In [83]:

```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
import category_encoders as ce
from catboost import CatBoostRegressor
from sklearn.model_selection import train_test_split,KFold, StratifiedKFold, cross_val_score
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
import matplotlib.pyplot as plt
from lightgbm import LGBMRegressor
#from sklearn.impute import KNNImputer

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

In [4]:

```
df= pd.read_csv('Housing_dataset_train.csv')
test = pd.read_csv('Housing_dataset_test.csv')
df.head()
```

Out[4]:

	ID	loc	title	bedroom	bathroom	parking_space	price
0	3583	Katsina	Semi-detached duplex	2.0	2.0	1.0	1149999.565
1	2748	Ondo	Apartment	NaN	2.0	4.0	1672416.689
2	9261	Ekiti	NaN	7.0	5.0	NaN	3364799.814
3	2224	Anambra	Detached duplex	5.0	2.0	4.0	2410306.756
4	10300	Kogi	Terrace duplex	NaN	5.0	6.0	2600700.898

In [5]:

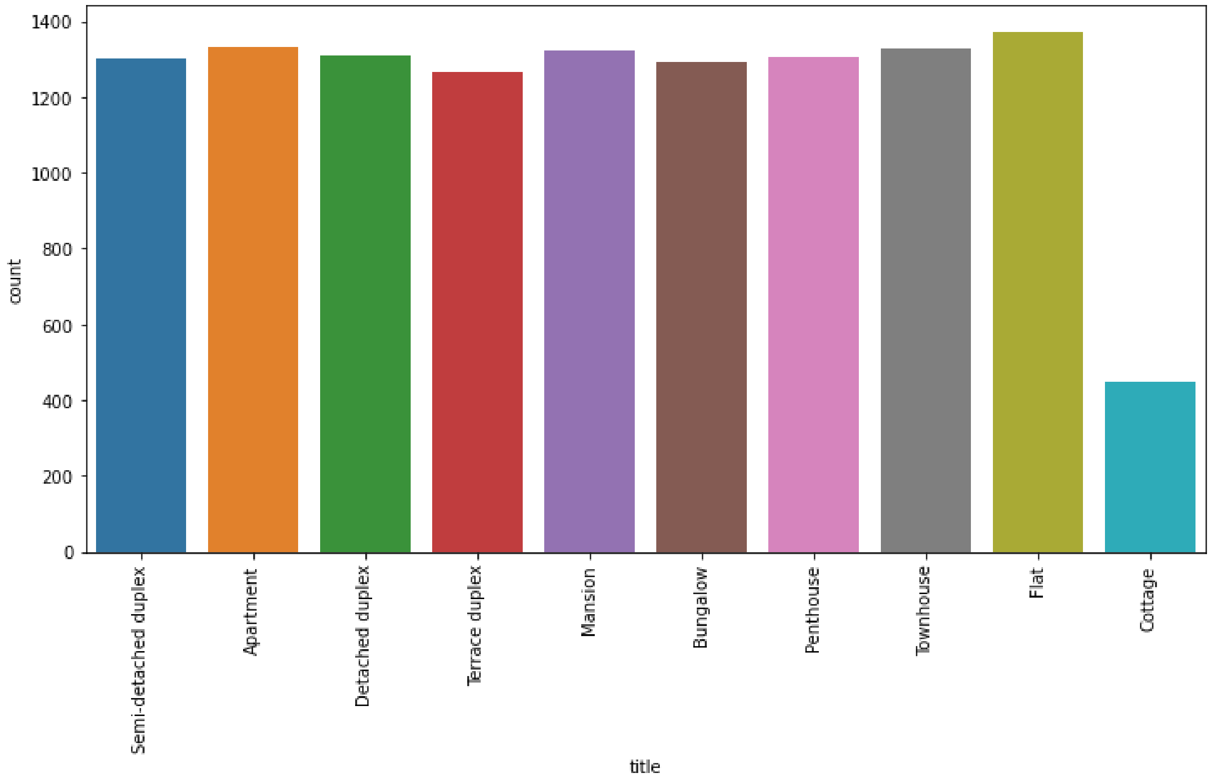
```
sub = pd.read_csv('Sample_submission.csv')
sub.head()
```

Out[5]:

	ID
0	845
1	1924
2	10718
3	12076
4	12254

In [6]:

```
#What is the distribution of house types in the dataset?
plt.figure(figsize=(12,6))
sns.countplot(x='title', data=df)
plt.xticks(rotation=90)
plt.show()
```



What is the distribution of house types in the dataset?

Cottage House types is low compared to others

In [7]:

```
#Which state has the highest number of houses in the dataset?

df['loc'].value_counts()
```

Out[7]:

```
Kaduna         370
Anambra        363
Benue          355
Yobe           353
Borno          351
Kano           351
Nasarawa       349
Cross River    349
Zamfara        348
Imo            348
Ebonyi         346
Kebbi          346
Katsina        345
Ogun           345
Ondo           344
Gombe          343
Bauchi         342
Oyo            341
Adamawa        341
Bayelsa        340
Plateau        338
Osun           338
Jigawa         337
Ekiti          336
Kwara          333
Niger          330
Akwa Ibom      329
Lagos          328
Sokoto         326
Delta          325
Enugu          324
Rivers         323
Kogi           321
Taraba         315
Abia           312
Edo            302
Name: loc, dtype: int64
```

Which state has the highest number of houses in the dataset?

Kaduna has the highest number of houses in the dataset

In [8]:

```
#What is the average house price in each state?

df.groupby('loc').mean()[['price']]
```

Out[8]:

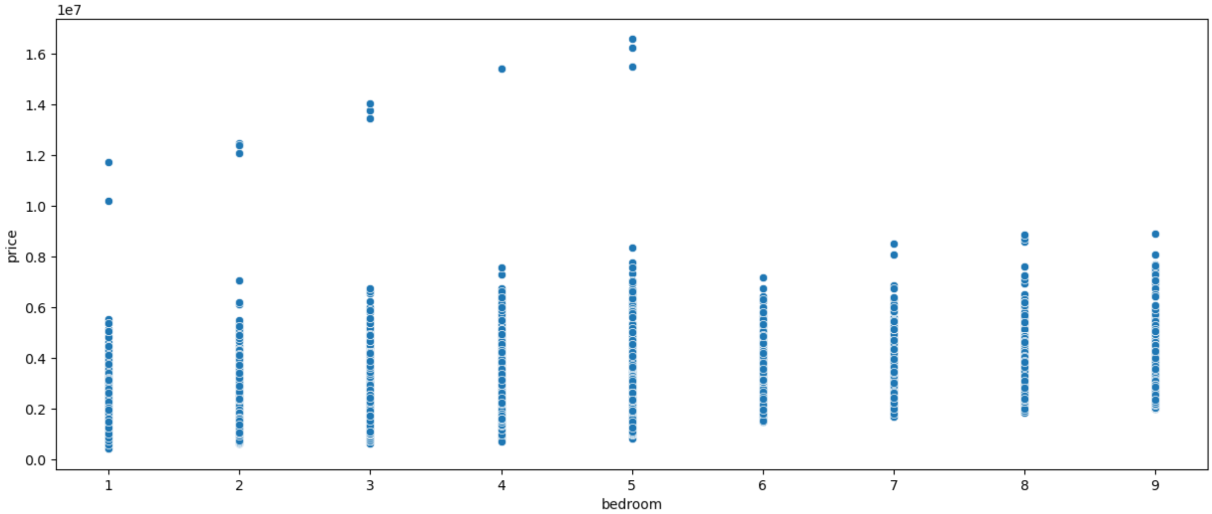
	price
loc	
Abia	1.717083e+06
Adamawa	1.905287e+06
Akwa Ibom	2.725454e+06
Anambra	2.337230e+06
Bauchi	1.772961e+06
Bayelsa	3.112322e+06
Benue	1.920461e+06
Borno	1.735704e+06
Cross River	2.507765e+06
Delta	2.712493e+06
Ebonyi	1.635850e+06
Edo	2.310452e+06
Ekiti	2.109220e+06
Enugu	2.272887e+06
Gombe	1.860851e+06
Imo	2.067489e+06
Jigawa	1.735867e+06
Kaduna	1.846993e+06
Kano	2.081931e+06
Katsina	1.947589e+06
Kebbi	1.616372e+06
Kogi	1.763416e+06
Kwara	1.903424e+06
Lagos	4.210546e+06
Nasarawa	2.061764e+06
Niger	1.885325e+06
Ogun	2.564020e+06
Ondo	2.277494e+06
Osun	2.180570e+06
Oyo	2.293159e+06
Plateau	1.942316e+06
Rivers	2.957098e+06
Sokoto	1.681016e+06
Taraba	1.855306e+06
Yobe	1.747938e+06
Zamfara	1.689541e+06

In [13]:

```
#Is there any relationship between the number of bedrooms and the house price?
plt.figure(figsize=(15,6),dpi=100)
sns.scatterplot(x='bedroom', y='price', data=df)
```

Out[13]:

```
<AxesSubplot:xlabel='bedroom', ylabel='price'>
```



Is there any relationship between the number of bedrooms and the house price?

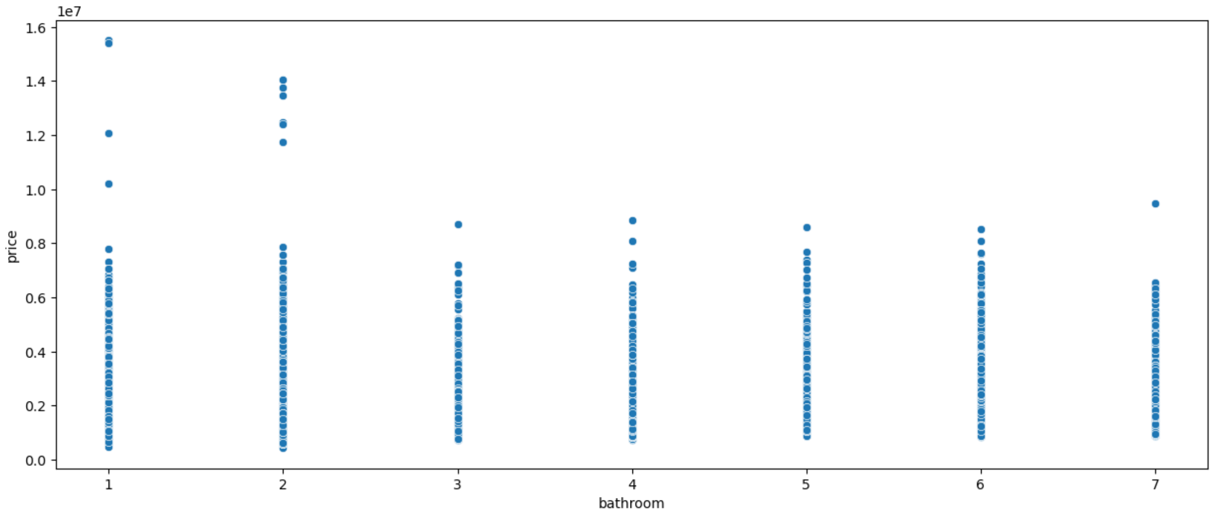
From the above Plot I can see that houses that have 5 bedrooms have the highest price

In [20]:

```
#Is there any relationship between the number of bathrooms and the house price?
plt.figure(figsize=(15,6),dpi=100)
sns.scatterplot(x='bathroom', y='price', data=df)
```

Out[20]:

```
<AxesSubplot:xlabel='bathroom', ylabel='price'>
```



Is there any relationship between the number of bathrooms and the house price?

From the above Plot I can see that houses that have 1 bathroom have the highest price

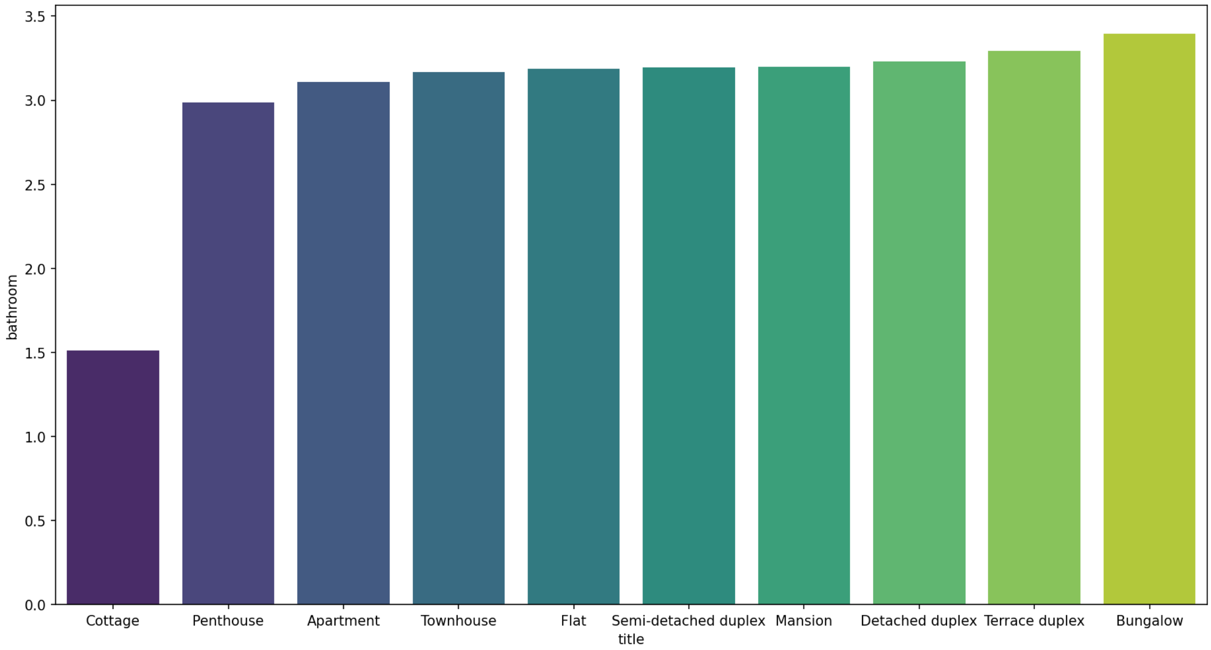
In [19]:

```
#Which house type has the highest average number of bathrooms?


bat = df.groupby('title').mean()[['bathroom']].sort_values('bathroom').reset_index()
plt.figure(figsize=(15,8),dpi=150)
sns.barplot(x='title', y='bathroom', data=bat, palette='viridis')
```

Out[19]:

```
<AxesSubplot:xlabel='title', ylabel='bathroom'>
```

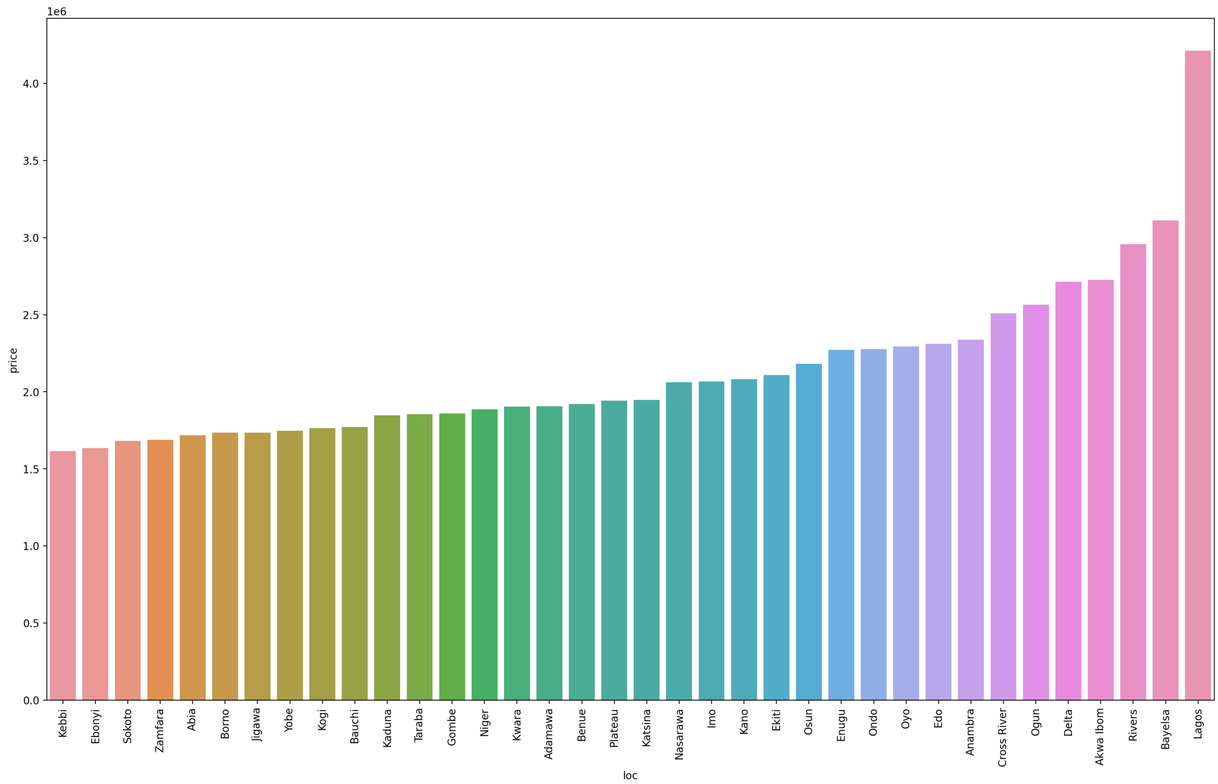


Insight

Bungalow house type has the highest number of bathroom at an average while cottage house type has the lowest

In [27]:

```
#Is there a significant difference in house prices between different states?
lag = df.groupby('loc').mean()[['price']].sort_values('price').reset_index()
plt.figure(figsize=(20,12),dpi=200)
sns.barplot(x='loc', y='price', data=lag)
plt.xticks(rotation=90);
```



Insight

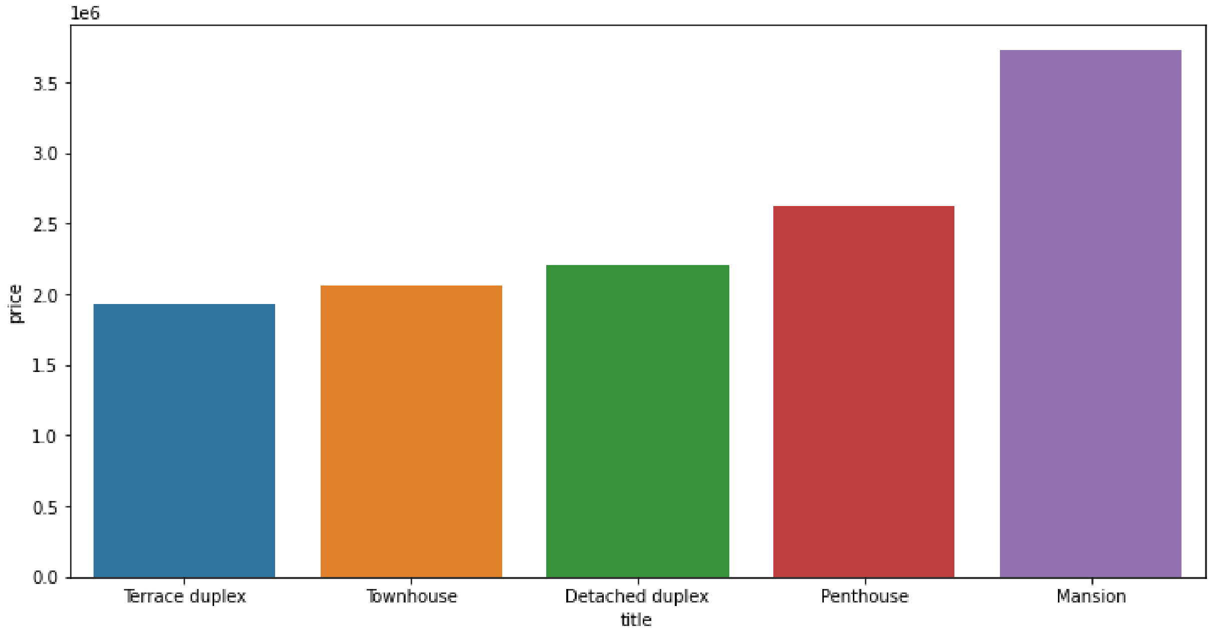
Lagos State has the highest number of Price

In [37]:

```
#What are the top 5 most expensive house types in the dataset?
title = df.groupby('title').mean()[['price']].sort_values('price').tail().reset_index()
plt.figure(figsize=(12,6))
sns.barplot(x='title', y='price', data=title)
```

Out[37]:

```
<AxesSubplot:xlabel='title', ylabel='price'>
```



Insight

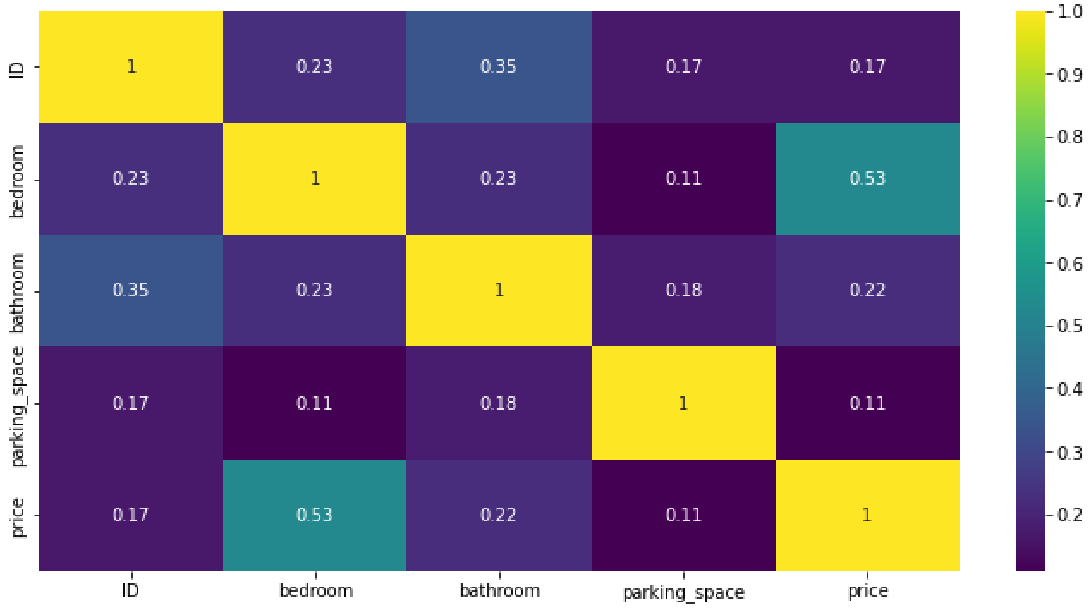
Mansion is the most expensive house type in the dataset

In [40]:

```
plt.figure(figsize=(12,6))
sns.heatmap(df.corr(), annot=True, cmap='viridis')
```

Out[40]:

```
<AxesSubplot:>
```



Insight

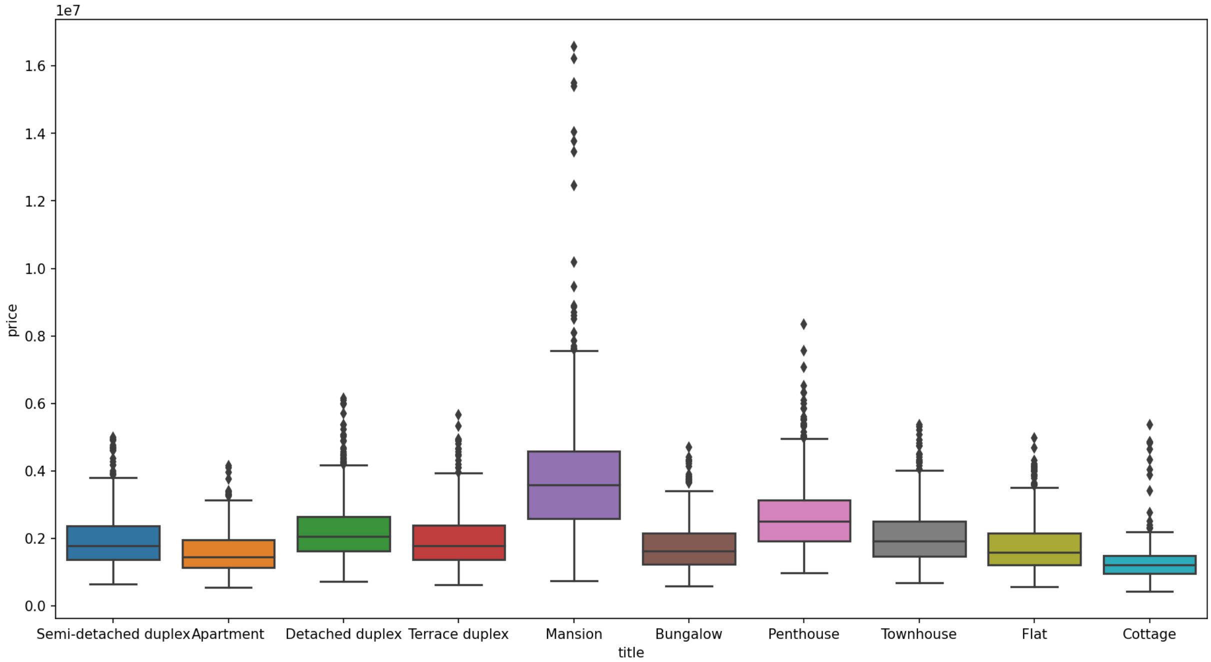
The number of bedrooms and bathrooms seem to be the most correlated of the numerical features

In [41]:

```
#How does the house price vary with different house types?
plt.figure(figsize=(15,8),dpi=150)
sns.boxplot(x='title', y='price' , data=df)
```

Out[41]:

```
<AxesSubplot:xlabel='title', ylabel='price'>
```



In [43]:

```
#What is the average number of bedrooms for each house type?
df.groupby('title').mean()[['bedroom']]
```

Out[43]:

	bedroom
title	
Apartment	4.344219
Bungalow	4.402852
Cottage	2.905512
Detached duplex	4.327840
Flat	4.378877
Mansion	4.333929
Penthouse	4.342982
Semi-detached duplex	4.414903
Terrace duplex	4.340639
Townhouse	4.298759

In [45]:

```
data = pd.concat([df,test],ignore_index=False)
```

In [48]:

```
data = data.drop('ID', axis=1)
```

In [49]:

```
data.head()
```

Out[49]:

	loc	title	bedroom	bathroom	parking_space	price
0	Katsina	Semi-detached duplex	2.0	2.0	1.0	1149999.565
1	Ondo	Apartment	NaN	2.0	4.0	1672416.689
2	Ekiti	NaN	7.0	5.0	NaN	3364799.814
3	Anambra	Detached duplex	5.0	2.0	4.0	2410306.756
4	Kogi	Terrace duplex	NaN	5.0	6.0	2600700.898

In [50]:

```
house_type_ranks = {
"Apartment":1,
"Flat":2,
"Cottage":3,
"Semi-detached duplex":4,
"Terrace duplex":5,
"Bungalow":6,
"Townhouse":7,
"Detached duplex":8,
"Penthouse":9,
"Mansion":10,
}



# Map the house types to numerical values based on size ranking
data['title'] = data['title'].map(house_type_ranks)
```

In [51]:

```
data.head()
```

Out[51]:

	loc	title	bedroom	bathroom	parking_space	price
0	Katsina	4.0	2.0	2.0	1.0	1149999.565
1	Ondo	1.0	NaN	2.0	4.0	1672416.689
2	Ekiti	NaN	7.0	5.0	NaN	3364799.814
3	Anambra	8.0	5.0	2.0	4.0	2410306.756
4	Kogi	5.0	NaN	5.0	6.0	2600700.898

In [52]:

```
# Create the 'Total Rooms' feature
data['Total_Rooms'] = data['bedroom'] + data['bathroom']


# Create the 'Bathroom-to-Bedroom Ratio' feature
data['Bathroom_to_Bedroom_Ratio'] = data['bathroom'] / data['bedroom']


data.head()
```

Out[52]:

	loc	title	bedroom	bathroom	parking_space	price	Total_Rooms	Bathroom_to_Bedroom_Ratio
0	Katsina	4.0	2.0	2.0	1.0	1149999.565	4.0	1.000000
1	Ondo	1.0	NaN	2.0	4.0	1672416.689	NaN	NaN
2	Ekiti	NaN	7.0	5.0	NaN	3364799.814	12.0	0.714286
3	Anambra	8.0	5.0	2.0	4.0	2410306.756	7.0	0.400000
4	Kogi	5.0	NaN	5.0	6.0	2600700.898	NaN	NaN

In [62]:

```
encoder = ce.TargetEncoder(return_df=True)
```

In [63]:

```
data = encoder.fit_transform(data, data['price'])
```

In [64]:

```
data
```

Out[64]:

	loc	title	bedroom	bathroom	parking_space	price	Total_Rooms	Bathroom_to_Bedroom_Ra
0	1.947589e+06	4.0	2.0	2.0	1.0	1149999.565	4.0	1.000
1	2.277494e+06	1.0	NaN	2.0	4.0	1672416.689	NaN	N
2	2.109220e+06	NaN	7.0	5.0	NaN	3364799.814	12.0	0.714
3	2.337230e+06	8.0	5.0	2.0	4.0	2410306.756	7.0	0.400
4	1.763416e+06	5.0	NaN	5.0	6.0	2600700.898	NaN	N
...	...	...	...	...	...	...	...	
5995	2.109220e+06	2.0	4.0	5.0	2.0	NaN	9.0	1.250
5996	1.905287e+06	5.0	5.0	7.0	1.0	NaN	12.0	1.400
5997	2.293159e+06	7.0	4.0	1.0	4.0	NaN	5.0	0.250
5998	1.772961e+06	2.0	3.0	7.0	5.0	NaN	10.0	2.333
5999	1.681016e+06	10.0	6.0	1.0	6.0	NaN	7.0	0.166

20000 rows × 8 columns

In [65]:

```
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression

# Assuming you have your dataframe 'data' and want to perform regression imputation on columns with missing

# Create a copy of the dataframe to avoid modifying the original data
impute_data = data.copy()

# Get the columns with missing values
columns_with_missing = impute_data.columns[impute_data.isnull().any()]

# Perform regression imputation for each column with missing values
for target in columns_with_missing:
    # Select features for regression imputation (consider using other relevant features if available)
    features = impute_data.columns.difference([target])

    # Split the data into known (non-missing) and missing values for the target feature
    known_data = impute_data.loc[impute_data[target].notnull(), features.to_list() + [target]]
    missing_data = impute_data.loc[impute_data[target].isnull(), features.to_list()]

    # Separate the target and features for known and missing data
    X_known = known_data[features]
    y_known = known_data[target]
    X_missing = missing_data[features]

    # Create a regression model
    regression_model = LGBMRegressor()

    # Fit the regression model on the known data
    regression_model.fit(X_known, y_known)

    # Predict the missing values using the regression model
    imputed_values = regression_model.predict(X_missing)

    # Fill the missing values in the original dataframe
    impute_data.loc[impute_data[target].isnull(), target] = imputed_values

# Print the updated dataframe with filled missing values
impute_data
```

```
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.0
01192 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 384
[LightGBM] [Info] Number of data points in the train set: 18278, number of used features: 7
[LightGBM] [Info] Start training from score 5.666594
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.0
00492 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 628
[LightGBM] [Info] Number of data points in the train set: 18201, number of used features: 7
[LightGBM] [Info] Start training from score 4.315312
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of testing was 0.0
01368 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 874
[LightGBM] [Info] Number of data points in the train set: 18195, number of used features: 7
[LightGBM] [Info] Start training from score 3.124815
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of testing was 0.0
01581 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1121
[LightGBM] [Info] Number of data points in the train set: 18189, number of used features: 7
[LightGBM] [Info] Start training from score 3.157458
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of testing was 0.0
00646 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1121
[LightGBM] [Info] Number of data points in the train set: 14000, number of used features: 7
[LightGBM] [Info] Start training from score 2138081.749330
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead of testing was 0.0
01347 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 866
[LightGBM] [Info] Number of data points in the train set: 16469, number of used features: 7
[LightGBM] [Info] Start training from score 7.438278
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.0
00296 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 837
[LightGBM] [Info] Number of data points in the train set: 16469, number of used features: 7
[LightGBM] [Info] Start training from score 1.053402
```

Out[65]:

	loc	title	bedroom	bathroom	parking_space	price	Total_Rooms	Bathroom_to_Bedroo
0	1.947589e+06	4.0000	2.000000	2.0	1.000000	1.150000e+06	4.000000	1
1	2.277494e+06	1.0000	4.278082	2.0	4.000000	1.672417e+06	5.174911	(
2	2.109220e+06	8.2512	7.000000	5.0	4.005657	3.364800e+06	12.000000	(
3	2.337230e+06	8.0000	5.000000	2.0	4.000000	2.410307e+06	7.000000	(
4	1.763416e+06	5.0000	8.623348	5.0	6.000000	2.600701e+06	13.978423	(
...	...	...	...	...	...	...	...	
5995	2.109220e+06	2.0000	4.000000	5.0	2.000000	1.656829e+06	9.000000	1
5996	1.905287e+06	5.0000	5.000000	7.0	1.000000	1.863149e+06	12.000000	1
5997	2.293159e+06	7.0000	4.000000	1.0	4.000000	2.044760e+06	5.000000	(
5998	1.772961e+06	2.0000	3.000000	7.0	5.000000	1.331210e+06	10.000000	2
5999	1.681016e+06	10.0000	6.000000	1.0	6.000000	3.233434e+06	7.000000	(

20000 rows × 8 columns

In [66]:

```
impute_data.isnull().sum()
```

Out[66]:

```
loc                          0
title                        0
bedroom                      0
bathroom                     0
parking_space                0
price                        0
Total_Rooms                  0
Bathroom_to_Bedroom_Ratio    0
dtype: int64
```

In [67]:

```
data = impute_data.copy()
```

In [70]:

```
data[df.shape[0]:]
```

Out[70]:

	loc	title	bedroom	bathroom	parking_space	price	Total_Rooms	Bathroom_to_Bedroom_F
0	2.081931e+06	9.0	4.0	1.0	2.0	2.357633e+06	5.0	0.25
1	1.905287e+06	1.0	2.0	2.0	4.0	1.024562e+06	4.0	1.00
2	1.905287e+06	6.0	2.0	7.0	2.0	1.253566e+06	9.0	3.50
3	4.210546e+06	10.0	9.0	5.0	2.0	8.494182e+06	14.0	0.55
4	1.860851e+06	4.0	5.0	6.0	1.0	1.828081e+06	11.0	1.20
...	...	...	...	...	...	...	...	
5995	2.109220e+06	2.0	4.0	5.0	2.0	1.656829e+06	9.0	1.25
5996	1.905287e+06	5.0	5.0	7.0	1.0	1.863149e+06	12.0	1.40
5997	2.293159e+06	7.0	4.0	1.0	4.0	2.044760e+06	5.0	0.25
5998	1.772961e+06	2.0	3.0	7.0	5.0	1.331210e+06	10.0	2.33
5999	1.681016e+06	10.0	6.0	1.0	6.0	3.233434e+06	7.0	0.16

6000 rows × 8 columns

In [73]:

```
train = data[:df.shape[0]]
y = train.price
test = data[df.shape[0]:]
```

In [78]:

```
y
```

Out[78]:

```
0        1149999.565
1        1672416.689
2        3364799.814
3        2410306.756
4        2600700.898
            ...
13995    2367927.861
13996    2228516.471
13997    2406812.693
13998    3348918.718
13999    2858516.890
Name: price, Length: 14000, dtype: float64
```

In [77]:

```
test.drop('price', axis=1, inplace=True)
```

In [79]:

```
X = train.drop('price', axis=1)
```

In [80]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

In [85]:

```
#cross val score
def score(model):
    cv = cross_val_score(model,X_train,y_train,scoring='neg_mean_squared_error',cv=5,n_jobs=-1)

    return np.sqrt(np.mean(-cv))
```

In [86]:

```
rf_cv = RandomForestRegressor()
score(rf_cv)
```

Out[86]:

```
456142.1222426775
```

In [114]:

```
catboost =CatBoostRegressor(learning_rate=0.102,max_depth=5,min_child_samples=3,random_state=0,silent=True,
                            n_estimators=312)
score(catboost)
```

Out[114]:

```
414591.2659374284
```

In [88]:

```
from sklearn.metrics import mean_squared_error
```

In [89]:

```
def report(model):
    model_name = model.fit(X_train,y_train)
    pred_model = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test,pred_model))

    return rmse
```

In [90]:

```
report(rf_cv)
```

Out[90]:

```
451122.8640492227
```

In [115]:

```
report(catboost)
```

Out[115]:

```
415472.4400116604
```

In [122]:

```
xgb = XGBRegressor(learning_rate= 0.102, max_depth=3)
```

In [123]:

```
report(xgb)
```

Out[123]:

```
417185.6669017697
```

In [111]:

```
lgbm = LGBMRegressor(learning_rate= 0.102, max_depth=3, n_estimators=312)
```

In [112]:

```
report(lgbm)
```

```
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

In [98]:

```
def make_submission(model, filename):
    sub_copy = sub.copy()
    prediction = model.predict(test)
    sub_copy['price'] = prediction
    sub_copy.to_csv(filename, index=False)
```

In [104]:

```
make_submission(catboost,'A12.csv')
```

In [124]:

```
make_submission(xgb,'xgb2.csv')
```

In [113]:

```
make_submission(lgbm,'lgbm2.csv')
```

In [125]:

```
xgb.feature_importances_
```

Out[125]:

```
array([0.18148068, 0.2652532 , 0.38319945, 0.00842201, 0.01292426,
       0.13518342, 0.01353693], dtype=float32)
```

In [147]:

```
feat = pd.DataFrame(xgb.feature_importances_, columns=['importance'])
```

In [148]:

```
feat['column'] = X.columns
```

In [149]:

```
feat
```

Out[149]:

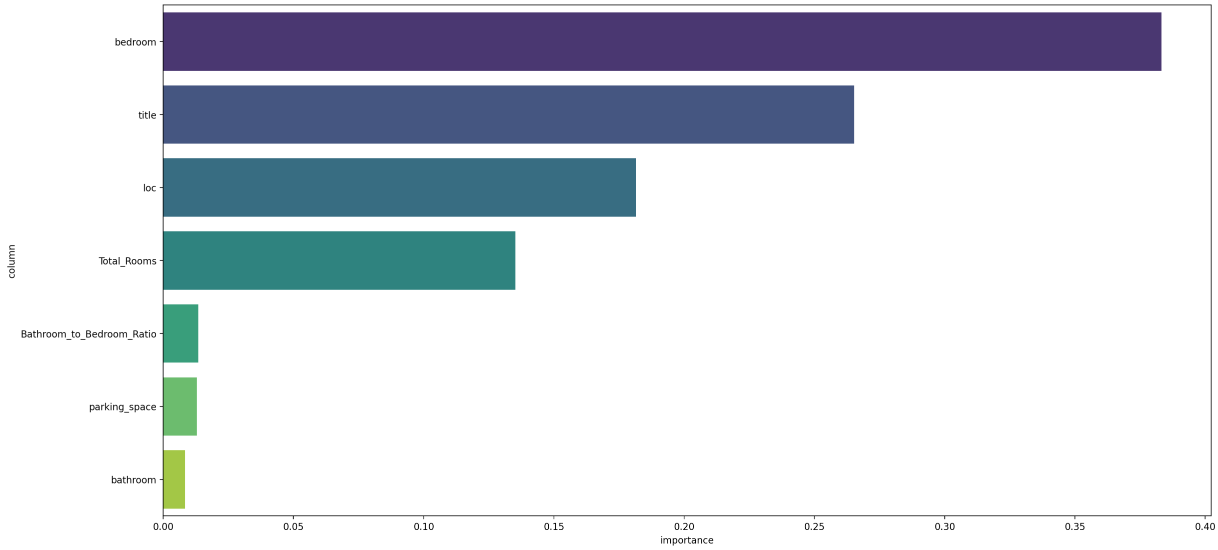
	importance	column
0	0.181481	loc
1	0.265253	title
2	0.383199	bedroom
3	0.008422	bathroom
4	0.012924	parking_space
5	0.135183	Total_Rooms
6	0.013537	Bathroom_to_Bedroom_Ratio

In [153]:

```
plt.figure(figsize=(20,10),dpi=200)
sns.barplot(y='column',x='importance', data=feat.sort_values('importance',ascending=False),palette='viridi
```

Out[153]:

<AxesSubplot:xlabel='importance', ylabel='column'>



In [ ]: