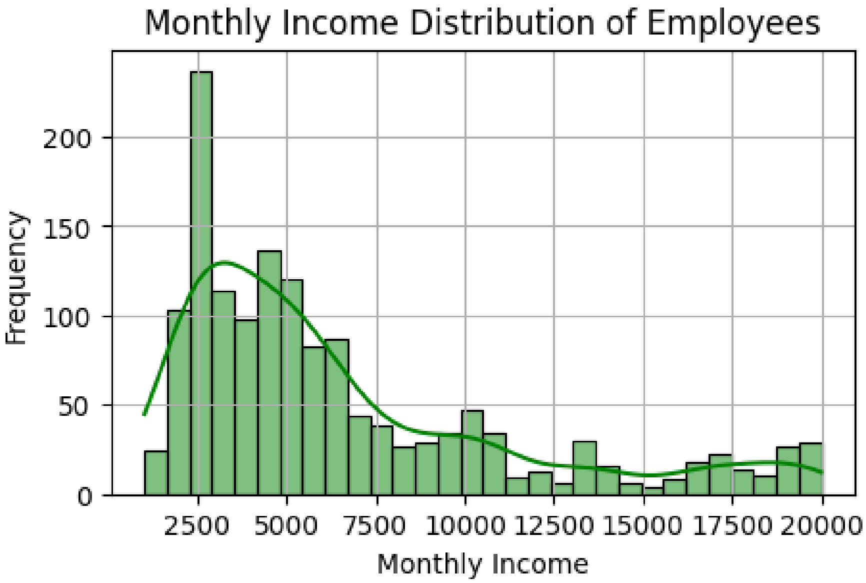
[73]:
```
# Age Distribution
plt.figure(figsize=(5, 3))
sns.histplot(data['Age'], bins=20, kde=True, color='skyblue')
plt.title('Age Distribution of Employees')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



0.2.2 Monthly Income Distribution among employees

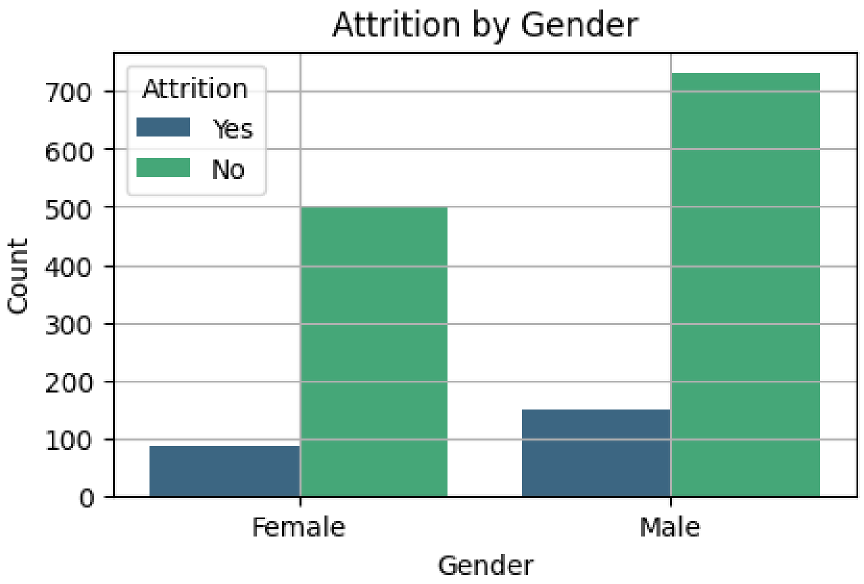
[74]:

```
# Monthly Income Distribution
plt.figure(figsize=(5, 3))
sns.histplot(data['Monthly_Income'], bins=30, kde=True, color='green')
plt.title('Monthly Income Distribution of Employees')
plt.xlabel('Monthly Income')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



0.2.3 Distribution of attrition across genders

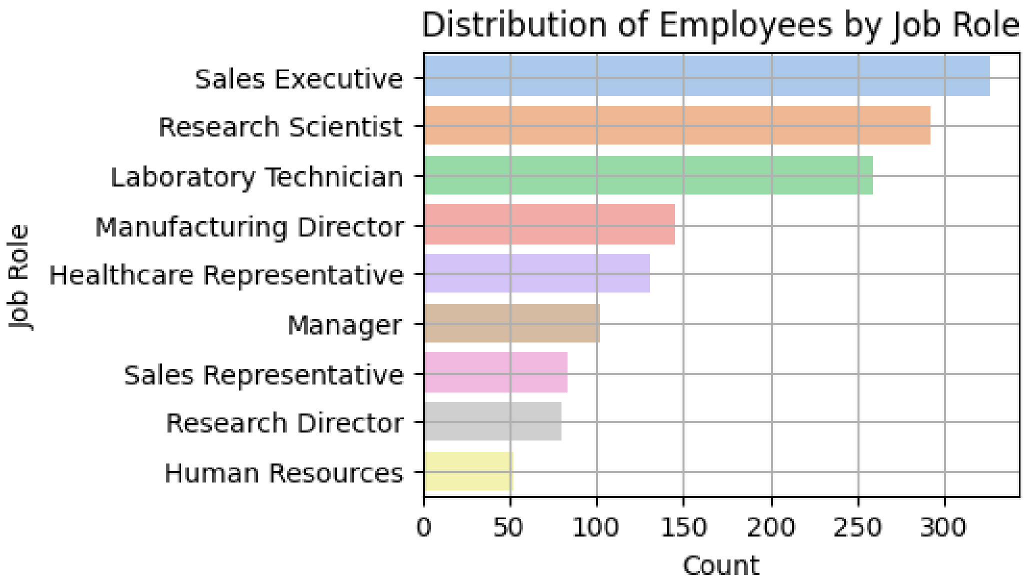
[75]:
```
# Attrition by Gender
plt.figure(figsize=(5, 3))
sns.countplot(x='Gender', hue='Attrition', data=data, palette='viridis')
plt.title('Attrition by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.grid(True)
plt.show()
```



0.2.4 Distribution of employees across different job roles

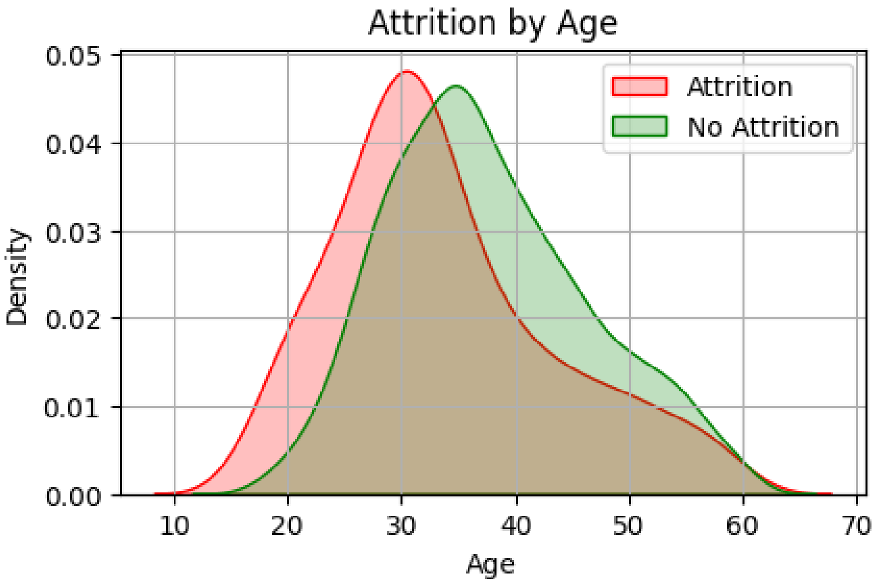
[76]:

```
# Job Role Distribution
plt.figure(figsize=(4, 3))
sns.countplot(y='Job_Role', data=data, palette='pastel', order=data['Job_Role'].
  ↪value_counts().index)
plt.title('Distribution of Employees by Job Role')
plt.xlabel('Count')
plt.ylabel('Job Role')
plt.grid(True)
plt.show()
warnings.filterwarnings("ignore", category=FutureWarning)
```



0.2.5 Attrition by Age

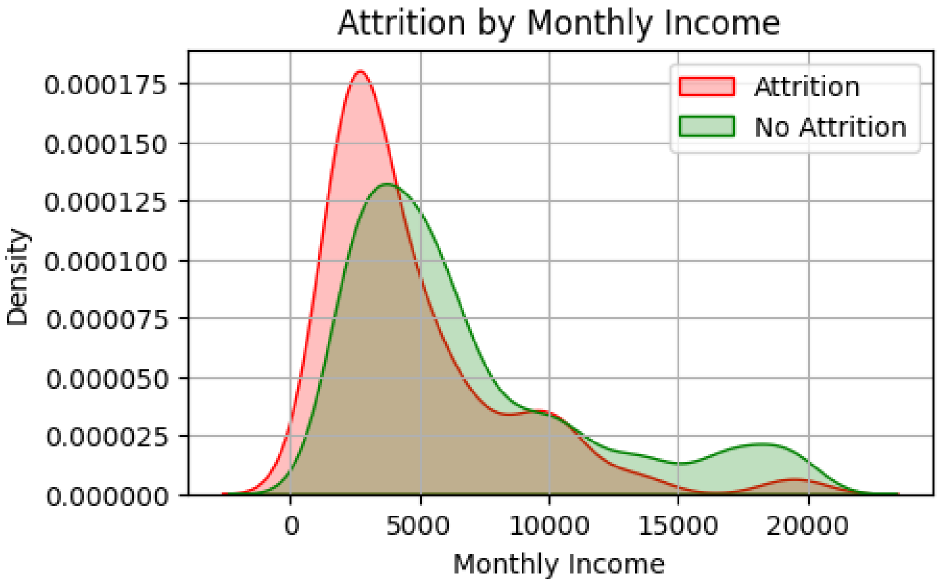
[77]:
```
plt.figure(figsize=(5, 3))
sns.kdeplot(data[data['Attrition'] == 'Yes']['Age'], label='Attrition',␣
 ↪shade=True, color='r')
sns.kdeplot(data[data['Attrition'] == 'No']['Age'], label='No Attrition',␣
 ↪shade=True, color='g')
plt.title('Attrition by Age')
plt.xlabel('Age')
plt.ylabel('Density')
plt.legend()
plt.grid(True)
plt.show()
warnings.filterwarnings("ignore", category=FutureWarning)
```



0.2.6 Attrition by Monthly Income

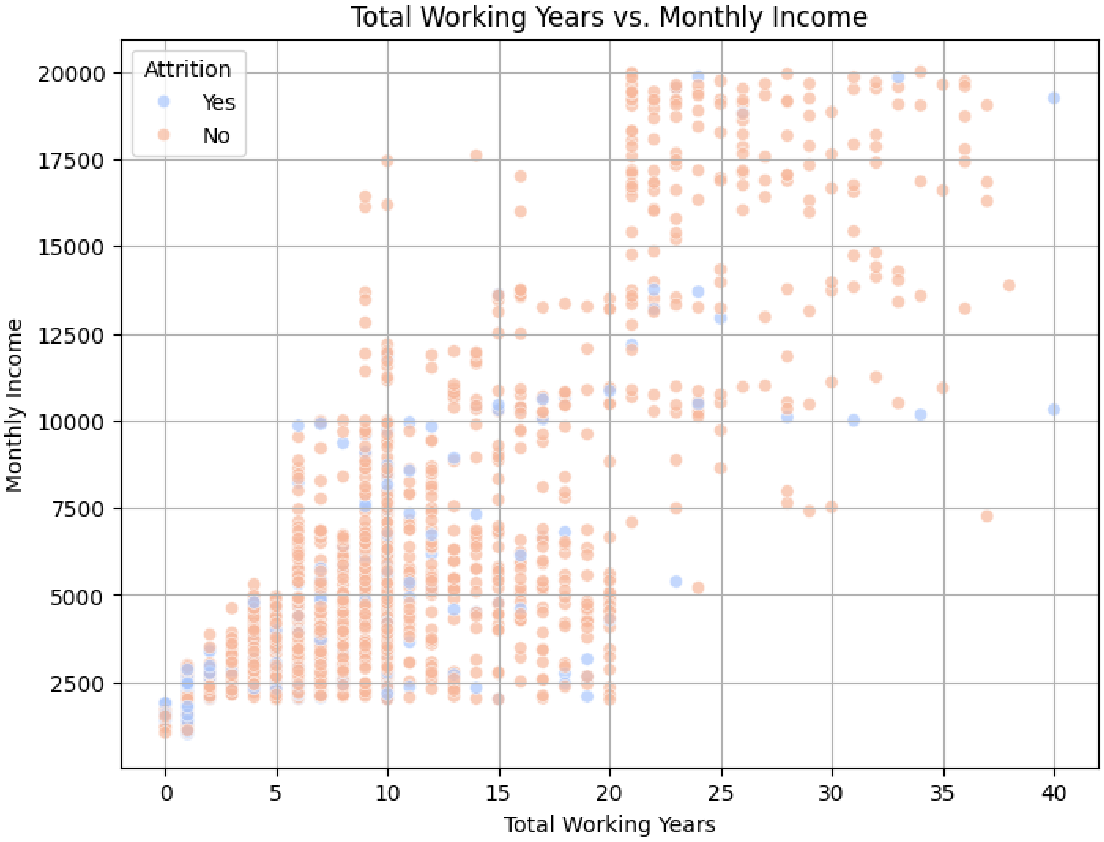
[78]:

```
plt.figure(figsize=(5, 3))
sns.kdeplot(data[data['Attrition'] == 'Yes']['Monthly_Income'],␣
 ↪label='Attrition', shade=True, color='r')
sns.kdeplot(data[data['Attrition'] == 'No']['Monthly_Income'], label='No␣
 ↪Attrition', shade=True, color='g')
plt.title('Attrition by Monthly Income')
plt.xlabel('Monthly Income')
plt.ylabel('Density')
plt.legend()
plt.grid(True)
plt.show()
warnings.filterwarnings("ignore", category=FutureWarning)
```



0.2.7 Relationship Between Total Working Years and Monthly Income

[79]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Total_Working_Years', y='Monthly_Income', hue='Attrition',␣
  ↪data=data, palette='coolwarm', alpha=0.7)
plt.title('Total Working Years vs. Monthly Income')
plt.xlabel('Total Working Years')
plt.ylabel('Monthly Income')
plt.grid(True)
plt.show()
```


Total Working Years vs. Monthly Income
Attrition
Yes
No
Monthly Income
20000
17500
15000
12500
10000
7500
5000
2500
0
5
10
15
20
25
30
35
40
Total Working Years