In [4]:
```
#!pip install xgboost
```

In [5]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge
from sklearn.linear_model import ElasticNet
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, r2_score

import warnings
warnings.filterwarnings('ignore')
```

In [6]:
```
df = pd.read_csv(r'/content/Airbnb_data - airbnb_data.csv')
```

In [7]:
```
df.head(5)
```

Out[7]:

	id	log_price	property_type	room_type	amenities	accommodates
0	6901257	5.010635	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	3
1	6304928	5.129899	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	7
2	7919400	4.976734	Apartment	Entire home/apt	{TV,"Cable TV","Wireless Internet","Air condit...	5
3	13418779	6.620073	House	Entire home/apt	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4
4	3808709	4.744932	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	2

5 rows × 29 columns

In [8]:
```
print(df.shape)
```

```
(74111, 29)
```

In [9]:
```
print(df.columns)
```

```
Index(['id', 'log_price', 'property_type', 'room_type', 'amenities',
       'accommodates', 'bathrooms', 'bed_type', 'cancellation_policy',
       'cleaning_fee', 'city', 'description', 'first_review',
       'host_has_profile_pic', 'host_identity_verified', 'host_response_rate',
       'host_since', 'instant_bookable', 'last_review', 'latitude',
       'longitude', 'name', 'neighbourhood', 'number_of_reviews',
       'review_scores_rating', 'thumbnail_url', 'zipcode', 'bedrooms', 'beds'],
      dtype='object')
```

In [10]:
```python
df.info()
```

```
<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             74111 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  object 
 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                    74111 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(7), int64(3), object(18)
memory usage: 15.9+ MB
```

Dropping Irrelevant columns:-

```
1. id :- Unique indentifier( It is only for refrence purpose).
2. name :- Listing title written by the host (text,
inconsistent).
3. description:- Free text, requiring NLP to be useful
4. thumbnail_url :- image link, not being analyzed.
```

In [11]:
```python
df.drop(['id','name','description','thumbnail_url'], axis = 1, inplace = True)
```

In [12]:
```
print('After dropping columns')
print(df.shape)
```

```
After dropping columns
(74111, 25)
```

In [13]:
```
df.isnull().sum()
```

Out[13]:

	0
log_price	0
property_type	0
room_type	0
amenities	0
accommodates	0
bathrooms	200
bed_type	0
cancellation_policy	0
cleaning_fee	0
city	0
first_review	15864
host_has_profile_pic	188
host_identity_verified	188
host_response_rate	18299
host_since	188
instant_bookable	0
last_review	15827
latitude	0
longitude	0
neighbourhood	6872
number_of_reviews	0
review_scores_rating	16722
zipcode	968
bedrooms	91
beds	131

dtype: int64

Function Explanation:-

```
1. df.isnull().sum(): - Counts the total number of missing
values in each columns.
2. Percentage Calculation: - Divides the number of missing
values by the total rows to understand the severity.
3. pd.concat() : - Combines the missing values and percentage
into one clean tabe.
4. Renaming columns :- Adds descriptive columns name(Missing
values, % of Total Values).
5. Filtering:- Removes columns that have no missing value, keeps
only those having null values.
6. Sorting & Rounding : - Makes the table easier to read by
ordering from most to least missing values.
```

In [14]:
```
def missing_values_table(df):
        mis_val = df.isnull().sum()
        missing_val_percent = 100 * df.isnull().sum() / len(df)
        mis_val_table = pd.concat([mis_val, missing_val_percent], axis = 1)
        mis_val_table = mis_val_table.rename(columns = {0 : 'Missing Values', 1

        mis_val_table = mis_val_table[mis_val_table['Missing Values'] > 0]
        mis_val_table = mis_val_table.sort_values('% of Total Values', ascending
        return mis_val_table
```

In [15]:
```
missing_values_table(df)
```

Out[15]:

	Missing Values	% of Total Values
host_response_rate	18299	24.69
review_scores_rating	16722	22.56
first_review	15864	21.41
last_review	15827	21.36
neighbourhood	6872	9.27
zipcode	968	1.31
bathrooms	200	0.27
host_has_profile_pic	188	0.25
host_identity_verified	188	0.25
host_since	188	0.25
beds	131	0.18
bedrooms	91	0.12

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Data columns (total 25 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   log_price               74111 non-null  float64
 1   property_type           74111 non-null  object 
 2   room_type               74111 non-null  object 
 3   amenities               74111 non-null  object 
 4   accommodates            74111 non-null  int64  
 5   bathrooms               73911 non-null  float64
 6   bed_type                74111 non-null  object 
 7   cancellation_policy     74111 non-null  object 
 8   cleaning_fee            74111 non-null  bool   
 9   city                    74111 non-null  object 
 10  first_review            58247 non-null  object 
 11  host_has_profile_pic    73923 non-null  object 
 12  host_identity_verified  73923 non-null  object 
 13  host_response_rate      55812 non-null  object 
 14  host_since              73923 non-null  object 
 15  instant_bookable        74111 non-null  object 
 16  last_review             58284 non-null  object 
 17  latitude                74111 non-null  float64
 18  longitude               74111 non-null  float64
 19  neighbourhood           67239 non-null  object 
 20  number_of_reviews       74111 non-null  int64  
 21  review_scores_rating    57389 non-null  float64
 22  zipcode                 73143 non-null  object 
 23  bedrooms                74020 non-null  float64
 24  beds                    73980 non-null  float64
dtypes: bool(1), float64(7), int64(2), object(15)
memory usage: 13.6+ MB
```

In [17]:
```
df.host_response_rate.unique()
```

Out[17]:
```
array([nan, '100%', '71%', '68%', '67%', '83%', '50%', '90%', '86%',
       '92%', '82%', '80%', '89%', '93%', '99%', '0%', '88%', '96%',
       '70%', '94%', '91%', '25%', '95%', '98%', '62%', '29%', '33%',
       '81%', '63%', '38%', '60%', '79%', '78%', '75%', '65%', '97%',
       '87%', '40%', '54%', '53%', '58%', '76%', '30%', '64%', '17%',
       '20%', '77%', '73%', '41%', '59%', '57%', '85%', '56%', '42%',
       '44%', '35%', '14%', '74%', '27%', '10%', '84%', '6%', '72%',
       '36%', '55%', '43%', '13%', '39%', '46%', '26%', '61%', '52%',
       '23%', '22%', '69%', '66%', '15%', '11%', '31%', '21%', '47%'],
      dtype=object)
```

In [18]:
```
df.host_response_rate = df.host_response_rate.str.replace('%', '', regex = True)
```

In [19]:
```
df.host_response_rate = df.host_response_rate.astype(float)
```

In [20]:
```
def detect_outliers(df):
    outlier_summary = {}
    numeric_columns = df.select_dtypes(include = [np.number]).columns

    for column in numeric_columns:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)

        IQR = Q3 - Q1
```

```
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        outliers = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
        outliers_percentage = round((len(outliers) / len(df)) * 100, 2)

        outlier_count = len(outliers)

        outlier_summary[column] = {
            "Total Values": len(df),
            "Outliers": len(outliers),
            "Outlier %": outliers_percentage
        }

    return pd.DataFrame(outlier_summary).T.sort_values(by="Outlier %", ascending
```

In [21]:
```
detect_outliers(df)
```

Out[21]:

	Total Values	Outliers	Outlier %
bedrooms	74111.0	24236.0	32.70
bathrooms	74111.0	15812.0	21.34
host_response_rate	74111.0	12558.0	16.94
number_of_reviews	74111.0	8203.0	11.07
beds	74111.0	5686.0	7.67
accommodates	74111.0	3604.0	4.86
review_scores_rating	74111.0	1719.0	2.32
log_price	74111.0	1532.0	2.07
longitude	74111.0	0.0	0.00
latitude	74111.0	0.0	0.00

High outliers:- Bedrooms and bathrooms have unusually high number of outliers.

Moderate outliers: - Host_reponse_rate, review_scores_rating and log_price have 7 - 17% outliers. These may represent extreme but possible cases(Hosts with thousands of reviews or beds in shared spaces).

Low outliers:- Accomadates, review_score_rating, and log_price have 2 - 5% outliers.

No Outliers: - latitude and longitude have no statistical outliers(as expected, since they are bounded by geography).

1. Capping extreme values for numerical columns like bedrooms and bathrooms to avoid unrealistic entries.

```
2. Handling outliers in features such as number_of_reviews,
beds, and host_response_rate using the 99th percentile, which
limits only the top 1% extreme values without affecting most of
the data.
3. Applying lower and upper limits on columns like log_price,
accommodates, and review_scores_rating using the interquartile
range (IQR) to reduce the impact of extreme low and high values.
```

In [22]:
```
def handle_outliers(df):
    df['bedrooms'] = np.where(df['bedrooms'] > 10, 10, df['bedrooms'])
    df['bathrooms'] = np.where(df['bathrooms'] > 8, 8, df['bathrooms'])

    for col in ['number_of_reviews', 'beds', 'host_response_rate']:
        upper_limit = df[col].quantile(0.99)
        df[col] = np.where(df[col] > upper_limit, upper_limit, df[col])

    for col in ['log_price', 'accommodates', 'review_scores_rating']:
        lower_limit = df[col].quantile(0.01)
        upper_limit = df[col].quantile(0.99)
        df[col] = np.where(df[col] < lower_limit, lower_limit, df[col])
        df[col] = np.where(df[col] > upper_limit, upper_limit, df[col])

    return df
```

Used the 99th percentile to handle extreme highs, but leave the lows if they are valid. In contrast, in the second loop, you handle both upper and lower limits for columns where extreme low values are also problematic (like log_price or review_scores_rating).

In [23]:
```
df = handle_outliers(df)

outlier_report_after = detect_outliers(df)
print(outlier_report_after)
```

```
                      Total Values  Outliers  Outlier %
bedrooms                   74111.0   24236.0      32.70
bathrooms                  74111.0   15812.0      21.34
host_response_rate         74111.0   12558.0      16.94
number_of_reviews          74111.0    8203.0      11.07
beds                       74111.0    5686.0       7.67
accommodates               74111.0    3604.0       4.86
review_scores_rating       74111.0    1719.0       2.32
log_price                  74111.0    1372.0       1.85
longitude                  74111.0       0.0       0.00
latitude                   74111.0       0.0       0.00
```

In [24]:
```
df
```

Out[24]:

	log_price	property_type	room_type	amenities	accommodates	bat
0	5.010635	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	3.0	
1	5.129899	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	7.0	
2	4.976734	Apartment	Entire home/apt	{TV,"Cable TV","Wireless Internet","Air condit...	5.0	
3	6.620073	House	Entire home/apt	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4.0	
4	4.744932	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	2.0	
...	...	...	...	...	...	
74106	4.605170	Apartment	Private room	{}	1.0	
74107	5.043425	Apartment	Entire home/apt	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4.0	
74108	5.220356	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	5.0	
74109	5.273000	Apartment	Entire home/apt	{TV,"Wireless Internet","Air conditioning",Kit...	2.0	
74110	4.852030	Boat	Entire home/apt	{TV,Internet,"Wireless Internet",Kitchen,"Free...	4.0	

74111 rows × 25 columns

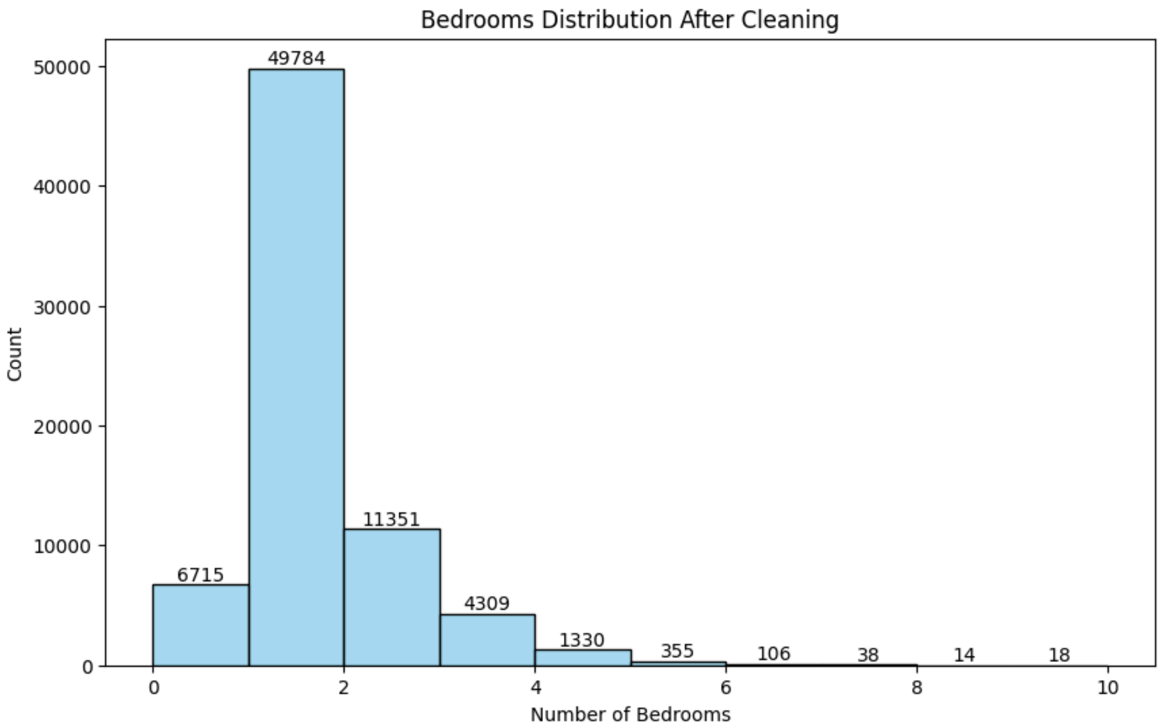
In [25]:
```
print("Bedrooms → Min:", df['bedrooms'].min(), "Max:", df['bedrooms'].max())
print("Bathrooms → Min:", df['bathrooms'].min(), "Max:", df['bathrooms'].max())
```

```
Bedrooms → Min: 0.0 Max: 10.0
Bathrooms → Min: 0.0 Max: 8.0
```

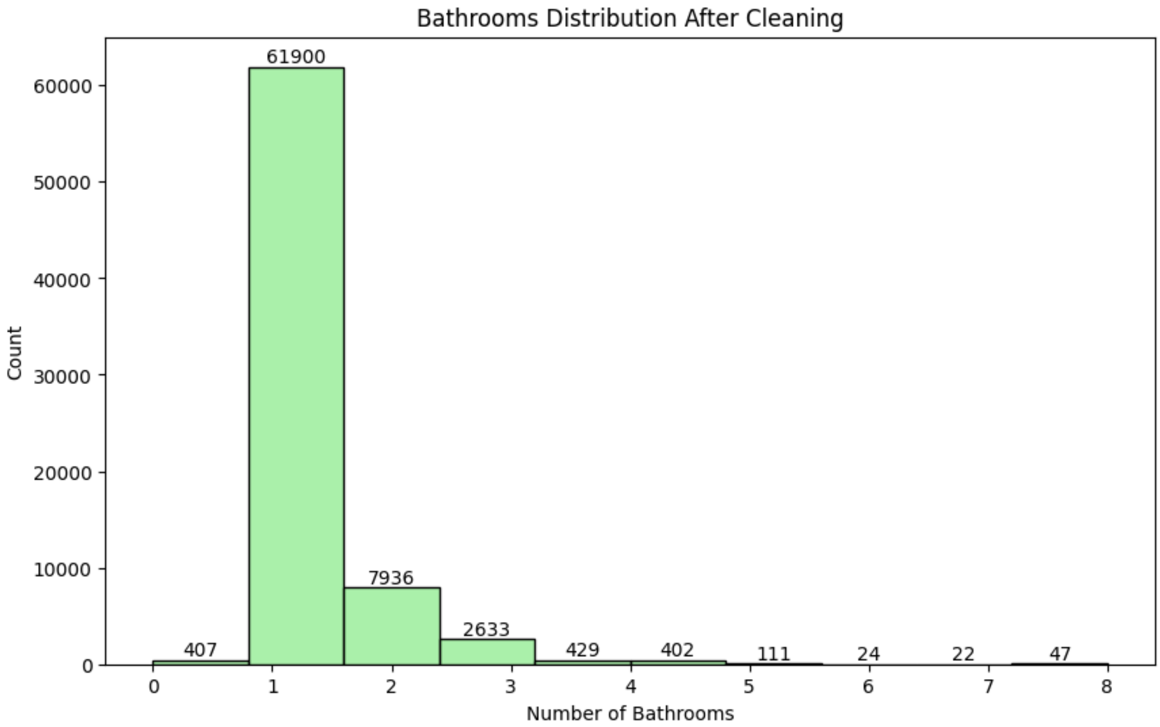
The distributions of bedrooms and bathrooms were visualized after cleaning using histograms. Count labels were added on each bar to clearly show the frequency of each value, helping identify the most common values and extreme cases

In [26]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
bed_plot = sns.histplot(df['bedrooms'].dropna(), bins=10, stat='count', color='s
plt.title("Bedrooms Distribution After Cleaning")
plt.xlabel("Number of Bedrooms")
plt.ylabel("Count")
```

```
for p in bed_plot.patches:
    bed_plot.annotate(int(p.get_height()), (p.get_x() + p.get_width()/2, p.get_h
                      ha='center', va='bottom', fontsize=10)

plt.show()
```



In [27]:
```
plt.figure(figsize=(10,6))
bath_plot = sns.histplot(df['bathrooms'].dropna(), bins=10, stat='count', color=
plt.title("Bathrooms Distribution After Cleaning")
plt.xlabel("Number of Bathrooms")
plt.ylabel("Count")

for p in bath_plot.patches:
    bath_plot.annotate(int(p.get_height()), (p.get_x() + p.get_width()/2, p.get_
                       ha='center', va='bottom', fontsize=10)

plt.show()
```



In [28]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Data columns (total 25 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   log_price               74111 non-null  float64
 1   property_type           74111 non-null  object 
 2   room_type               74111 non-null  object 
 3   amenities               74111 non-null  object 
 4   accommodates            74111 non-null  float64
 5   bathrooms               73911 non-null  float64
 6   bed_type                74111 non-null  object 
 7   cancellation_policy     74111 non-null  object 
 8   cleaning_fee            74111 non-null  bool   
 9   city                    74111 non-null  object 
 10  first_review            58247 non-null  object 
 11  host_has_profile_pic    73923 non-null  object 
 12  host_identity_verified  73923 non-null  object 
 13  host_response_rate      55812 non-null  float64
 14  host_since              73923 non-null  object 
 15  instant_bookable        74111 non-null  object 
 16  last_review             58284 non-null  object 
 17  latitude                74111 non-null  float64
 18  longitude               74111 non-null  float64
 19  neighbourhood           67239 non-null  object 
 20  number_of_reviews       74111 non-null  float64
 21  review_scores_rating    57389 non-null  float64
 22  zipcode                 73143 non-null  object 
 23  bedrooms                74020 non-null  float64
 24  beds                    73980 non-null  float64
dtypes: bool(1), float64(10), object(14)
memory usage: 13.6+ MB
```

I impute missing values in the dataset to ensure that our analysis and modeling are not affected by null entries. The

strategy depends on the type of data in each column:-

```
1. Numerical Columns:-
    (a). For columns with numerical values(like bedrooms,
bathrooms, review_scores_rating, host_response_rate), missing
values are replaced with the median.
    (b). The median is used because it is robust to outliers and
represents the central tendency of the data more accurately than
the mean, especially in skewed distributions.

2. Categorical columns:-
    (a). For columns with categorical values (like
neighbourhood, zipcode, host_identity_verified), missing values
are replaced with the 'Unknown'.
    (b). This explicitly marks missing entries, prevents bias,
and allows models to treat them as a separate category.
```

In [29]:
```
def impute_missing_values(df):

    for col in df.columns:
        if df[col].dtype in [np.float64, np.int64]:
            median_val = df[col].median()
            df[col].fillna(median_val, inplace=True)
        else:
            mode_val = df[col].mode()[0]
            df[col].fillna('Unknown', inplace=True)
    return df
```

In [30]:
```
df = impute_missing_values(df)
```

In [31]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Data columns (total 25 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   log_price               74111 non-null  float64
 1   property_type           74111 non-null  object 
 2   room_type               74111 non-null  object 
 3   amenities               74111 non-null  object 
 4   accommodates            74111 non-null  float64
 5   bathrooms               74111 non-null  float64
 6   bed_type                74111 non-null  object 
 7   cancellation_policy     74111 non-null  object 
 8   cleaning_fee            74111 non-null  bool   
 9   city                    74111 non-null  object 
 10  first_review            74111 non-null  object 
 11  host_has_profile_pic    74111 non-null  object 
 12  host_identity_verified  74111 non-null  object 
 13  host_response_rate      74111 non-null  float64
 14  host_since              74111 non-null  object 
 15  instant_bookable        74111 non-null  object 
 16  last_review             74111 non-null  object 
 17  latitude                74111 non-null  float64
 18  longitude               74111 non-null  float64
 19  neighbourhood           74111 non-null  object 
 20  number_of_reviews       74111 non-null  float64
 21  review_scores_rating    74111 non-null  float64
 22  zipcode                 74111 non-null  object 
 23  bedrooms                74111 non-null  float64
 24  beds                    74111 non-null  float64
dtypes: bool(1), float64(10), object(14)
memory usage: 13.6+ MB
```

Data Analysis

With the dataset fully cleaned and preprocessed, we now move to Data Analysis. This step is crucial to understand patterns, distributions, and relationships in the data. It helps to extract meaningful insights that can guide business decisions or predictive modeling.

We will perform the analysis in three main stages:

```
1. Univariate Analysis
2. Bivariate Analysis
3. Multivariate Analysis
```

1. Univariate Analysis

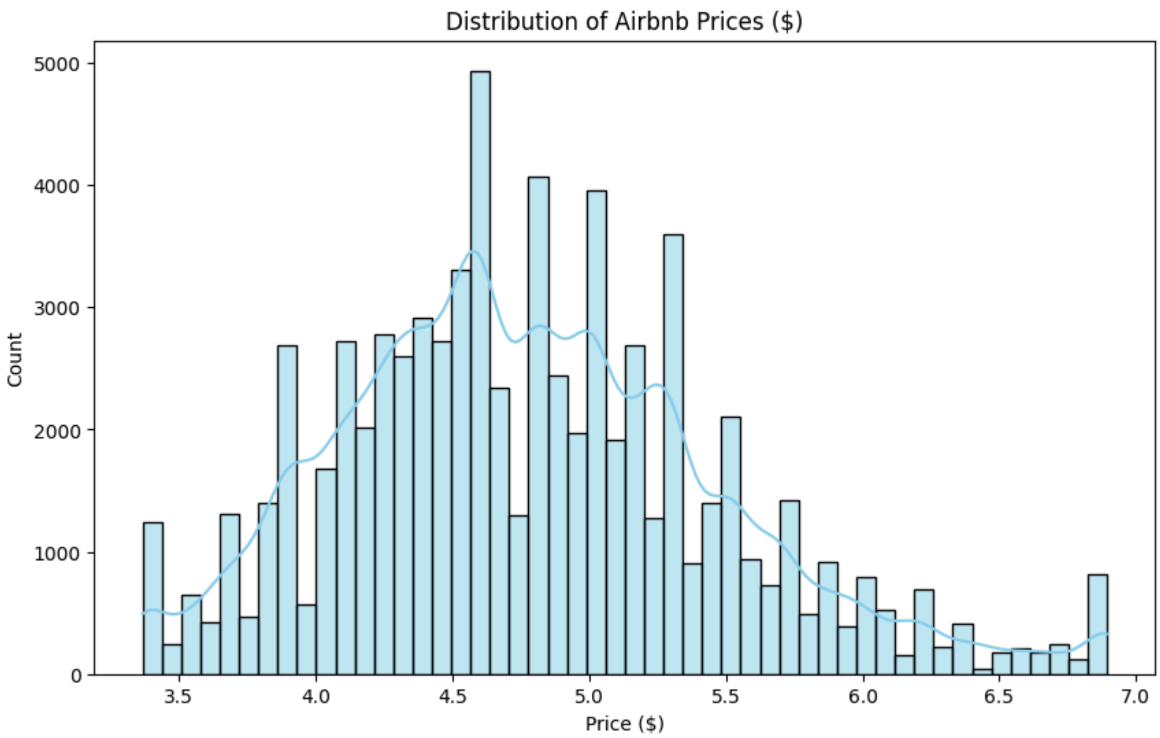
Why Univariate Analysis is Important:-

```
Provides basic understanding of each variable.

Helps to detect errors, skewness, and outliers.
```

Guides further analysis, feature engineering, and modeling decisions.

Gives insights into customer preferences (e.g., common room types, price ranges).

In [32]:
```
plt.figure(figsize=(10,6))
sns.histplot(df['log_price'], bins=50, color='skyblue', kde=True)
plt.title("Distribution of Airbnb Prices ($)")
plt.xlabel("Price ($)")
plt.ylabel("Count")
plt.show()

# Basic statistics
df['log_price'].describe()
```

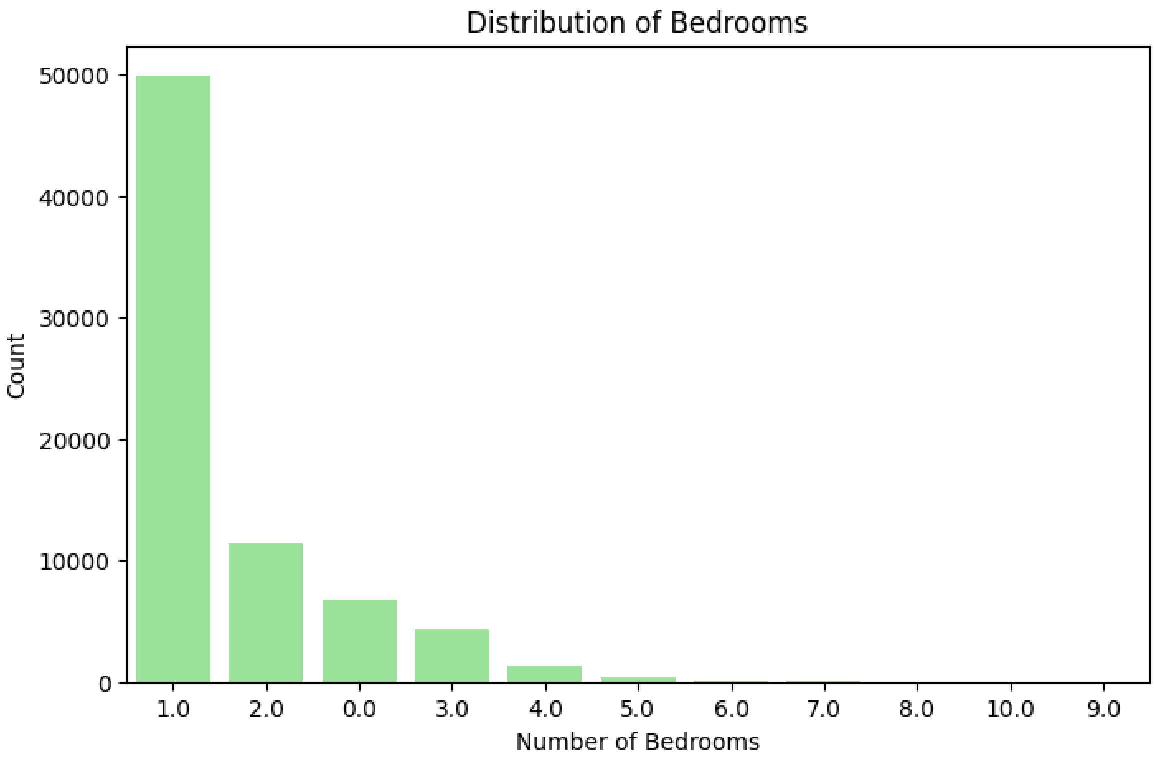


Out[32]:

	log_price
count	74111.000000
mean	4.782618
std	0.703489
min	3.367296
25%	4.317488
50%	4.709530
75%	5.220356
max	6.894467

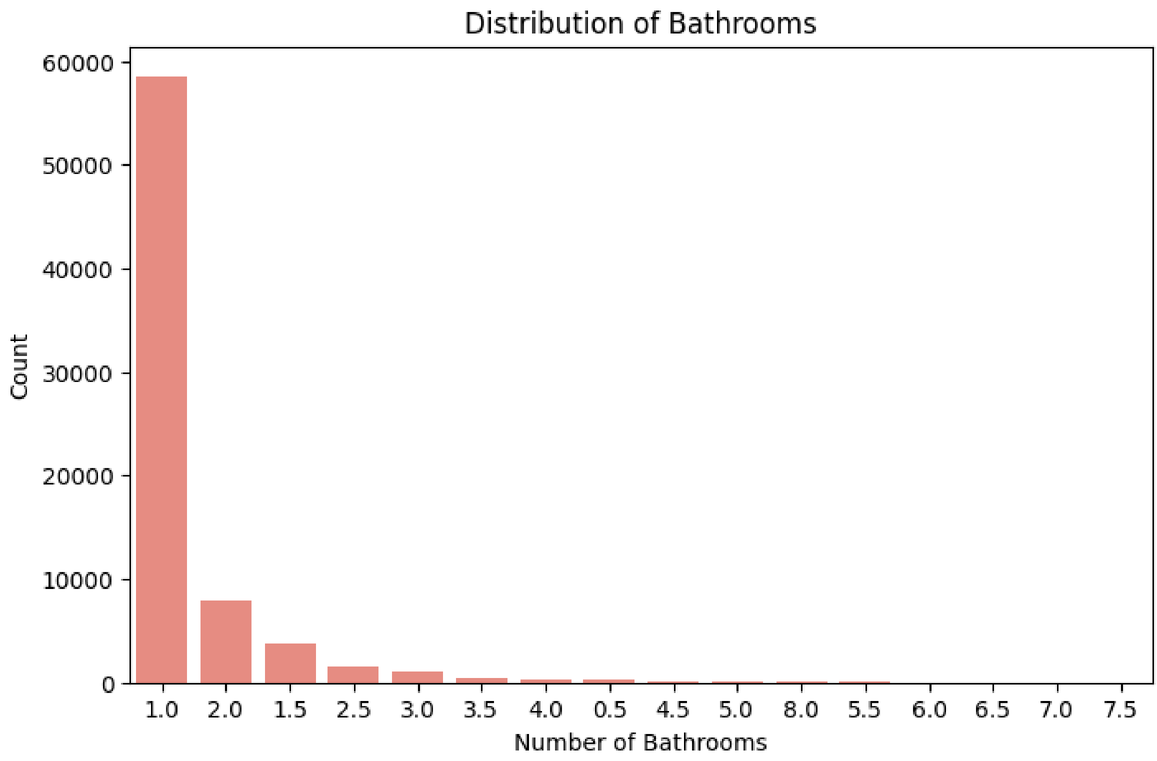
dtype: float64

In [33]:
```
# Bedrooms
plt.figure(figsize=(8,5))
sns.countplot(x='bedrooms', data=df, color='lightgreen', order=df['bedrooms'].va
plt.title("Distribution of Bedrooms")
plt.xlabel("Number of Bedrooms")
plt.ylabel("Count")
plt.show()
```

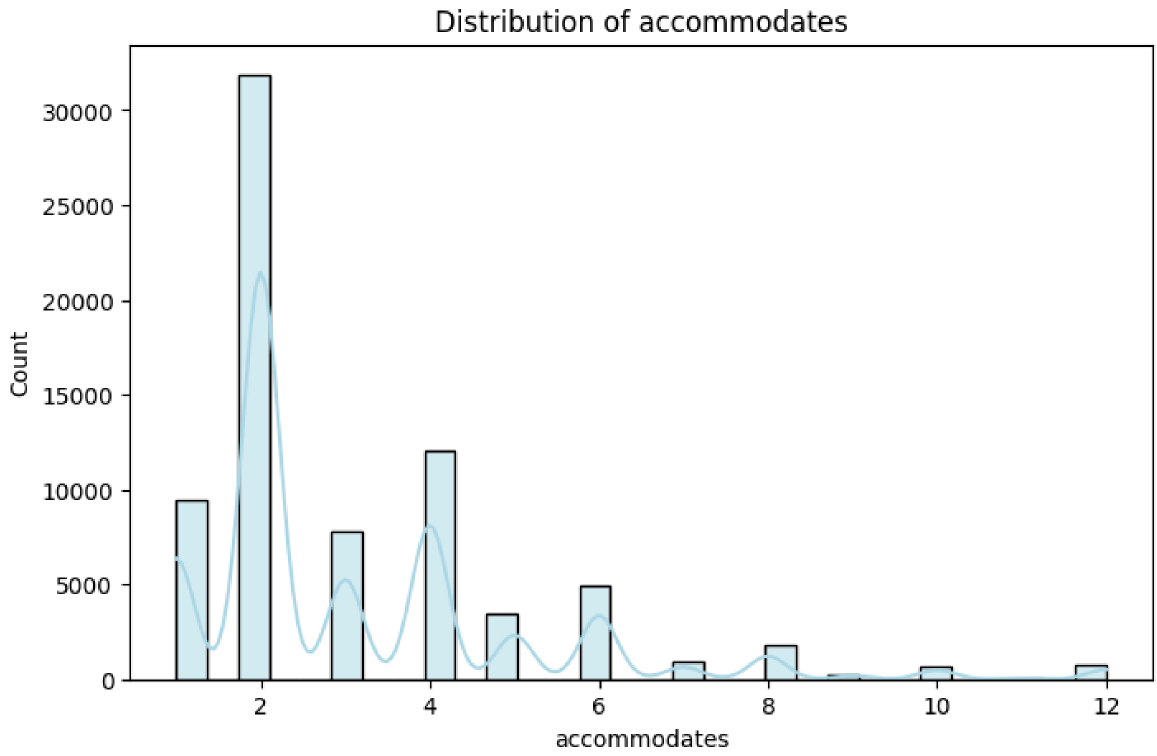


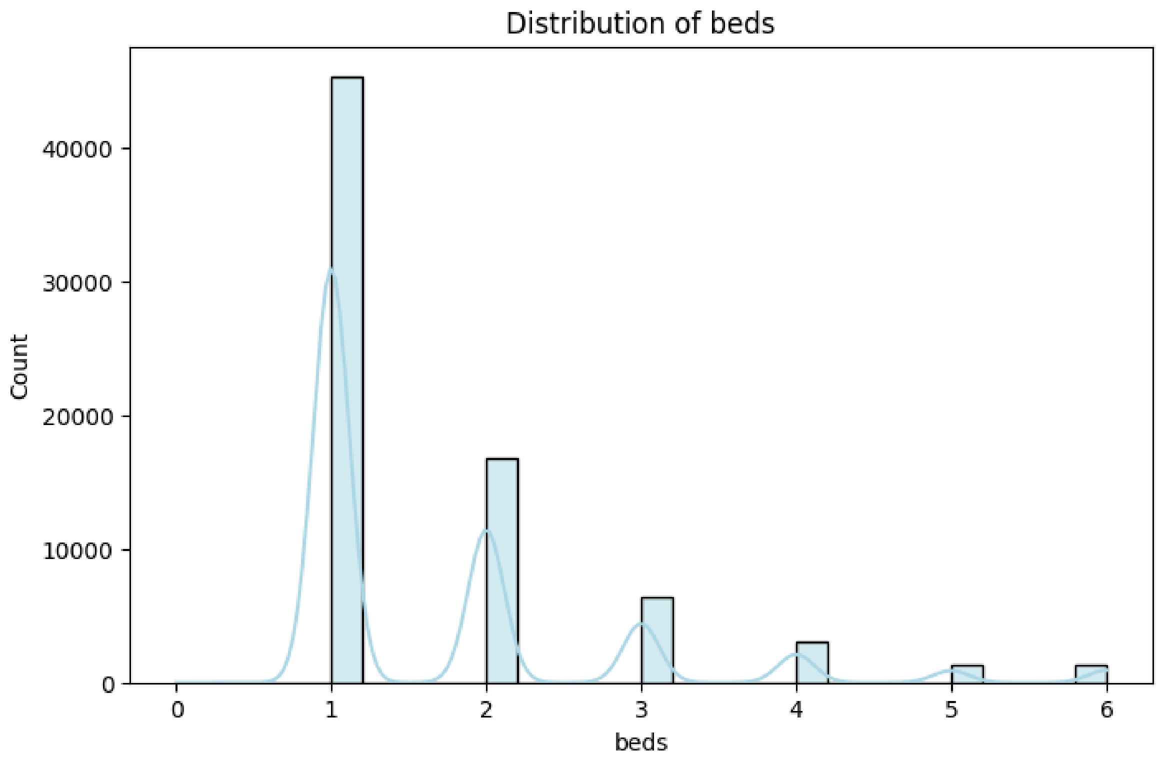
In [34]:
```
df['bathrooms'] = df['bathrooms'].replace(0, 1)
```

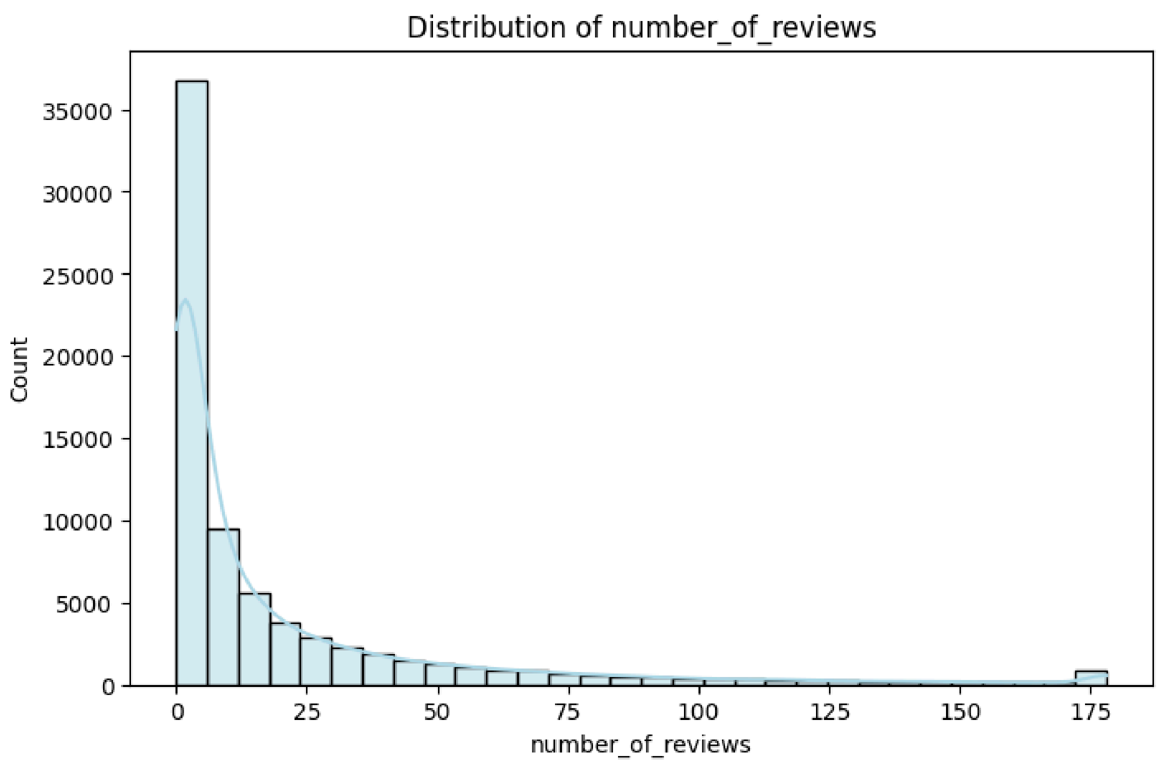
In [35]:
```
plt.figure(figsize=(8,5))
sns.countplot(x='bathrooms', data=df, color='salmon', order=df['bathrooms'].valu
plt.title("Distribution of Bathrooms")
plt.xlabel("Number of Bathrooms")
plt.ylabel("Count")
plt.show()
```

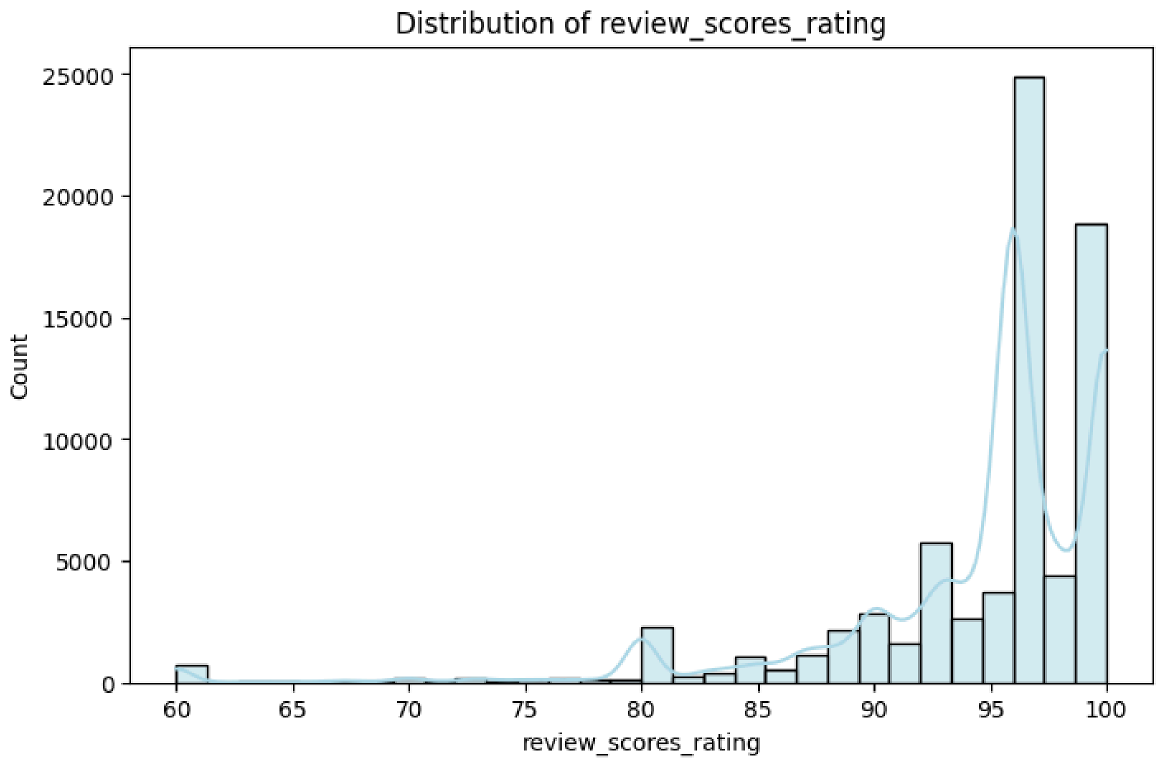


In [36]:
```
numerical_cols = ['accommodates', 'beds', 'number_of_reviews', 'review_scores_ra
for col in numerical_cols:
    plt.figure(figsize=(8,5))
    sns.histplot(df[col], bins=30, kde=True, color='lightblue')
    plt.title(f"Distribution of {col}")
    plt.xlabel(col)
    plt.ylabel("Count")
    plt.show()
```




Distribution of beds
Count
40000
30000
20000
10000
0
0
1
2
3
4
5
6
beds


Distribution of number_of_reviews
Count
35000
30000
25000
20000
15000
10000
5000
0
0
25
50
75
100
125
150
175
number_of_reviews

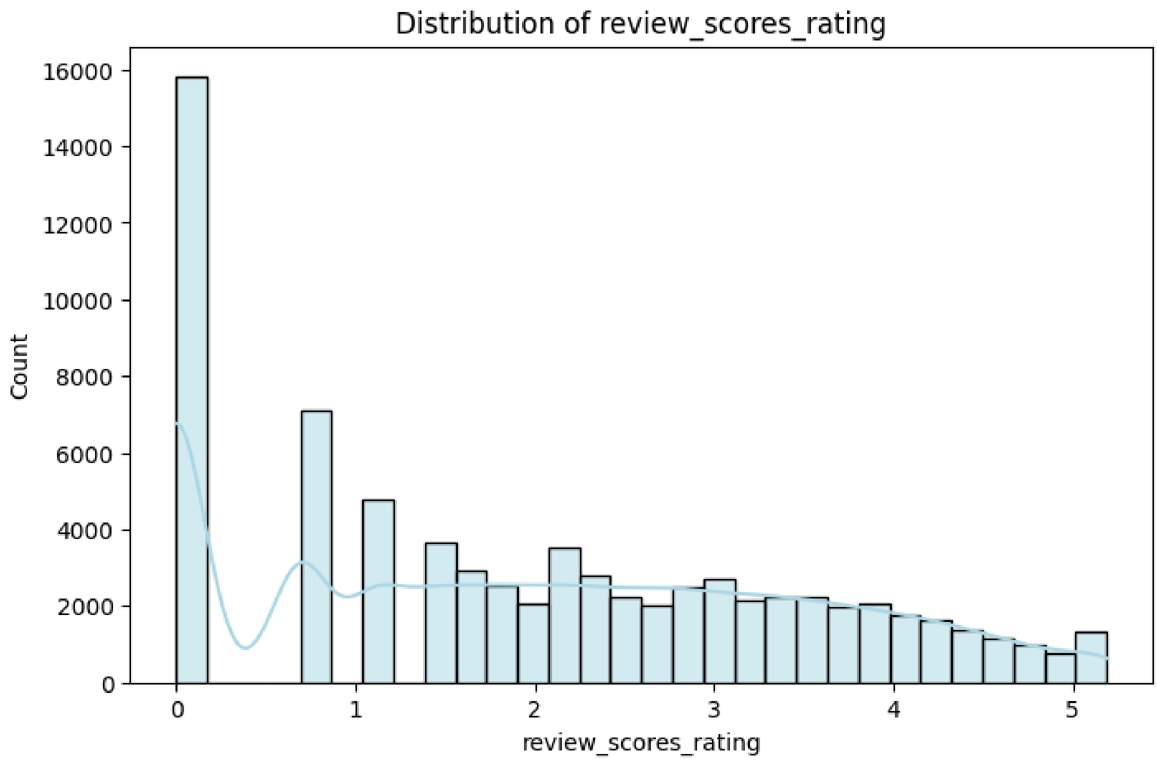


Before training our Linear Regression model to predict price, it's important to handle skewed features and the target variable. Skewed data can affect model performance and residuals.

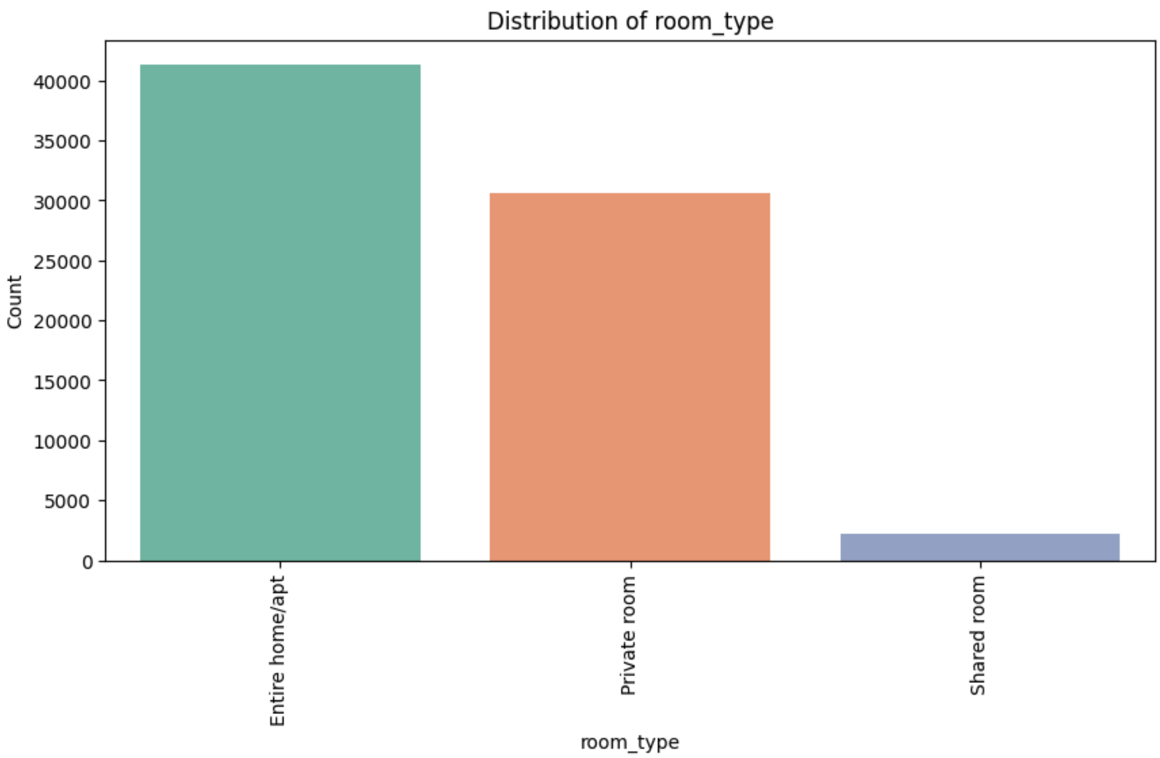
1. Number_of_reviews column is right-skewed, with most listings having few reviews and a few having hundreds.
2. Applied log transformation (np.log1p) to reduce the influence of extreme values.
3. This makes the relationship between number of reviews and price more linear, which is ideal for Linear Regression.

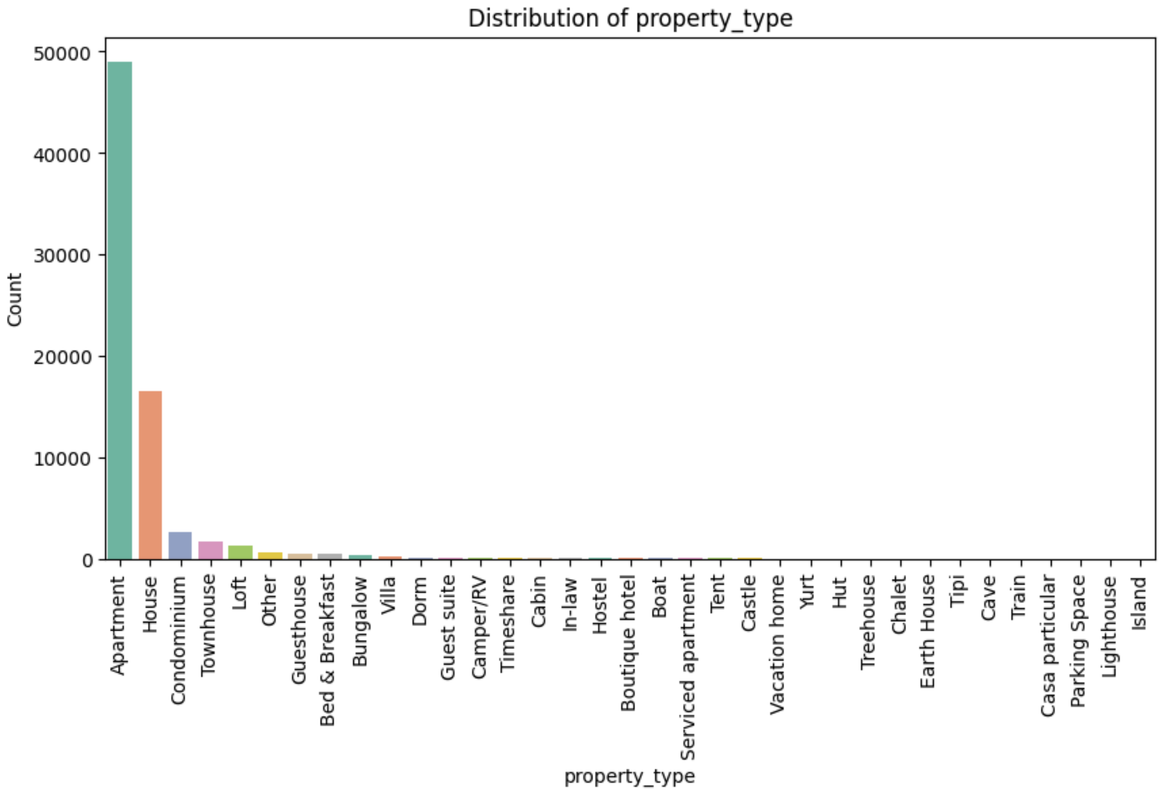
In [37]:
```
df['log_reviews'] = np.log1p(df['number_of_reviews'])
df.drop('number_of_reviews', axis =1 , inplace = True)
```

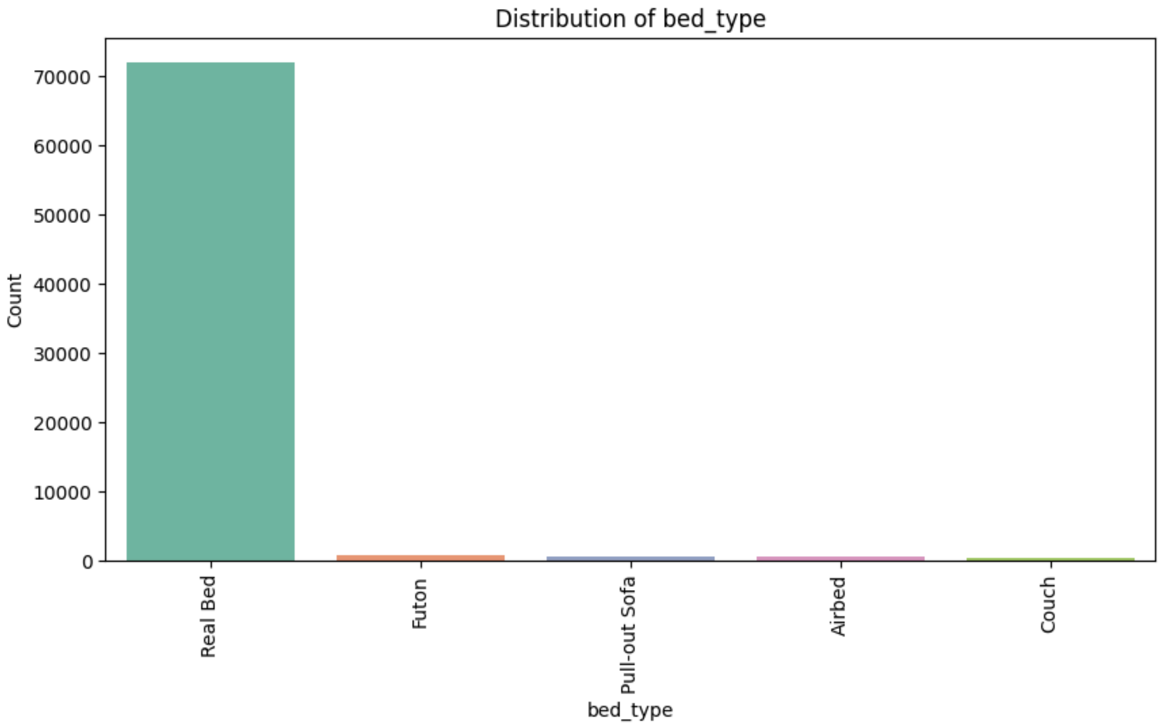
In [38]:
```
plt.figure(figsize=(8,5))
sns.histplot(df['log_reviews'], bins=30, kde=True, color='lightblue')
plt.title(f"Distribution of {col}")
plt.xlabel(col)
plt.ylabel("Count")
plt.show()
```

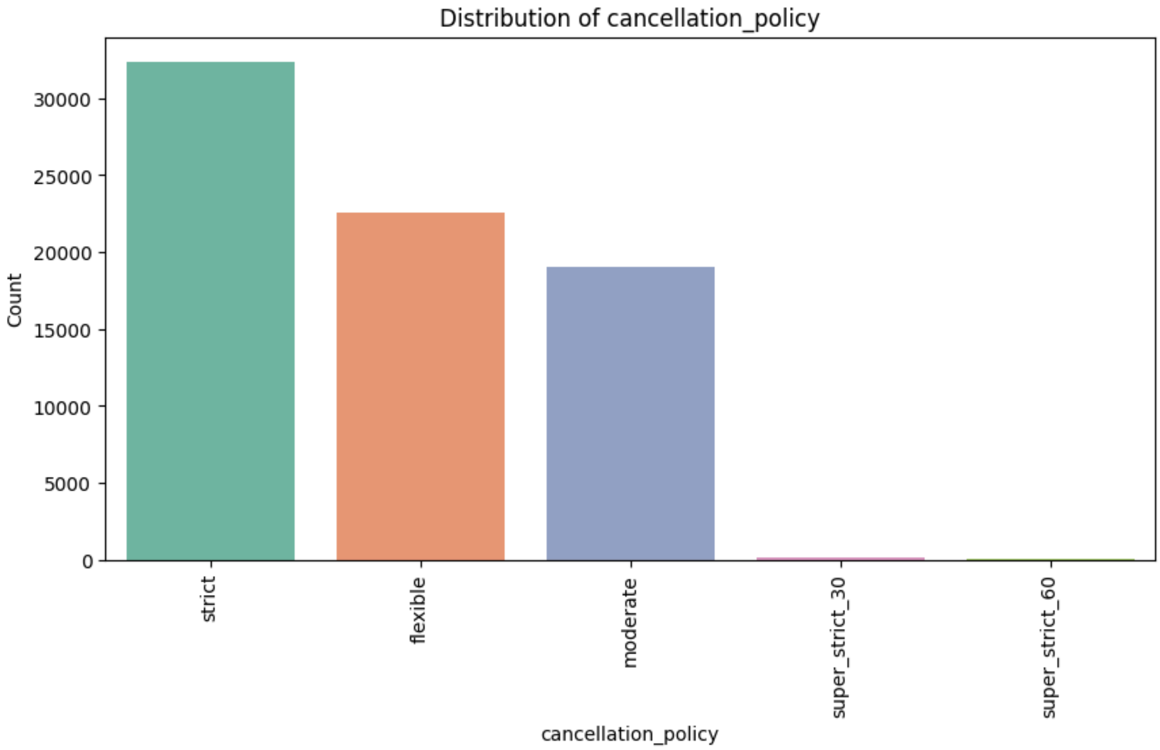


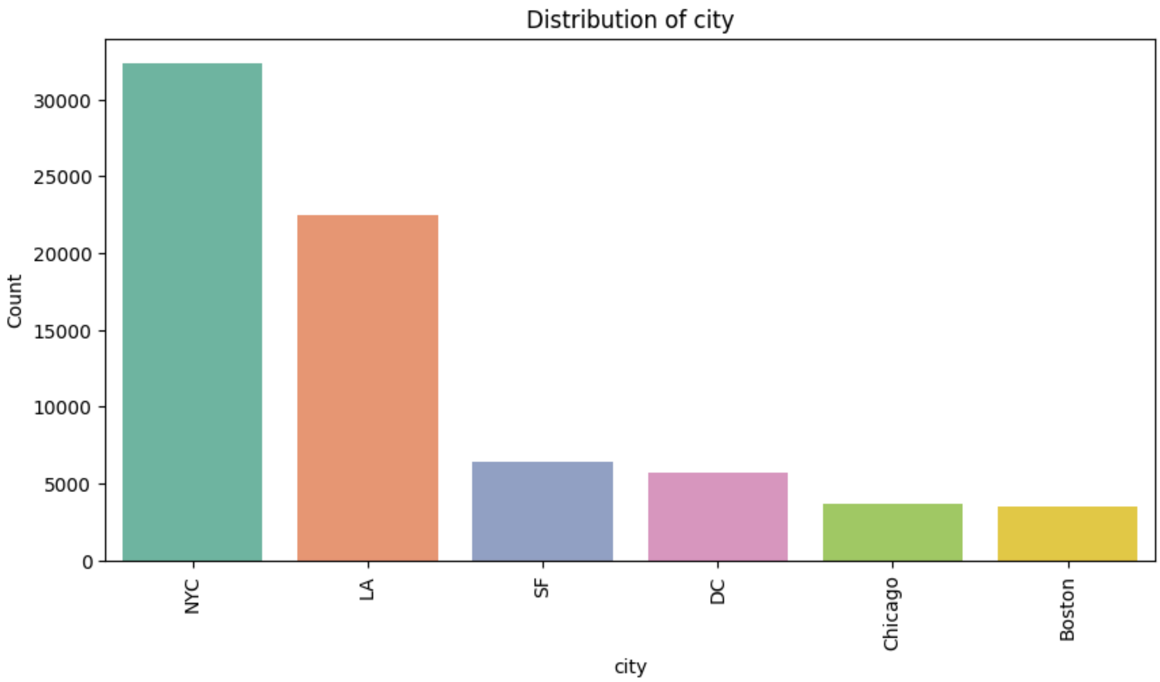
In [39]:
```
categorical_cols = ['room_type', 'property_type', 'bed_type', 'cancellation_poli
for col in categorical_cols:
    plt.figure(figsize=(10,5))
    sns.countplot(x=col, data=df, order=df[col].value_counts().index, palette='S
    plt.title(f"Distribution of {col}")
    plt.xlabel(col)
    plt.ylabel("Count")
    plt.xticks(rotation=90)
    plt.show()
```




Distribution of property_type
Count
50000
40000
30000
20000
10000
0
Apartment
House
Condominium
Townhouse
Loft
Other
Guesthouse
Bed & Breakfast
Bungalow
Villa
Dorm
Guest suite
Camper/RV
Timeshare
Cabin
In-law
Hostel
Boutique hotel
Boat
Serviced apartment
Tent
Castle
Vacation home
Yurt
Hut
Treehouse
Chalet
Earth House
Tipi
Cave
Train
Casa particular
Parking Space
Lighthouse
Island
property_type

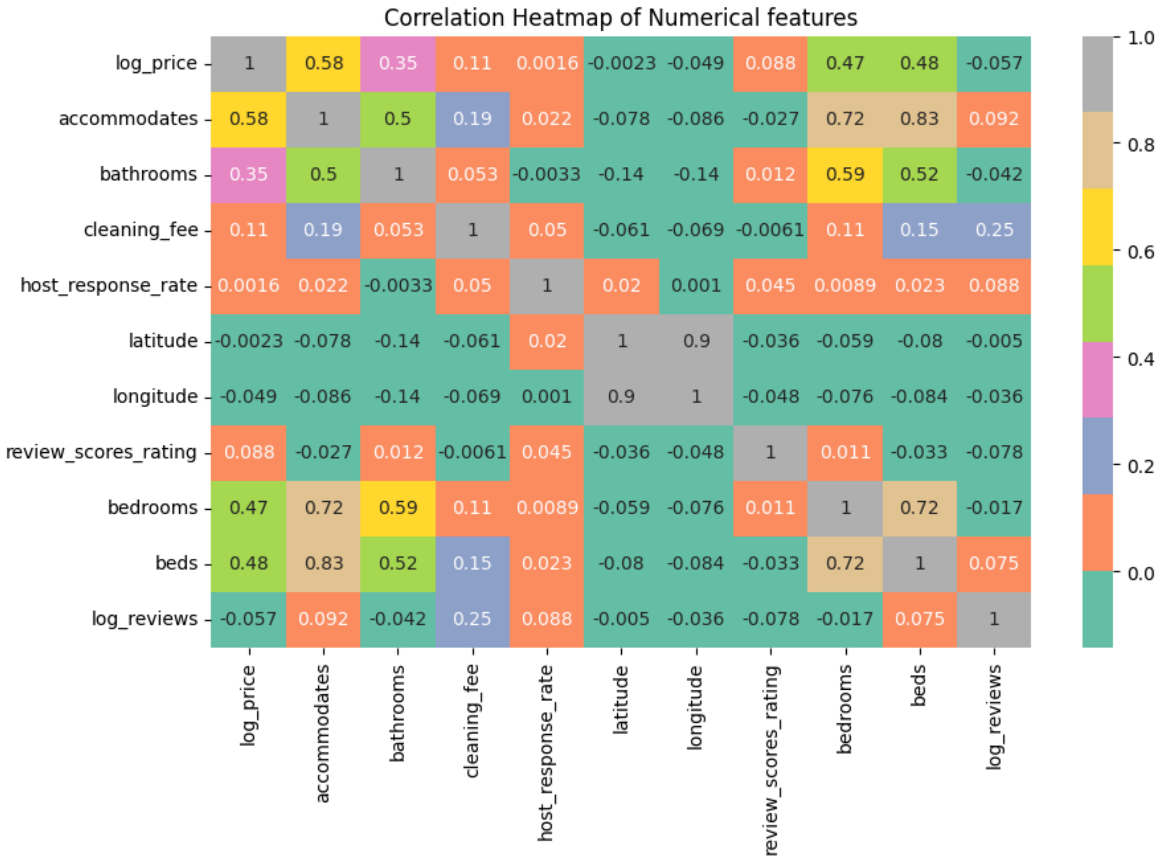

Distribution of bed_type
Count
70000
60000
50000
40000
30000
20000
10000
0
Real Bed
Futon
Pull-out Sofa
Airbed
Couch
bed_type





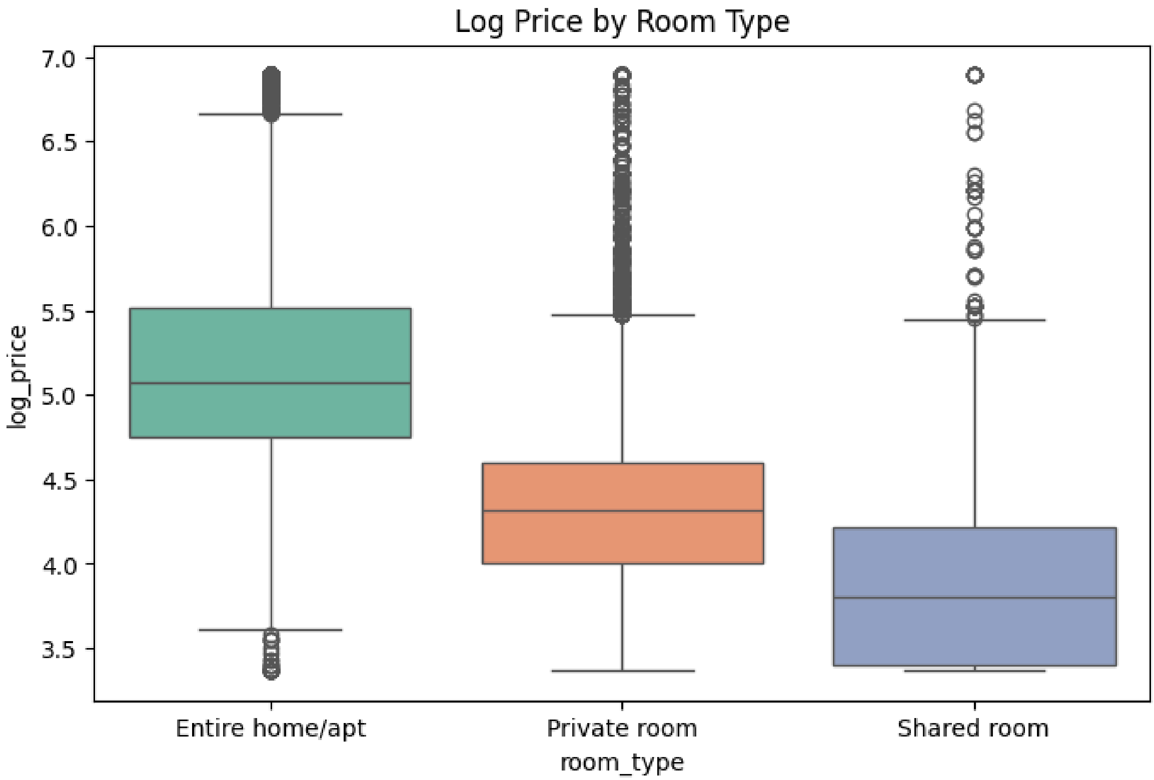
2. Bivariate Analysis

In [40]:
```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(numeric_only= True), annot = True, cmap = 'Set2')
plt.title("Correlation Heatmap of Numerical features")
plt.show()
```



Correlation heatmap shows moderate positive correlation of accommodates, bedrooms, and bathrooms with log_price. The correlation between review_scores_rating and price is weak, meaning ratings don’t strongly drive price.

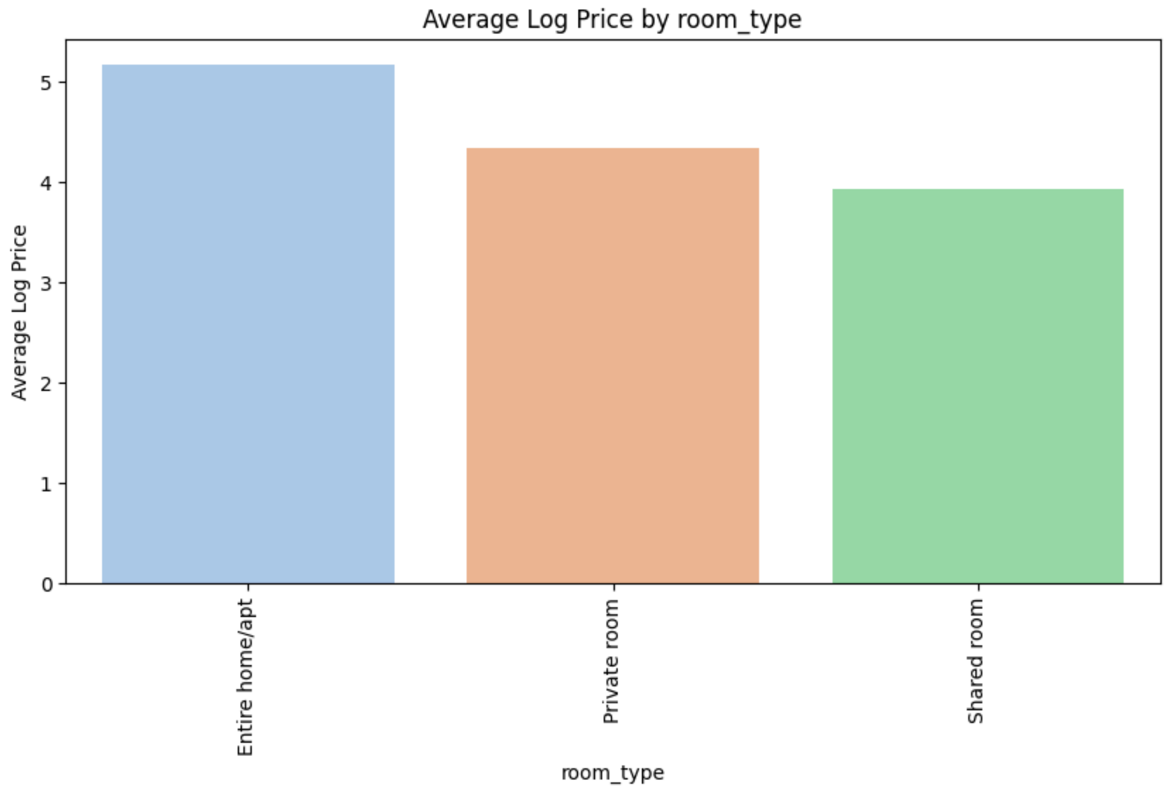
In [41]:
```
plt.figure(figsize=(8,5))
sns.boxplot(x='room_type', y='log_price', data=df, palette='Set2')
plt.title("Log Price by Room Type")
plt.show()
```

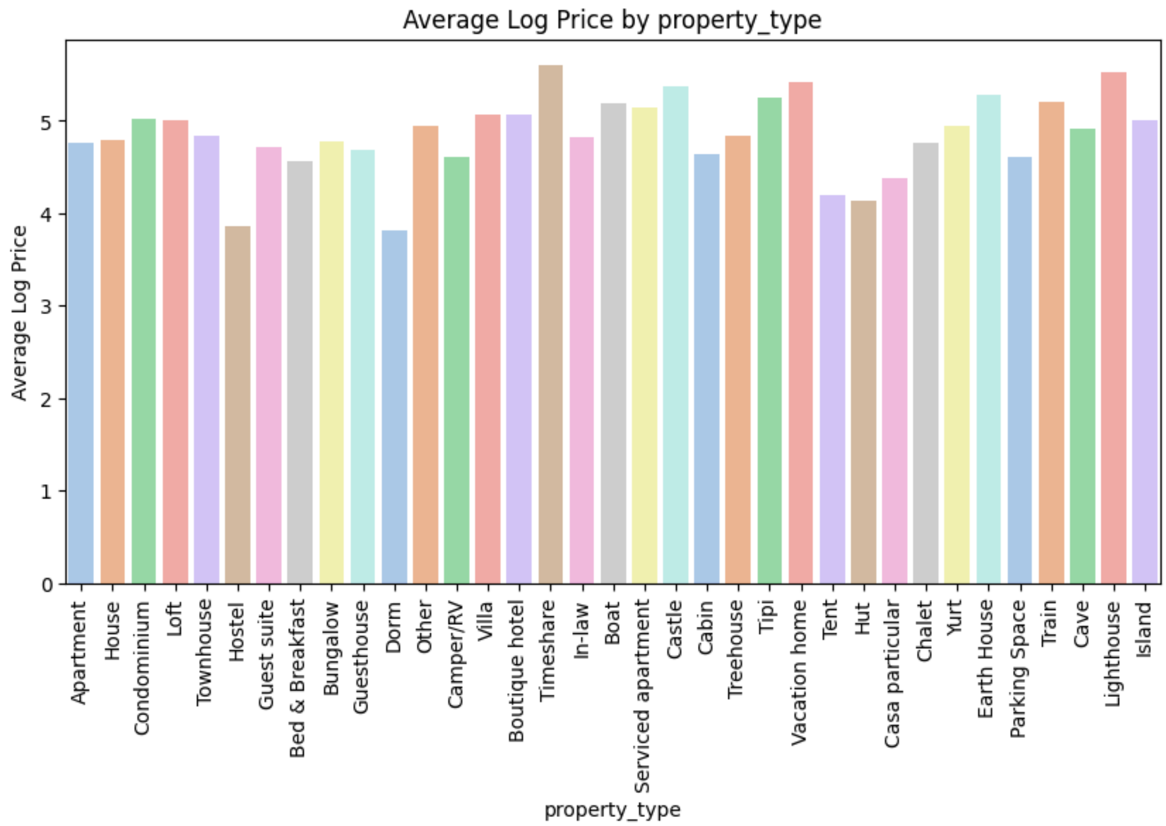


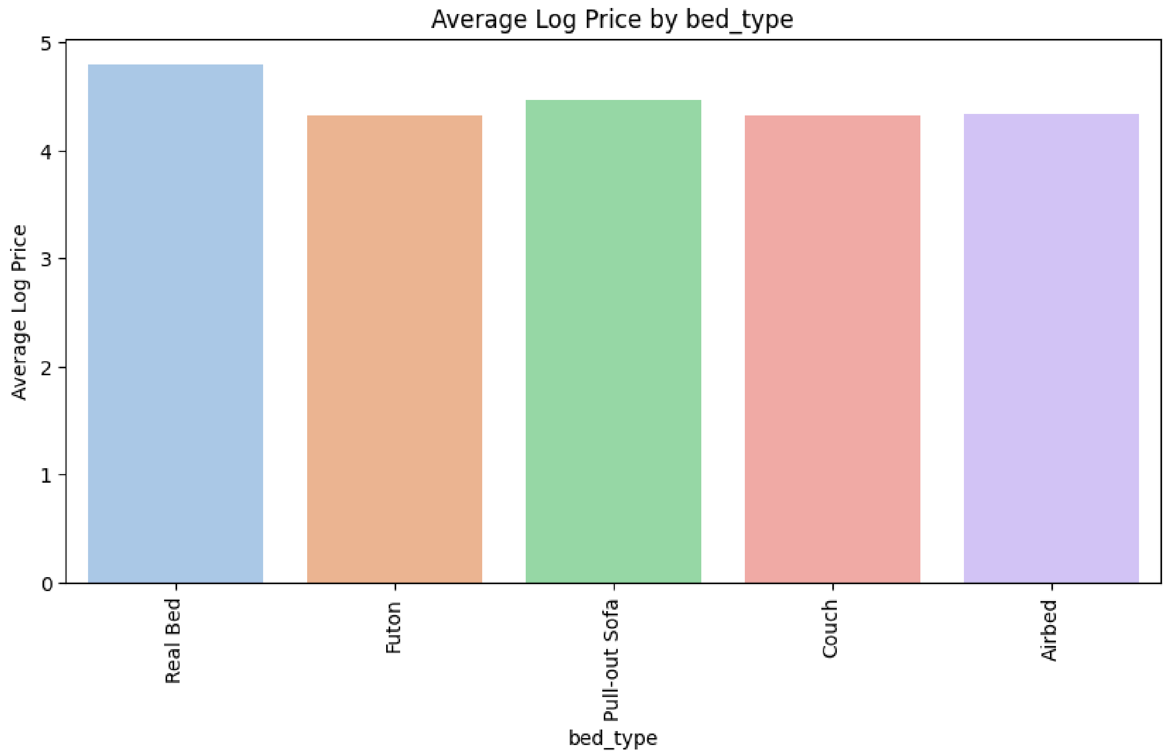
Log Price by Room Type:-

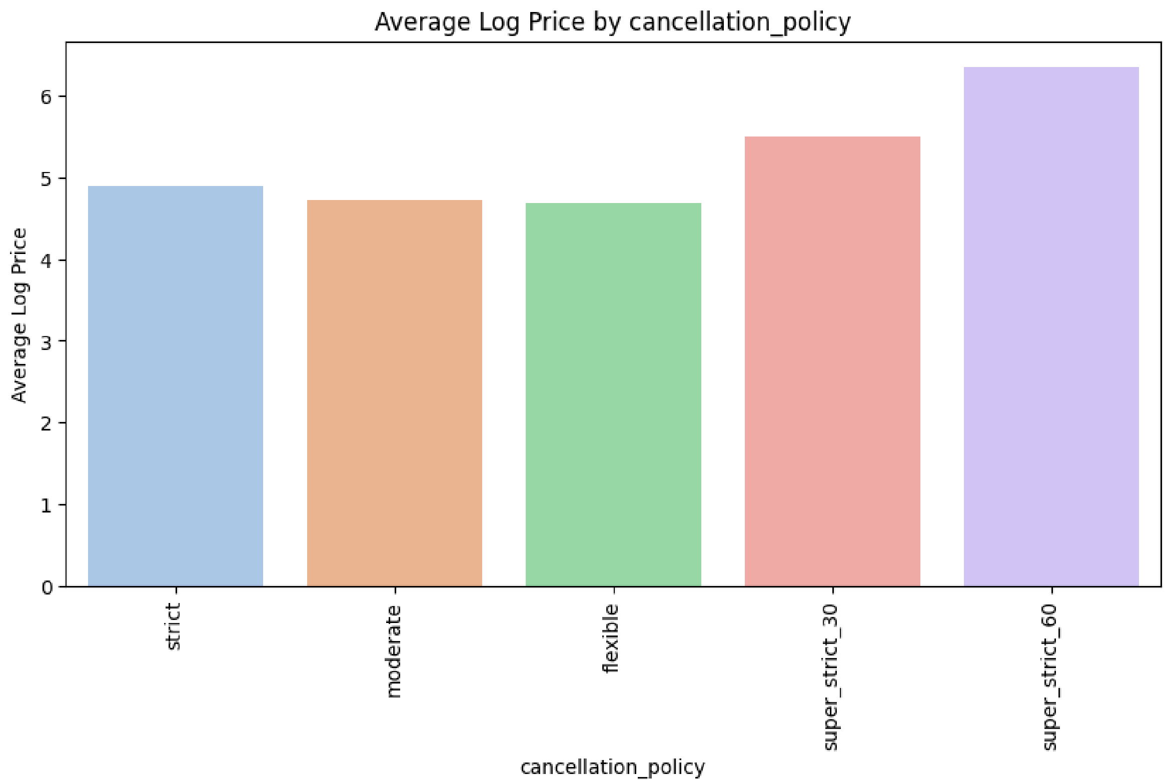
1. Entire home/apt listings have the highest median log price and the widest spread, indicating that they are generally the most expensive but vary a lot depending on property size and amenities.
2. Private rooms fall in the mid-range, with a lower median compared to entire homes, but still showing a wide distribution due to location and property differences.
3. Shared rooms have the lowest prices overall, with very limited variation, confirming that they are the most budget-friendly option on Airbnb.

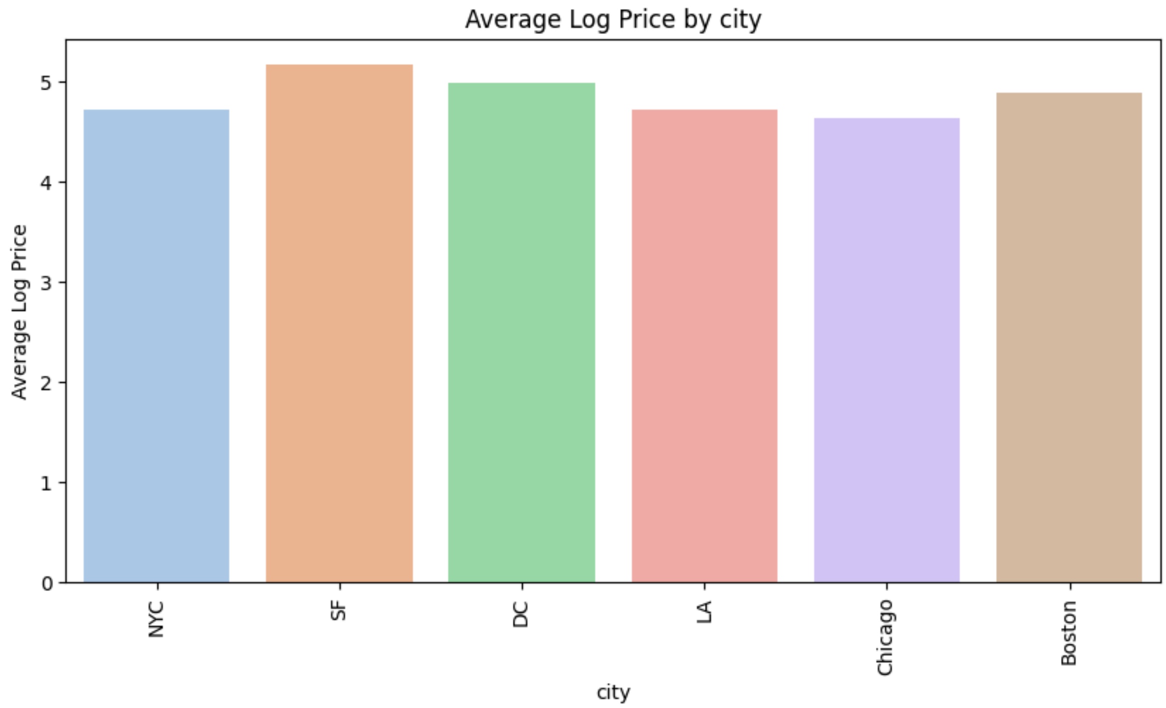
In [42]:
```
categorical_cols = ['room_type', 'property_type', 'bed_type', 'cancellation_poli
for col in categorical_cols:
  plt.figure(figsize=(10,5))
  sns.barplot(x=col, y = 'log_price', data= df,  ci=None, palette='pastel')
  plt.title(f"Average Log Price by {col}")
  plt.xlabel(col)
  plt.ylabel("Average Log Price")
  plt.xticks(rotation=90)
  plt.show()
```


Average Log Price by room_type
Average Log Price
0
1
2
3
4
5
Entire home/apt
Private room
Shared room
room_type


Average Log Price by property_type
Average Log Price
0
1
2
3
4
5
Apartment
House
Condominium
Loft
Townhouse
Hostel
Guest suite
Bed & Breakfast
Bungalow
Guesthouse
Dorm
Other
Camper/RV
Villa
Boutique hotel
Timeshare
In-law
Boat
Serviced apartment
Castle
Cabin
Treehouse
Tipi
Vacation home
Tent
Hut
Casa particular
Chalet
Yurt
Earth House
Parking Space
Train
Cave
Lighthouse
Island
property_type


Average Log Price by bed_type
Average Log Price
0
1
2
3
4
5
Real Bed
Futon
Pull-out Sofa
Couch
Airbed
bed_type


Average Log Price by cancellation_policy
Average Log Price
0
1
2
3
4
5
6
strict
moderate
flexible
super_strict_30
super_strict_60
cancellation_policy

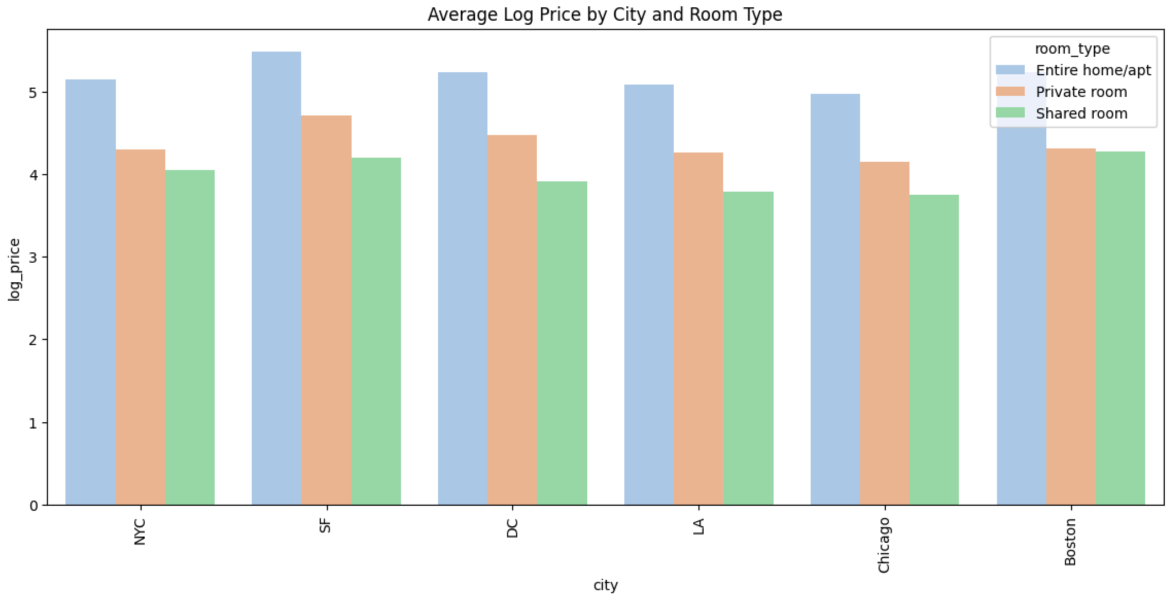


Categorical Features V/S Log_Price By using Barplots:-

```
1. Room Type:-
    (a). Entire home/apt listings have the highest log Price,
makeing them the most expensive option.
    (b). Private rooms are priced moderatly, while shared rooms
have the lowest prices.
2. Property Type:-
    (a). Houses, lofts, and villas show higher log prices
compared to apartments.
    (b). Smaller or budget-friendly property types such as
hostels and Dorm are priced lower.
3. Bed Type:-
    (a). Listing with real beds dominate the dataset and also
tend to have higher log Price.
    (b). Other types (like futons, sofa beds, or pull-out
couches) are linked to relatively lower prices.
4. Cancellation Policy
    (a). Listing with a super_strict_60 cancellation policy tend
to have higher average log prices compared to Moderate or
Flexible policies.
5. City:-
    (a). The log price across all cities lies in a narrow range
between 4.5 and 5.
    (b). This indicates that while there are small differences,
Airbnb prices are fairly consistent across different cities in
the dataset.
```

In [43]:
```
plt.figure(figsize=(14,6))
sns.barplot(x='city', y='log_price', hue='room_type', data=df, ci=None, palette=
plt.title("Average Log Price by City and Room Type")
```

```
plt.xticks(rotation=90)
plt.show()
```



City and Room Type V/s Log Price:-

```
1. Across cities, Entire home/apt consistently has the highest
average prices, while Shared rooms remain the cheapest option
everywhere.
2. Although overall city averages are close (4-5), the
difference between room types within the same city is
significant, confirming that room type is a stronger driver of
price than location alone.
```

In [44]:
```
df['amenities_count'] = df['amenities'].apply(lambda x: len(x.split(',')))
```

Why we used Amenities_count?

Ans:- amenities column is a long text string with a list of items. instead of using the raw text, we extracted the number of amenities available in each listing. This matters because properties with more amenities(Wi-Fi, AC, Kitchen, etc) usually charge higher prices. By converting it into a count, we provide the model with a simple numerical feature that captures the effect of amenities on price.

In [45]:
```
df['last_review'] = pd.to_datetime(df['last_review'], errors='coerce')
df['days_since_last_review'] = (pd.to_datetime('today') - df['last_review']).dt.
# Missing values were filled with the median so the model can still use this fea
df['days_since_last_review'] = df['days_since_last_review'].fillna(df['days_sinc
```

In [46]:
```
df['host_since'] = pd.to_datetime(df['host_since'], errors='coerce')
df['host_tenure'] = (pd.to_datetime('today') - df['host_since']).dt.days
# Missing values were replaced with the median to avoid losing records and to ma
df['host_tenure'] = df['host_tenure'].fillna(df['host_tenure'].median())
```

Date-Based Feature:-

```
1. days_since_last_review:-
    (a). Number of days b/w today's date and the most recent
review date for listing.
    (b). Caputures the recency of guest activity. Properties
with very recent reviews may signal higher popularity and
reliablity, while listing with older or no reviews may indecate
lower engagement or trust.
2. Host Tenure:-
    (a). Number of days b/w today's date and the date when the
host first joined Airbnb.
    (b). Reflects the host's expreiance on the plateform. More
expreienced hosts are likely to have better guest handling,
which can influence pricing and booking likelihood.
```

In [47]:
```python
df.drop(['amenities','first_review','last_review','host_since','zipcode'], axis=
```

In [48]:
```python
cat_cols = ['property_type', 'room_type', 'bed_type',
            'cancellation_policy', 'city', 'neighbourhood']

df = pd.get_dummies(df, columns=cat_cols, drop_first=True)
```

In [49]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Columns: 685 entries, log_price to neighbourhood_Wrigleyville
dtypes: bool(669), float64(12), int64(1), object(3)
memory usage: 56.3+ MB
```

In [50]:
```python
df = df.drop(columns=['host_identity_verified', 'host_has_profile_pic'])
```

In [51]:
```python
df.instant_bookable.unique()
```

Out[51]:
```
array(['f', 't'], dtype=object)
```

In [52]:
```python
df.select_dtypes('object').head()
```

Out[52]:

	instant_bookable
0	f
1	t
2	t
3	f
4	t

In [53]:
```python
df['instant_bookable'] = df['instant_bookable'].str.lower().map({'t': True, 'f':
```

In [54]:
```python
df.select_dtypes('object').info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Empty DataFrame
```

In [54]:

In [54]:

In [55]:
```
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Columns: 683 entries, log_price to neighbourhood_Wrigleyville
dtypes: bool(670), float64(12), int64(1)
memory usage: 54.7 MB
```

Out[55]:

	log_price	accommodates	bathrooms	cleaning_fee	host_response_rate	instant_book
0	5.010635	3.0	1.0	True	100.0	
1	5.129899	7.0	1.0	True	100.0	
2	4.976734	5.0	1.0	True	100.0	
3	6.620073	4.0	1.0	True	100.0	
4	4.744932	2.0	1.0	True	100.0	

5 rows × 683 columns

Spliting the Target Variable to Y

In [56]:
```
X = df.drop('log_price', axis = 1)
y = df['log_price']
```

Train-Test Split

In [57]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

Standard Scale: -

In [58]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled= scaler.transform(X_test)
```

Linear Regression: -

In [59]:
```
lr = LinearRegression()
lr.fit(X_train_scaled, y_train)
y_pred_lr = lr.predict(X_test_scaled)
```

In [60]:
```
rmse = np.sqrt(mean_squared_error(y_test, y_pred_lr))
r2 = r2_score(y_test, y_pred_lr)
```

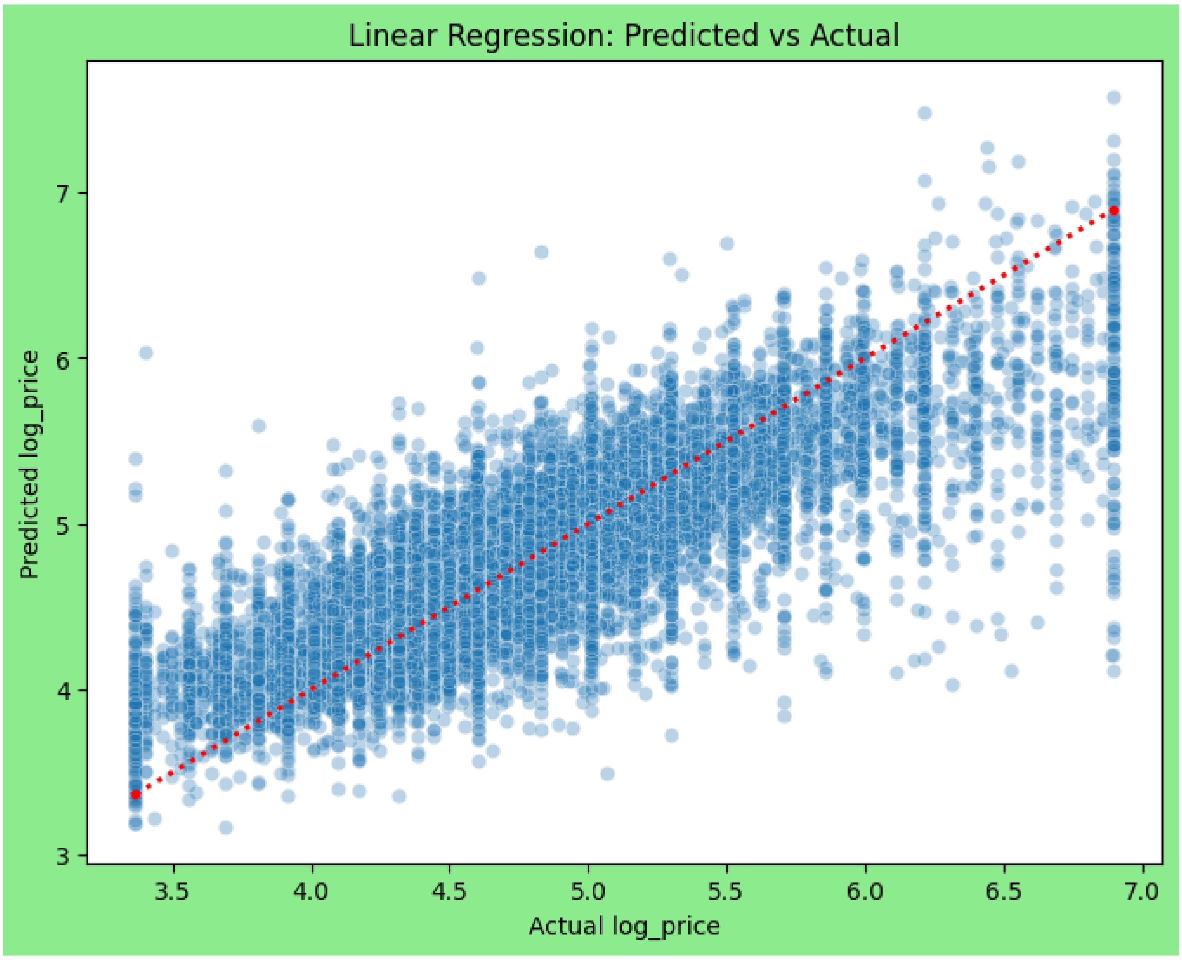
```
print(f"Linear Regression -> RMSE: {rmse:.4f}, R2: {r2:.4f}")
```

```
Linear Regression -> RMSE: 0.4033, R2: 0.6703
```

I trained a Linear Regression model to predict log_price using 683 features, including numeric and one-hot encoded categorical variables. After splitting the dataset into 80% training and 20% testing and scaling the features:

```
RMSE (Root Mean Squared Error): 0.4033

R² (Coefficient of Determination): 0.6703
```

In [61]:
```
plt.figure(figsize=(8,6), facecolor= 'lightgreen')
sns.scatterplot(x=y_test, y=y_pred_lr, alpha=0.3)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r:.', line
plt.xlabel('Actual log_price')
plt.ylabel('Predicted log_price')
plt.title('Linear Regression: Predicted vs Actual')
plt.show()
```



Ridge Regression: -

To improve performance, we can use regularized linear models like Ridge or ElasticNet, which handle multicollinearity and can reduce overfitting.

In [62]:
```
alpha_values = [0.01, 0.1, 0.2, 1, 10, 50, 100]
ridge = Ridge()

ridge_cv = GridSearchCV(ridge, param_grid={'alpha': alpha_values}, scoring='neg_
ridge_cv.fit(X_train_scaled, y_train)
```

Out[62]:
```
▸ GridSearchCV
▸ best_estimator_: Ridge
  ▸ Ridge
```

In [63]:
```
best_alpha_ridge = ridge_cv.best_params_['alpha']
print(f"Best alpha for Ridge Regression: {best_alpha_ridge}")

ridge_model = Ridge(alpha = best_alpha_ridge)
ridge_model.fit(X_train_scaled, y_train)
```

```
Best alpha for Ridge Regression: 0.01
```

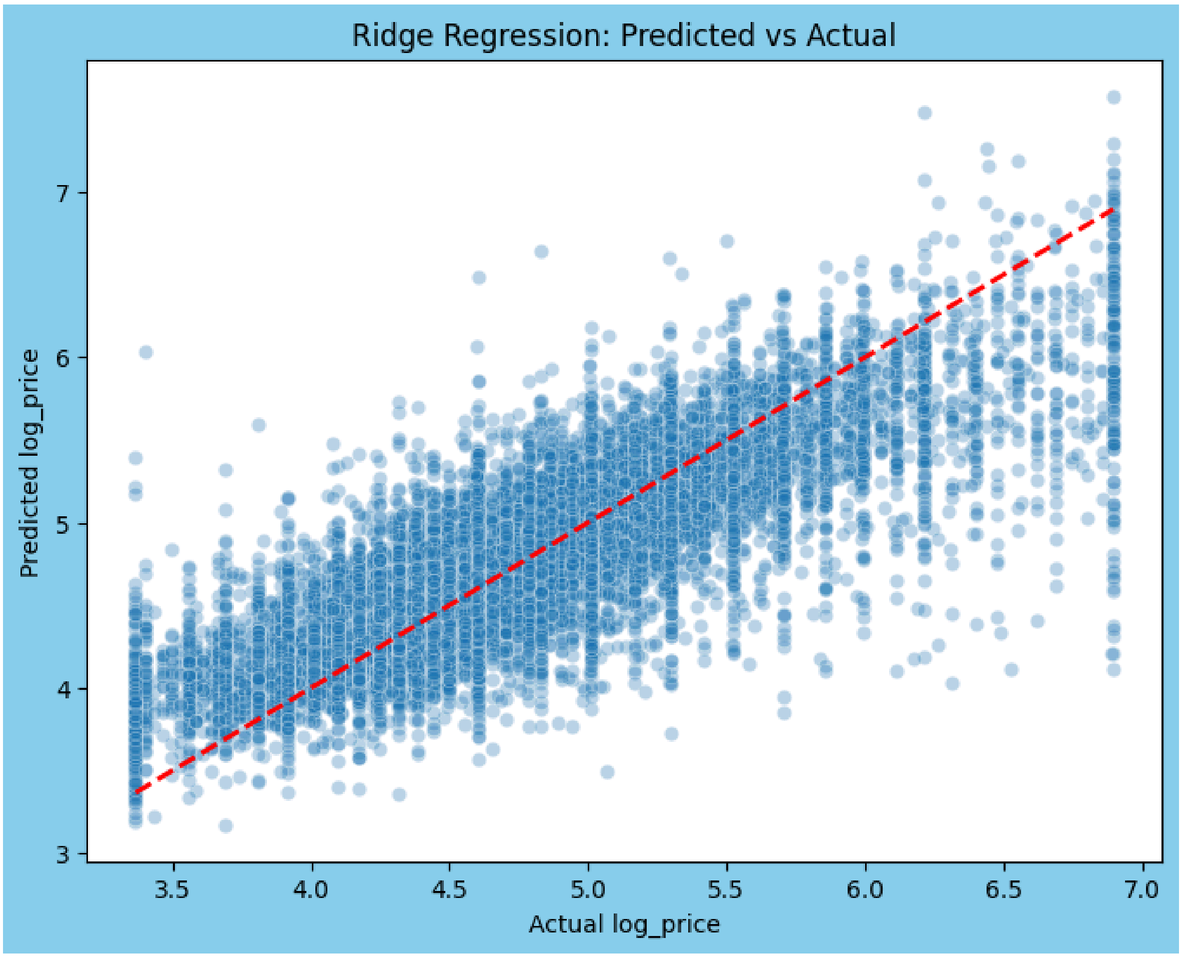
Out[63]:
```
▾ Ridge
Ridge(alpha=0.01)
```

In [64]:
```
y_pred_ridge = ridge_model.predict(X_test_scaled)
```

In [65]:
```
rmse = np.sqrt(mean_squared_error(y_test, y_pred_ridge))
r2 = r2_score(y_test, y_pred_ridge)

print(f"Ridge Regression -> RMSE: {rmse:.4f}, R2: {r2:.4f}")
```

```
Ridge Regression -> RMSE: 0.4033, R2: 0.6704
```

In [66]:
```
plt.figure(figsize=(8,6), facecolor= 'skyblue')
sns.scatterplot(x=y_test, y=y_pred_ridge, alpha=0.3)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', line
plt.xlabel('Actual log_price')
plt.ylabel('Predicted log_price')
plt.title('Ridge Regression: Predicted vs Actual')
plt.show()
```



In our Airbnb price prediction project, we started with Linear Regression and then tried Ridge Regression to reduce overfitting due to high-dimensional features. Ridge performed well, but it retains all features, even those with little predictive power.

Our dataset has 670 one-hot encoded boolean features, and many of them might be redundant or low-importance.

ElasticNet: -

ElasticNet, which combines L1 (Lasso) and L2 (Ridge) regularization, offers two key advantages:

```
1. Feature Selection:-
  (*). L1 regularization can shrink some co-efficient to zero,
automatically removing unimportant features.
2. Regularization & Generalization:-
  (a). L2 regularization keeps coefficients small, reducing
overfitting.
  (b). Combining L1 + L2 ensures a sparse yet stable model.
```

In [67]:
```
param_grid = {
    'alpha': [0.01, 0.1, 1, 10],
    'l1_ratio': [0.2, 0.5, 0.7, 0.9]
}
```

```
enet = ElasticNet(max_iter = 5000)

enet_cv = GridSearchCV(enet, param_grid= param_grid, scoring = 'neg_mean_squared
enet_cv.fit(X_train_scaled, y_train)
```

Out[67]:

```
▸ GridSearchCV
▸ best_estimator_: ElasticNet
  ▸ ElasticNet
```

In [68]:

```
best_params = enet_cv.best_params_
print(f"Best Hyperparameters: {best_params}")

#Train Final ElasticNet model

enet_model = ElasticNet(
    alpha=best_params['alpha'],
    l1_ratio=best_params['l1_ratio'],
    max_iter=5000
)
enet_model.fit(X_train_scaled, y_train)
```

```
Best Hyperparameters: {'alpha': 0.01, 'l1_ratio': 0.2}
```

Out[68]:

```
▾ ElasticNet
ElasticNet(alpha=0.01, l1_ratio=0.2, max_iter=5000)
```

In [69]:

```
y_pred_enet = enet_model.predict(X_test_scaled)
rmse = np.sqrt(mean_squared_error(y_test, y_pred_enet))
r2 = r2_score(y_test, y_pred_enet)

print(f"ElasticNet Regression -> RMSE: {rmse:.4f}, R2: {r2:.4f}")
```

```
ElasticNet Regression -> RMSE: 0.4074, R2: 0.6636
```

After trying Linear Regression, Ridge, and ElasticNet, we have a good understanding of how linear relationships and regularization affect Airbnb price prediction. ElasticNet helped by removing unimportant features and reducing overfitting, but the model is still limited to linear relationships between features and the target.

XGBoost Regressor: -

ElasticNet cannot capture these interactions, but XGBoost, a gradient boosting tree-based model, can:

```
1. Handles non-linear relationships naturally

2. Captures interactions between features

3. Works efficiently on wide, sparse datasets (like our 670
```

boolean features)

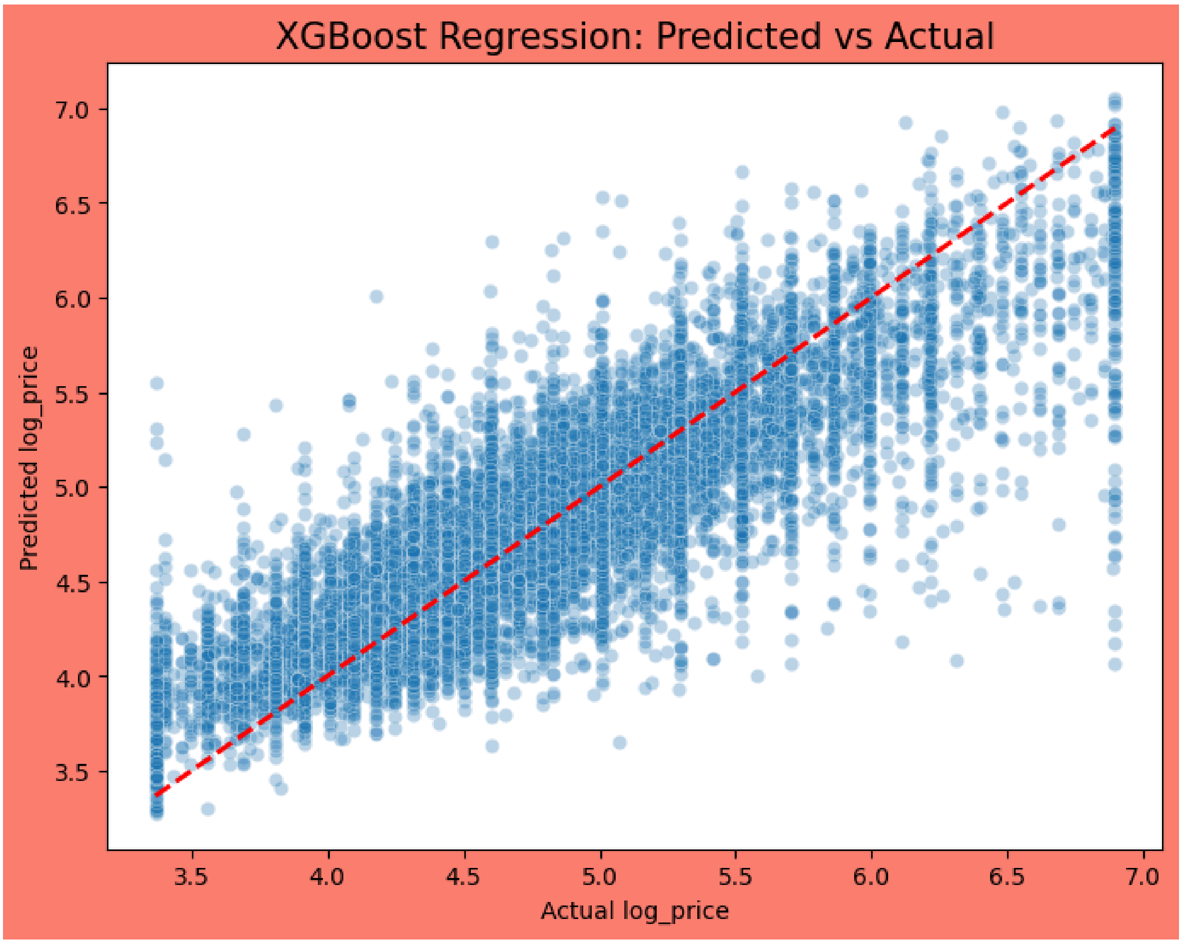
4. Often provides better predictive accuracy than linear models

In [70]:
```
xgb_model = XGBRegressor(
    n_estimators=500,
    learning_rate=0.05,
    max_depth=6,
    subsample=0.8,
    colsample_bytree=0.8,
    random_state=42,
    n_jobs=-1
)

# Train the model
xgb_model.fit(X_train, y_train)
y_pred_xgb = xgb_model.predict(X_test)
```

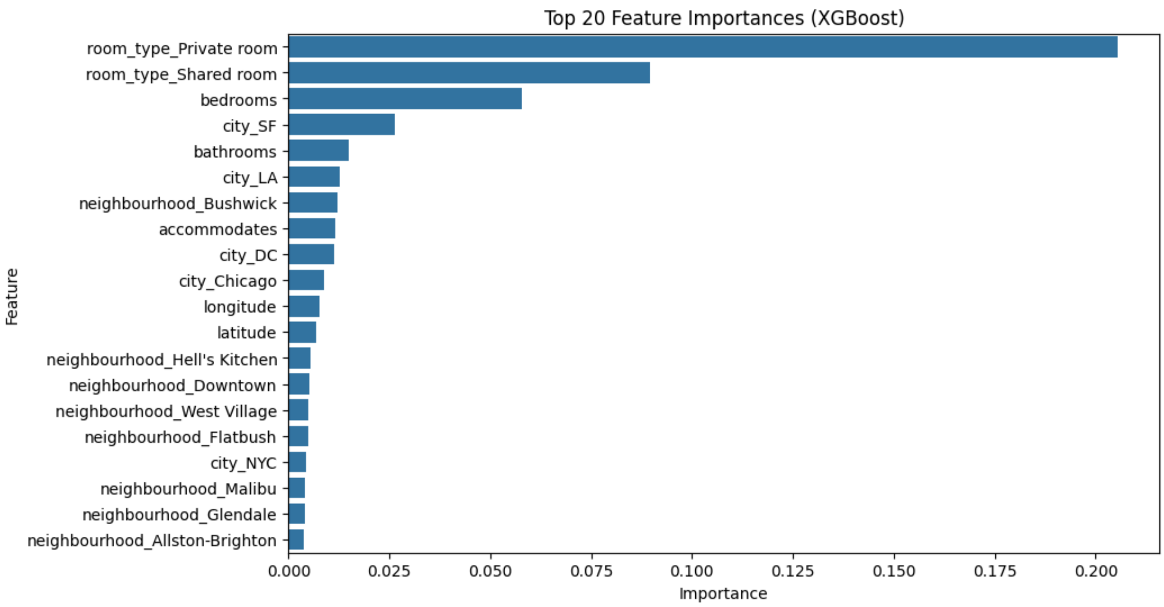
In [71]:
```
rmse = np.sqrt(mean_squared_error(y_test, y_pred_xgb))
r2 = r2_score(y_test, y_pred_xgb)

print(f"XGBoost Regression -> RMSE: {rmse:.4f}, R2: {r2:.4f}")
```

```
XGBoost Regression -> RMSE: 0.3727, R2: 0.7185
```

In [72]:
```
plt.figure(figsize=(8,6), facecolor= 'salmon')
sns.scatterplot(x=y_test, y=y_pred_xgb, alpha=0.3)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', line
plt.xlabel('Actual log_price')
plt.ylabel('Predicted log_price')
plt.title('XGBoost Regression: Predicted vs Actual', fontsize = 15, color = 'k')
plt.show()
```



In [73]:
```
feat_imp = pd.DataFrame({
    'Feature': X.columns,
    'Importance': xgb_model.feature_importances_
}).sort_values(by='Importance', ascending=False).head(20)

plt.figure(figsize=(10,6))
sns.barplot(x='Importance', y='Feature', data=feat_imp)
plt.title('Top 20 Feature Importances (XGBoost)')
plt.show()
```



Model Mertics:-

```
1. Linear Regression:- RMSE = 0.4033, R2 = 0.67
2. Ridge Regression :- RMSE = 4033, R2 = 0.67
3. ElasticNet Regression:- 4074, R2: 0.6636
4. XGBoost Regression:- RMSE: 0.3727, R2: 0.7185
```

Buisness Conclusion:-

```
1. Key Factors influencing Price:-
    * Room type, property type, number of amenities, and host
experience (tenure) strongly affect Airbnb prices.
2. Insights:-
    * Entire homes/apartments command the higest prices, wihile
shared rooms are the cheapest.
    * More amenities and longer-tenured hosts correlate with
higher prices.
3. Best Model:- XGBoost acheived the lowest RMSE(0.37) and
highest R2(0.71), making it the most reliable model for price
prediction.
```

Conclusion: -

```
> Linear and regularized linear model provide a strong baseline.
> XGBoost outperforms them by capturing complex patterns and
intersections in Airbnb pricing data.
```