In [1]:
```
import pandas as pd
```

Q1 A. Create 2 dataframes out of this dataframe – 1 with all numerical variables and other with all categorical variables.

In [4]:
```
# Load the dataset
df = pd.read_excel("C:/Users/praga/Downloads/Worksheet in Assignment (4) (2).xls

# Separate numerical and categorical variables
df_numeric = df.select_dtypes(include=['number'])
df_categorical = df.select_dtypes(include=['object'])

# Display first few rows of each DataFrame
print("Numerical Variables:\n", df_numeric.head())
print("\nCategorical Variables:\n", df_categorical.head())
```

```
Numerical Variables:
    carat  depth  table  weight  size  price
0   0.23   61.5   55.0    3.95  3.98    326
1   0.21   59.8   61.0    3.89  3.84    326
2   0.23   56.9   65.0    4.05  4.07    327
3   0.29   62.4   58.0    4.20  4.23    334
4   0.31   63.3   58.0    4.34  4.35    335

Categorical Variables:
        cut color clarity
0    Ideal     E     SI2
1  Premium     E     SI1
2     Good     E     VS1
3  Premium     I     VS2
4     Good     J     SI2
```

Q1 B. Calculate the measure of central tendency of numerical variables using Pandas and statistics libraries and check if the calculated values are different between these 2 libraries.

In [7]:
```
import statistics

# Using Pandas
mean_pandas = df_numeric.mean()
median_pandas = df_numeric.median()
mode_pandas = df_numeric.mode().iloc[0]

# Using statistics module
mean_stats = {col: statistics.mean(df_numeric[col]) for col in df_numeric.column
median_stats = {col: statistics.median(df_numeric[col]) for col in df_numeric.cc
mode_stats = {col: statistics.mode(df_numeric[col]) for col in df_numeric.column

print("Pandas Mean:\n", mean_pandas)
print("Statistics Mean:\n", mean_stats)

# Compare if the values differ
diff = mean_pandas - pd.Series(mean_stats)
print("\nDifference in Mean:\n", diff)
```

```
Pandas Mean:
 carat        0.797940
depth       61.749405
table       57.457184
weight       5.731157
size         5.734526
price     3932.799722
dtype: float64
Statistics Mean:
 {'carat': 0.7979397478680015, 'depth': 61.74940489432703, 'table': 57.4571839080
4598, 'weight': 5.731157211716722, 'size': 5.734525954764553, 'price': 3932.79972
1913237}

Difference in Mean:
 carat    -1.110223e-16
depth     7.105427e-15
table     0.000000e+00
weight    0.000000e+00
size      0.000000e+00
price     0.000000e+00
dtype: float64
```

Q1 C. Check the skewness of all numeric variables. Mention against each variable if its highly skewed/light skewed/ Moderately skwewed.

In [19]:
```python
# C.Check the skewness of all numeric variables. Mention against each variable i
skewness = df_numeric.skew()

# Categorizing skewness levels
def skew_category(value):
    if abs(value) > 1:
        return "Highly Skewed"
    elif 0.5 < abs(value) <= 1:
        return "Moderately Skewed"
    else:
        return "Lightly Skewed"

skewness_category = skewness.apply(skew_category)
print("Skewness Levels:\n", skewness_category)
```

```
Skewness Levels:
 carat          Highly Skewed
depth         Lightly Skewed
table      Moderately Skewed
weight        Lightly Skewed
size           Highly Skewed
price          Highly Skewed
dtype: object
```

Q1 D. Use the different transformation techniques to convert skewed data found in previous question into normal distribution.

In [22]:
```python
import numpy as np

# Applying log transformation
df_numeric_transformed = df_numeric.copy()
for col in df_numeric.columns:
    if df_numeric[col].skew() > 1:
        df_numeric_transformed[col] = np.log1p(df_numeric[col])
```

```
print(df_numeric_transformed.skew())  # Check if skewness is reduced
```

```
carat     0.580654
depth    -0.082294
table     0.796896
weight    0.378676
size      0.006600
price     0.115926
dtype: float64
```

Q1 E. Create a user defined function in python to check the outliers using IQR method. Then pass all numeric variables in that function to check outliers.

In [25]:
```
def detect_outliers_iqr(data):
    Q1 = data.quantile(0.25)
    Q3 = data.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return ((data < lower_bound) | (data > upper_bound)).sum()

outliers = df_numeric.apply(detect_outliers_iqr)
print("Outliers count:\n", outliers)
```

```
Outliers count:
 carat     1889
depth     2545
table      605
weight      32
size        29
price     3540
dtype: int64
```

Q1 F. Convert categorical variables into numerical variables using LabelEncoder technique.

In [28]:
```
from sklearn.preprocessing import LabelEncoder

label_encoders = {}
df_encoded = df_categorical.copy()

for col in df_categorical.columns:
    label_encoders[col] = LabelEncoder()
    df_encoded[col] = label_encoders[col].fit_transform(df_categorical[col])

print(df_encoded.head())
```

```
   cut  color  clarity
0    2      1        3
1    3      1        2
2    1      1        4
3    3      5        5
4    1      6        3
```

Q1 G. Use both the feature scaling techniques (standardscaler/min max scaler) on all the variables.

In [31]:

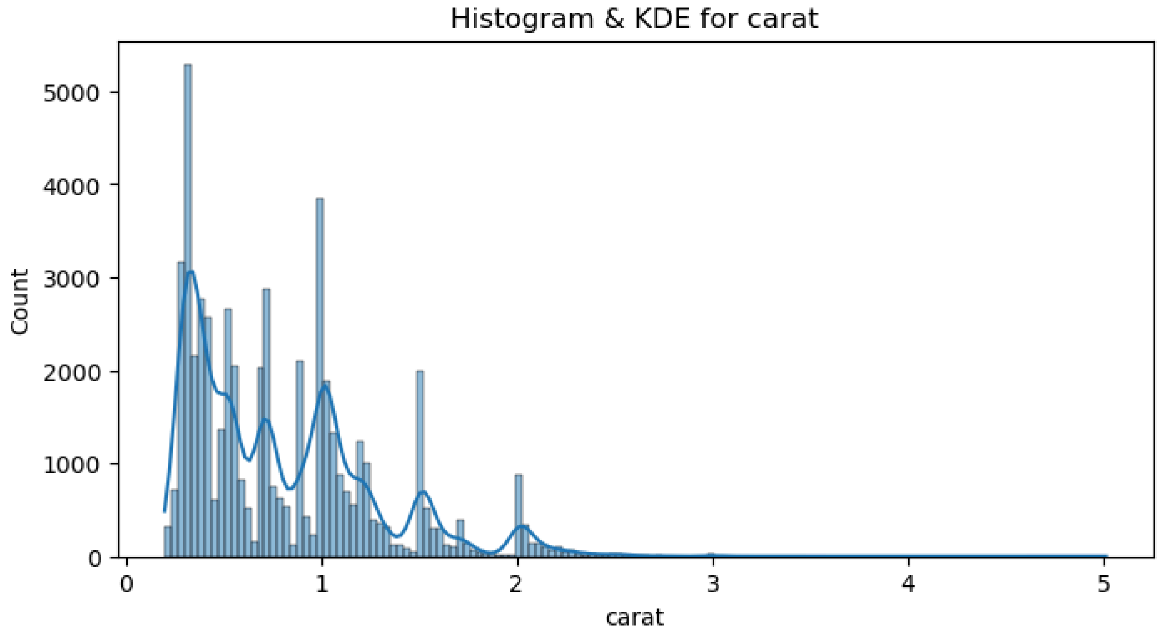
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Standardization
scaler_standard = StandardScaler()
df_standardized = pd.DataFrame(scaler_standard.fit_transform(df_numeric), column

# Normalization
scaler_minmax = MinMaxScaler()
df_normalized = pd.DataFrame(scaler_minmax.fit_transform(df_numeric), columns=df

print("Standardized Data:\n", df_standardized.head())
print("\nNormalized Data:\n", df_normalized.head())
```

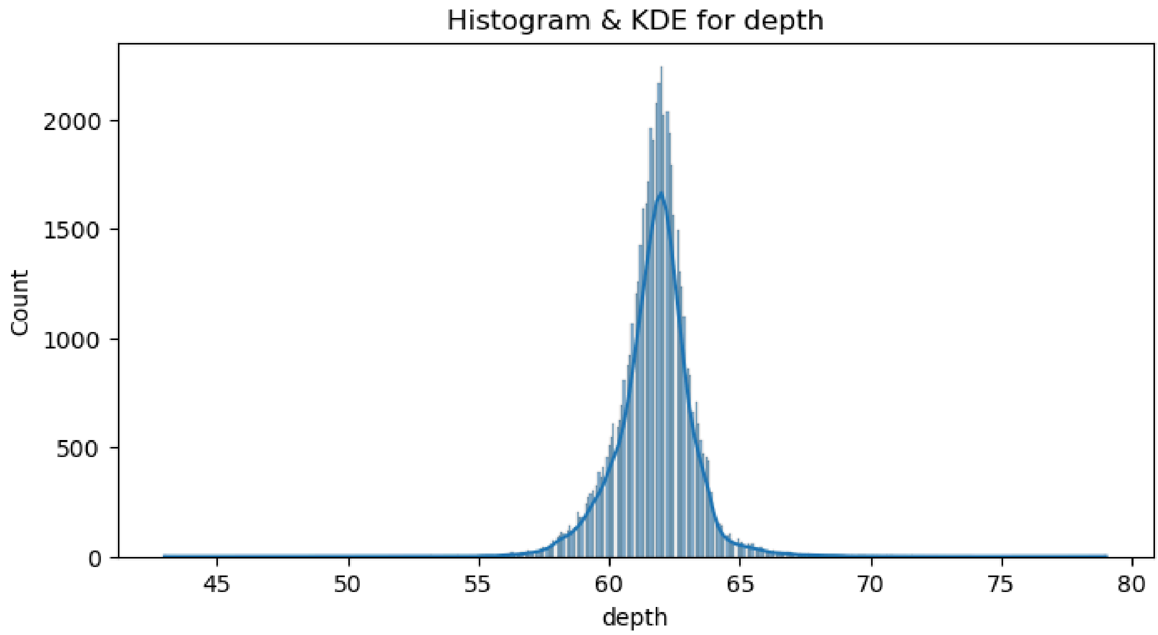
```
Standardized Data:
       carat     depth     table    weight      size     price
0 -1.198168 -0.174092 -1.099672 -1.587837 -1.536196 -0.904095
1 -1.240361 -1.360738  1.585529 -1.641325 -1.658774 -0.904095
2 -1.198168 -3.385019  3.375663 -1.498691 -1.457395 -0.903844
3 -1.071587  0.454133  0.242928 -1.364971 -1.317305 -0.902090
4 -1.029394  1.082358  0.242928 -1.240167 -1.212238 -0.901839

Normalized Data:
       carat     depth     table    weight      size     price
0  0.006237  0.513889  0.230769  0.367784  0.067572  0.000000
1  0.002079  0.466667  0.346154  0.362197  0.065195  0.000000
2  0.006237  0.386111  0.423077  0.377095  0.069100  0.000054
3  0.018711  0.538889  0.288462  0.391061  0.071817  0.000433
4  0.022869  0.563889  0.288462  0.404097  0.073854  0.000487
```

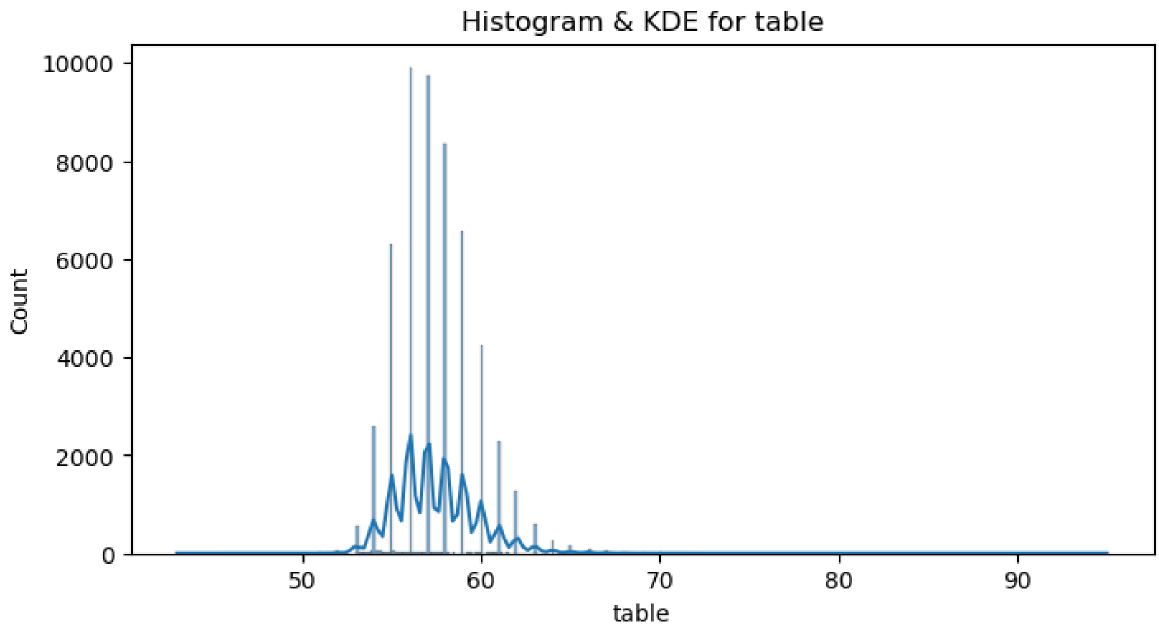
Q1 H. Create the Histogram for all numeric variables and draw the KDE plot on that.

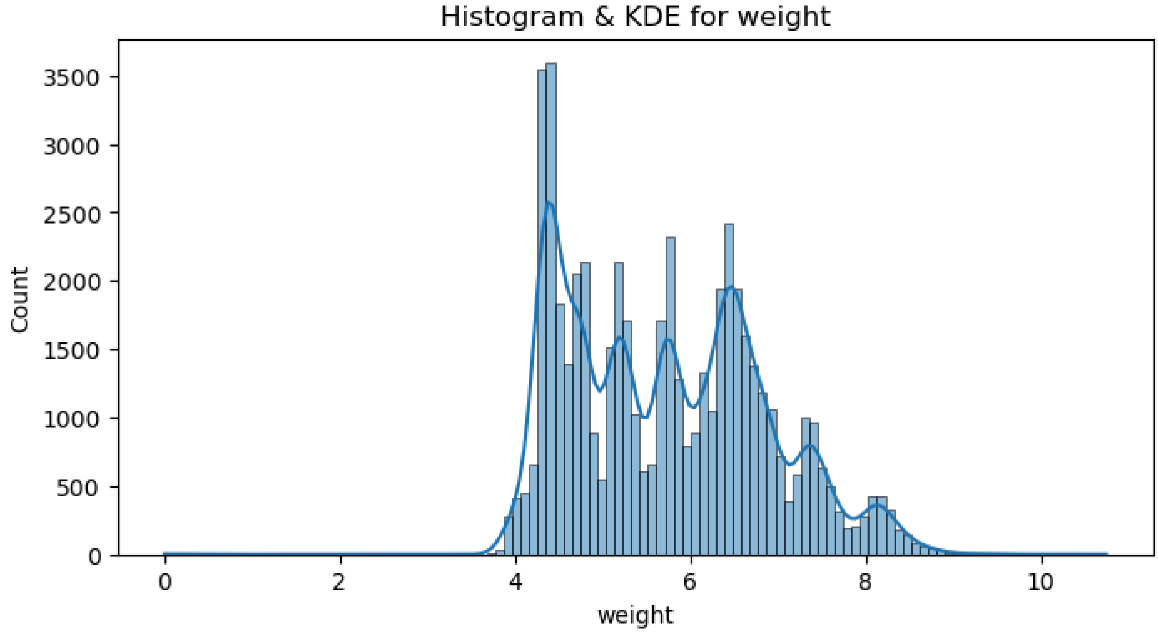
In [34]:

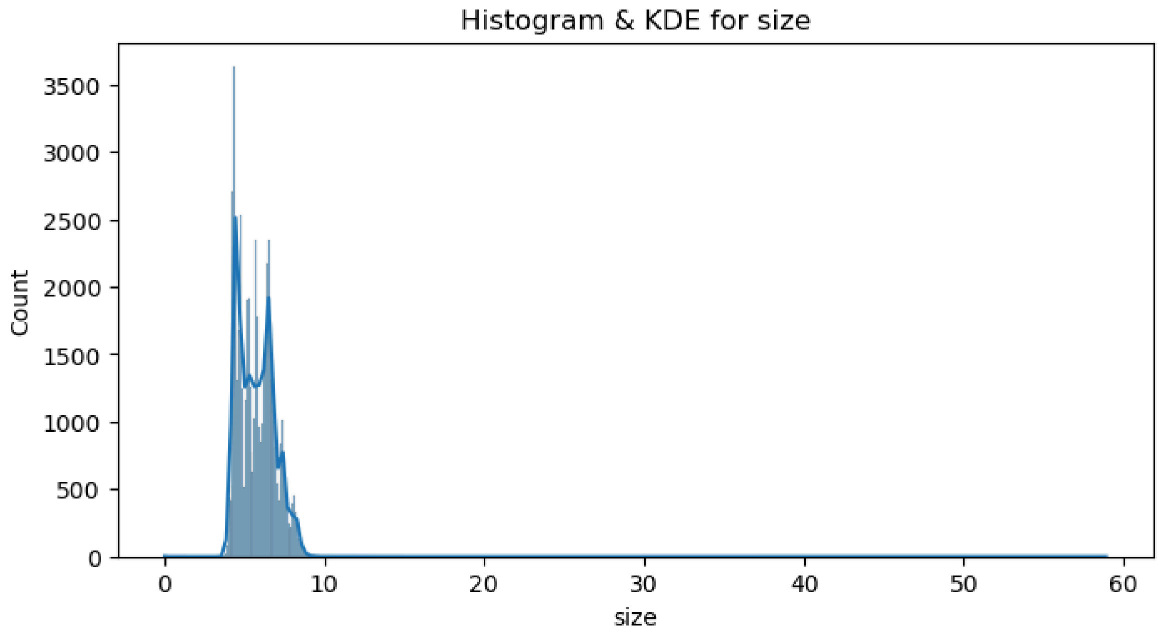
```
import seaborn as sns
import matplotlib.pyplot as plt

# Plot histogram with KDE
for col in df_numeric.columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(df_numeric[col], kde=True)
    plt.title(f"Histogram & KDE for {col}")
    plt.show()
```

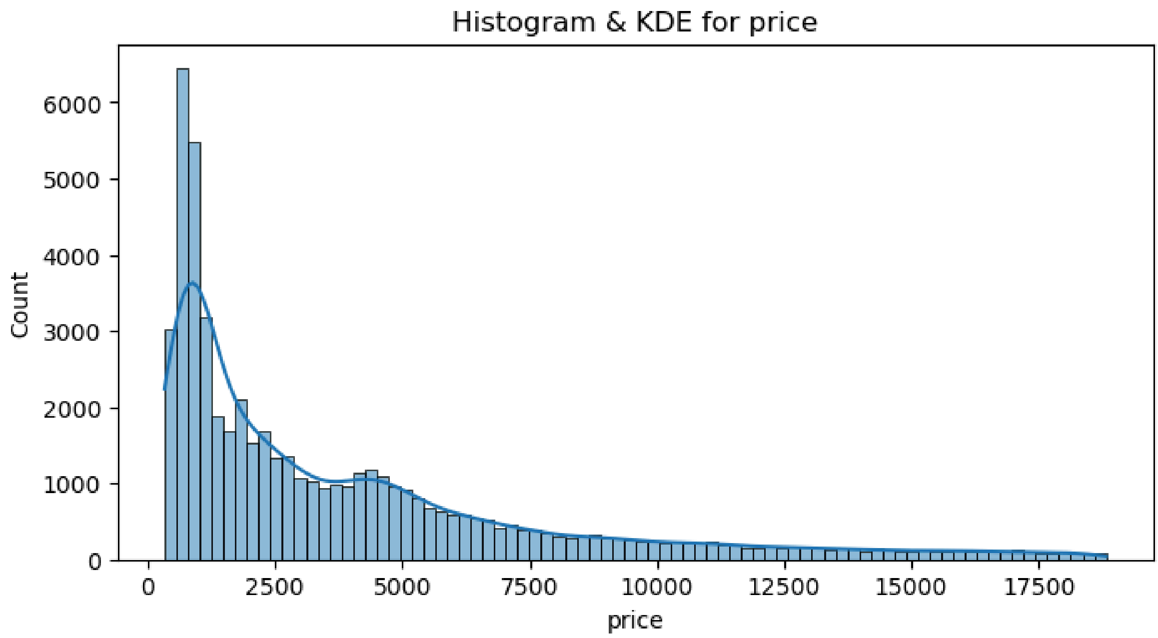

Histogram & KDE for carat
Count
0
1000
2000
3000
4000
5000
0
1
2
3
4
5
carat


Histogram & KDE for depth
Count
0
500
1000
1500
2000
45
50
55
60
65
70
75
80
depth


Histogram & KDE for table
Count
0
2000
4000
6000
8000
10000
50
60
70
80
90
table

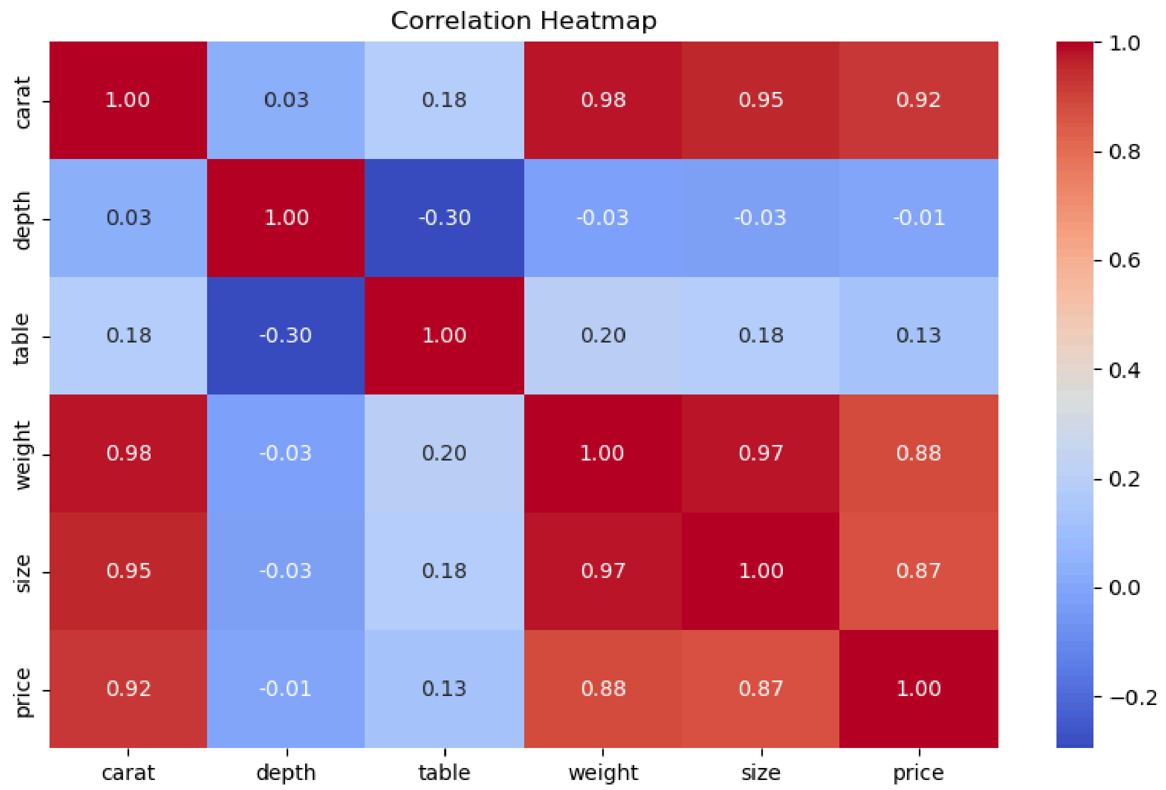

Histogram & KDE for weight
Count
weight
0
500
1000
1500
2000
2500
3000
3500
0
2
4
6
8
10


Histogram & KDE for size
Count
size
0
500
1000
1500
2000
2500
3000
3500
0
10
20
30
40
50
60


Histogram & KDE for price
Count
price
0
1000
2000
3000
4000
5000
6000
0
2500
5000
7500
10000
12500
15000
17500

Q1 I. Check the correlation between all the numeric variables using HeatMap and try to draw some conclusion about the data.

In [37]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(df_numeric.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



Q2: Gradient Descent and Learning Rate Impact

Gradient Descent Explanation Gradient Descent is an optimization algorithm used to minimize the loss function in machine learning models by iteratively adjusting model parameters. The process follows these steps:

1.Initialize Parameters: Start with random weights.

2.Compute the Gradient: Calculate the derivative of the loss function.

3.Update Weights: Adjust weights using the formula:

$\theta=\theta-\alpha*\partial J/\partial\theta$ where:

θ = parameter (weight) α = learning rate J = loss function

4.Repeat Until Convergence: Continue updating until the loss stops decreasing.

Impact of Learning Rate

The learning rate (α) plays a crucial role in convergence:

Too Small: Converges very slowly.

Too Large: May overshoot or fail to converge.

Optimal: Finds the minimum efficiently.

In [ ]:

```

```