MagicBricks Data Analysis

In [2]:
```
#Importing Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

In [3]:
```
#Loading Dataset

df = pd.read_csv('Magicbricks.csv')
```

In [6]:
```
df
```

Out[6]:

	Listing_ID	Location	Locality	BHK	Size	Price	Bathroo
0	MB101137	Kolkata	Salt Lake	3	524.0	3597233.0	4
1	MB100222	Pune	Viman Nagar	4	2547.0	22189240.0	3
2	MB100973	Kolkata	New Town	4	1719.0	15137167.0	3
3	MB101370	Jaipur	Malviya Nagar	3	1393.0	6190887.0	3
4	MB100939	Delhi NCR	Rohini	5	2071.0	26041798.0	3
...	...	...	...	...	...	...	
1525	MB101092	Jaipur	Vaishali Nagar	1	820.0	6106246.0	1
1526	MB101192	Jaipur	Jagatpura	3	866.0	4630904.0	3
1527	MB101209	Hyderabad	Banjara Hills	2	1195.0	12180125.0	2
1528	MB101059	Chennai	Chromepet	3	1223.0	22979362.0	3
1529	MB100641	Ahmedabad	Gota	3	840.0	4821182.0	3

1530 rows × 12 columns

In [7]:
```
#Clean Dataset

# Clean Size: extract numeric
df['Size'] = df['Size'].astype(str).str.extract(r'(\d+\.?\d*)').ast

# Clean Listing_Date: parse flexible
```

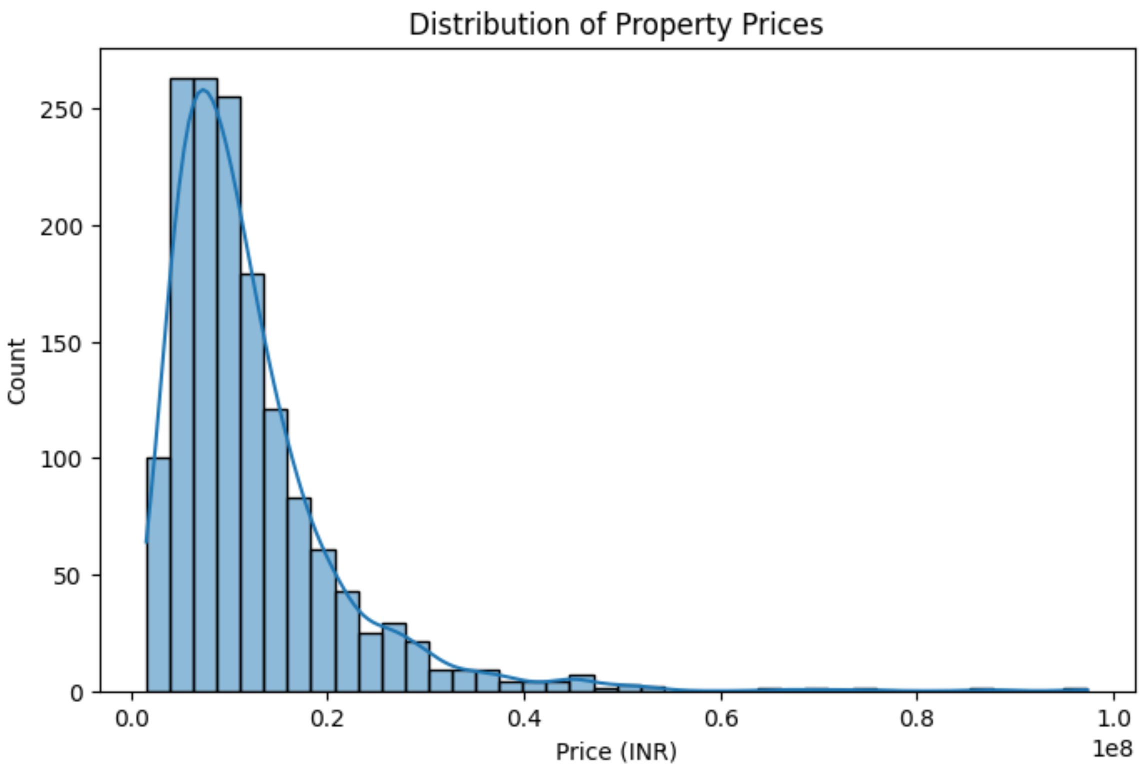
```
df['Listing_Date'] = pd.to_datetime(df['Listing_Date'], errors='coe

# Basic missing handling: drop rows where Price or Size missing
clean_df = df.dropna(subset=['Price','Size'])
```

📌Price Distribution (Histogram + KDE)

In [8]:
```
plt.figure(figsize=(8,5))
sns.histplot(df['Price'], kde=True, bins=40)
plt.title("Distribution of Property Prices")
plt.xlabel("Price (INR)")
plt.ylabel("Count")
```

Out[8]: Text(0, 0.5, 'Count')



Insights

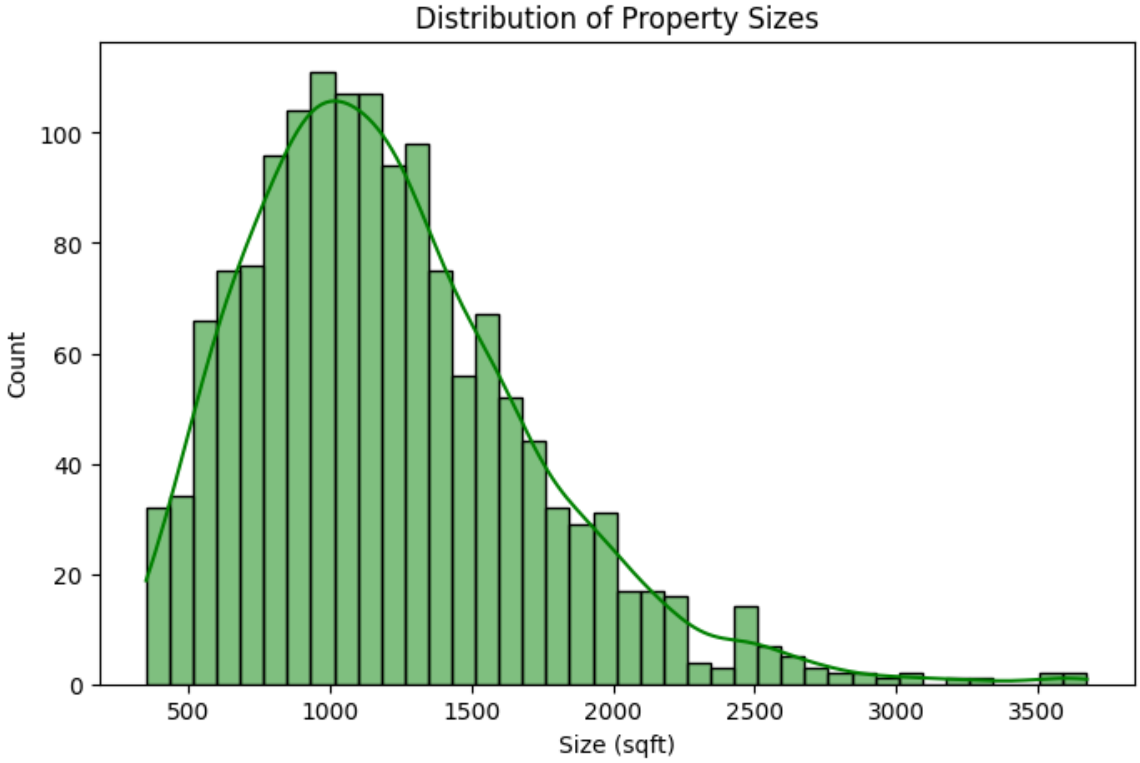
- Price is right-skewed → most properties are affordable/mid-range, while a few expensive listings pull the tail.
- Majority properties fall between ₹40 lakh to ₹1.6 crore.
- Very high-value properties (> ₹5 crore) are outliers — likely luxury areas.

📌 Size Distribution (Histogram + KDE)

In [9]:
```
plt.figure(figsize=(8,5))
sns.histplot(df['Size'], kde=True, bins=40, color='green')
plt.title("Distribution of Property Sizes")
```

```
plt.xlabel("Size (sqft)")
plt.ylabel("Count")
```

Out[9]: Text(0, 0.5, 'Count')



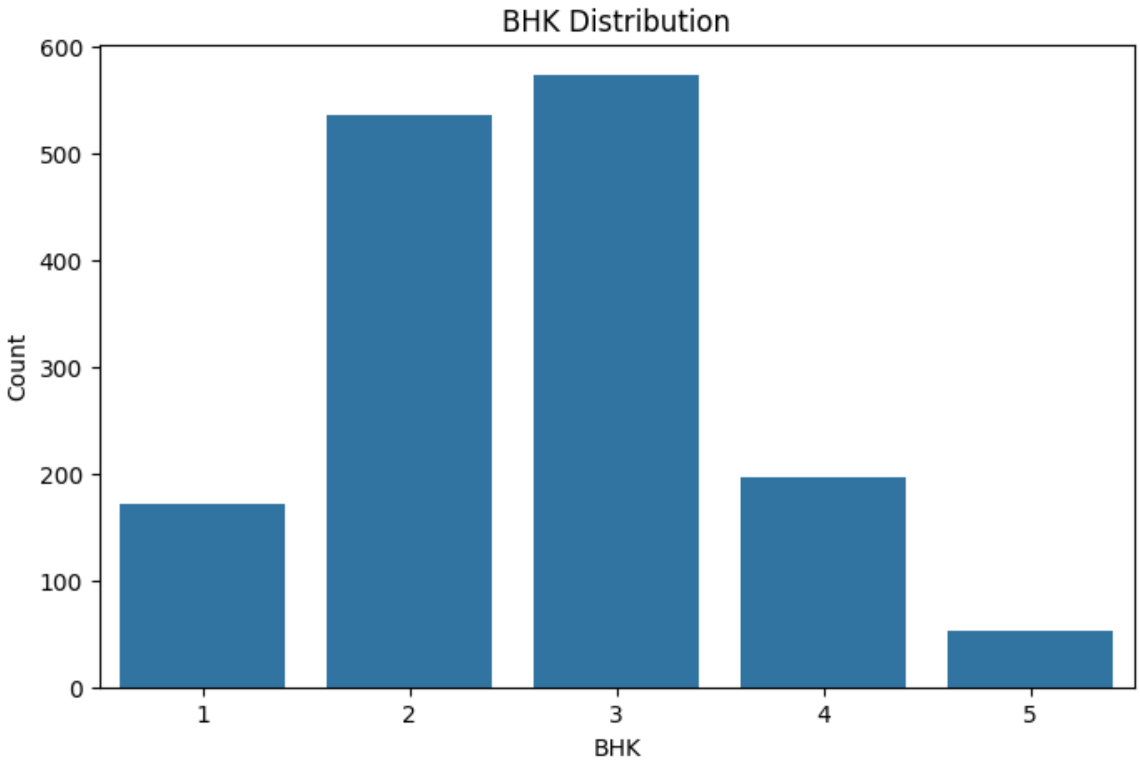
Insights

- Most houses are between 800–1500 sqft, matching typical 2–3 BHK apartments.
- Few very large units above 2500 sqft, indicating premium/luxury category.

📌 BHK Count Distribution (Count Plot)

In [10]:
```
plt.figure(figsize=(8,5))
sns.countplot(x='BHK', data=df)
plt.title("BHK Distribution")
plt.xlabel("BHK")
plt.ylabel("Count")
```

Out[10]: Text(0, 0.5, 'Count')



Insights

- 2 BHK and 3 BHK dominate the dataset (70%+ of listings).
- 1 BHK and 5 BHK are rare — niche market segments.

📌 Price vs Size (Scatter Plot)

In [11]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(x='Size', y='Price', data=df)
plt.title("Price vs Size")
```

Out[11]:
```
Text(0.5, 1.0, 'Price vs Size')
```

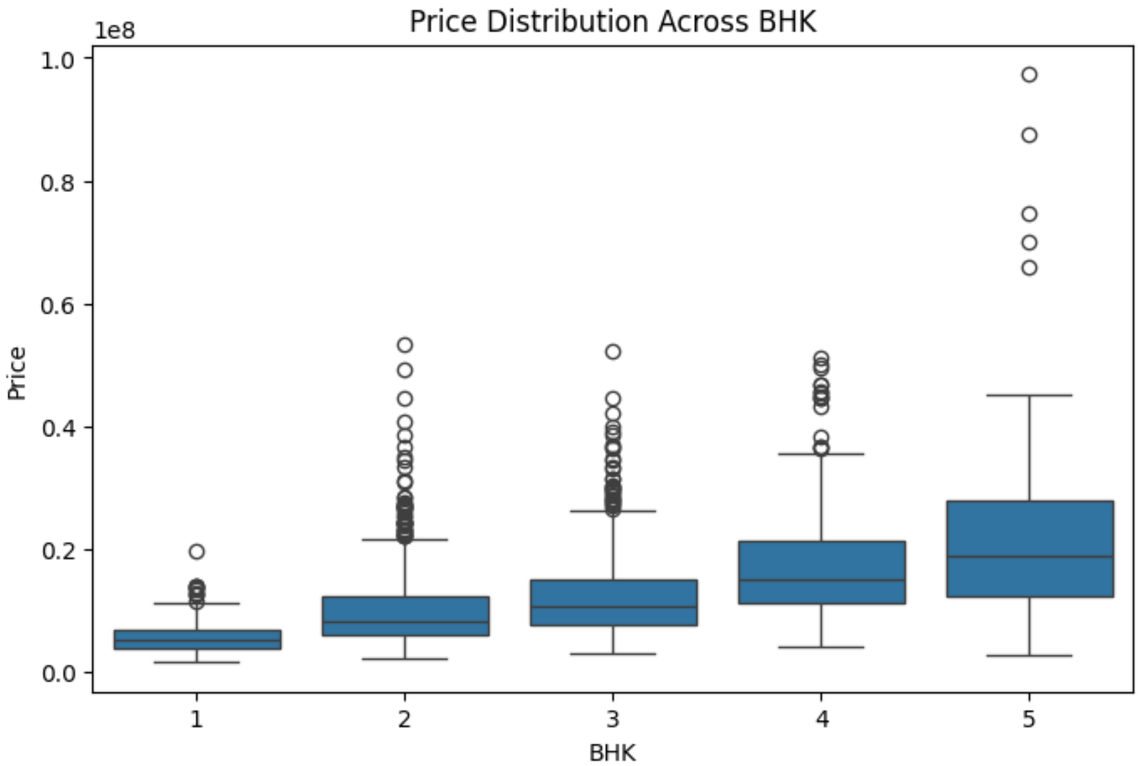
Insights

- Strong positive relationship → larger homes cost more.
- Significant spread shows influence of location, BHK, and amenities.
- Outliers suggest luxury/ultra-luxury real estate.

📌 Price vs BHK (Box Plot)

In [12]:
```
plt.figure(figsize=(8,5))
sns.boxplot(x='BHK', y='Price', data=df)
plt.title("Price Distribution Across BHK")
```

Out[12]: `Text(0.5, 1.0, 'Price Distribution Across BHK')`



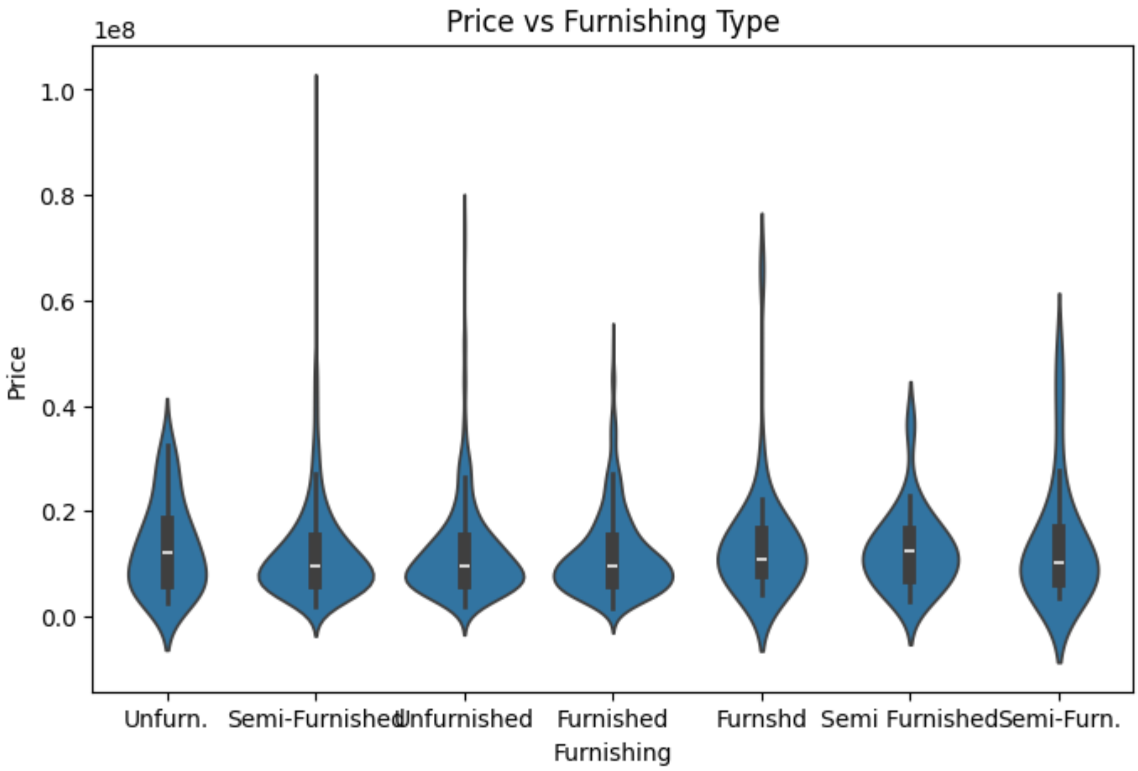
Insights

- Price generally increases from 1 → 5 BHK.
- Overlapping ranges (especially 2 vs 3 BHK) show BHK is not the only factor influencing price.

📌 Price vs Furnishing Type (Violin Plot)

In [13]:
```
plt.figure(figsize=(8,5))
sns.violinplot(x='Furnishing', y='Price', data=df)
plt.title("Price vs Furnishing Type")
```

Out[13]: `Text(0.5, 1.0, 'Price vs Furnishing Type')`



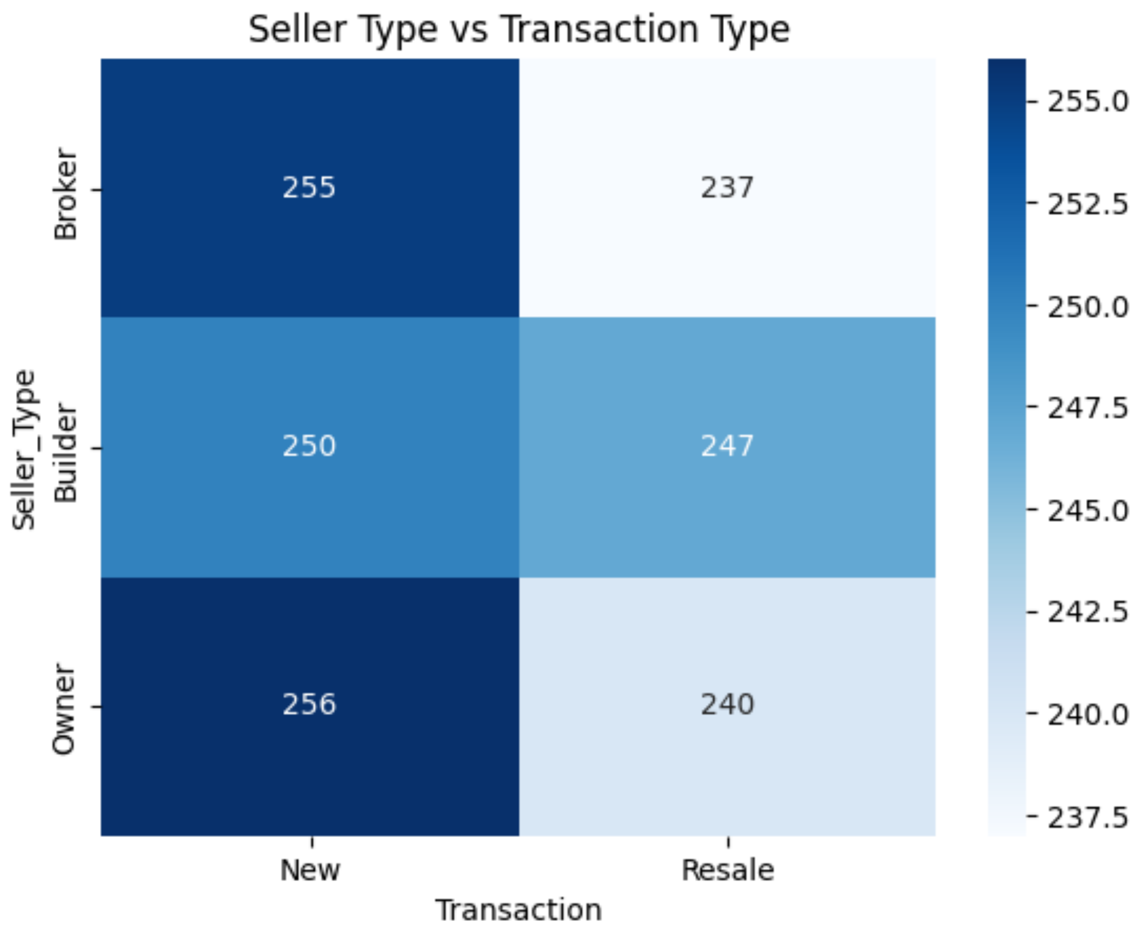
Insights

- Fully furnished units tend to have slightly higher prices.
- Unfurnished units have broad variance → depends heavily on location.

📌 Seller Type vs Transaction (HeapMap)

In [14]:
```
ct = pd.crosstab(df['Seller_Type'], df['Transaction'])
sns.heatmap(ct, annot=True, fmt='d', cmap='Blues')
plt.title("Seller Type vs Transaction Type")
```

Out[14]:
```
Text(0.5, 1.0, 'Seller Type vs Transaction Type')
```



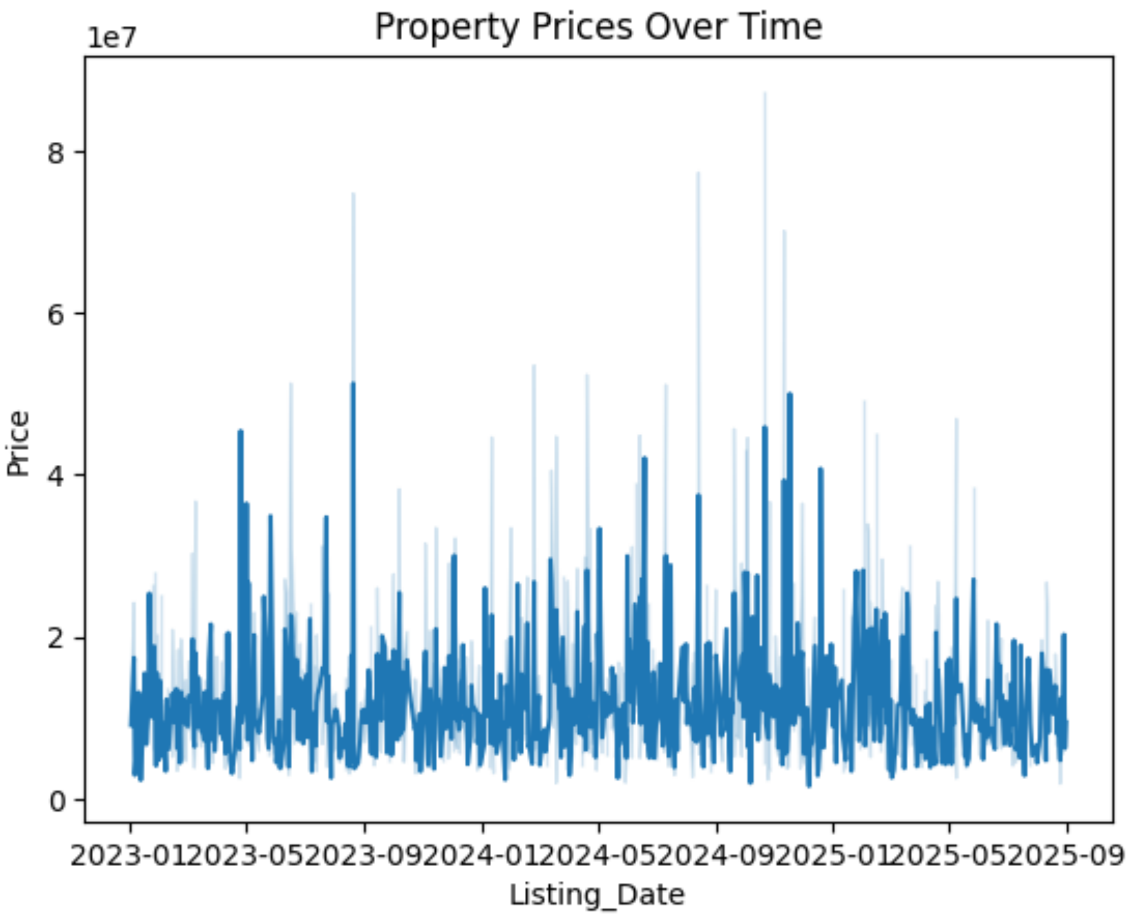
Insights

- Brokers contribute the highest number of both resale and new listings.
- Owner-listed properties are mostly resale, not new construction.

📌 Price Over Time (Line Plot)

In [15]:
```
df_sorted = df.sort_values("Listing_Date")
sns.lineplot(x="Listing_Date", y="Price", data=df_sorted)
plt.title("Property Prices Over Time")
```

Out[15]:
```
Text(0.5, 1.0, 'Property Prices Over Time')
```



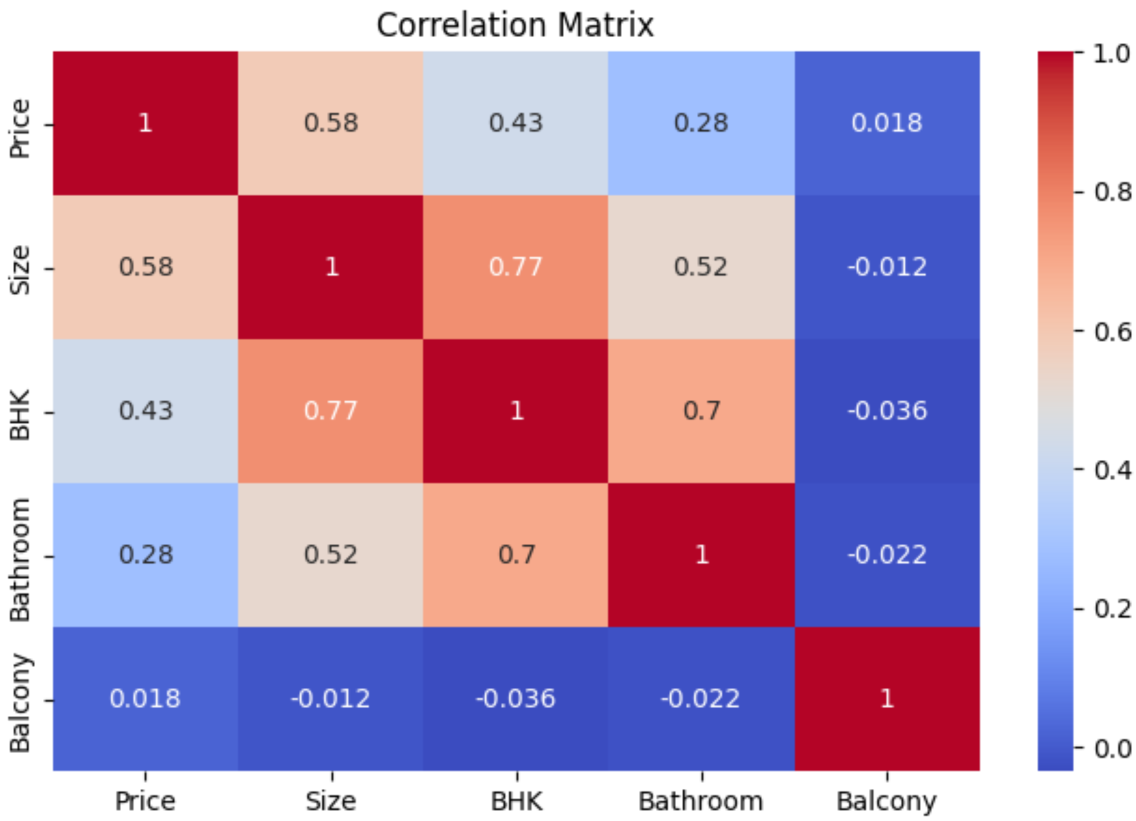
Insights

- No strong trend → prices remain volatile, likely due to location-wise differences.
- Certain peaks correspond to high-value listings added on those dates.

📌 Correlation Heatmap

In [16]:
```
plt.figure(figsize=(8,5))
sns.heatmap(df[['Price','Size','BHK','Bathroom','Balcony']].corr(),
            annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
```

Out[16]:
```
Text(0.5, 1.0, 'Correlation Matrix')
```



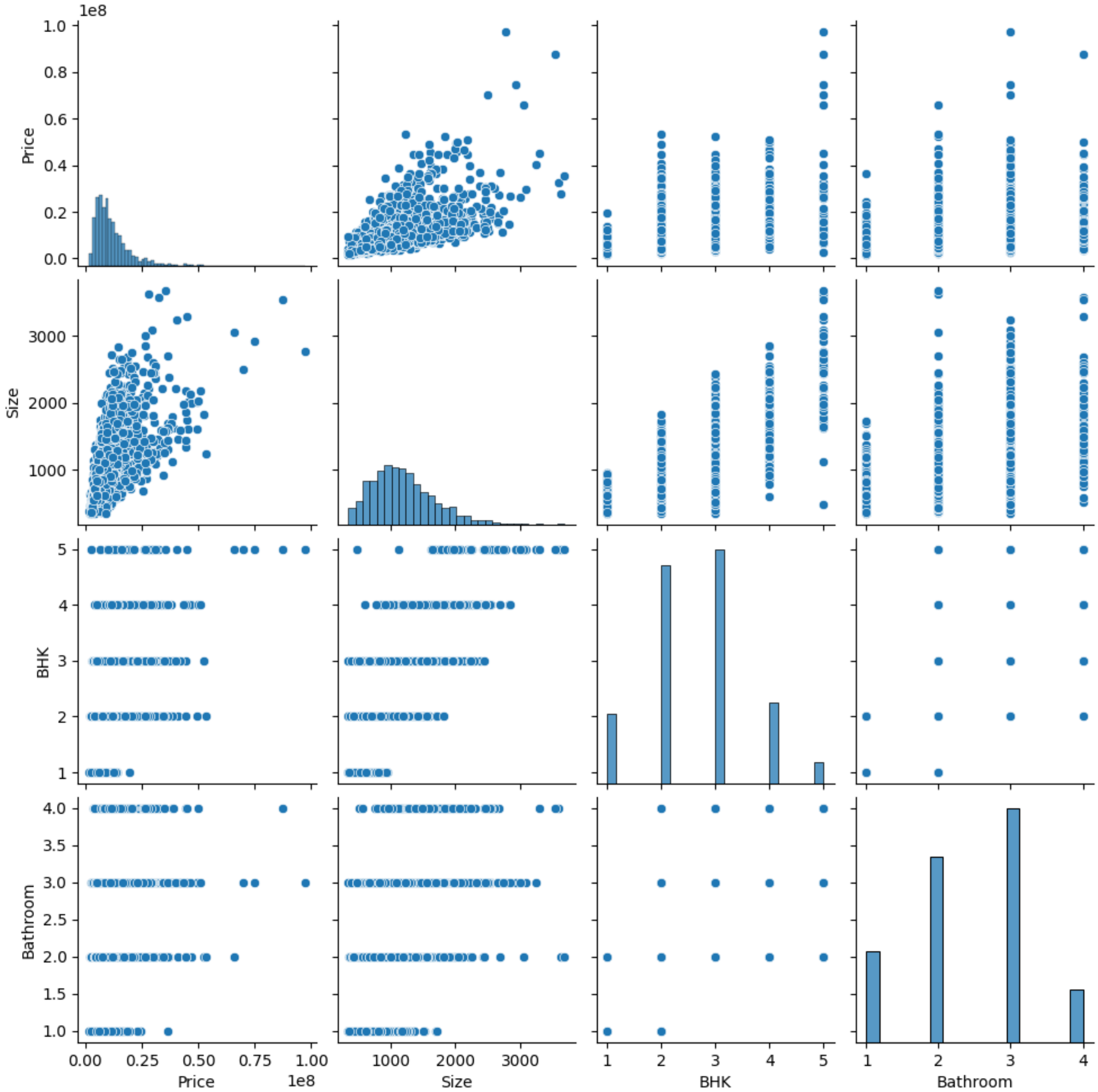
Insights

- Price is most strongly correlated with:
  - Size (highest)
  - Bathroom count
  - BHK
- Bathrooms correlate more strongly with price than balconies.

📌 Pairplot

In [17]:
```
sns.pairplot(df[['Price','Size','BHK','Bathroom']])
```

Out[17]: <seaborn.axisgrid.PairGrid at 0x114bf6cf0>



Insights

- Shows pairwise relationships clearly.
- Confirms: Larger homes have more rooms and bathrooms → higher price.

In [ ]: