House Prices : Linear Regression

In [24]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import KFold
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Reading the dataset into a Pandas DataFrame.

In [25]:
```
df = pd.read_csv('train.csv', keep_default_na=False)
df.head()
```

Out[25]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandConto
0	1	60	RL	65	8450	Pave	NA	Reg	L
1	2	20	RL	80	9600	Pave	NA	Reg	L
2	3	60	RL	68	11250	Pave	NA	IR1	L
3	4	70	RL	60	9550	Pave	NA	IR1	L
4	5	60	RL	84	14260	Pave	NA	IR1	L

5 rows × 81 columns

In [26]:
```
df.tail()
```

Out[26]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Land
1455	1456	60	RL	62	7917	Pave	NA	Reg	
1456	1457	20	RL	85	13175	Pave	NA	Reg	
1457	1458	70	RL	66	9042	Pave	NA	Reg	
1458	1459	20	RL	68	9717	Pave	NA	Reg	
1459	1460	20	RL	75	9937	Pave	NA	Reg	

5 rows × 81 columns

2 Data Preprocessing

2.1 Data Types and non-null values

In [27]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1460 non-null   object
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          1460 non-null   object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
 18  OverallCond    1460 non-null   int64
 19  YearBuilt      1460 non-null   int64
 20  YearRemodAdd   1460 non-null   int64
 21  RoofStyle      1460 non-null   object
 22  RoofMatl       1460 non-null   object
 23  Exterior1st    1460 non-null   object
 24  Exterior2nd    1460 non-null   object
 25  MasVnrType     1460 non-null   object
 26  MasVnrArea     1460 non-null   object
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1460 non-null   object
 31  BsmtCond       1460 non-null   object
 32  BsmtExposure   1460 non-null   object
 33  BsmtFinType1   1460 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1460 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1460 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
```

```
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    1460 non-null   object
 58  GarageType     1460 non-null   object
 59  GarageYrBlt    1460 non-null   object
 60  GarageFinish   1460 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1460 non-null   object
 64  GarageCond     1460 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         1460 non-null   object
 73  Fence          1460 non-null   object
 74  MiscFeature    1460 non-null   object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: int64(35), object(46)
memory usage: 924.0+ KB
```

2.2 Statistical Summary

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

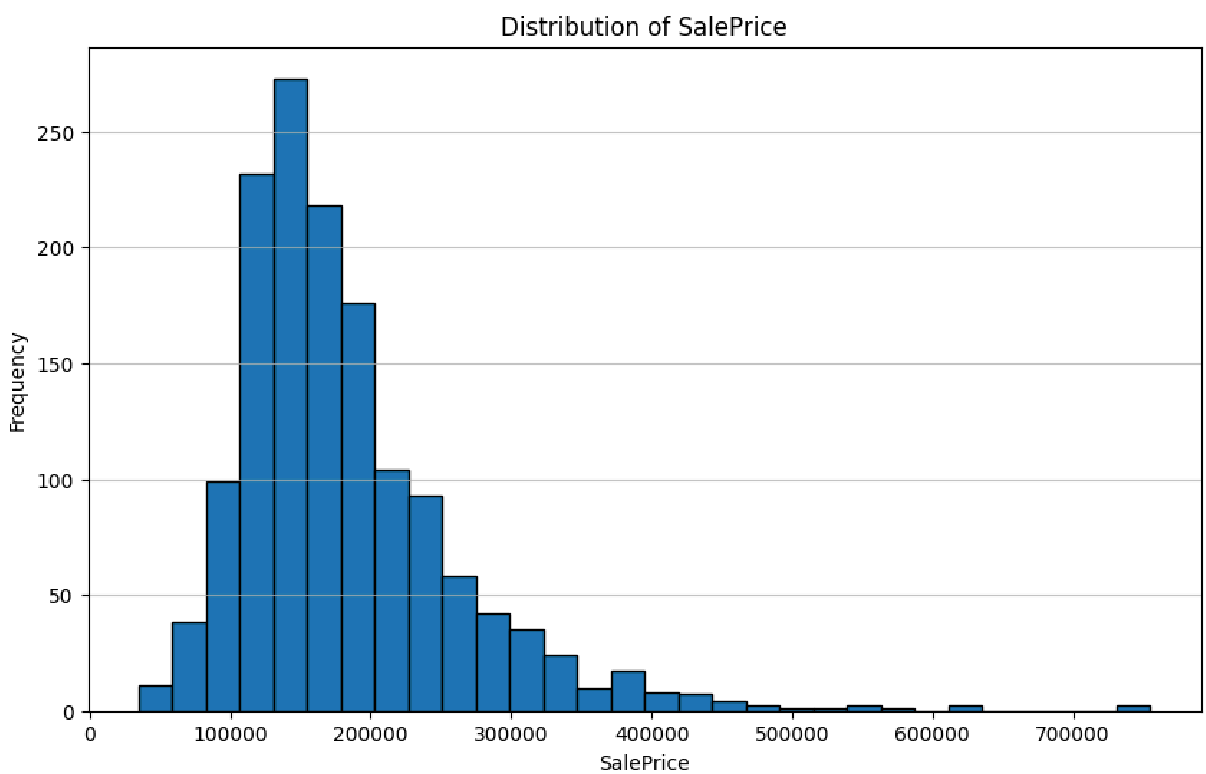
Out[28]:

	Id	MSSubClass	LotArea	OverallQual	OverallCond	YearBuilt
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	730.500000	56.897260	10516.828082	6.099315	5.575342	1971.267808
std	421.610009	42.300571	9981.264932	1.382997	1.112799	30.202904
min	1.000000	20.000000	1300.000000	1.000000	1.000000	1872.000000
25%	365.750000	20.000000	7553.500000	5.000000	5.000000	1954.000000
50%	730.500000	50.000000	9478.500000	6.000000	5.000000	1973.000000
75%	1095.250000	70.000000	11601.500000	7.000000	6.000000	2000.000000
max	1460.000000	190.000000	215245.000000	10.000000	9.000000	2010.000000

8 rows × 35 columns

In [29]:

```
# Plotting the distribution of SalePrice
plt.figure(figsize=(10, 6))
plt.hist(df['SalePrice'], bins=30, edgecolor='black')
plt.title('Distribution of SalePrice')
plt.xlabel('SalePrice')
plt.ylabel('Frequency')
plt.grid(axis='y', alpha=0.75)
plt.show()
```



In [30]:

```
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns.t
print("Numerical Columns:", numerical_columns)
```

```
Numerical Columns: ['Id', 'MSSubClass', 'LotArea', 'OverallQual', 'OverallCo
nd', 'YearBuilt', 'YearRemodAdd', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFul
lBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvG
r', 'TotRmsAbvGrd', 'Fireplaces', 'GarageCars', 'GarageArea', 'WoodDeckSF',
'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'Mis
cVal', 'MoSold', 'YrSold', 'SalePrice']
```

In [31]:

```
#List of Categorical variables
categorical_vars = df.select_dtypes(include=['object']).columns.tolist()
print("Categorical Variables:", categorical_vars)
#LotFrontage is a numerical variable, which contains 'NA' replacing by mean
df['LotFrontage'] = df['LotFrontage'].replace('NA', np.nan)
df['LotFrontage'] = df['LotFrontage'].astype(float)
df['LotFrontage'].fillna(df['LotFrontage'].mean(), inplace=True)
df.head()
```

```
Categorical Variables: ['MSZoning', 'LotFrontage', 'Street', 'Alley', 'LotSh
ape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood',
'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMat
l', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'ExterQual',
'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinT
ype1', 'BsmtFinType2', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical',
'KitchenQual', 'Functional', 'FireplaceQu', 'GarageType', 'GarageYrBlt', 'Ga
rageFinish', 'GarageQual', 'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'M
iscFeature', 'SaleType', 'SaleCondition']
```

```
/tmp/ipykernel_11894/2609515672.py:7: FutureWarning: A value is trying to be
set on a copy of a DataFrame or Series through chained assignment using an i
nplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behave
s as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'd
f.method({col: value}, inplace=True)' or df[col] = df[col].method(value) ins
tead, to perform the operation inplace on the original object.


  df['LotFrontage'].fillna(df['LotFrontage'].mean(), inplace=True)
```

Out[31]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandConto
0	1	60	RL	65.0	8450	Pave	NA	Reg	L
1	2	20	RL	80.0	9600	Pave	NA	Reg	L
2	3	60	RL	68.0	11250	Pave	NA	IR1	L
3	4	70	RL	60.0	9550	Pave	NA	IR1	L
4	5	60	RL	84.0	14260	Pave	NA	IR1	L

5 rows × 81 columns

2.3 Handling Missing Values

In [32]:
```
df.isnull().sum()
```

Out[32]:
```
Id               0
MSSubClass       0
MSZoning         0
LotFrontage      0
LotArea          0
                ..
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
Length: 81, dtype: int64
```

3. Splitting the dataset

Divide the dataset into two sets using k-fold cross validation technique entitled to train and test set respectively.

In [33]:
```
# First, let's prepare our features and handle any remaining missing values
# Select relevant numerical features for our models
features_model1 = ['LotFrontage', 'LotArea']
features_model2 = ['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond']
features_model3 = ['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', '

# Check for missing values in our target variable and features
print("Missing values in SalePrice:", df['SalePrice'].isnull().sum())
print("Missing values in features:")
for feature in features_model3:
    missing_count = df[feature].isnull().sum()
    print(f"{feature}: {missing_count}")

# Check data types
print(f"\nData types for features:")
for feature in features_model3:
    print(f"{feature}: {df[feature].dtype}")

# Remove any rows with missing values in our target variable or key features
print(f"\nOriginal dataset shape: {df.shape}")
df_clean = df.dropna(subset=['SalePrice'] + features_model3)
print(f"Dataset shape after removing missing values: {df_clean.shape}")

# Prepare target variable
y = df_clean['SalePrice']

# Prepare feature sets
X_model1 = df_clean[features_model1]
X_model2 = df_clean[features_model2]
X_model3 = df_clean[features_model3]

print(f"\nFeature sets prepared:")
print(f"Model 1 features: {features_model1}")
```

```python
print(f"Model 2 features: {features_model2}")
print(f"Model 3 features: {features_model3}")
print(f"\nTarget variable (y) shape: {y.shape}")
print(f"Model 1 features shape: {X_model1.shape}")
print(f"Model 2 features shape: {X_model2.shape}")
print(f"Model 3 features shape: {X_model3.shape}")
```

```
Missing values in SalePrice: 0
Missing values in features:
LotFrontage: 0
LotArea: 0
OverallQual: 0
OverallCond: 0
1stFlrSF: 0
GrLivArea: 0

Data types for features:
LotFrontage: float64
LotArea: int64
OverallQual: int64
OverallCond: int64
1stFlrSF: int64
GrLivArea: int64

Original dataset shape: (1460, 81)
Dataset shape after removing missing values: (1460, 81)

Feature sets prepared:
Model 1 features: ['LotFrontage', 'LotArea']
Model 2 features: ['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond']
Model 3 features: ['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
'1stFlrSF', 'GrLivArea']

Target variable (y) shape: (1460,)
Model 1 features shape: (1460, 2)
Model 2 features shape: (1460, 4)
Model 3 features shape: (1460, 6)
```

In [34]:
```python
k = 5
kf = KFold(n_splits=k, shuffle=True, random_state=42)

# Initialize lists to store results for each model
models_data = {
    'Simple Linear Regression (LotArea only)': {'features': ['LotArea'], 'X'
    'Model 1 (LotFrontage, LotArea)': {'features': features_model1, 'X': X_m
    'Model 2 (LotFrontage, LotArea, OverallQual, OverallCond)': {'features':
    'Model 3 (All features)': {'features': features_model3, 'X': X_model3}
}

# Store results for each model
results = {model_name: {
    'train_mse': [], 'test_mse': [], 'train_r2': [], 'test_r2': [],
    'coefficients': [], 'intercepts': []
} for model_name in models_data.keys()}

print("Starting K-Fold Cross Validation...")
```

```
print(f"Using {k}-fold cross validation")
print("="*60)
```

```
Starting K-Fold Cross Validation...
Using 5-fold cross validation
============================================================
```

In [35]:

```
fold = 1
for train_index, test_index in kf.split(y):
    print(f"\nFold {fold}:")
    print("-" * 20)

    # Split data for this fold
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Train and evaluate each model
    for model_name, model_info in models_data.items():
        X = model_info['X']
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]

        # Create and train linear regression model
        lr = LinearRegression()
        lr.fit(X_train, y_train)

        # Make predictions
        y_train_pred = lr.predict(X_train)
        y_test_pred = lr.predict(X_test)

        # Calculate metrics
        train_mse = mean_squared_error(y_train, y_train_pred)
        test_mse = mean_squared_error(y_test, y_test_pred)
        train_r2 = r2_score(y_train, y_train_pred)
        test_r2 = r2_score(y_test, y_test_pred)

        # Store results
        results[model_name]['train_mse'].append(train_mse)
        results[model_name]['test_mse'].append(test_mse)
        results[model_name]['train_r2'].append(train_r2)
        results[model_name]['test_r2'].append(test_r2)
        results[model_name]['coefficients'].append(lr.coef_)
        results[model_name]['intercepts'].append(lr.intercept_)

        print(f"{model_name}:")
        print(f"  Train MSE: {train_mse:.2f}, Test MSE: {test_mse:.2f}")
        print(f"  Train R²: {train_r2:.4f}, Test R²: {test_r2:.4f}")

    fold += 1

print("\nK-Fold Cross Validation completed!")
print("="*60)
```

```
Fold 1:
--------------------
Simple Linear Regression (LotArea only):
  Train MSE: 5541876621.93, Test MSE: 7189094014.83
  Train R²: 0.0709, Test R²: 0.0627
Model 1 (LotFrontage, LotArea):
  Train MSE: 5187706359.35, Test MSE: 6391769244.79
  Train R²: 0.1302, Test R²: 0.1667
Model 2 (LotFrontage, LotArea, OverallQual, OverallCond):
  Train MSE: 2031959572.87, Test MSE: 2326923040.59
  Train R²: 0.6593, Test R²: 0.6966
Model 3 (All features):
  Train MSE: 1594275967.62, Test MSE: 1702504242.03
  Train R²: 0.7327, Test R²: 0.7780

Fold 2:
--------------------
Simple Linear Regression (LotArea only):
  Train MSE: 5743207806.18, Test MSE: 6393512739.93
  Train R²: 0.0700, Test R²: 0.0597
Model 1 (LotFrontage, LotArea):
  Train MSE: 5300597764.38, Test MSE: 5910512870.46
  Train R²: 0.1417, Test R²: 0.1307
Model 2 (LotFrontage, LotArea, OverallQual, OverallCond):
  Train MSE: 2053062935.08, Test MSE: 2218379551.32
  Train R²: 0.6676, Test R²: 0.6737
Model 3 (All features):
  Train MSE: 1657148893.40, Test MSE: 1443066802.25
  Train R²: 0.7317, Test R²: 0.7878

Fold 3:
--------------------
Simple Linear Regression (LotArea only):
  Train MSE: 6044530616.25, Test MSE: 5181360177.35
  Train R²: 0.0704, Test R²: 0.0621
Model 1 (LotFrontage, LotArea):
  Train MSE: 5505585780.80, Test MSE: 5189460880.98
  Train R²: 0.1533, Test R²: 0.0607
Model 2 (LotFrontage, LotArea, OverallQual, OverallCond):
  Train MSE: 1998877019.06, Test MSE: 2545077057.47
  Train R²: 0.6926, Test R²: 0.5393
Model 3 (All features):
  Train MSE: 1312417880.99, Test MSE: 3069513195.16
  Train R²: 0.7982, Test R²: 0.4444

Fold 4:
--------------------
Simple Linear Regression (LotArea only):
  Train MSE: 5790195671.80, Test MSE: 6500497232.62
  Train R²: 0.0828, Test R²: -0.0353
Model 1 (LotFrontage, LotArea):
  Train MSE: 5432144092.74, Test MSE: 5564972429.36
  Train R²: 0.1395, Test R²: 0.1137
Model 2 (LotFrontage, LotArea, OverallQual, OverallCond):
  Train MSE: 2121618371.57, Test MSE: 2002857872.51
  Train R²: 0.6639, Test R²: 0.6810
```

```
Model 3 (All features):
  Train MSE: 1676454936.75, Test MSE: 1351667140.21
  Train R²: 0.7344, Test R²: 0.7847

Fold 5:
--------------------
Simple Linear Regression (LotArea only):
  Train MSE: 6160516422.26, Test MSE: 4714667164.94
  Train R²: 0.0633, Test R²: 0.0980
Model 1 (LotFrontage, LotArea):
  Train MSE: 5601182550.95, Test MSE: 4722809022.10
  Train R²: 0.1483, Test R²: 0.0964
Model 2 (LotFrontage, LotArea, OverallQual, OverallCond):
  Train MSE: 2168161716.58, Test MSE: 1756509217.54
  Train R²: 0.6703, Test R²: 0.6639
Model 3 (All features):
  Train MSE: 1737070127.12, Test MSE: 1107656712.95
  Train R²: 0.7359, Test R²: 0.7881

K-Fold Cross Validation completed!
============================================================
```

In [36]:

```python
print("\n" + "="*80)
print("SUMMARY OF MODEL PERFORMANCE ACROSS ALL FOLDS")
print("="*80)

summary_results = {}
for model_name in models_data.keys():
    avg_train_mse = np.mean(results[model_name]['train_mse'])
    avg_test_mse = np.mean(results[model_name]['test_mse'])
    avg_train_r2 = np.mean(results[model_name]['train_r2'])
    avg_test_r2 = np.mean(results[model_name]['test_r2'])

    std_train_mse = np.std(results[model_name]['train_mse'])
    std_test_mse = np.std(results[model_name]['test_mse'])
    std_train_r2 = np.std(results[model_name]['train_r2'])
    std_test_r2 = np.std(results[model_name]['test_r2'])

    summary_results[model_name] = {
        'avg_train_mse': avg_train_mse, 'avg_test_mse': avg_test_mse,
        'avg_train_r2': avg_train_r2, 'avg_test_r2': avg_test_r2,
        'std_train_mse': std_train_mse, 'std_test_mse': std_test_mse,
        'std_train_r2': std_train_r2, 'std_test_r2': std_test_r2
    }

    print(f"\n{model_name}:")
    print(f"  Average Train MSE: {avg_train_mse:.2f} (±{std_train_mse:.2f})"
    print(f"  Average Test MSE:  {avg_test_mse:.2f} (±{std_test_mse:.2f})")
    print(f"  Average Train R²:  {avg_train_r2:.4f} (±{std_train_r2:.4f})")
    print(f"  Average Test R²:   {avg_test_r2:.4f} (±{std_test_r2:.4f})")

print("\n" + "="*80)
```

```
================================================================================
====
SUMMARY OF MODEL PERFORMANCE ACROSS ALL FOLDS
================================================================================
====

Simple Linear Regression (LotArea only):
  Average Train MSE: 5856065427.68 (±220907133.67)
  Average Test MSE:  5995826265.93 (±910105366.24)
  Average Train R²:  0.0715 (±0.0063)
  Average Test R²:   0.0495 (±0.0447)

Model 1 (LotFrontage, LotArea):
  Average Train MSE: 5405443309.64 (±146599634.94)
  Average Test MSE:  5555904889.54 (±574948379.69)
  Average Train R²:  0.1426 (±0.0079)
  Average Test R²:   0.1136 (±0.0352)

Model 2 (LotFrontage, LotArea, OverallQual, OverallCond):
  Average Train MSE: 2074735923.03 (±61612418.77)
  Average Test MSE:  2169949347.89 (±270761639.02)
  Average Train R²:  0.6707 (±0.0115)
  Average Test R²:   0.6509 (±0.0568)

Model 3 (All features):
  Average Train MSE: 1595473561.18 (±148683132.60)
  Average Test MSE:  1734881618.52 (±693932279.90)
  Average Train R²:  0.7466 (±0.0258)
  Average Test R²:   0.7166 (±0.1362)

================================================================================
====
```

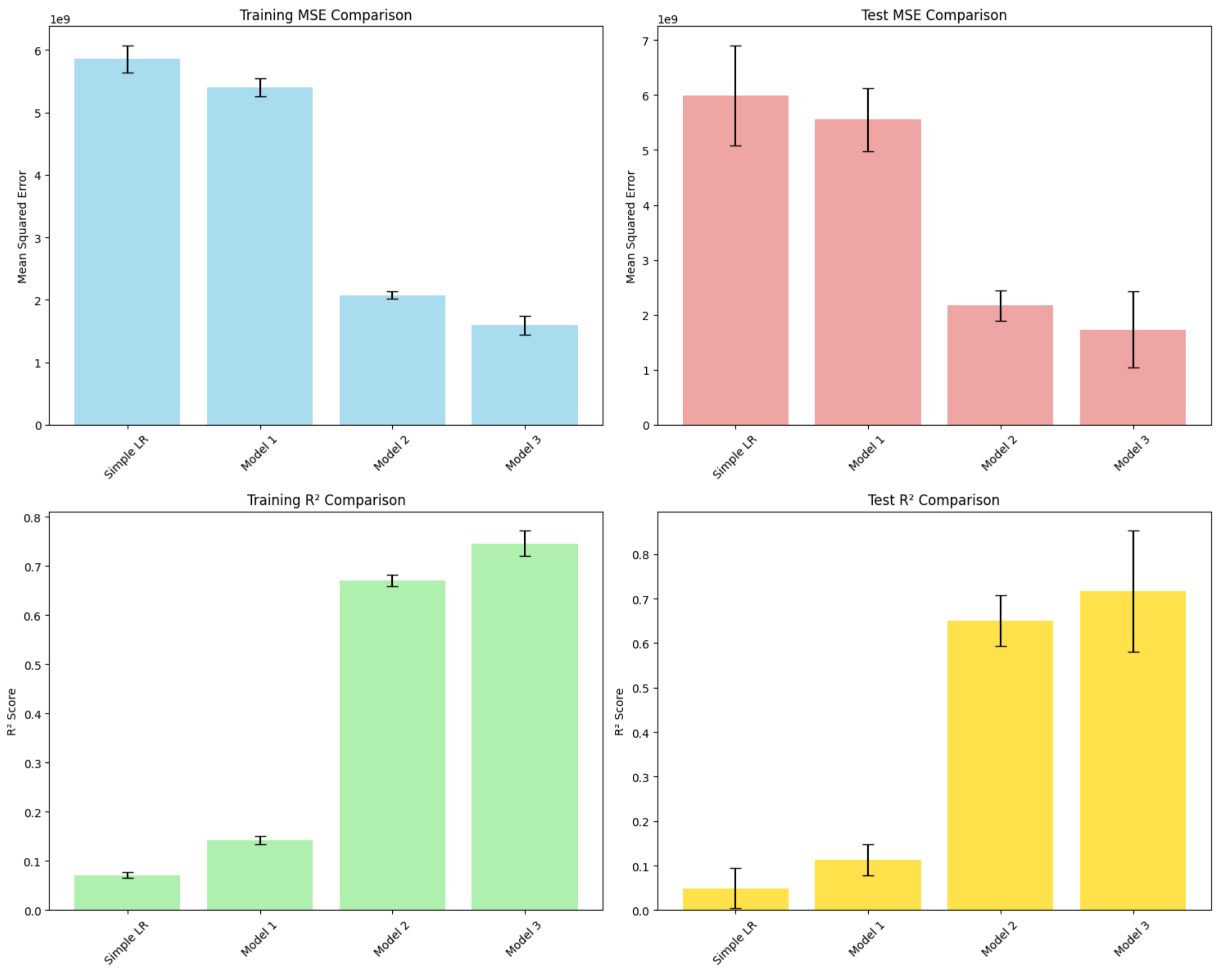
In [37]:

```python
print("DETAILED COEFFICIENT ANALYSIS")
print("="*80)

for model_name, model_info in models_data.items():
    print(f"\n{model_name}:")
    print("-" * len(model_name))

    # Calculate average coefficients and intercept
    avg_coefficients = np.mean(results[model_name]['coefficients'], axis=0)
    avg_intercept = np.mean(results[model_name]['intercepts'])

    std_coefficients = np.std(results[model_name]['coefficients'], axis=0)
    std_intercept = np.std(results[model_name]['intercepts'])

    print(f"  Intercept: {avg_intercept:.2f} (±{std_intercept:.2f})")

    features = model_info['features']
    for i, feature in enumerate(features):
        print(f"  {feature}: {avg_coefficients[i]:.2f} (±{std_coefficients[i

    # Display the regression equation
    equation = f"SalePrice = {avg_intercept:.2f}"
    for i, feature in enumerate(features):
```

```
        if avg_coefficients[i] >= 0:
            equation += f" + {avg_coefficients[i]:.2f}×{feature}"
        else:
            equation += f" - {abs(avg_coefficients[i]):.2f}×{feature}"

    print(f"\n  Regression Equation: {equation}")

print("\n" + "="*80)
```

```
DETAILED COEFFICIENT ANALYSIS
============================================================================
====

Simple Linear Regression (LotArea only):
---------------------------------------
  Intercept: 157978.16 (±3664.22)
  LotArea: 2.18 (±0.39)

  Regression Equation: SalePrice = 157978.16 + 2.18×LotArea

Model 1 (LotFrontage, LotArea):
------------------------------
  Intercept: 94361.69 (±7890.40)
  LotFrontage: 1013.78 (±123.14)
  LotArea: 1.48 (±0.32)

  Regression Equation: SalePrice = 94361.69 + 1013.78×LotFrontage + 1.48×Lot
Area

Model 2 (LotFrontage, LotArea, OverallQual, OverallCond):
--------------------------------------------------------
  Intercept: -122296.92 (±12246.28)
  LotFrontage: 414.37 (±86.96)
  LotArea: 1.24 (±0.19)
  OverallQual: 42961.40 (±754.04)
  OverallCond: -143.80 (±414.39)

  Regression Equation: SalePrice = -122296.92 + 414.37×LotFrontage + 1.24×Lo
tArea + 42961.40×OverallQual - 143.80×OverallCond

Model 3 (All features):
----------------------
  Intercept: -129666.74 (±14067.21)
  LotFrontage: 67.12 (±65.07)
  LotArea: 0.66 (±0.06)
  OverallQual: 31123.91 (±741.01)
  OverallCond: 1385.18 (±695.95)
  1stFlrSF: 34.87 (±4.77)
  GrLivArea: 40.16 (±3.93)

  Regression Equation: SalePrice = -129666.74 + 67.12×LotFrontage + 0.66×Lot
Area + 31123.91×OverallQual + 1385.18×OverallCond + 34.87×1stFlrSF + 40.16×G
rLivArea

============================================================================
====
```

In [38]:
```
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(15, 12))

# Prepare data for plotting
model_names = list(models_data.keys())
train_mse_means = [summary_results[name]['avg_train_mse'] for name in model_
test_mse_means = [summary_results[name]['avg_test_mse'] for name in model_na
train_r2_means = [summary_results[name]['avg_train_r2'] for name in model_na
test_r2_means = [summary_results[name]['avg_test_r2'] for name in model_name

train_mse_stds = [summary_results[name]['std_train_mse'] for name in model_r
test_mse_stds = [summary_results[name]['std_test_mse'] for name in model_nam
train_r2_stds = [summary_results[name]['std_train_r2'] for name in model_nam
test_r2_stds = [summary_results[name]['std_test_r2'] for name in model_names

# Shorten model names for better visualization
short_names = ['Simple LR', 'Model 1', 'Model 2', 'Model 3']

# Plot 1: Training MSE Comparison
ax1.bar(short_names, train_mse_means, yerr=train_mse_stds, capsize=5, alpha=
ax1.set_title('Training MSE Comparison')
ax1.set_ylabel('Mean Squared Error')
ax1.tick_params(axis='x', rotation=45)

# Plot 2: Test MSE Comparison
ax2.bar(short_names, test_mse_means, yerr=test_mse_stds, capsize=5, alpha=0.
ax2.set_title('Test MSE Comparison')
ax2.set_ylabel('Mean Squared Error')
ax2.tick_params(axis='x', rotation=45)

# Plot 3: Training R² Comparison
ax3.bar(short_names, train_r2_means, yerr=train_r2_stds, capsize=5, alpha=0.
ax3.set_title('Training R² Comparison')
ax3.set_ylabel('R² Score')
ax3.tick_params(axis='x', rotation=45)

# Plot 4: Test R² Comparison
ax4.bar(short_names, test_r2_means, yerr=test_r2_stds, capsize=5, alpha=0.7,
ax4.set_title('Test R² Comparison')
ax4.set_ylabel('R² Score')
ax4.tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()

# Also create a summary table
print("\nMODEL PERFORMANCE SUMMARY TABLE")
print("="*80)
print(f"{'Model':<30} {'Train MSE':<12} {'Test MSE':<12} {'Train R²':<12} {'
print("-" * 80)
for i, name in enumerate(model_names):
    short_name = short_names[i]
    print(f"{short_name:<30} {train_mse_means[i]:<12.2f} {test_mse_means[i]:
print("="*80)
```




```
MODEL PERFORMANCE SUMMARY TABLE
================================================================================
Model                           Train MSE     Test MSE      Train R²      Test R²
--------------------------------------------------------------------------------
Simple LR                       5856065427.68 5995826265.93 0.0715        0.0495
Model 1                         5405443309.64 5555904889.54 0.1426        0.1136
Model 2                         2074735923.03 2169949347.89 0.6707        0.6509
Model 3                         1595473561.18 1734881618.52 0.7466        0.7166
================================================================================
```

In [39]:
```python
# Model Analysis and Conclusions
print("MODEL ANALYSIS AND INSIGHTS")
print("="*80)

# Find the best performing model
best_test_r2_idx = np.argmax(test_r2_means)
best_test_mse_idx = np.argmin(test_mse_means)

print(f"\nBest Model by Test R² Score: {short_names[best_test_r2_idx]} (R² =
```

```
print(f"Best Model by Test MSE: {short_names[best_test_mse_idx]} (MSE = {tes

# Calculate improvement from simple to complex models
simple_test_r2 = test_r2_means[0]
best_test_r2 = test_r2_means[best_test_r2_idx]
improvement = ((best_test_r2 - simple_test_r2) / simple_test_r2) * 100

print(f"\nImprovement from Simple Linear Regression to Best Model: {improvem

# Check for overfitting
print(f"\nOverfitting Analysis (Train R² - Test R²):")
for i, name in enumerate(short_names):
    overfitting = train_r2_means[i] - test_r2_means[i]
    print(f"  {name}: {overfitting:.4f}")

print(f"1. Simple Linear Regression (LotArea only) achieved R² = {simple_tes


# Display feature importance (from the best model)
best_model_name = list(models_data.keys())[best_test_r2_idx]
best_features = models_data[best_model_name]['features']
best_coeffs = np.mean(results[best_model_name]['coefficients'], axis=0)

print(f"\nFeature Importance in Best Model ({short_names[best_test_r2_idx]})
feature_importance = list(zip(best_features, np.abs(best_coeffs)))
feature_importance.sort(key=lambda x: x[1], reverse=True)

for feature, importance in feature_importance:
    print(f"  {feature}: {importance:.2f}")

print("="*80)
```

```
MODEL ANALYSIS AND INSIGHTS
================================================================================
====

Best Model by Test R² Score: Model 3 (R² = 0.7166)
Best Model by Test MSE: Model 3 (MSE = 1734881618.52)

Improvement from Simple Linear Regression to Best Model: 1348.91%

Overfitting Analysis (Train R² - Test R²):
  Simple LR: 0.0220
  Model 1: 0.0290
  Model 2: 0.0198
  Model 3: 0.0300
1. Simple Linear Regression (LotArea only) achieved R² = 0.0495

Feature Importance in Best Model (Model 3):
  OverallQual: 31123.91
  OverallCond: 1385.18
  LotFrontage: 67.12
  GrLivArea: 40.16
  1stFlrSF: 34.87
  LotArea: 0.66
================================================================================
====
```

4. Multiple Regression with Mixed Features (Numerical + Categorical)

In [40]:

```python
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
import pandas as pd

print("Examining categorical features:")
print("Street unique values:", df['Street'].unique())
print("Street value counts:", df['Street'].value_counts())
print("\nNeighborhood unique values (first 10):", df['Neighborhood'].unique(
print("Neighborhood value counts (top 10):")
print(df['Neighborhood'].value_counts().head(10))

# Checking if we have YearBuilt or need to create Year feature
print(f"\nAvailable year-related columns:")
year_columns = [col for col in df.columns if 'year' in col.lower() or 'yr' i
print(year_columns)

# Using YearBuilt as our Year feature
if 'YearBuilt' in df.columns:
    print(f"Using YearBuilt as Year feature")
    print(f"YearBuilt range: {df['YearBuilt'].min()} - {df['YearBuilt'].max(
else:
    print("YearBuilt not found, will create a dummy Year feature")
```

```
Examining categorical features:
Street unique values: ['Pave' 'Grvl']
Street value counts: Street
Pave    1454
Grvl       6
Name: count, dtype: int64

Neighborhood unique values (first 10): ['CollgCr' 'Veenker' 'Crawfor' 'NoRid
ge' 'Mitchel' 'Somerst' 'NWAmes'
 'OldTown' 'BrkSide' 'Sawyer']
Neighborhood value counts (top 10):
Neighborhood
NAmes      225
CollgCr    150
OldTown    113
Edwards    100
Somerst     86
Gilbert     79
NridgHt     77
Sawyer      74
NWAmes      73
SawyerW     59
Name: count, dtype: int64

Available year-related columns:
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
Using YearBuilt as Year feature
YearBuilt range: 1872 - 2010
```

In [41]:

```python
from sklearn.preprocessing import LabelEncoder

mixed_features_model4 = {
    'numerical': ['LotArea'],
    'categorical': ['Street']
}

mixed_features_model5 = {
    'numerical': ['LotArea', 'OverallCond'],
    'categorical': ['Street', 'Neighborhood']
}

mixed_features_model6 = {
    'numerical': ['LotArea', 'OverallCond', '1stFlrSF'],
    'categorical': ['Street', 'Neighborhood', 'YearBuilt']  # Using YearBuil
}

def prepare_mixed_features_simple(df, numerical_features, categorical_featur
    """
    Prepare mixed features using Label Encoding for categorical variables
    to keep the exact number of features as specified in the assignment
    """
    # Start with numerical features
    X_mixed = df[numerical_features].copy()

    # Add label-encoded categorical features
    le = LabelEncoder()
```

```python
    for cat_feature in categorical_features:
        if cat_feature == 'YearBuilt':
            # Use YearBuilt as-is (it's already numerical, but we'll treat i
            X_mixed[f'{cat_feature}_encoded'] = le.fit_transform(df[cat_feat
        else:
            # Standard label encoding for other categorical variables
            X_mixed[f'{cat_feature}_encoded'] = le.fit_transform(df[cat_feat

    return X_mixed

print("Preparing mixed feature datasets with correct feature counts...")
print("Using Label Encoding to maintain exact feature counts as per assignme

X_model4 = prepare_mixed_features_simple(df,
                                          mixed_features_model4['numerical']
                                          mixed_features_model4['categorical

X_model5 = prepare_mixed_features_simple(df,
                                          mixed_features_model5['numerical']
                                          mixed_features_model5['categorical

X_model6 = prepare_mixed_features_simple(df,
                                          mixed_features_model6['numerical']
                                          mixed_features_model6['categorical

print(f"Model 4 shape: {X_model4.shape} (Expected: 2 features)")
print(f"Model 5 shape: {X_model5.shape} (Expected: 4 features)")
print(f"Model 6 shape: {X_model6.shape} (Expected: 6 features)")

print(f"\nModel 4 features: {list(X_model4.columns)}")
print(f"Model 5 features: {list(X_model5.columns)}")
print(f"Model 6 features: {list(X_model6.columns)}")

print(f"\nFeature specifications as per assignment:")
print(f"Model 4: LotArea, Street")
print(f"Model 5: LotArea, OverallCond, Street, Neighborhood")
print(f"Model 6: LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year"
```

```
Preparing mixed feature datasets with correct feature counts...
Using Label Encoding to maintain exact feature counts as per assignment
Model 4 shape: (1460, 2) (Expected: 2 features)
Model 5 shape: (1460, 4) (Expected: 4 features)
Model 6 shape: (1460, 6) (Expected: 6 features)

Model 4 features: ['LotArea', 'Street_encoded']
Model 5 features: ['LotArea', 'OverallCond', 'Street_encoded', 'Neighborhood
_encoded']
Model 6 features: ['LotArea', 'OverallCond', '1stFlrSF', 'Street_encoded',
'Neighborhood_encoded', 'YearBuilt_encoded']

Feature specifications as per assignment:
Model 4: LotArea, Street
Model 5: LotArea, OverallCond, Street, Neighborhood
Model 6: LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year
```

In [42]:
```python
mixed_models_data = {
    'Model 4 (LotArea, Street)': {'X': X_model4, 'features': mixed_features_
    'Model 5 (LotArea, OverallCond, Street, Neighborhood)': {'X': X_model5,
    'Model 6 (LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year)':
}

# Store results for mixed models
mixed_results = {model_name: {
    'train_mse': [], 'test_mse': [], 'train_r2': [], 'test_r2': [],
    'coefficients': [], 'intercepts': [], 'feature_names': []
} for model_name in mixed_models_data.keys()}

print("Starting K-Fold Cross Validation for Mixed Models...")
print(f"Using {k}-fold cross validation")
print("="*60)

# Perform K-Fold Cross Validation for mixed models
fold = 1
for train_index, test_index in kf.split(y):
    print(f"\nFold {fold}:")
    print("-" * 20)

    # Split data for this fold
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Train and evaluate each mixed model
    for model_name, model_info in mixed_models_data.items():
        X = model_info['X']
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]

        # Create and train linear regression model
        lr = LinearRegression()
        lr.fit(X_train, y_train)

        # Make predictions
        y_train_pred = lr.predict(X_train)
        y_test_pred = lr.predict(X_test)

        # Calculate metrics
        train_mse = mean_squared_error(y_train, y_train_pred)
        test_mse = mean_squared_error(y_test, y_test_pred)
        train_r2 = r2_score(y_train, y_train_pred)
        test_r2 = r2_score(y_test, y_test_pred)

        # Store results
        mixed_results[model_name]['train_mse'].append(train_mse)
        mixed_results[model_name]['test_mse'].append(test_mse)
        mixed_results[model_name]['train_r2'].append(train_r2)
        mixed_results[model_name]['test_r2'].append(test_r2)
        mixed_results[model_name]['coefficients'].append(lr.coef_)
        mixed_results[model_name]['intercepts'].append(lr.intercept_)
        mixed_results[model_name]['feature_names'] = list(X.columns)

        print(f"{model_name}:")
        print(f"  Train MSE: {train_mse:.2f}, Test MSE: {test_mse:.2f}")
```

```
        print(f"  Train R²: {train_r2:.4f}, Test R²: {test_r2:.4f}")

    fold += 1

print("\nK-Fold Cross Validation for Mixed Models completed!")
print("="*60)
```

```
Starting K-Fold Cross Validation for Mixed Models...
Using 5-fold cross validation
============================================================

Fold 1:
--------------------
Model 4 (LotArea, Street):
  Train MSE: 5501517875.25, Test MSE: 7066617147.62
  Train R²: 0.0776, Test R²: 0.0787
Model 5 (LotArea, OverallCond, Street, Neighborhood):
  Train MSE: 5255968054.67, Test MSE: 6627543389.01
  Train R²: 0.1188, Test R²: 0.1360
Model 6 (LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year):
  Train MSE: 2731781241.83, Test MSE: 3112864268.77
  Train R²: 0.5420, Test R²: 0.5942

Fold 2:
--------------------
Model 4 (LotArea, Street):
  Train MSE: 5681823026.86, Test MSE: 6353847486.19
  Train R²: 0.0800, Test R²: 0.0655
Model 5 (LotArea, OverallCond, Street, Neighborhood):
  Train MSE: 5420442699.55, Test MSE: 5973014669.19
  Train R²: 0.1223, Test R²: 0.1215
Model 6 (LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year):
  Train MSE: 2770274250.89, Test MSE: 2928670148.33
  Train R²: 0.5514, Test R²: 0.5693

Fold 3:
--------------------
Model 4 (LotArea, Street):
  Train MSE: 5963391668.40, Test MSE: 5251925666.86
  Train R²: 0.0829, Test R²: 0.0494
Model 5 (LotArea, OverallCond, Street, Neighborhood):
  Train MSE: 5683235215.79, Test MSE: 4919492989.28
  Train R²: 0.1259, Test R²: 0.1095
Model 6 (LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year):
  Train MSE: 2633470532.62, Test MSE: 3653198890.14
  Train R²: 0.5950, Test R²: 0.3387

Fold 4:
--------------------
Model 4 (LotArea, Street):
  Train MSE: 5756539473.50, Test MSE: 6312944192.43
  Train R²: 0.0881, Test R²: -0.0054
Model 5 (LotArea, OverallCond, Street, Neighborhood):
  Train MSE: 5430058237.50, Test MSE: 6261618030.70
  Train R²: 0.1398, Test R²: 0.0028
Model 6 (LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year):
  Train MSE: 2857270497.66, Test MSE: 2644853107.39
  Train R²: 0.5474, Test R²: 0.5788

Fold 5:
--------------------
Model 4 (LotArea, Street):
  Train MSE: 6093110687.71, Test MSE: 4703317777.04
```

```
  Train R²: 0.0735, Test R²: 0.1002
Model 5 (LotArea, OverallCond, Street, Neighborhood):
  Train MSE: 5772070001.46, Test MSE: 4560069474.27
  Train R²: 0.1223, Test R²: 0.1276
Model 6 (LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year):
  Train MSE: 2948996154.60, Test MSE: 2223596122.89
  Train R²: 0.5516, Test R²: 0.5746

K-Fold Cross Validation for Mixed Models completed!
============================================================
```

In [43]:

```python
# Calculate and display average performance metrics for mixed models
print("\n" + "="*80)
print("SUMMARY OF MIXED MODEL PERFORMANCE ACROSS ALL FOLDS")
print("="*80)

mixed_summary_results = {}
for model_name in mixed_models_data.keys():
    avg_train_mse = np.mean(mixed_results[model_name]['train_mse'])
    avg_test_mse = np.mean(mixed_results[model_name]['test_mse'])
    avg_train_r2 = np.mean(mixed_results[model_name]['train_r2'])
    avg_test_r2 = np.mean(mixed_results[model_name]['test_r2'])

    std_train_mse = np.std(mixed_results[model_name]['train_mse'])
    std_test_mse = np.std(mixed_results[model_name]['test_mse'])
    std_train_r2 = np.std(mixed_results[model_name]['train_r2'])
    std_test_r2 = np.std(mixed_results[model_name]['test_r2'])

    mixed_summary_results[model_name] = {
        'avg_train_mse': avg_train_mse, 'avg_test_mse': avg_test_mse,
        'avg_train_r2': avg_train_r2, 'avg_test_r2': avg_test_r2,
        'std_train_mse': std_train_mse, 'std_test_mse': std_test_mse,
        'std_train_r2': std_train_r2, 'std_test_r2': std_test_r2
    }

    print(f"\n{model_name}:")
    print(f"  Average Train MSE: {avg_train_mse:.2f} (±{std_train_mse:.2f})"
    print(f"  Average Test MSE:  {avg_test_mse:.2f} (±{std_test_mse:.2f})")
    print(f"  Average Train R²:  {avg_train_r2:.4f} (±{std_train_r2:.4f})")
    print(f"  Average Test R²:   {avg_test_r2:.4f} (±{std_test_r2:.4f})")

print("\n" + "="*80)
```

```
================================================================================
====
SUMMARY OF MIXED MODEL PERFORMANCE ACROSS ALL FOLDS
================================================================================
====

Model 4 (LotArea, Street):
  Average Train MSE: 5799276546.34 (±208592563.99)
  Average Test MSE:  5937730454.03 (±846454578.12)
  Average Train R²:  0.0804 (±0.0049)
  Average Test R²:   0.0577 (±0.0357)

Model 5 (LotArea, OverallCond, Street, Neighborhood):
  Average Train MSE: 5512354841.79 (±188471124.56)
  Average Test MSE:  5668347710.49 (±794218108.66)
  Average Train R²:  0.1258 (±0.0074)
  Average Test R²:   0.0995 (±0.0491)

Model 6 (LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year):
  Average Train MSE: 2788358535.52 (±107769780.68)
  Average Test MSE:  2912636507.51 (±476500887.22)
  Average Train R²:  0.5575 (±0.0191)
  Average Test R²:   0.5311 (±0.0965)

================================================================================
====
```

In [44]:

```
# Extract LotArea coefficients from all models
print("LOTAREA COEFFICIENT ANALYSIS ACROSS ALL MODELS")
print("="*80)

# Function to extract LotArea coefficient from model results
def get_lotarea_coefficient(model_results, feature_names):
    """Extract the LotArea coefficient from model results"""
    coefficients = np.mean(model_results['coefficients'], axis=0)

    # Find the index of LotArea in the feature names
    if 'LotArea' in feature_names:
        lotarea_idx = feature_names.index('LotArea')
        return coefficients[lotarea_idx]
    else:
        return None

# Collect LotArea coefficients from all models
lotarea_coefficients = {}
model_labels = []

# Original models (1-3)
original_model_names = ['Simple Linear Regression (LotArea only)', 'Model 1
                        'Model 2 (LotFrontage, LotArea, OverallQual, OverallC

for model_name in original_model_names:
    if model_name in results:
        features = models_data[model_name]['features']
        coef = get_lotarea_coefficient(results[model_name], features)
        if coef is not None:
```

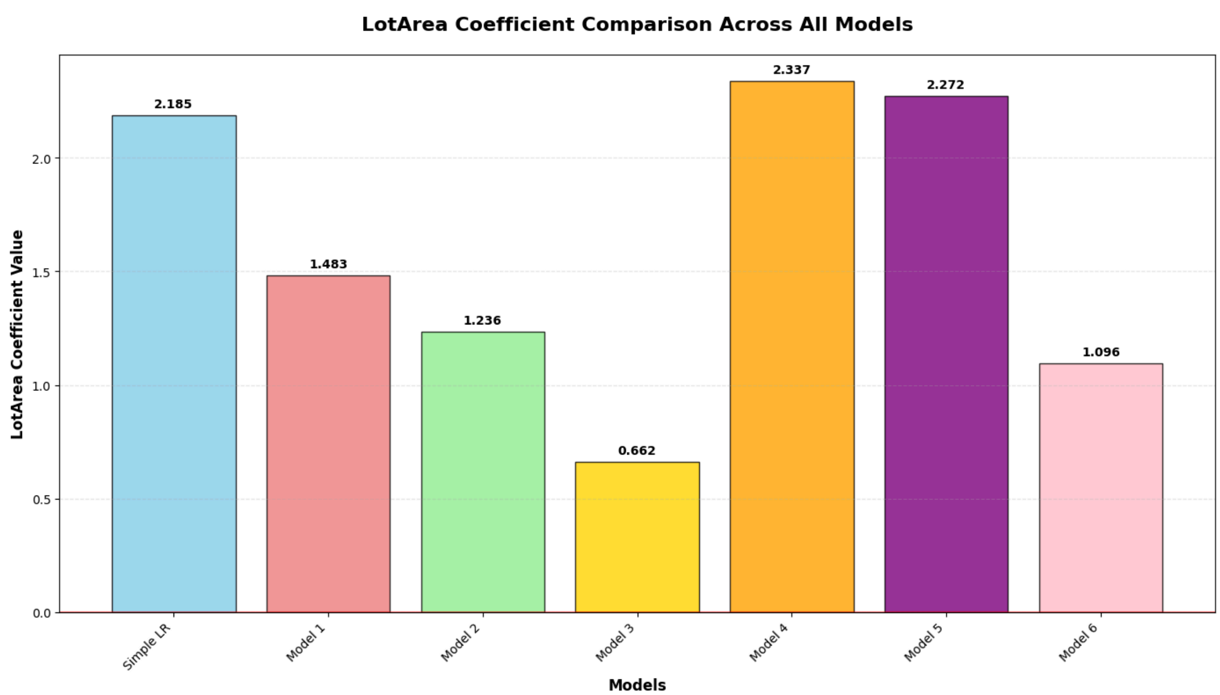
```
            lotarea_coefficients[model_name] = coef
            model_labels.append(model_name.split('(')[0].strip())

# Mixed models (4-6)
mixed_model_names = list(mixed_models_data.keys())
for model_name in mixed_model_names:
    feature_names = mixed_results[model_name]['feature_names']
    coef = get_lotarea_coefficient(mixed_results[model_name], feature_names)
    if coef is not None:
        lotarea_coefficients[model_name] = coef
        model_labels.append(model_name.split('(')[0].strip())

# Display the coefficients
print("LotArea coefficients across all models:")
print("-" * 50)
for i, (model_name, coef) in enumerate(lotarea_coefficients.items()):
    print(f"{model_labels[i]}: {coef:.4f}")

print("\n" + "="*80)
```

```
LOTAREA COEFFICIENT ANALYSIS ACROSS ALL MODELS
============================================================================
====
LotArea coefficients across all models:
--------------------------------------------------
Simple Linear Regression: 2.1849
Model 1: 1.4830
Model 2: 1.2357
Model 3: 0.6618
Model 4: 2.3371
Model 5: 2.2721
Model 6: 1.0959

============================================================================
====
```

In [45]:

```
# Create visualization of LotArea coefficients across all models
plt.figure(figsize=(14, 8))

# Prepare data for plotting
coefficients_values = list(lotarea_coefficients.values())
short_model_names = ['Simple LR', 'Model 1', 'Model 2', 'Model 3', 'Model 4'

# Create the bar plot
bars = plt.bar(range(len(coefficients_values)), coefficients_values,
               color=['skyblue', 'lightcoral', 'lightgreen', 'gold', 'orange
               alpha=0.8, edgecolor='black', linewidth=1)

# Customize the plot
plt.title('LotArea Coefficient Comparison Across All Models', fontsize=16, f
plt.xlabel('Models', fontsize=12, fontweight='bold')
plt.ylabel('LotArea Coefficient Value', fontsize=12, fontweight='bold')
plt.xticks(range(len(coefficients_values)), short_model_names, rotation=45,

# Add value labels on top of each bar
for i, (bar, value) in enumerate(zip(bars, coefficients_values)):
```

```python
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + max(coeffic
             f'{value:.3f}', ha='center', va='bottom', fontweight='bold', fo

# Add grid for better readability
plt.grid(axis='y', alpha=0.3, linestyle='--')

# Add a horizontal line at y=0 for reference
plt.axhline(y=0, color='red', linestyle='-', alpha=0.5)

plt.tight_layout()
plt.show()

# Create a detailed comparison table
print("\nDETAILED LOTAREA COEFFICIENT COMPARISON")
print("="*80)
print(f"{'Model':<15} {'LotArea Coeff':<15} {'Features Description':<50}")
print("-" * 80)

model_descriptions = [
    "LotArea only",
    "LotFrontage + LotArea",
    "LotFrontage + LotArea + OverallQual + OverallCond",
    "LotFrontage + LotArea + OverallQual + OverallCond + 1stFlrSF + GrLivAre
    "LotArea + Street (categorical)",
    "LotArea + OverallCond + Street + Neighborhood (categorical)",
    "LotArea + OverallCond + Street + 1stFlrSF + Neighborhood + Year (catego
]

for i, (coef, desc) in enumerate(zip(coefficients_values, model_descriptions
    print(f"{short_model_names[i]:<15} {coef:<15.4f} {desc:<50}")

print("="*80)
```



```
DETAILED LOTAREA COEFFICIENT COMPARISON
================================================================================
====
Model           LotArea Coeff   Features Description
--------------------------------------------------------------------------------
----
Simple LR       2.1849          LotArea only
Model 1         1.4830          LotFrontage + LotArea
Model 2         1.2357          LotFrontage + LotArea + OverallQual + Overal
lCond
Model 3         0.6618          LotFrontage + LotArea + OverallQual + Overal
lCond + 1stFlrSF + GrLivArea
Model 4         2.3371          LotArea + Street (categorical)
Model 5         2.2721          LotArea + OverallCond + Street + Neighborhoo
d (categorical)
Model 6         1.0959          LotArea + OverallCond + Street + 1stFlrSF +
Neighborhood + Year (categorical)
================================================================================
====
```

In [46]:

```
# Analysis of LotArea coefficient changes
print("ANALYSIS OF LOTAREA COEFFICIENT CHANGES")
print("="*80)

# Calculate percentage changes
base_coef = coefficients_values[0]  # Simple LR coefficient
print(f"Base LotArea coefficient (Simple LR): {base_coef:.4f}")
print("\nPercentage changes from base model:")
print("-" * 40)

for i, (model_name, coef) in enumerate(zip(short_model_names[1:], coefficier
    change = ((coef - base_coef) / base_coef) * 100
    print(f"{model_name}: {change:+.2f}%")

# Statistical analysis
print(f"\nStatistical Summary of LotArea Coefficients:")
print(f"Mean: {np.mean(coefficients_values):.4f}")
print(f"Standard Deviation: {np.std(coefficients_values):.4f}")
print(f"Range: {min(coefficients_values):.4f} to {max(coefficients_values):.



# Compare model performance
print(f"\nModel Performance Summary (Test R²):")
print("-" * 40)

# Get test R² scores for all models
all_test_r2 = []
all_model_names = []

# Original models
for model_name in original_model_names:
    if model_name in summary_results:
        all_test_r2.append(summary_results[model_name]['avg_test_r2'])
        all_model_names.append(model_name.split('(')[0].strip())
```

```python
# Mixed models
for model_name in mixed_model_names:
    if model_name in mixed_summary_results:
        all_test_r2.append(mixed_summary_results[model_name]['avg_test_r2'])
        all_model_names.append(model_name.split('(')[0].strip())

for i, (model_name, r2) in enumerate(zip(short_model_names, all_test_r2)):
    print(f"{model_name}: {r2:.4f}")

print("="*80)
```

```
ANALYSIS OF LOTAREA COEFFICIENT CHANGES
============================================================================
====
Base LotArea coefficient (Simple LR): 2.1849

Percentage changes from base model:
----------------------------------------
Model 1: -32.13%
Model 2: -43.45%
Model 3: -69.71%
Model 4: +6.97%
Model 5: +3.99%
Model 6: -49.84%

Statistical Summary of LotArea Coefficients:
Mean: 1.6101
Standard Deviation: 0.6115
Range: 0.6618 to 2.3371

Model Performance Summary (Test R²):
----------------------------------------
Simple LR: 0.0495
Model 1: 0.1136
Model 2: 0.6509
Model 3: 0.7166
Model 4: 0.0577
Model 5: 0.0995
Model 6: 0.5311
============================================================================
====
```