Experiment 3 : EDA on *income-dataset.csv*

load dataset

In [12]:
```
import pandas as pd
column_names = [
    "age", "workclass", "fnlwgt", "education", "education_num",
    "marital_status", "occupation", "relationship", "race", "gender",
    "capital_gain", "capital_loss", "hours_per_week", "native_country", "income"
]
df = pd.read_csv('income-dataset.csv',header=None,names = column_names)
df.head()
```

Out[12]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relat
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	H
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	H
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	

1. What are the key attributes in the given dataset, and what types of data do they contain?

In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education_num   32561 non-null  int64 
 5   marital_status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   gender          32561 non-null  object
 10  capital_gain    32561 non-null  int64 
 11  capital_loss    32561 non-null  int64 
 12  hours_per_week  32561 non-null  int64 
 13  native_country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [14]:
```
df.describe()
```

Out[14]:

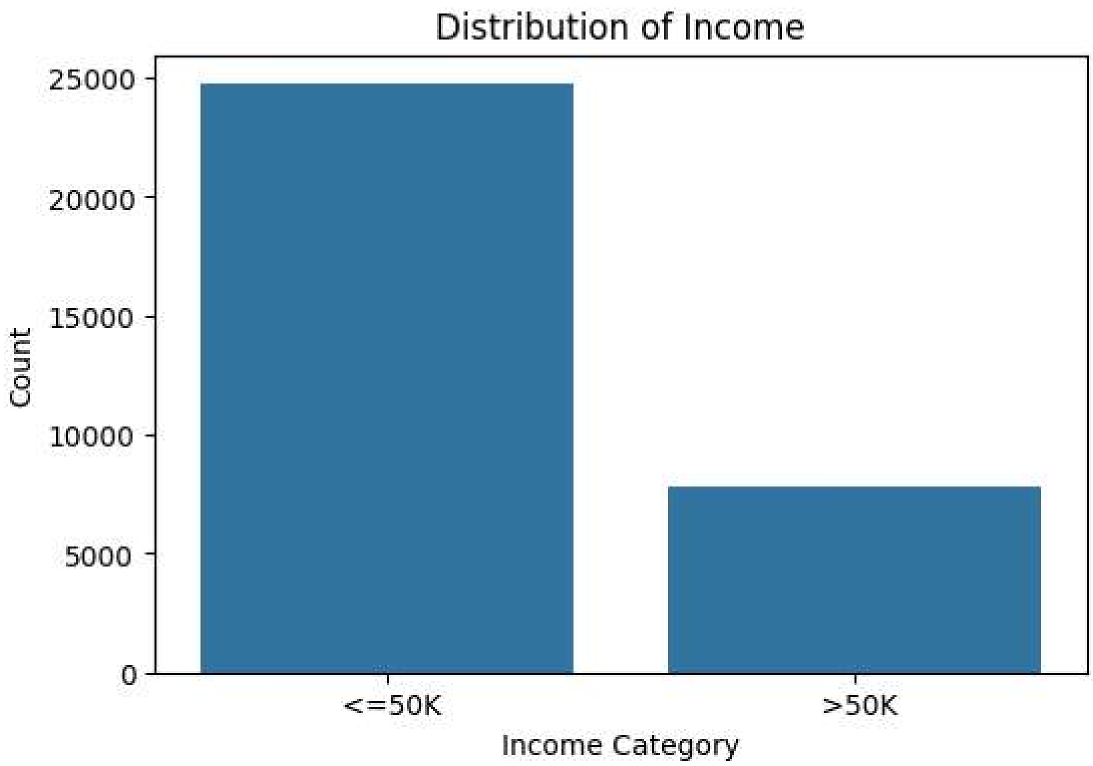
	age	fnlwgt	education_num	capital_gain	capital_loss	hours_
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	3256
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	4
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	1
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	4
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	4
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	4
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	9

In [15]:
```
# Check categorical features
print(df.describe(include='object'))
```

```
       workclass education      marital_status      occupation relationship  \
count      32561     32561               32561           32561        32561   
unique         9        16                   7              15            6   
top      Private   HS-grad  Married-civ-spouse  Prof-specialty      Husband   
freq       22696     10501               14976            4140        13193   

         race gender native_country income  
count   32561  32561          32561  32561  
unique      5      2             42      2  
top     White   Male  United-States  <=50K  
freq    27816  21790          29170  24720  
```

2. What is the distribution of income in the dataset? (Use histograms or boxplots for visualization)

In [17]:
```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(6,4))
sns.countplot(x='income', data=df)

plt.title("Distribution of Income")
plt.xlabel("Income Category")
plt.ylabel("Count")
plt.show()
```



3. Are there any missing or null values in the dataset? How would you handle them?

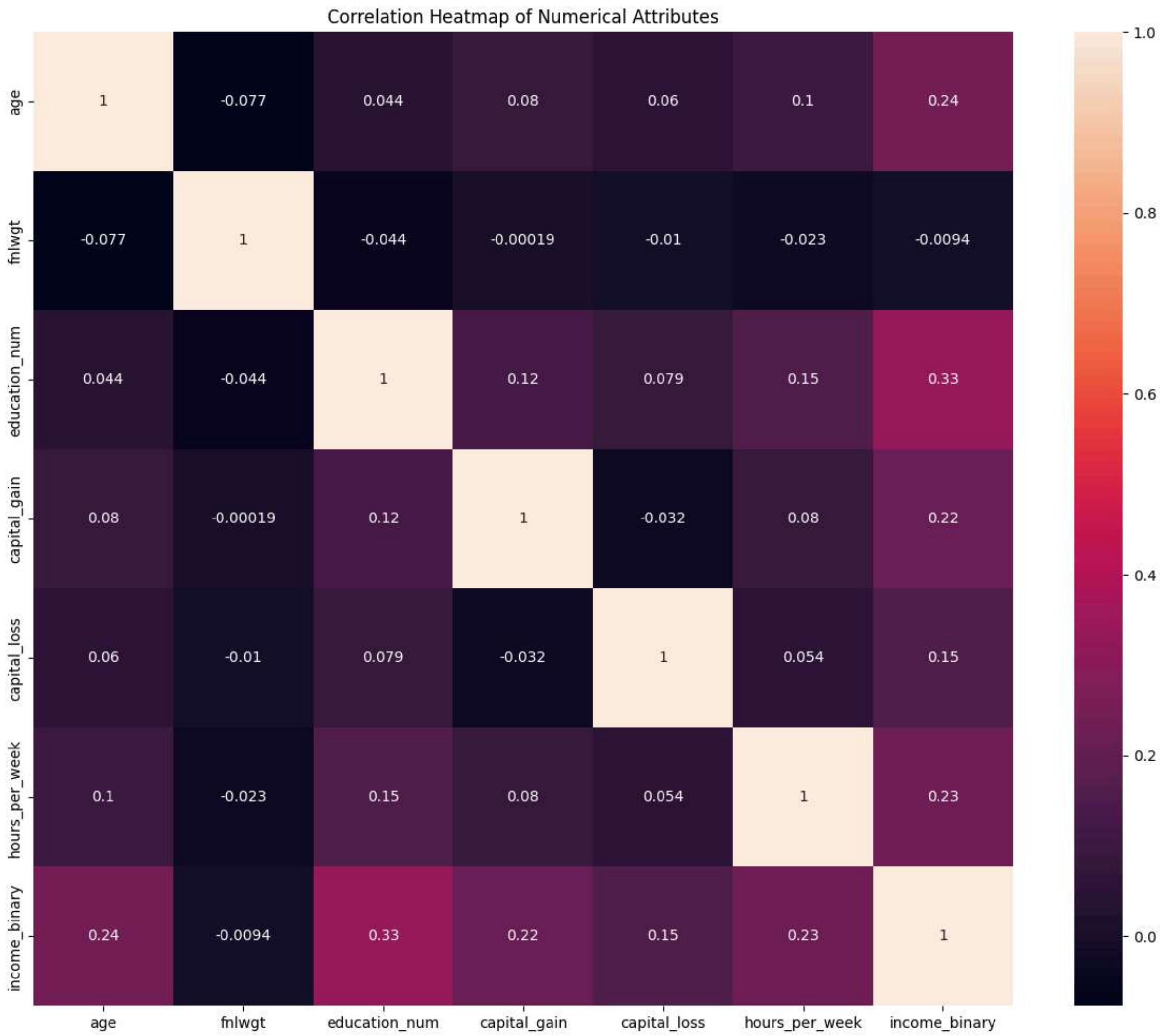
In [18]:
```
df.isnull().sum()
```

Out[18]:
```
age               0
workclass         0
fnlwgt            0
education         0
education_num     0
marital_status    0
occupation        0
relationship      0
race              0
gender            0
capital_gain      0
capital_loss      0
hours_per_week    0
native_country    0
income            0
dtype: int64
```

there's no null values in our dataset.
Missing values in a dataset can be handled in several ways. You can remove the rows or columns if the number of missing values is small. For numerical data, missing values can be replaced with the mean or median. For categorical data, they can be filled with the most frequent value (mode). Sometimes, missing values can be replaced with a constant such as “Unknown.” In advanced cases, predictive methods like KNN imputation can be used. The method chosen depends on the amount of missing data and the type of variable.

4. What is the correlation between different numerical attributes? Use a heatmap to visualize this.

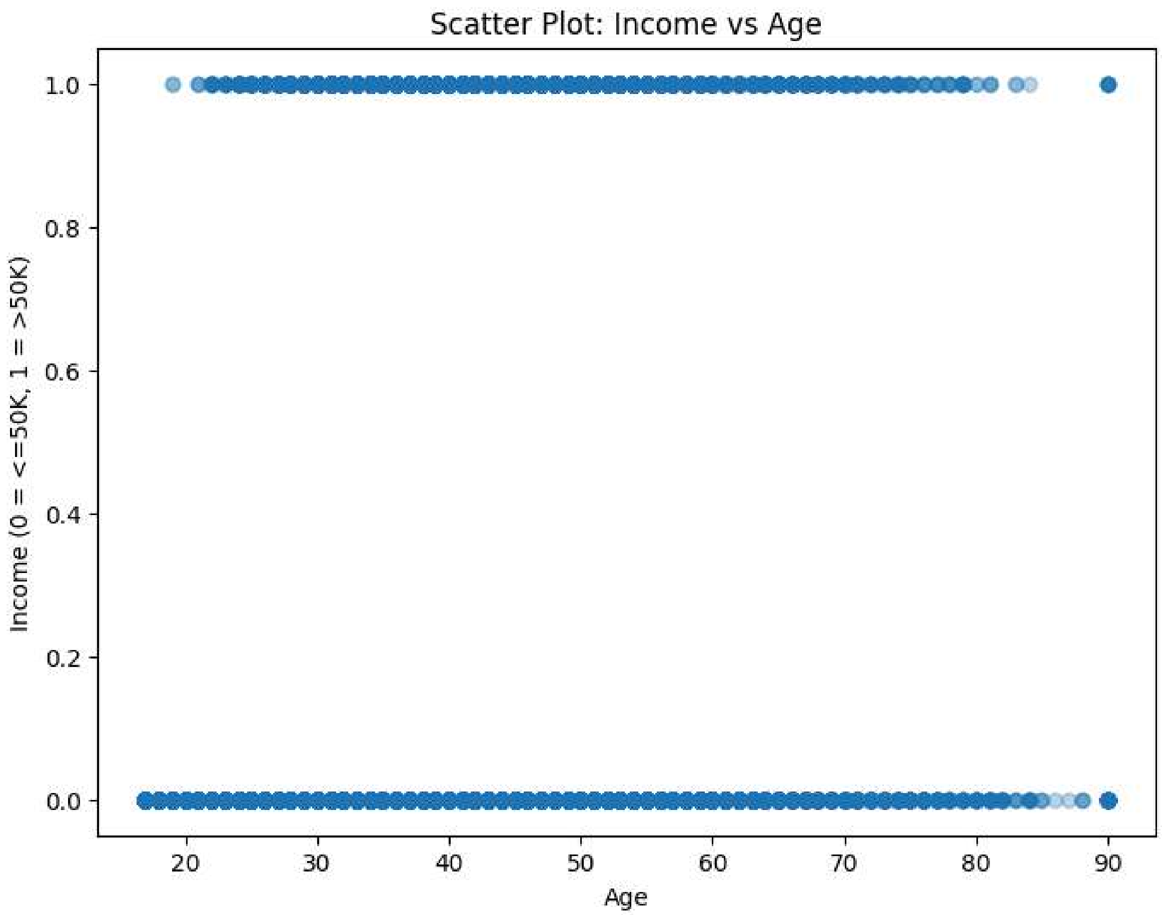
In [26]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(15,12))
sns.heatmap(df.select_dtypes(include=['Int64']).corr(),annot=True)
plt.title("Correlation Heatmap of Numerical Attributes")
plt.show()
```



5. How does income vary with respect to age? Generate a scatter plot to analyze the relationship.

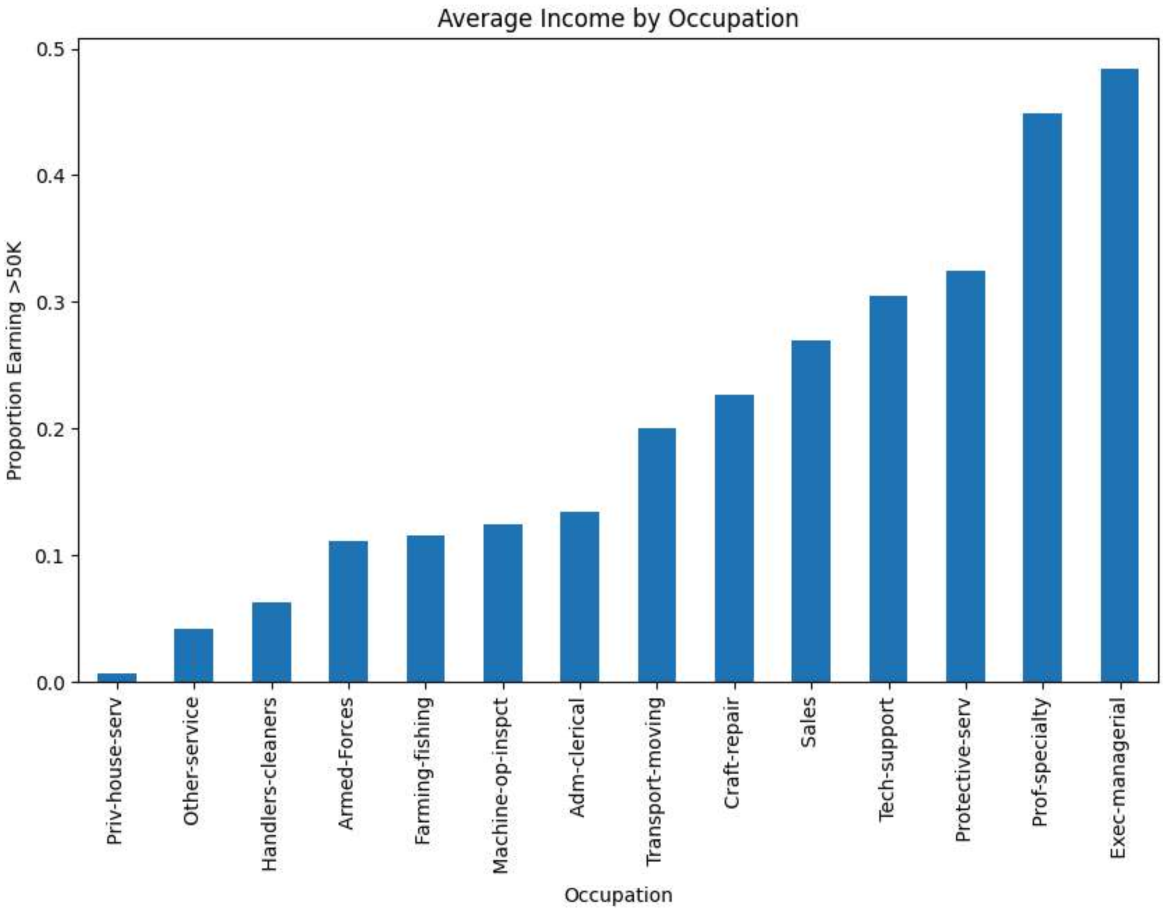
In [20]:

```
df['income'] = df['income'].str.strip()

# Convert income to binary
df['income_binary'] = df['income'].apply(lambda x: 1 if x == '>50K' else 0)

# Scatter plot
plt.figure(figsize=(8,6))
plt.scatter(df['age'], df['income_binary'], alpha=0.3)
plt.xlabel("Age")
plt.ylabel("Income (0 = <=50K, 1 = >50K)")
plt.title("Scatter Plot: Income vs Age")
plt.show()
```



6. Which profession has the highest and lowest average income? Visualize this using a bar chart.

In [21]:
```
# Clean whitespace
df['income'] = df['income'].str.strip()

# Convert income to binary
df['income_binary'] = df['income'].apply(lambda x: 1 if x == '>50K' else 0)

# Remove missing occupation values if any
df = df[df['occupation'] != ' ?']

# Calculate average income by occupation
occupation_income = df.groupby('occupation')['income_binary'].mean().sort_values

# Plot bar chart
plt.figure(figsize=(10,6))
occupation_income.plot(kind='bar')
plt.title("Average Income by Occupation")
plt.ylabel("Proportion Earning >50K")
plt.xlabel("Occupation")
plt.xticks(rotation=90)
plt.show()

# Print highest and lowest
print("Highest Average Income Profession:", occupation_income.idxmax())
print("Lowest Average Income Profession:", occupation_income.idxmin())
```

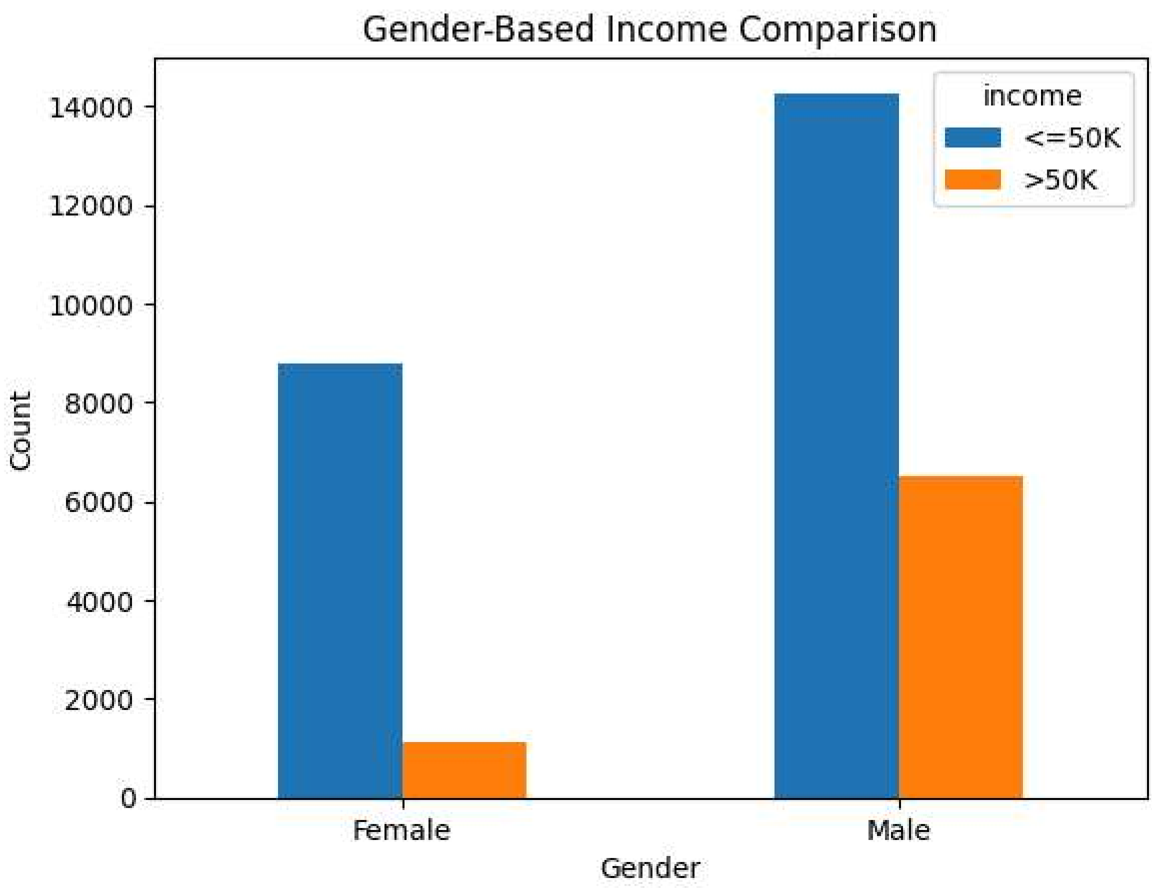



```
Highest Average Income Profession:  Exec-managerial
Lowest Average Income Profession:  Priv-house-serv
```

7. Is there any gender-based income disparity in the dataset? Use a grouped bar chart to compare.

In [22]:

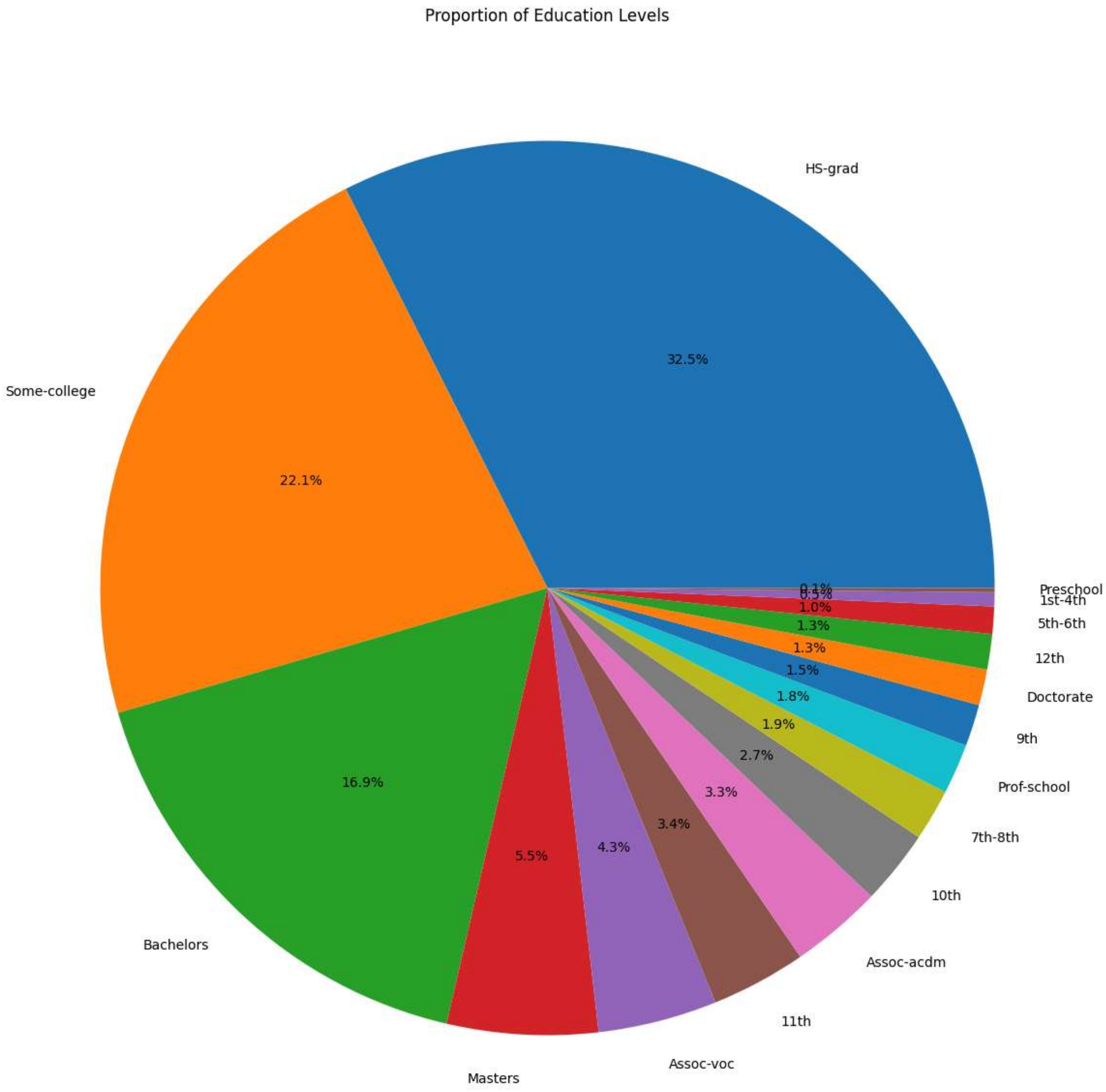
```
# Clean whitespace
df.loc[:,'income'] = df['income'].str.strip()
df.loc[:,'gender'] = df['gender'].str.strip()

# Create grouped count table
gender_income = df.groupby(['gender', 'income']).size().unstack()

# Plot grouped bar chart
gender_income.plot(kind='bar')
plt.title("Gender-Based Income Comparison")
plt.xlabel("Gender")
plt.ylabel("Count")
plt.xticks(rotation=0)
plt.show()
```



8. Can you create a pie chart showing the proportion of different education levels in the dataset?

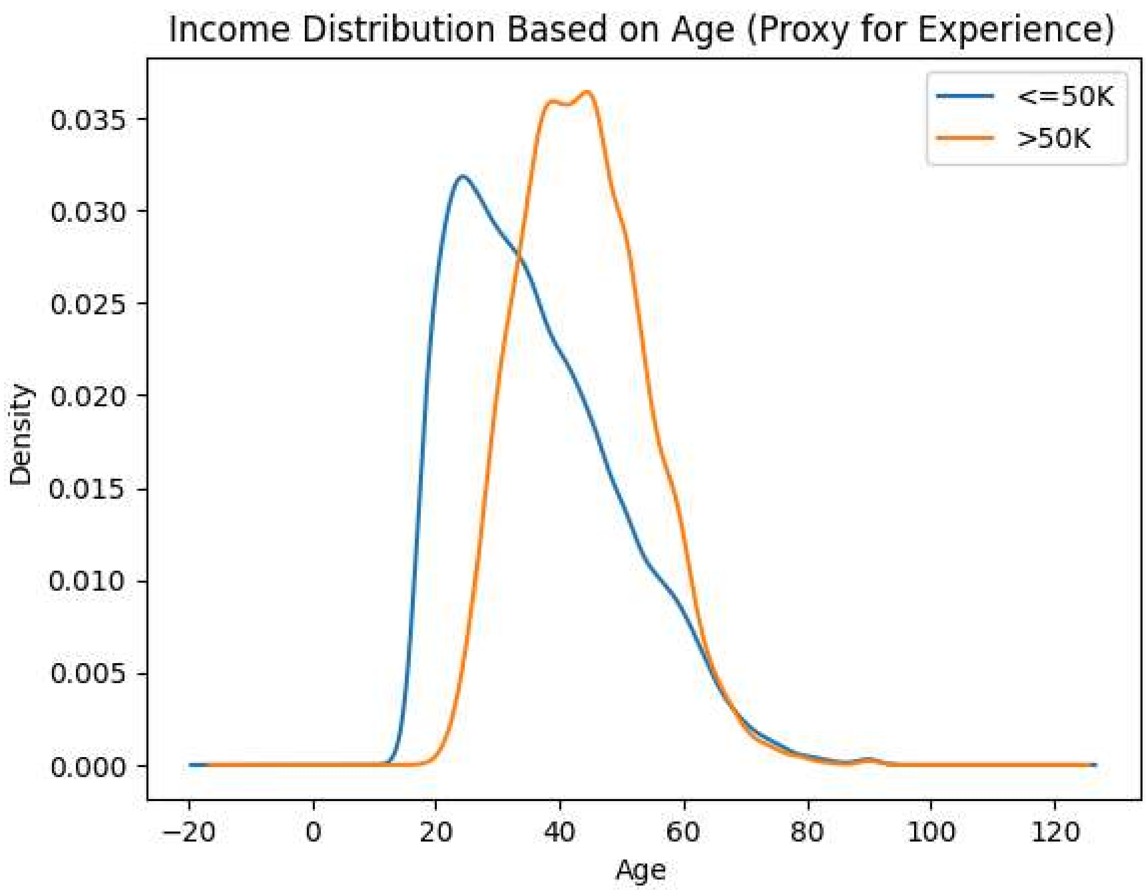
In [30]:

```
# Clean whitespace
df.loc[:,'education'] = df['education'].str.strip()

# Count education levels
education_counts = df['education'].value_counts()

# Plot pie chart
plt.figure(figsize=(15,15))
education_counts.plot(kind='pie', autopct='%1.1f%%')
plt.title("Proportion of Education Levels")
plt.ylabel("")
plt.show()
```



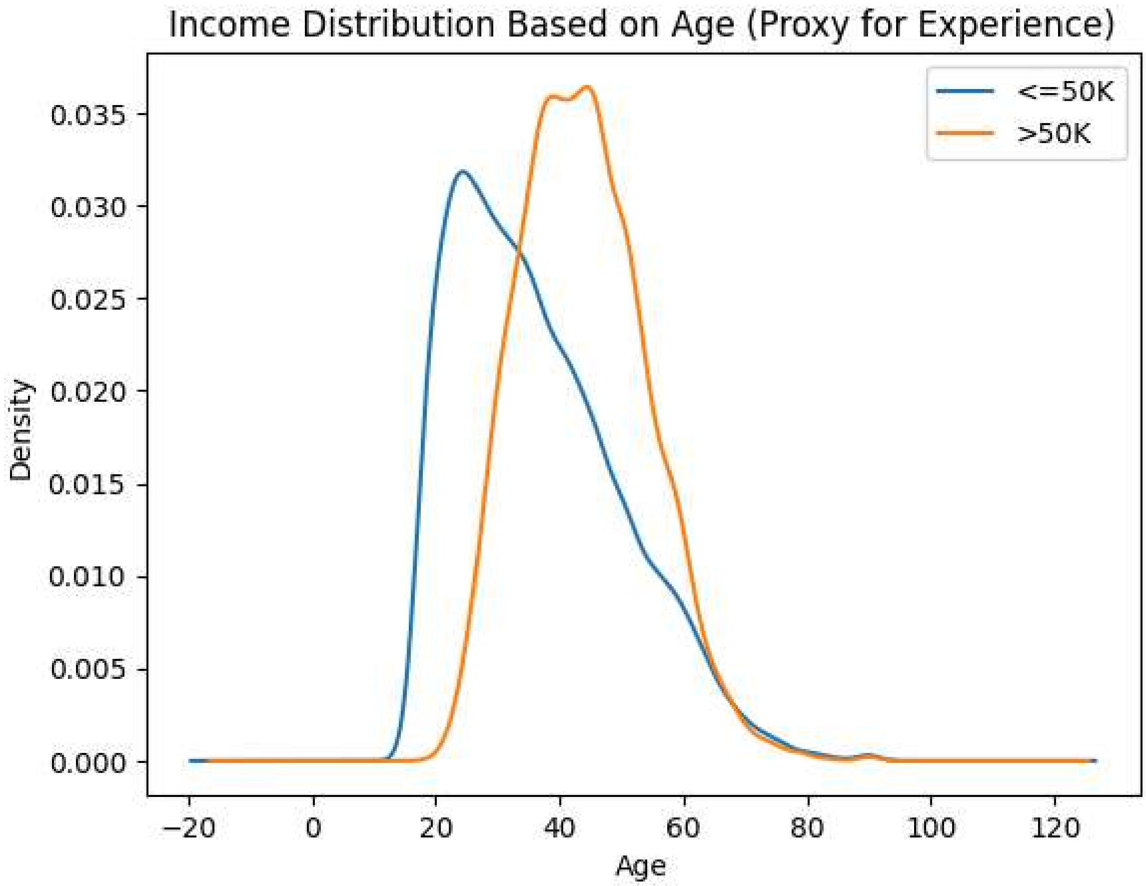
9. Use a violin plot or KDE plot to analyze the spread of income based on work experience.

In [24]:
```
# Clean whitespace
df.loc[:,'income'] = df['income'].str.strip()

# Separate income groups
low_income = df[df['income'] == '<=50K']['age']
high_income = df[df['income'] == '>50K']['age']

# KDE plots
low_income.plot(kind='kde')
high_income.plot(kind='kde')

plt.legend(['<=50K', '>50K'])
plt.title("Income Distribution Based on Age (Proxy for Experience)")
plt.xlabel("Age")
plt.show()
```



In [25]:

```
# Clean whitespace
df['income'] = df['income'].str.strip()

# Separate income groups
low_income = df[df['income'] == '<=50K']['age']
high_income = df[df['income'] == '>50K']['age']

# KDE plots
low_income.plot(kind='kde')
high_income.plot(kind='kde')

plt.legend(['<=50K', '>50K'])
plt.title("Income Distribution Based on Age (Proxy for Experience)")
plt.xlabel("Age")
plt.show()
```



10. Create an interactive dashboard (using tools like Tableau or Power BI) to analyze multiple variables together.