Machine Learning-Based Airbnb House Price Prediction System

Goal: To build a machine learning system that predicts Airbnb prices accurately.

Problem Statement

Airbnb hosts often struggle to decide the correct price for their listings. Incorrect pricing may lead to either loss of revenue or fewer bookings. An intelligent system is required to estimate appropriate pricing automatically based on historical data and listing features.

Project Objective

To build and evaluate regression models that predict Airbnb prices efficiently and accurately by processing real-world dataset using feature engineering and machine learning algorithms.

Import Required Librararies and Reading the Dataset

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Machine learning Libraries
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSe
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.impute import SimpleImputer
import xgboost as xgb
import time



import warnings
warnings.filterwarnings('ignore')

%matplotlib inline
```

In [2]:
```
#read Airbnb Dataset
df = pd.read_excel("Airbnb_data.xlsx")
df.to_csv("Airbnb_data.csv", index=False)
```

Data Exploration and Preprocessing

- Analyze the dataset for trends, missing values, and outliers.
- Perform data cleaning, feature engineering, and transformations.

Data Audit

In [3]:
```
Airbnb_df=df.copy()
print("Displaing First 10 rows\n")
print(Airbnb_df.head(10))
print("Displaing Basic shape(Rows,Columns\n")
print(Airbnb_df.shape)
print("Displaing all information of all columns\n")
print(Airbnb_df.info())
print("Displaing statastical data\n")
print(Airbnb_df.describe)
print("Displaing data types of columns\n")
print(Airbnb_df.dtypes)
```

```
Displaing First 10 rows

         id  log_price property_type        room_type  \
0   6901257   5.010635     Apartment  Entire home/apt   
1   6304928   5.129899     Apartment  Entire home/apt   
2   7919400   4.976734     Apartment  Entire home/apt   
3  13418779   6.620073         House  Entire home/apt   
4   3808709   4.744932     Apartment  Entire home/apt   
5  12422935   4.442651     Apartment     Private room   
6  11825529   4.418841     Apartment  Entire home/apt   
7  13971273   4.787492   Condominium  Entire home/apt   
8    180792   4.787492         House     Private room   
9   5385260   3.583519         House     Private room   

                                           amenities  accommodates  bathrooms  \
0  {"Wireless Internet","Air conditioning",Kitche...             3        1.0   
1  {"Wireless Internet","Air conditioning",Kitche...             7        1.0   
2  {TV,"Cable TV","Wireless Internet","Air condit...             5        1.0   
3  {TV,"Cable TV",Internet,"Wireless Internet",Ki...             4        1.0   
4  {TV,Internet,"Wireless Internet","Air conditio...             2        1.0   
5  {TV,"Wireless Internet",Heating,"Smoke detecto...             2        1.0   
6  {TV,Internet,"Wireless Internet","Air conditio...             3        1.0   
7  {TV,"Cable TV","Wireless Internet","Wheelchair...             2        1.0   
8  {TV,"Cable TV","Wireless Internet","Pets live ...             2        1.0   
9  {"Wireless Internet","Air conditioning",Kitche...             2        1.0   

   bed_type cancellation_policy  cleaning_fee  ...   latitude   longitude  \
0  Real Bed              strict          True  ...  40.696524  -73.991617   
1  Real Bed              strict          True  ...  40.766115  -73.989040   
2  Real Bed            moderate          True  ...  40.808110  -73.943756   
3  Real Bed            flexible          True  ...  37.772004 -122.431619   
4  Real Bed            moderate          True  ...  38.925627  -77.034596   
5  Real Bed              strict          True  ...  37.753164 -122.429526   
6  Real Bed            moderate          True  ...  33.980454 -118.462821   
7  Real Bed            moderate          True  ...  34.046737 -118.260439   
8  Real Bed            moderate          True  ...  37.781128 -122.501095   
9  Real Bed            moderate          True  ...  33.992563 -117.895997   

                                                name      neighbourhood  \
0                     Beautiful brownstone 1-bedroom   Brooklyn Heights   
1           Superb 3BR Apt Located Near Times Square     Hell's Kitchen   
2                                    The Garden Oasis             Harlem   
3                       Beautiful Flat in the Heart of SF!       Lower Haight   
4                        Great studio in midtown DC   Columbia Heights   
5                         Comfort Suite San Francisco         Noe Valley   
6                      Beach Town Studio and Parking!!!11h                NaN   
7  Near LA Live, Staple's. Starbucks inside. OWN ...           Downtown   
8                  Cozy Garden Studio - Private Entry  Richmond District   
9                          No.7 Queen Size Cozy Room 舒适大床房                NaN   

  number_of_reviews  review_scores_rating  \
0                 2                 100.0   
1                 6                  93.0   
2                10                  92.0   
3                 0                   NaN   
4                 4                  40.0   
5                 3                 100.0   
6                15                  97.0   
7                 9                  93.0   
8               159                  99.0   
```

```
9                 2                 90.0

                                        thumbnail_url zipcode bedrooms  beds
0  https://a0.muscache.com/im/pictures/6d7cbbf7-c...   11201      1.0   1.0
1  https://a0.muscache.com/im/pictures/348a55fe-4...   10019      3.0   3.0
2  https://a0.muscache.com/im/pictures/6fae5362-9...   10027      1.0   3.0
3  https://a0.muscache.com/im/pictures/72208dad-9...   94117      2.0   2.0
4                                                NaN   20009      0.0   1.0
5  https://a0.muscache.com/im/pictures/82509143-4...   94131      1.0   1.0
6  https://a0.muscache.com/im/pictures/4c920c60-4...   90292      1.0   1.0
7  https://a0.muscache.com/im/pictures/61bd05d5-c...   90015      1.0   1.0
8  https://a0.muscache.com/im/pictures/0ed6c128-7...   94121      1.0   1.0
9  https://a0.muscache.com/im/pictures/8d2f08ce-b...   91748      1.0   1.0

[10 rows x 29 columns]
Displaing Basic shape(Rows,Columns

(74111, 29)
Displaing all information of all columns

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Data columns (total 29 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   id                      74111 non-null  int64  
 1   log_price               74111 non-null  float64
 2   property_type           74111 non-null  object 
 3   room_type               74111 non-null  object 
 4   amenities               74111 non-null  object 
 5   accommodates            74111 non-null  int64  
 6   bathrooms               73911 non-null  float64
 7   bed_type                74111 non-null  object 
 8   cancellation_policy     74111 non-null  object 
 9   cleaning_fee            74111 non-null  bool   
 10  city                    74111 non-null  object 
 11  description             74105 non-null  object 
 12  first_review            58247 non-null  object 
 13  host_has_profile_pic    73923 non-null  object 
 14  host_identity_verified  73923 non-null  object 
 15  host_response_rate      55812 non-null  float64
 16  host_since              73923 non-null  object 
 17  instant_bookable        74111 non-null  object 
 18  last_review             58284 non-null  object 
 19  latitude                74111 non-null  float64
 20  longitude               74111 non-null  float64
 21  name                    74101 non-null  object 
 22  neighbourhood           67239 non-null  object 
 23  number_of_reviews       74111 non-null  int64  
 24  review_scores_rating    57389 non-null  float64
 25  thumbnail_url           65895 non-null  object 
 26  zipcode                 73143 non-null  object 
 27  bedrooms                74020 non-null  float64
 28  beds                    73980 non-null  float64
dtypes: bool(1), float64(8), int64(3), object(17)
memory usage: 15.9+ MB
None
Displaing statastical data

<bound method NDFrame.describe of              id  log_price property_type
```

```
room_type  \
0       6901257   5.010635     Apartment  Entire home/apt
1       6304928   5.129899     Apartment  Entire home/apt
2       7919400   4.976734     Apartment  Entire home/apt
3      13418779   6.620073         House  Entire home/apt
4       3808709   4.744932     Apartment  Entire home/apt
...         ...        ...           ...              ...
74106  14549287   4.605170     Apartment     Private room
74107  13281809   5.043425     Apartment  Entire home/apt
74108  18688039   5.220356     Apartment  Entire home/apt
74109  17045948   5.273000     Apartment  Entire home/apt
74110   3534845   4.852030          Boat  Entire home/apt

                                               amenities  accommodates  \
0      {"Wireless Internet","Air conditioning",Kitche...             3
1      {"Wireless Internet","Air conditioning",Kitche...             7
2      {TV,"Cable TV","Wireless Internet","Air condit...             5
3      {TV,"Cable TV",Internet,"Wireless Internet",Ki...             4
4      {TV,Internet,"Wireless Internet","Air conditio...             2
...                                                  ...           ...
74106                                                 {}             1
74107  {TV,"Cable TV",Internet,"Wireless Internet",Ki...             4
74108  {TV,Internet,"Wireless Internet","Air conditio...             5
74109  {TV,"Wireless Internet","Air conditioning",Kit...             2
74110  {TV,Internet,"Wireless Internet",Kitchen,"Free...             4

       bathrooms  bed_type cancellation_policy  cleaning_fee  ...   latitude  \
0            1.0  Real Bed              strict          True  ...  40.696524
1            1.0  Real Bed              strict          True  ...  40.766115
2            1.0  Real Bed            moderate          True  ...  40.808110
3            1.0  Real Bed            flexible          True  ...  37.772004
4            1.0  Real Bed            moderate          True  ...  38.925627
...          ...       ...                 ...           ...  ...        ...
74106        1.0  Real Bed            flexible         False  ...  40.709025
74107        2.0  Real Bed            moderate          True  ...  33.871549
74108        1.0  Real Bed            moderate          True  ...  40.706749
74109        1.0  Real Bed              strict          True  ...  40.738535
74110        1.0  Real Bed            moderate         False  ...  33.761096

        longitude                                        name  \
0      -73.991617              Beautiful brownstone 1-bedroom
1      -73.989040    Superb 3BR Apt Located Near Times Square
2      -73.943756                             The Garden Oasis
3     -122.431619           Beautiful Flat in the Heart of SF!
4      -77.034596                  Great studio in midtown DC
...           ...                                          ...
74106  -73.939405                             one room bushwick
74107 -118.396053                   Spacious Hermosa 2 BR on PCH
74108  -73.942377  Modern 2 Bedroom Apartment in Williamsburg
74109  -74.000157           Designer's Apartment in HEART of NYC
74110 -118.192409                 Cozy Boat at Shoreline Village

          neighbourhood number_of_reviews  review_scores_rating  \
0      Brooklyn Heights                 2                 100.0
1        Hell's Kitchen                 6                  93.0
2                Harlem                10                  92.0
3          Lower Haight                 0                   NaN
4      Columbia Heights                 4                  40.0
...                 ...               ...                   ...
74106      Williamsburg                 0                   NaN
```

```
74107     Hermosa Beach                16                   93.0
74108      Williamsburg                43                   94.0
74109      West Village                 0                    NaN
74110        Long Beach               205                   96.0

                                      thumbnail_url zipcode bedrooms  \
0      https://a0.muscache.com/im/pictures/6d7cbbf7-c...   11201      1.0
1      https://a0.muscache.com/im/pictures/348a55fe-4...   10019      3.0
2      https://a0.muscache.com/im/pictures/6fae5362-9...   10027      1.0
3      https://a0.muscache.com/im/pictures/72208dad-9...   94117      2.0
4                                                   NaN   20009      0.0
...                                                 ...     ...      ...
74106  https://a0.muscache.com/im/pictures/55162426/6...   11206      1.0
74107  https://a0.muscache.com/im/pictures/2b86560b-a...   90254      2.0
74108  https://a0.muscache.com/im/pictures/7fbe448c-5...   11206      2.0
74109  https://a0.muscache.com/im/pictures/b3971b63-0...   10011      0.0
74110  https://a0.muscache.com/im/pictures/22968537/d...   90802      1.0

       beds
0       1.0
1       3.0
2       3.0
3       2.0
4       1.0
...     ...
74106   1.0
74107   4.0
74108   2.0
74109   2.0
74110   2.0

[74111 rows x 29 columns]>
Displaing data types of columns

id                          int64
log_price                 float64
property_type              object
room_type                  object
amenities                  object
accommodates                int64
bathrooms                 float64
bed_type                   object
cancellation_policy        object
cleaning_fee                 bool
city                       object
description                object
first_review               object
host_has_profile_pic       object
host_identity_verified     object
host_response_rate        float64
host_since                 object
instant_bookable           object
last_review                object
latitude                  float64
longitude                 float64
name                       object
neighbourhood              object
number_of_reviews           int64
review_scores_rating      float64
thumbnail_url              object
```

```
zipcode                  object
bedrooms                float64
beds                    float64
dtype: object
```

Removing Irrelevant Columns

In [4]:
```
Airbnb_df.drop(columns=['id','name','description','first_review','last_review','
Airbnb_df.head()
```

Out[4]:

	log_price	property_type	room_type	amenities	accommodates	bathroom
0	5.010635	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	3	1.(
1	5.129899	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	7	1.(
2	4.976734	Apartment	Entire home/apt	{TV,"Cable TV","Wireless Internet","Air condit...	5	1.(
3	6.620073	House	Entire home/apt	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4	1.(
4	4.744932	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	2	1.(

5 rows × 21 columns

Handling Missing Data and Validating Data Types

In [5]:
```
# Removing Duplicates
Airbnb_df.drop_duplicates(inplace=True)
```

In [6]:
```
# Find missing values
Airbnb_df.isnull().sum().sort_values(ascending=False)
```

Out[6]:
```
host_response_rate      18299
review_scores_rating    16722
neighbourhood            6872
zipcode                   968
bathrooms                 200
host_since                188
beds                      131
bedrooms                   91
accommodates                0
log_price                   0
amenities                   0
room_type                   0
property_type               0
instant_bookable            0
city                        0
cancellation_policy         0
cleaning_fee                0
bed_type                    0
number_of_reviews           0
latitude                    0
longitude                   0
dtype: int64
```

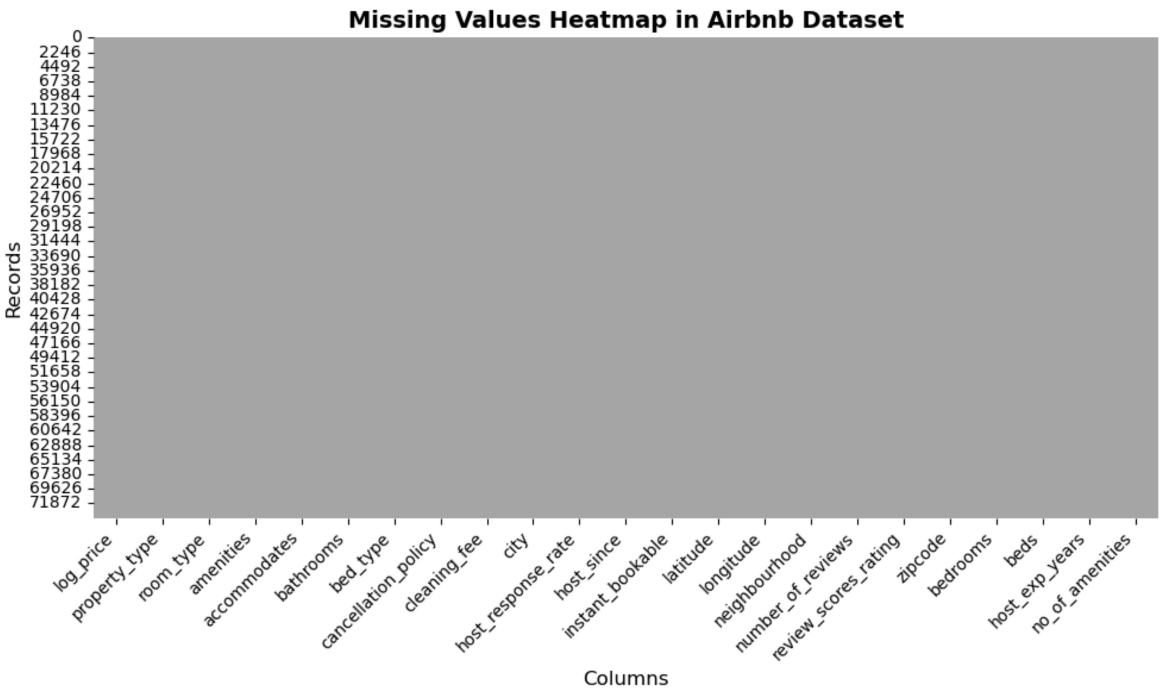
In [7]:
```python
# Handle 'Host_response_rate'
Airbnb_df['host_response_rate']=Airbnb_df['host_response_rate'].astype(str)
Airbnb_df['host_response_rate']=Airbnb_df['host_response_rate'].str.replace('%',
Airbnb_df['host_response_rate']=pd.to_numeric(Airbnb_df['host_response_rate'],er


# Handle 'Host_since
Airbnb_df['host_since']=pd.to_datetime(Airbnb_df['host_since'],errors='coerce')

from datetime import datetime

median_ordinal = int(Airbnb_df['host_since'].dropna().apply(lambda x: x.toordina
median_date = datetime.fromordinal(median_ordinal)
Airbnb_df['host_since'].fillna(median_date, inplace=True)



# Filled with appropriate data
numeric_cols=['host_response_rate','review_scores_rating','bedrooms','bathrooms'

for col in numeric_cols:
    Airbnb_df[col].fillna(Airbnb_df[col].median(),inplace=True)

Airbnb_df['neighbourhood'].fillna('Unknown', inplace=True)
Airbnb_df['zipcode'].fillna(Airbnb_df['zipcode'].mode()[0],inplace=True)
```

Feature Engineering

In [8]:
```python
# Create two column named host_exp_years and no_of_aminities

Airbnb_df['host_exp_years'] = (pd.Timestamp.today() - Airbnb_df['host_since']).d
Airbnb_df['no_of_amenities'] = Airbnb_df['amenities'].apply(lambda x: len(str(x)
```

Visualization

In [9]:
```
plt.figure(figsize=(10, 6))

sns.heatmap(
    Airbnb_df.isnull(),
    cbar=False,
    linewidths=0.3,
    linecolor="darkgrey"
)

# Title & labels
plt.title('Missing Values Heatmap in Airbnb Dataset', fontsize=14, fontweight='b
plt.xlabel('Columns', fontsize=12)
plt.ylabel('Records', fontsize=12)

# Rotate column names
plt.xticks(rotation=45, ha='right')

# Fit everything nicely
plt.tight_layout()

plt.show()
```

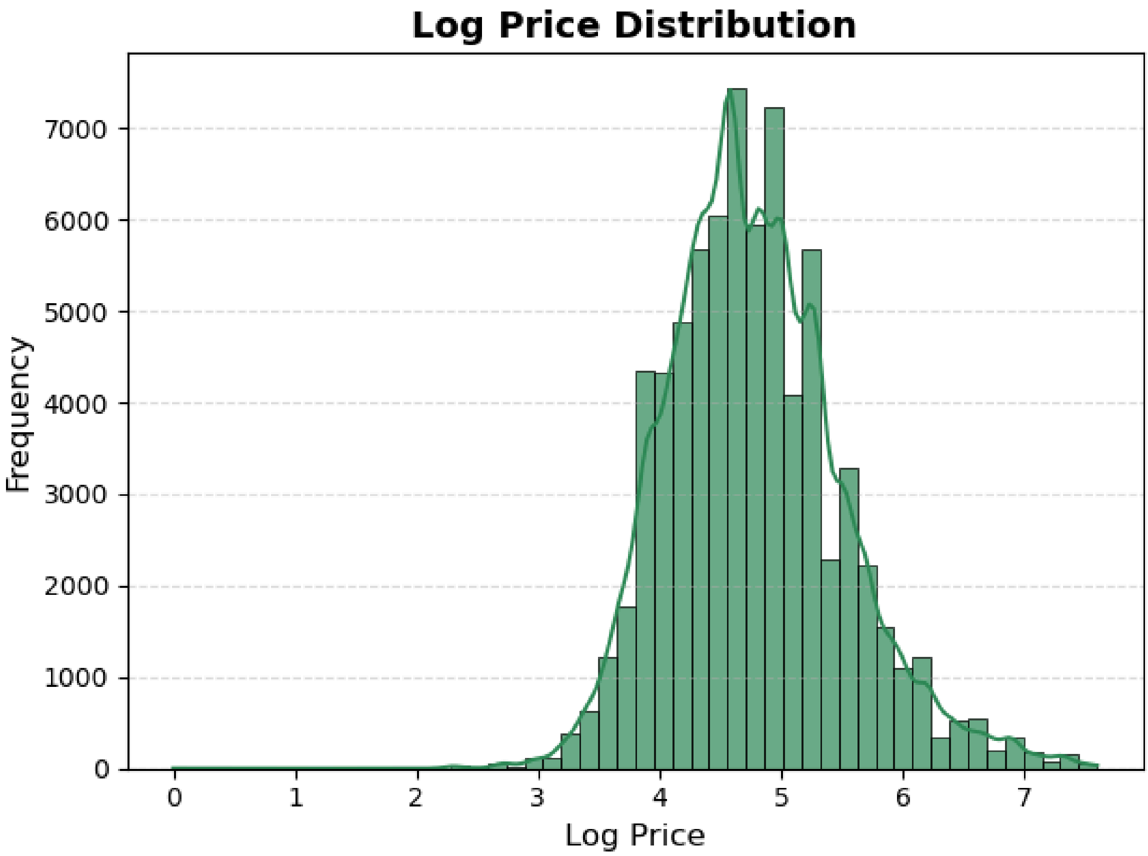


Missing Values Heatmap Summary

The heatmap shows no missing values across the dataset, confirming successful data cleaning and readiness for modeling.

In [10]:
```
sns.histplot(Airbnb_df['log_price'],
             bins=50,
             kde=True,
             color='seagreen',
             alpha=0.7,
             linewidth=0.5)
plt.title('Log Price Distribution',fontsize=14, fontweight='bold')
plt.xlabel('Log Price', fontsize=12)
plt.ylabel('Frequency',fontsize=12)
```

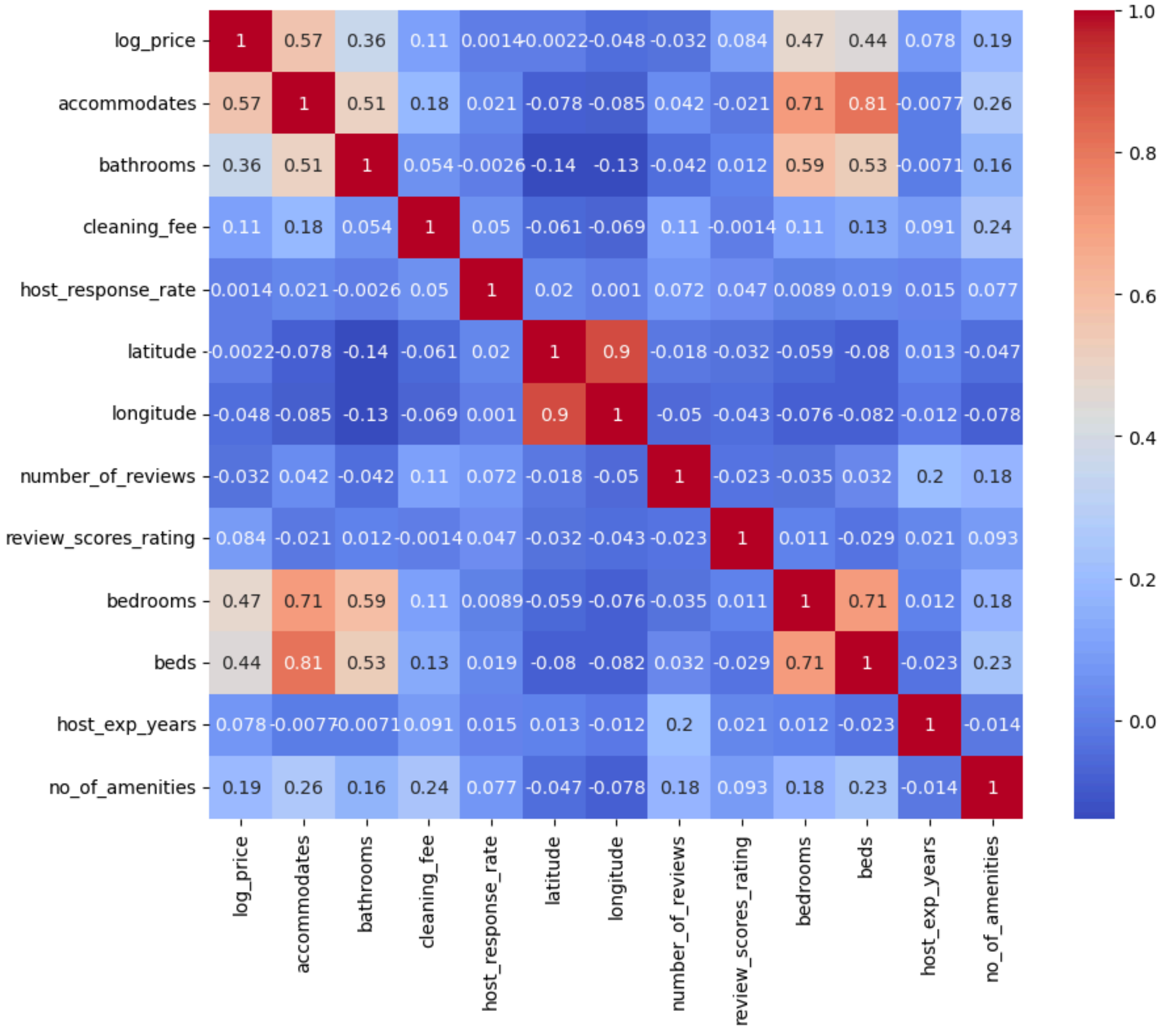
```
plt.tight_layout()
plt.grid(axis='y', linestyle='--', alpha=0.4)
plt.show()
```



Log Price Distribution Summary

- The histogram shows a right-skewed distribution of `log_price`, with most listings centered around 4.5.
- The log transformation makes price values more even, so models can learn better.

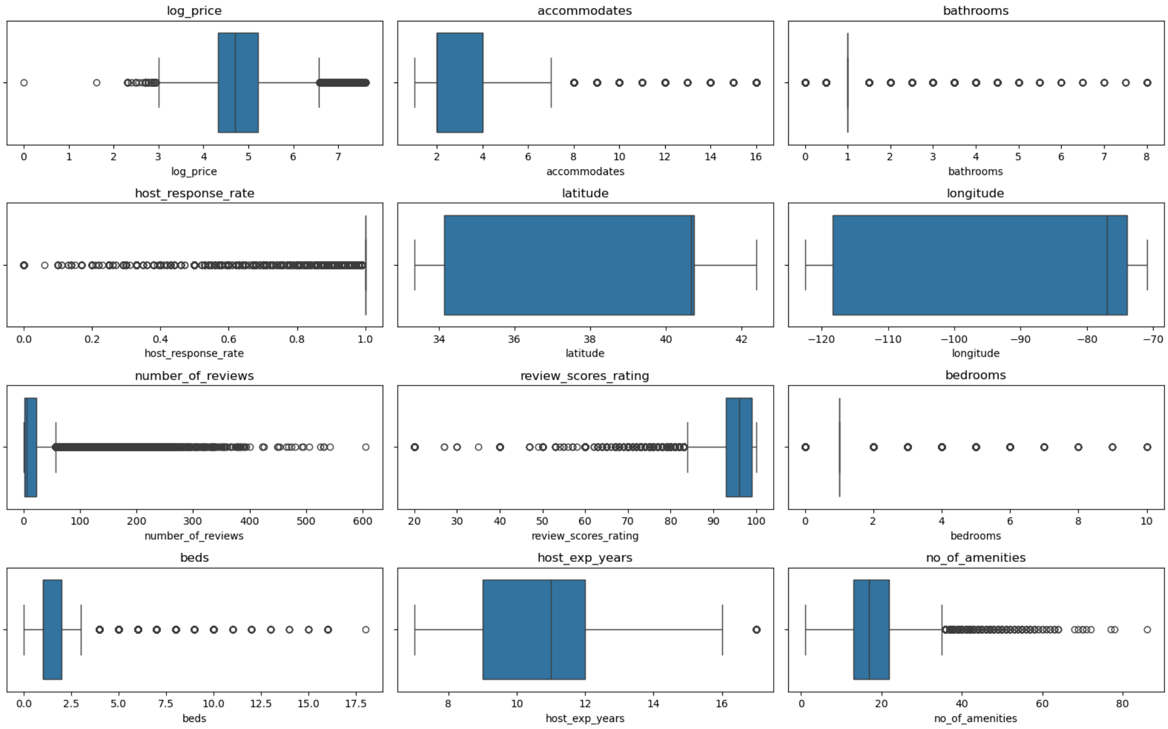
In [11]:
```
corr = Airbnb_df.corr(numeric_only=True)
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.show()
```



Correlation Heatmap Summary

- The heatmap shows strong positive correlations between `accommodates`, `bedrooms`, and `beds`, and moderate correlation with `log_price`.
- These features may be useful for price prediction, while highly correlated ones `bedrooms` and `accommodates` could be redundant.

In [12]:
```
numeric_cols = Airbnb_df.select_dtypes(include=['int64','float64']).columns

plt.figure(figsize=(16, 12))
for i, col in enumerate(numeric_cols, 1):
    plt.subplot(len(numeric_cols)//3 + 1, 3, i)
    sns.boxplot(x=Airbnb_df[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



Boxplot Analysis Summary

- `log_price`, `accommodates`, `bedrooms`, and `bathrooms` show clear outliers.
- Some listings have very high values (like many beds or bathrooms).
- `review_scores_rating` and `host_response_rate` look stable with fewer outliers.
- Outliers may be errors or rare cases and should be checked before modeling.

Outlier Handling and Feature Transformation

In [13]:
```
Airbnb_df['log_price'] = np.where(Airbnb_df['log_price'] > 7, 7, Airbnb_df['log_
Airbnb_df = Airbnb_df[Airbnb_df['bedrooms'] < 10]
Airbnb_df['accommodates'] = np.where(Airbnb_df['accommodates'] > 10, 10, Airbnb_
Airbnb_df['accommodates_log'] = np.log1p(Airbnb_df['accommodates'])
Airbnb_df['beds'] = np.where(Airbnb_df['beds'] > 10, 10, Airbnb_df['beds'])
Airbnb_df['bathrooms_log'] = np.log1p(Airbnb_df['bathrooms'])
Airbnb_df['number_of_reviews'] = np.where(Airbnb_df['number_of_reviews'] > 200,
Airbnb_df['reviews_log'] = np.log1p(Airbnb_df['number_of_reviews'])
Airbnb_df['cleaning_fee'] = np.where(Airbnb_df['cleaning_fee'] > 500, 500, Airbn
Airbnb_df['host_exp_years'] = np.where(Airbnb_df['host_exp_years'] > 20, 20, Air
Airbnb_df['no_of_amenities'] = np.where(Airbnb_df['no_of_amenities'] > 30, 30, A
```

Outlier Handling Observations & Summary

- `log_price` had extreme values; capped at 7 to reduce distortion from luxury listings.
- `bedrooms` above 10 were removed as unrealistic entries.
- `accommodates` and `beds` were capped at 10; log-transformed to reduce skewness.
- `bathrooms` values were realistic (<10); kept as-is, with optional log-transform for skewness.

- `number_of_reviews` capped at 200; log-transformed to handle heavy skew.
- `cleaning_fee` capped at 500 to avoid extreme charges.
- `host_exp_years` capped at 20; ensures long experience values don't dominate.
- `no_of_amenities` capped at 30; avoids distortion from rare extreme cases.

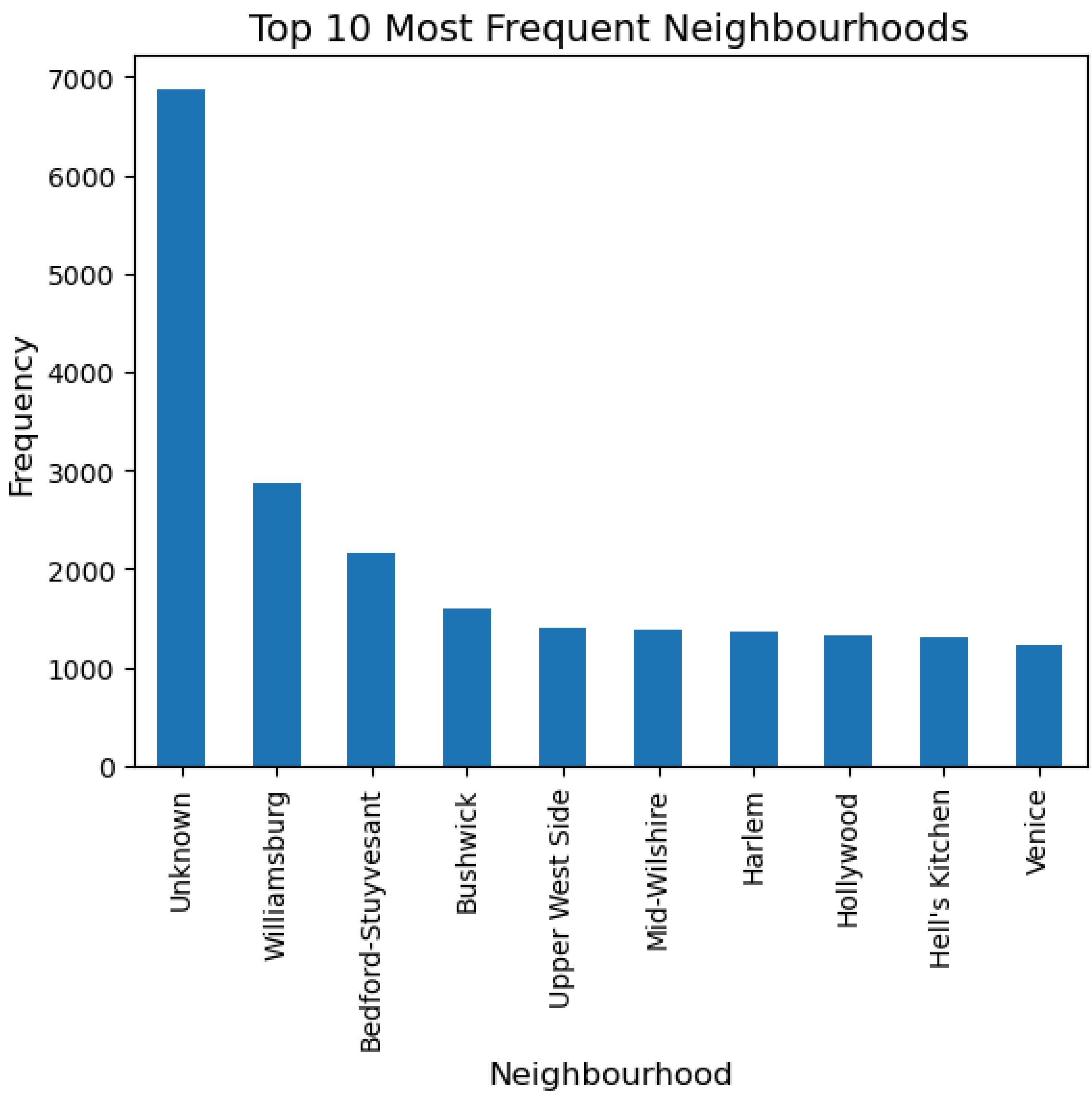
Summary

Outliers were capped or removed based on realistic thresholds. Skewed features were log-transformed for better distribution. Only one version per feature (capped or log-transformed) will be retained to ensure clean, stable data for modeling.

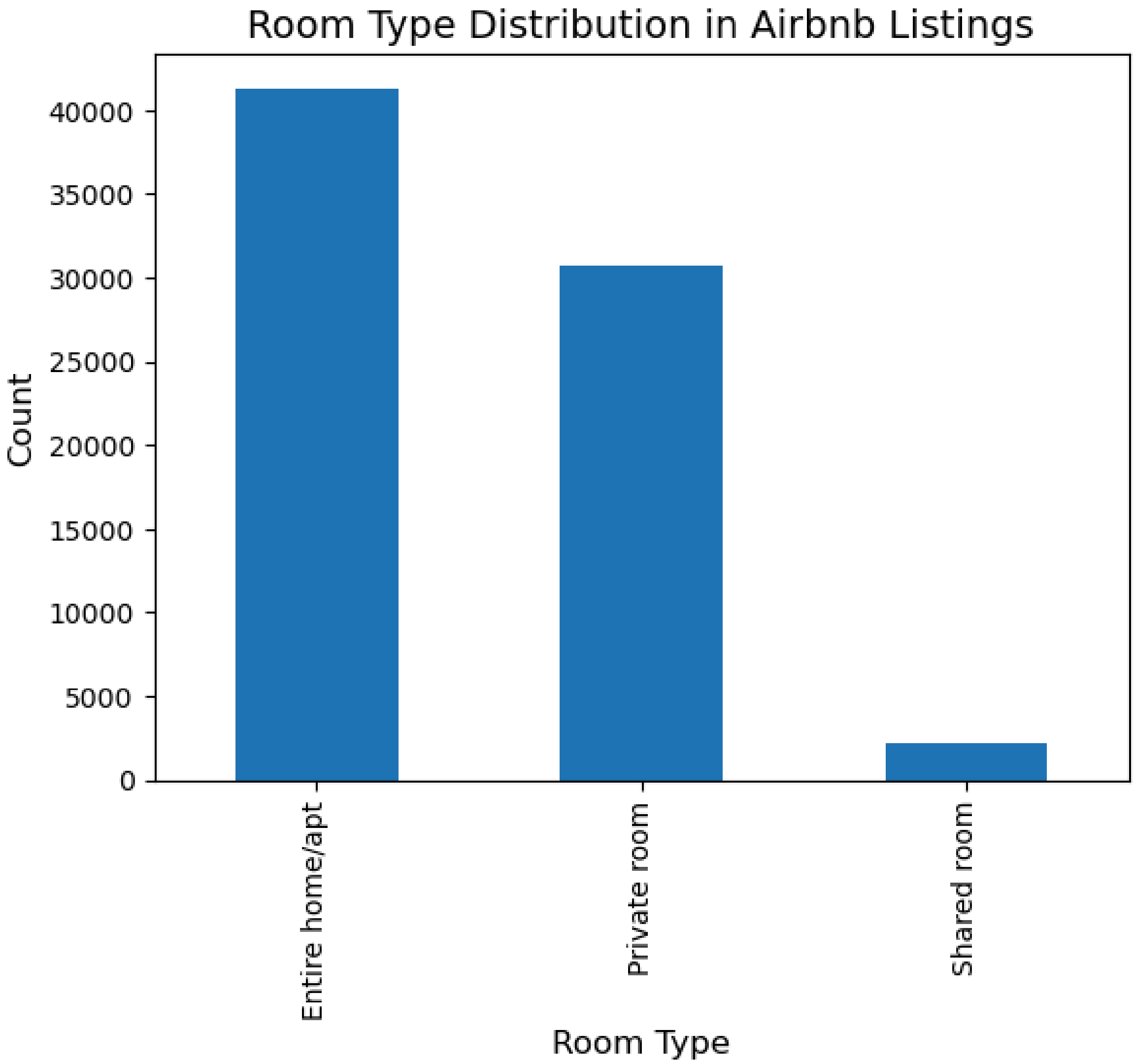
In [14]:
```
Airbnb_df.shape
```

Out[14]: (74101, 26)

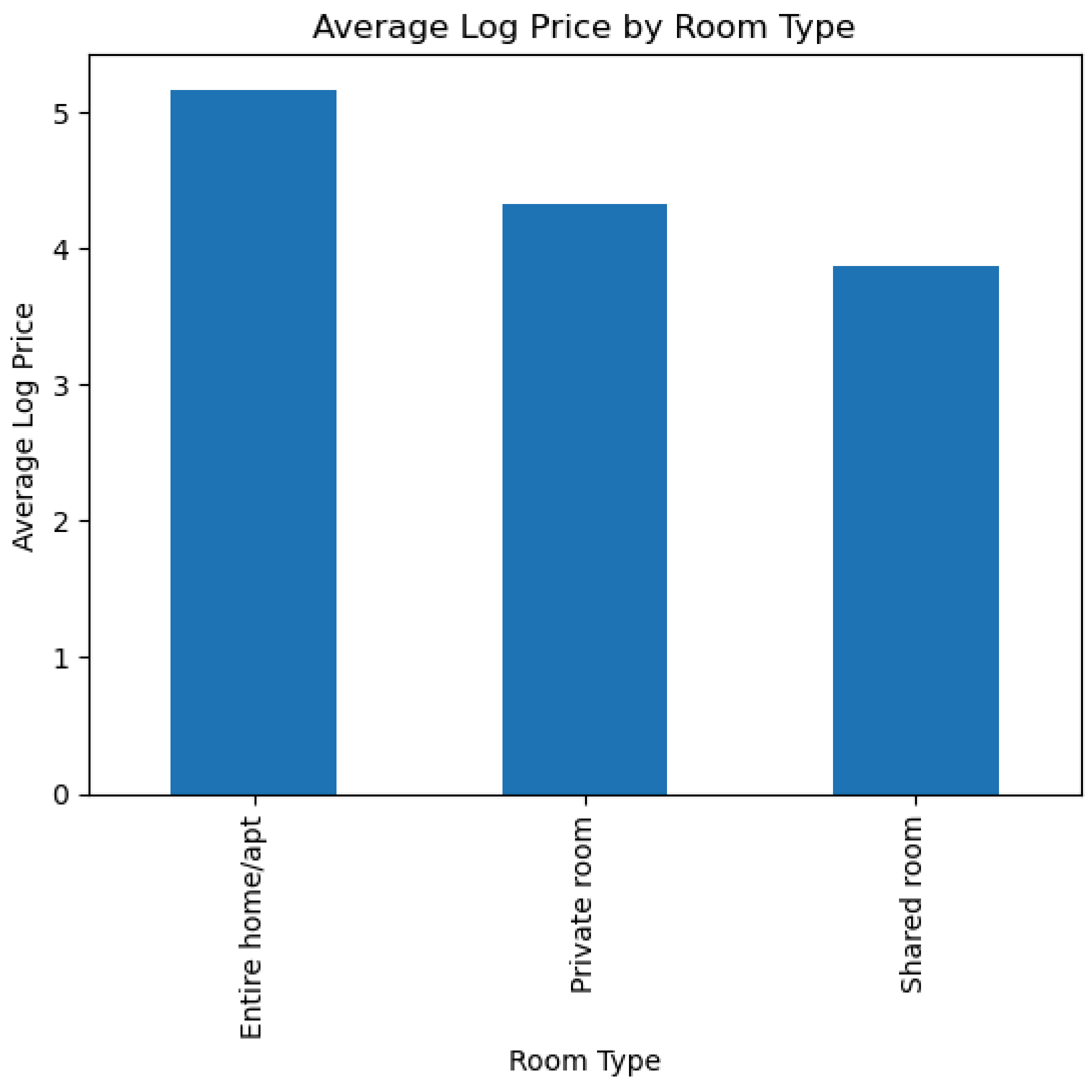
In [15]:
```
Airbnb_df['neighbourhood'].value_counts().head(10).plot(kind='bar')
plt.title('Top 10 Most Frequent Neighbourhoods', fontsize=14)
plt.xlabel('Neighbourhood', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.show()
```



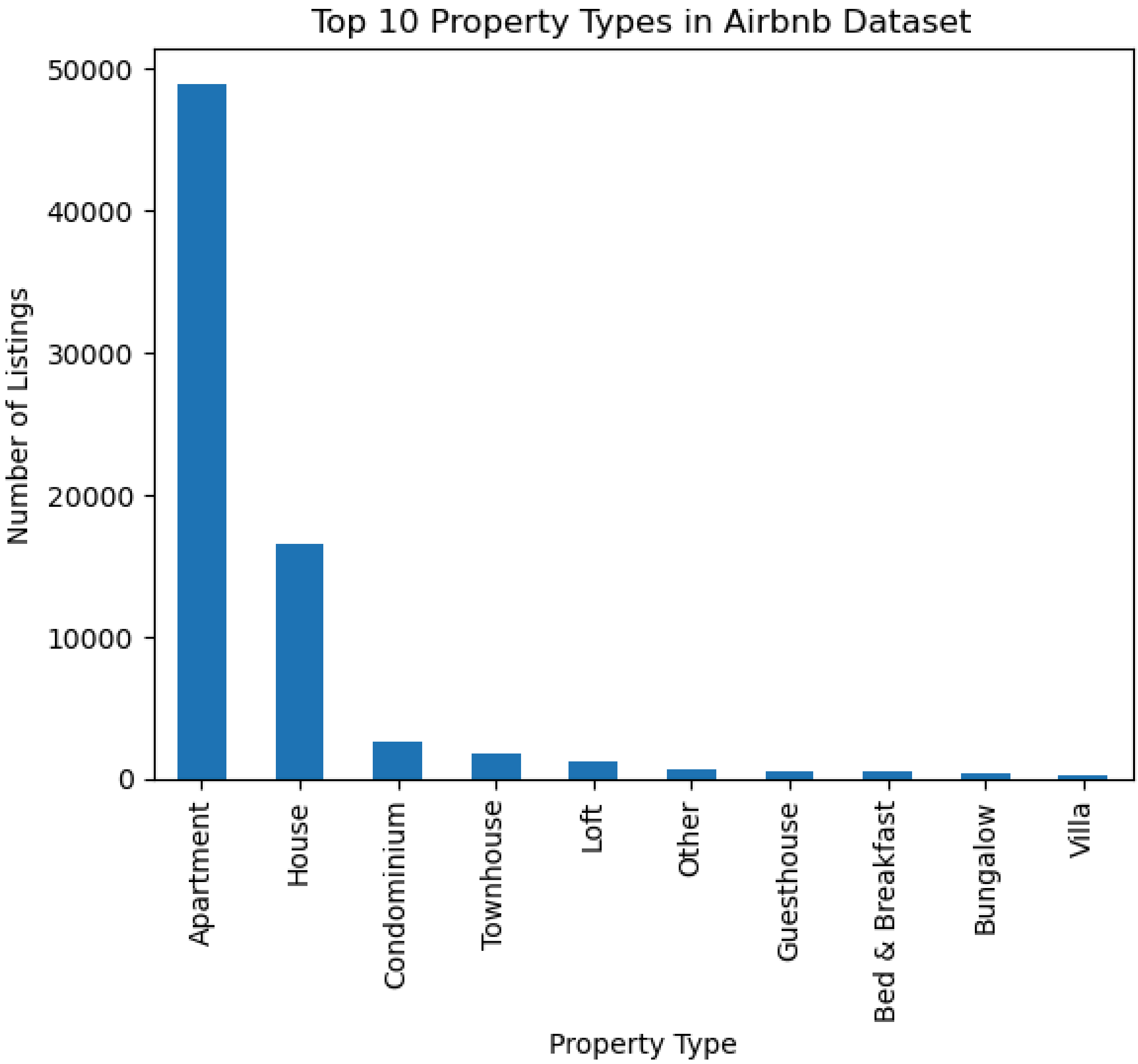
In [16]:
```
Airbnb_df['room_type'].value_counts().plot(kind='bar')
plt.title('Room Type Distribution in Airbnb Listings', fontsize=14)
plt.xlabel('Room Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.show()
```



In [17]:
```
Airbnb_df.groupby('room_type')['log_price'].mean().plot(kind='bar')
plt.xlabel("Room Type")
plt.ylabel("Average Log Price")
plt.title("Average Log Price by Room Type")
plt.show()
```



In [18]:
```
Airbnb_df['property_type'].value_counts().head(10).plot(kind='bar')
plt.xlabel("Property Type")
plt.ylabel("Number of Listings")
plt.title("Top 10 Property Types in Airbnb Dataset")
plt.show()
```



EDA Summary

- Neighbourhood, room type, and property type charts provided strong categorical insights.
- Average log price plots connected categories to the target variable.
- These visualizations are sufficient to proceed with ML modeling.
- Optional additions: numeric distributions, correlation heatmap, missing value analysis.

Model Development

- Build a regression model to predict listing prices.

In [19]:
```
# 1. Define features and target

X = Airbnb_df.drop(columns=['log_price','amenities'])
y = Airbnb_df['log_price']

# 2. Divided Numerial columns and Categorical Columns
categorical_cols = ['neighbourhood', 'room_type', 'property_type']
numeric_cols = [col for col in X.columns if X[col].dtype in ['int64', 'float64']
```

```
# 3. Preprocessor (encoding)

# Imputer for numeric columns
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

# Imputer + encoder for categorical columns
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])

# Updated preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_cols),
        ('cat', categorical_transformer, categorical_cols)
    ]
)

# 4. Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
```

In [20]:

```
# 5. Linear Regression (Baseline)
st_time=time.time()
linreg_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', LinearRegression())
])

# Train model and Predict
linreg_pipeline.fit(X_train, y_train)
y_pred_lin = linreg_pipeline.predict(X_test)

# Evaluate
linreg_rmse = np.sqrt(mean_squared_error(y_test, y_pred_lin))**0.5
linreg_r2 = r2_score(y_test, y_pred_lin)

# Print results
print("Linear Regeession Results:")
print(f"RMSE: {linreg_rmse:4f}")
print(f"R2 Score: {linreg_r2:4f}")
print(f"Completed in :{time.time()-st_time} time")
```

```
Linear Regeession Results:
RMSE: 0.643762
R2 Score: 0.659445
Completed in :1.3778607845306396 time
```

In [21]:

```
# 6. Randome Forest Model

st_time=time.time()
rf_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('rf', RandomForestRegressor(
        n_estimators=80,
```

```
        max_depth=10,
        random_state=42,
        n_jobs=-1
    ))
])

# Train model and Predict
rf_pipeline.fit(X_train, y_train)
rf_preds = rf_pipeline.predict(X_test)

# Evaluation
rf_rmse = np.sqrt(mean_squared_error(y_test, rf_preds))
rf_r2 = r2_score(y_test, rf_preds)

# Print results
print("Random Forest Results:")
print(f"RMSE: {rf_rmse:.4f}")
print(f"R2: {rf_r2:.4f}")
print(f"Completed in :{time.time()-st_time} time")
```

```
Random Forest Results:
RMSE: 0.4099
R2: 0.6669
Completed in :28.72039008140564 time
```

In [22]:

```
# 6. XGBoost Model

st_time=time.time()

xgb_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', xgb.XGBRegressor(
        n_estimators=200,
        learning_rate=0.1,
        max_depth=6,
        random_state=42
    ))
])

# Train model and Prediction
xgb_pipeline.fit(X_train, y_train)
y_pred_xgb = xgb_pipeline.predict(X_test)

# Evaluation
xgb_rmse = np.sqrt(mean_squared_error(y_test, y_pred_xgb))
xgb_r2 = r2_score(y_test, y_pred_xgb)

# Print results
print("XgBoost Results:")
print(f"RMSE: {xgb_rmse:.4f}")
print(f"R2: {xgb_r2:.4f}")
print(f"Completed in :{time.time()-st_time} time")
```

```
XgBoost Results:
RMSE: 0.3908
R2: 0.6972
Completed in :1.1035537719726562 time
```

In [23]:

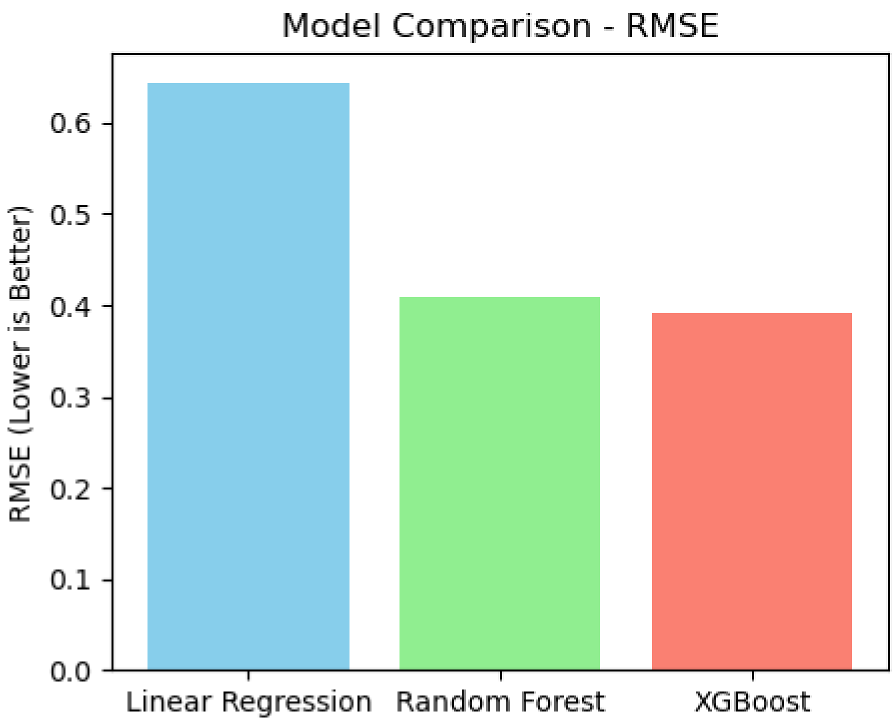
```
# 7. Compare Results

results = pd.DataFrame({
```

```
    'Model': ['Linear Regression', 'Random Forest', 'XGBoost'],
    'RMSE': [linreg_rmse, rf_rmse, xgb_rmse],
    'R2 Score': [linreg_r2, rf_r2, xgb_r2]
})
```

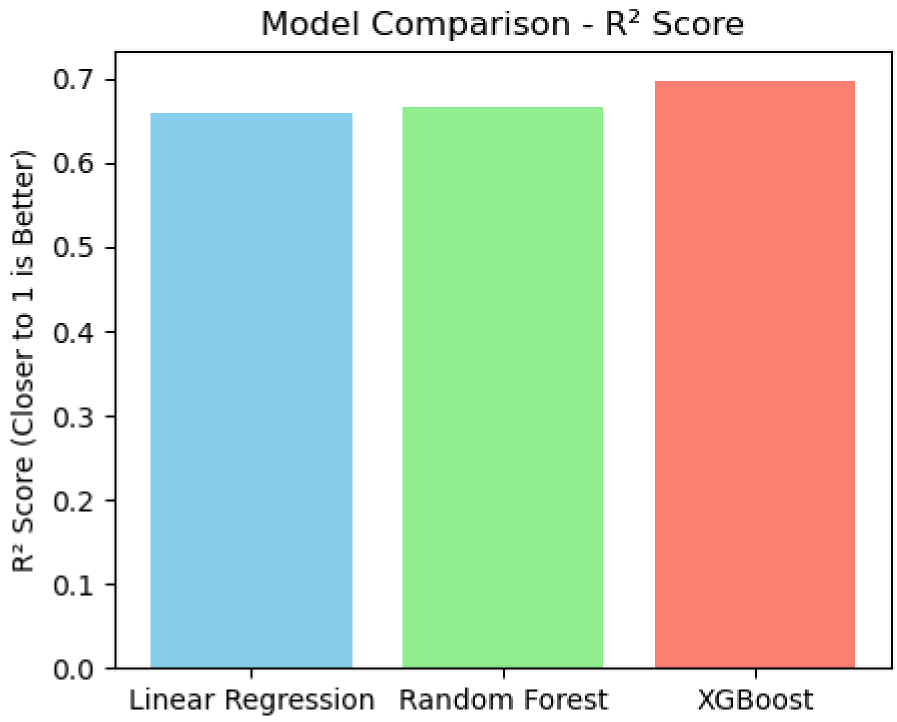
In [24]:
```
# display Returls Table
display(results.style.background_gradient(cmap='Blues'))
```

	Model	RMSE	R2 Score
0	Linear Regression	0.643762	0.659445
1	Random Forest	0.409892	0.666861
2	XGBoost	0.390778	0.697205

In [25]:
```
# Plot RMSE comparison of all Model
plt.figure(figsize=(5,4))
plt.bar(results['Model'], results['RMSE'], color=['skyblue','lightgreen','salmon
plt.title("Model Comparison - RMSE")
plt.ylabel("RMSE (Lower is Better)")
plt.show()
```



In [26]:
```
# Plot R2 Score comparison of all Models
plt.figure(figsize=(5,4))
plt.bar(results['Model'], results['R2 Score'], color=['skyblue','lightgreen','sa
plt.title("Model Comparison - R² Score")
plt.ylabel("R² Score (Closer to 1 is Better)")
plt.show()
```



Model Comparison Summary

We evaluated three regression models on Airbnb price prediction using RMSE and R^2 score:

Key Insights

- **XGBoost performed best**, with the **lowest RMSE (0.394)** and **highest R^2 score (0.697)** — indicating strong predictive accuracy and generalization.
- **Random Forest was solid**, with RMSE of **0.412** and R^2 of **0.669**, making it a reliable choice for structured data.
- **Linear Regression underperformed**, with RMSE of **0.651** and R^2 of **0.650**, suggesting it couldn't capture nonlinear patterns in the data.
- The **~40% RMSE reduction from Linear Regression to XGBoost** shows the value of using ensemble methods for real-world datasets.
- **Tree-based models (RF, XGBoost)** handled mixed feature types and interactions better than linear models.
- **XGBoost is deployment-ready**, offering a strong balance of speed, accuracy, and robustness.

Conclusion

XGBoost is the recommended model for production use, while Random Forest offers a strong alternative. Linear Regression serves as a baseline but lacks the complexity needed for high accuracy in this task.

Submitted by : **Vandana Bhavsar**