Random Forest

In [27]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_scor
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import warnings
from collections import defaultdict
warnings.filterwarnings('ignore')

def remove_outliers_iqr(df, column):
    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

    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
```

In [28]:
```
# import dataset
private_data = "../datasets/cleaned/cleaned_private.csv"

df = pd.read_csv(private_data, quotechar='"', escapechar='\\', thousands=','
```

In [29]:
```
# Preprocess data: Extract 'Sale Month-Year' from 'Sale Date'
df['Sale Month-Year'] = pd.to_datetime(df['Sale Date']).dt.to_period('M').as

#choose features to train model
selected_features = [
    'Area (SQFT)',
    'Postal District',
    'Type of Sale',
    'Property Type',
    'Floor Level',
    'Distance to MRT (km)',
    'Sale Month-Year',
    'Lease_Category'
]

#select feature to predict
target = 'Price'

#remove price outliers
df = remove_outliers_iqr(df, 'Price')

#create a new df with only these features
```

```
df_selected = df[selected_features + [target]].copy()

categorical_cols = ['Postal District', 'Type of Sale', 'Property Type', 'Flo
numerical_cols = ['Area (SQFT)', 'Distance to MRT (km)']

categorical_cols_to_check = [col for col in categorical_cols]
df_selected.dropna(subset=categorical_cols_to_check, inplace=True)
```

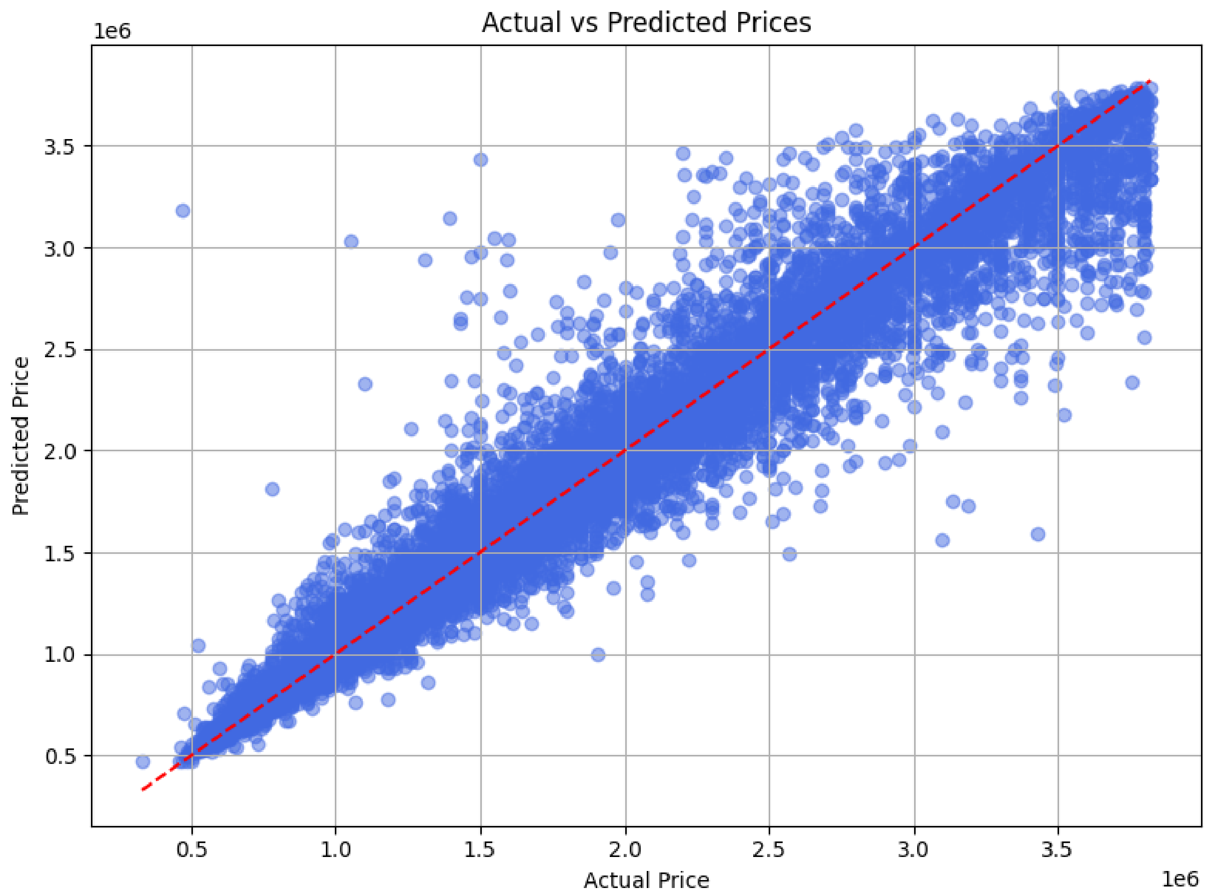
In [30]:
```
# train test split
X = df_selected.drop(target, axis=1)
y = df_selected[target]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, ra

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
    ])

rf_model = Pipeline([
    ('preprocessor', preprocessor),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=40))
])

# train model
rf_model.fit(X_train, y_train)

# make predictions
y_pred = rf_model.predict(X_test)
```

In [31]:
```
#print stats
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("\nModel Evaluation:")
print(f"1. Mean Squared Error (MSE): {mse:.2f}")
print(f"2. Mean Absolute Error (MAE): {mae:.2f}")
print(f"3. R² Score: {r2:.4f}")
```

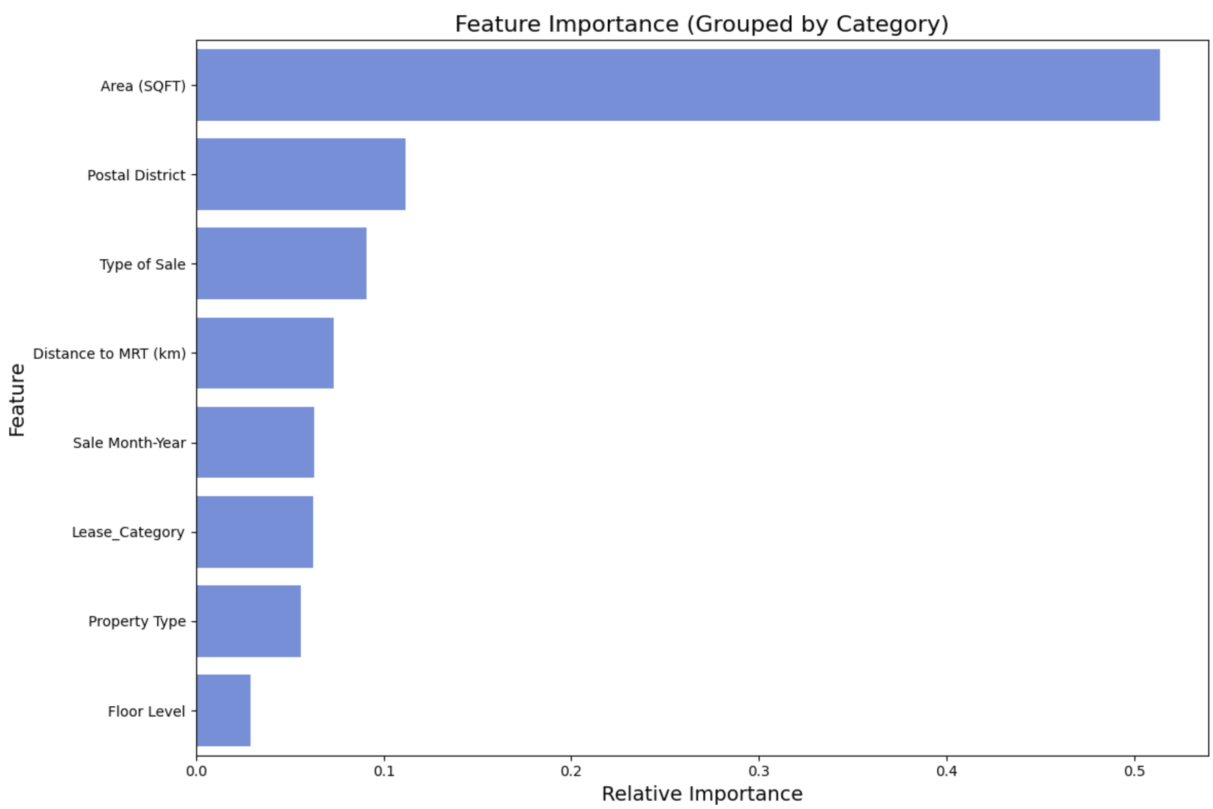
```
Model Evaluation:
1. Mean Squared Error (MSE): 20850923454.98
2. Mean Absolute Error (MAE): 79341.01
3. R² Score: 0.9577
```

In [32]:
```
plt.figure(figsize=(8, 6),  facecolor='none')
ax = plt.axes()
ax.patch.set_alpha(0)
plt.scatter(y_test, y_pred, alpha=0.5, color='royalblue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs Predicted Prices')
plt.grid(True)
plt.tight_layout()
```

```python
plt.show()

# extract feature importances
feature_importance = rf_model.named_steps['regressor'].feature_importances_

# get the feature names from the preprocessor
ohe = rf_model.named_steps['preprocessor'].transformers_[1][1]
cat_features = ohe.get_feature_names_out(categorical_cols)
feature_names = np.concatenate([numerical_cols, cat_features])

# create mapping from feature names to their importance
importances = dict(zip(feature_names, feature_importance))

# group by original feature categories
grouped_importances = defaultdict(float)

# add numerical features
for col in numerical_cols:
    grouped_importances[col] = importances[col]

# sum importances for each categorical feature
for full_feature_name in cat_features:
    for cat_col in categorical_cols:
        if cat_col in full_feature_name:
            grouped_importances[cat_col] += importances[full_feature_name]
            break

# convert to df for easier plotting
importance_df = pd.DataFrame({
    'Feature': list(grouped_importances.keys()),
    'Importance': list(grouped_importances.values())
})

# sort
importance_df = importance_df.sort_values('Importance', ascending=False)

plt.figure(figsize=(12, 8), facecolor='none')
ax = sns.barplot(x='Importance', y='Feature', data=importance_df, color='roy
ax.patch.set_alpha(0)  # Transparent axes background
plt.title('Feature Importance (Grouped by Category)', fontsize=16)
plt.xlabel('Relative Importance', fontsize=14)
plt.ylabel('Feature', fontsize=14)
plt.tight_layout()
plt.show()

#print vals
print("\nFeature Importance Ranking:")
for idx, row in importance_df.iterrows():
    print(f"{row['Feature']}: {row['Importance']:.4f}")
```



Actual vs Predicted Prices
1e6
Predicted Price
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Actual Price
1e6



Feature Importance (Grouped by Category)
Feature
Area (SQFT)
Postal District
Type of Sale
Distance to MRT (km)
Sale Month-Year
Lease_Category
Property Type
Floor Level
0.0
0.1
0.2
0.3
0.4
0.5
Relative Importance

```
Feature Importance Ranking:
Area (SQFT): 0.5136
Postal District: 0.1116
Type of Sale: 0.0908
Distance to MRT (km): 0.0734
Sale Month-Year: 0.0632
Lease_Category: 0.0626
Property Type: 0.0557
Floor Level: 0.0290
```