Predicting Hospital Emergency Room Admissions in California

Final Paper

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Abstract

This project focuses on harnessing predictive analytics to optimize hospital resource management by accurately forecasting daily Emergency Room admissions. By concentrating on key variables like hospital type, size, and location, the project aims to enhance patient flow and overall hospital operational efficiency. Effective predictions from this study will enable better resource allocation, reduced patient wait times, and improved care quality. The project's targeted approach is designed to streamline analysis and yield practical, actionable insights for hospital management in California.

The Data

The data for this analysis is sourced from the Hospital Annual Financial Data, which was retrieved from the California Health and Human Services Agency. This data is official and reliable. This comprehensive dataset covers 439 hospitals across California, offering a wide-ranging and representative sample of the state's healthcare system. It includes key operational metrics such as daily admissions, daily discharges, and the number of licensed beds, among others. This extensive dataset is crucial for our analysis, as it provides the necessary depth and breadth of information to accurately predict hospital admissions and discharges.

Preliminary Analysis

In my Exploratory Data Analysis (EDA), I meticulously analyzed the hospital dataset, focusing on the structure and variables. Each feature was evaluated for data types, distributions, and the presence of any missing values. The dataset displayed a high level of dimensionality, which was more intricate than initially anticipated. This was evident in the trends and anomalies observed in the dataset, where certain variables exhibited unexpected patterns and outliers, necessitating further investigation.

To comprehend these complexities, I utilized visualization techniques like PCA scatter plots, which provided a two-dimensional representation of the highly dimensional data. This visualization highlighted clusters and variations within the dataset, suggesting underlying patterns that were not immediately obvious. Additionally, correlation heatmaps were used to identify relationships between variables, indicating the need for advanced data processing methods such as dimensionality reduction and feature selection.

The insights from the EDA influenced my approach to model selection. The initial strategy of using regression analysis, gradient boosting, and Random Forests was expanded upon. The complexity and nuances of the dataset underscored the necessity for more robust data preprocessing techniques. It became clear that integrating sophisticated methods like feature engineering and dimensionality reduction would be crucial to capture the intricate relationships within the data effectively. This fine-tuning of my modeling strategy aimed not only at enhancing accuracy but also at handling the dataset's diverse and complex characteristics more efficiently.

Model Selection

In this analysis, a combination of machine learning models and statistical techniques were utilized. The selection of specific models included advanced methods such as gradient boosting and Random Forests, alongside regression analysis. These models are adept at handling large datasets and excel in uncovering complex, non-linear relationships between variables, which is crucial for accurately predicting ER Admissions and Discharges in California. The use of these sophisticated models ensured a thorough analysis of the intricate patterns within the healthcare data.

Feature Selection: The investigation focused on primary features analyzed in relation to hospital characteristics including type (e.g., general, specialty), size (as indicated by Licensed Beds), and geographical location. This approach is complemented by a robust feature selection process using methods such as feature importance from tree-based models and correlation analysis. By honing in on the most relevant features, the analysis aims to provide a more nuanced understanding of the dynamics influencing hospital admissions and discharges.

Plan for Evaluating Results

The performance of the predictive models in this project was evaluated using a diverse set of metrics to ensure a thorough assessment. In addition to the traditional Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which offer insights into the magnitude and direction of prediction errors, the R-squared metric was also included. This additional metric is crucial as it quantifies the proportion of variance in the dependent variable that is predictable from the independent variables, providing a more holistic view of model performance. This comprehensive evaluation strategy enabled a nuanced understanding of the models' accuracy and effectiveness in predicting hospital admissions and discharges.

Learning Objectives

The objective of this analysis was to delve into the intricacies of ER hospital admissions and discharges, identifying key patterns and drivers that influence these metrics. The goal was to unearth significant temporal trends and regional variances, as well as to understand how various hospital characteristics impact patient flow. The insights gained from this analysis are expected to be of practical significance, aiding in better informed staffing decisions, optimized resource allocation, and the formulation of effective hospital management strategies. Ultimately, these findings aim to contribute towards more efficient and patient-focused healthcare service delivery.

Risks and Ethical Implications

In this project, the safeguarding of patient data privacy is a primary concern. All analysis will be conducted in strict adherence to data privacy guidelines, ensuring that individual patient data remains secure and anonymized. Additionally, the dataset was rigorously examined for potential biases, such as those associated with hospital location or type. Efforts were focused on identifying and mitigating these biases to ensure the fairness and impartiality of the model predictions. Recognizing the risk of misinterpreting model outputs, care has been taken to accompany predictions with clear explanations and caveats, minimizing the possibility of making ineffective or potentially harmful decisions in hospital operations.

Contingency Plan

A contingency plan was put in place in the event that the initial models underperform. This included pivoting to alternative predictive methods, including simpler statistical techniques or different machine learning models. Challenges concerning data quality or completeness was tackled through refined data collection methods, the application of data imputation strategies, and a reevaluation of our data requirements. The scope of the project had to be recalibrated based on initial results or data constraints, potentially leading to a focus on specific hospital types and narrowed scope of variables for a more targeted analysis.

Overall Project Goal

This project aims to enhance the operational efficiency of hospitals through predictive analytics. By focusing on daily Emergency Room admissions and discharges and considering key factors like hospital type, size, and location, the project expects to provide actionable insights for hospital management. The anticipated impact of this project can potentially be significant. It aims to improve hospital efficiency, patient care, and resource management, contributing to the broader field of healthcare analytics.

Data Preparation

The dataset used comprises financial and operational metrics from various hospitals, including gross and net patient revenue, inpatient and outpatient expenses, bed count, staff numbers, and ER visits. The initial step involved loading the data from an Excel file, followed by an exploratory data analysis (EDA) to understand its structure and identify any missing values. My findings showed a comprehensive dataset with minimal missing values across 248 columns.

Cleaning and Preprocessing

I focused on hospitals with ER visits, filtering out entries without ER visit data to ensure relevance to our predictive goal. I then selected relevant features for the analysis, including financial metrics (gross and net patient revenue), operational metrics (bed availability, licensed bed count, and staffing), and ER visits. Feature scaling was applied to normalize the data and enhance model performance.

Model Building and Evaluation

I employed several machine learning models to predict ER visits, starting with a RandomForestRegressor and progressing to more complex models like LightGBM and a StackingRegressor incorporating RandomForest, LightGBM, and GradientBoostingRegressor. Model performance was evaluated based on Mean Squared Error (MSE) and R-squared (R2) metrics.

LightGBM Model

The LightGBM model was chosen for its efficiency and effectiveness in handling large data with categorical features. We fine-tuned the model using GridSearchCV, optimizing parameters such as **n_estimators**, **max_depth**, **learning_rate**, and **num_leaves**. The best configuration achieved an MSE of 361674983.19 and an R2 of 0.675, indicating a strong predictive capability.

Stacked Ensemble Model

To leverage the strengths of multiple models, I then implemented a StackingRegressor with RandomForest, LightGBM, and GradientBoostingRegressor as base models and LinearRegression as the meta-model. This ensemble approach resulted in an improved MSE of 148943417.71 and an R2 of 0.786, showcasing the enhanced predictive accuracy of combining multiple models.

Interpretation of Results

The analysis revealed that net patient revenue and gross patient revenue are among the most significant predictors of ER visits. This finding suggests a strong relationship between the financial performance of hospitals and the volume of ER visits. Operational metrics like bed availability and staffing also showed significant predictive power, underscoring the importance of resource allocation in managing ER operations.

This study demonstrates the potential of using hospital financial and operational data to predict ER visits accurately. The LightGBM and stacked ensemble models both showed promising results, with the ensemble model providing the best performance. These findings can assist hospital administrators in strategic planning and resource allocation to better accommodate the expected volume of ER visits.

Recommendations

The project underscores the potential of machine learning models, especially LightGBM and ensemble methods, to forecast ER demand effectively. For deployment, integrating the model into hospital information systems with real-time data processing and developing a user-friendly interface for staff are critical steps. These strategies aim to optimize hospital operations, ensuring efficient resource allocation and improved patient care.

1. **Data-Driven Planning and Deployment:** Hospitals should leverage predictive analytics for resource allocation, staffing, and financial planning to improve operational efficiency.
2. **Investment in Analytics:** Investing in analytical capabilities and tools can enable hospitals to extract actionable insights from their data, enhancing decision-making processes.
3. **Continuous Model Improvement:** Regularly updating models with new data and incorporating additional relevant features can improve predictive accuracy over time.

Future Work

Further research could explore the integration of additional data sources, such as patient demographics and clinical data, to enhance the predictive models. Additionally, exploring other machine learning techniques and deep learning could uncover more complex patterns and relationships within the data. By harnessing the power of predictive analytics, hospitals can not only improve their operational efficiency but also enhance patient care by proactively managing resources to meet demand.

References

Abbott, D. (2014). Applied Predictive Analytics: Principles and Techniques for the Professional Data Analyst. ISBN 978-1118727966

California Health and Human Services Agency. (n.d.). Hospital Annual Financial Data - Selected Data [Data set]. Retrieved from https://data.chhs.ca.gov/dataset/hospital-annual-financial-data-selected-data-pivot-tables/resource/a6745a1c-7edb-47b2-a483-cd003a6293e5

Appendix

Import Libraries and Load the Dataset

In [76]:
```
# import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import lightgbm as lgb
import warnings
warnings.filterwarnings('ignore')


# Load the data
file_path = "C:/Users/salin/OneDrive/Desktop/DSC630 Predictive Analytics\Term Project Milestones/HospitalFinancialData21-22.xlsx"
data = pd.read_excel(file_path)
```

Data Inspection

In [77]:
```
# Display the columns to get an overview of all available metrics
data.columns

# Display the first few rows of the dataframe
print(data.head())
```

```
   Unnamed: 0.1  Unnamed: 0  Facility_ID                 Hospital_Name  \
0             0           0    106580996  ADVENTIST HEALTH AND RIDEOUT
1             1           1    106150788  ADVENTIST HEALTH BAKERSFIELD
2             2           2    106171049    ADVENTIST HEALTH CLEARLAKE
3             3           3    106150706       ADVENTIST HEALTH DELANO
4             4           4    106190323     ADVENTIST HEALTH GLENDALE

  Financial_Year_Start Financial_Year_End  Reporting_Period Data_Indicator  \
0           2021-01-01         2021-12-31               365     In Process
1           2021-01-01         2021-12-31               365        Audited
2           2021-01-01         2021-12-31               365        Audited
3           2021-01-01         2021-12-31               365        Audited
4           2021-01-01         2021-12-31               365        Audited

         Audit_Indicator  County_Name  ...  PRD_HR_ADM  PRD_HR_NON PD_HR_DLY  \
0  Incl. Ind. Audit Adj.         Yuba  ...      248287           0   1782545
1  Incl. Ind. Audit Adj.         Kern  ...      170906           0    961859
2  Incl. Ind. Audit Adj.         Lake  ...       96741           0    105165
3  Incl. Ind. Audit Adj.         Kern  ...       65665           0    305898
4  Excl. Ind. Audit Adj.  Los Angeles  ...      293440           0   1525982

  PD_HR_AMB PD_HR_ANC PD_HR_ED PD_HR_GEN PD_HR_FIS PD_HR_ADM PD_HR_NON
0    145457   1468094        0    288521     20056    272085         0
1    480782    834805     1664    196079      5566    187074         0
2    694222    218209        0     79039         0    105005         0
3    138057    240843        0     86216     48319     70925         0
4    339475    944281    80580    350605     28726    383895         0

[5 rows x 248 columns]
```

In [78]:

```
# Check for missing values
missing_values = data.isnull().sum()

# Summary statistics for numerical columns
summary_statistics = data.describe()

print(missing_values)
```

```
Unnamed: 0.1            0
Unnamed: 0              0
Facility_ID             0
Hospital_Name           0
Financial_Year_Start    0
                       ..
PD_HR_ED                0
PD_HR_GEN               0
PD_HR_FIS               0
PD_HR_ADM               0
PD_HR_NON               0
Length: 248, dtype: int64
```

Filter Out Hospitals Without ER Visits

In [79]:
```
# Filter out hospitals without ER visits
data_with_er = data[data['VIS_ER'] > 0]
```

Summary Statistics

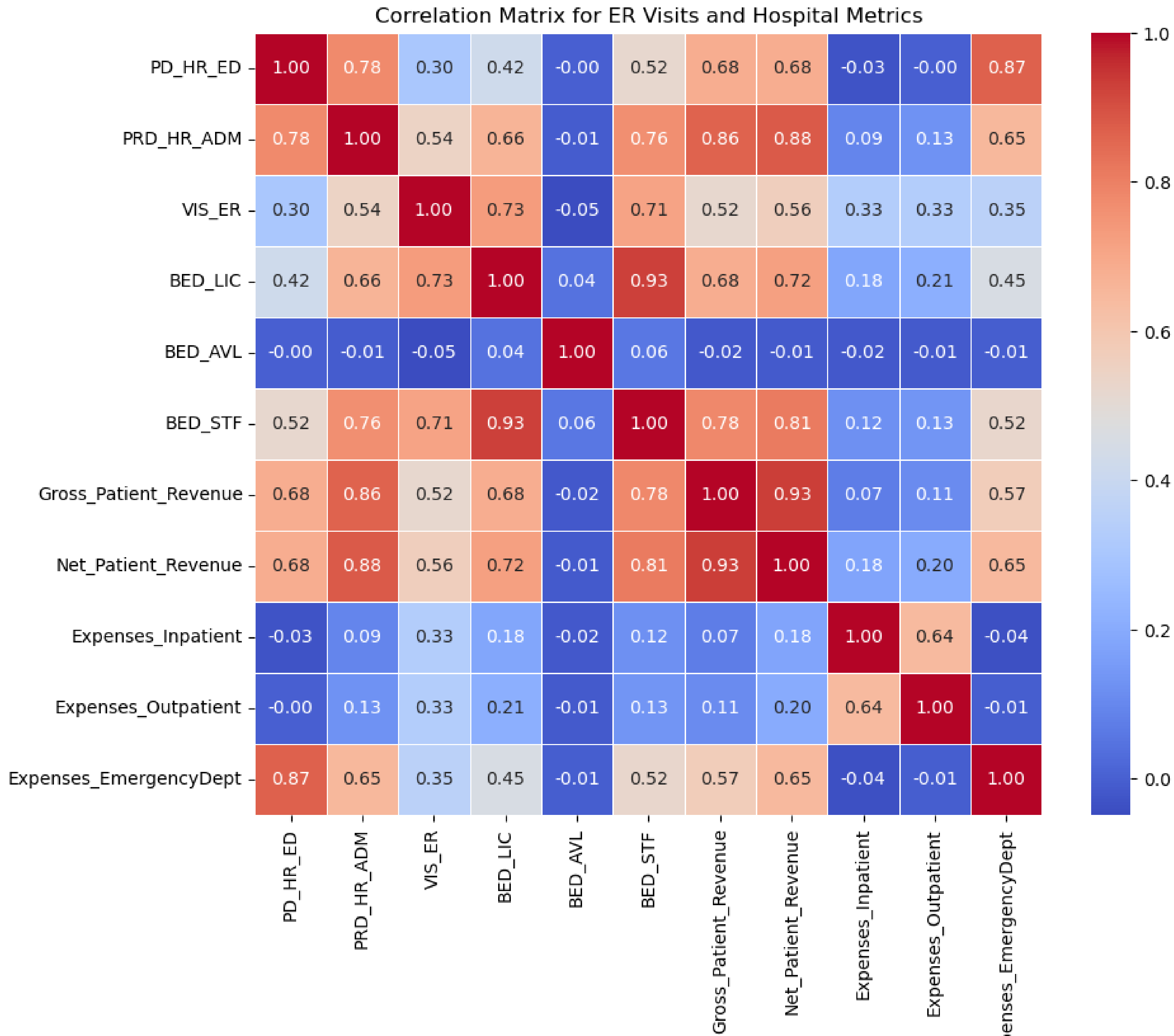
In [80]:
```
# Summary statistics and distribution plot for ER visits
er_visits_summary = data_with_er['VIS_ER'].describe()

print(er_visits_summary)
```

```
count       308.000000
mean      45540.253247
std       33430.295777
min          10.000000
25%       21122.250000
50%       39003.500000
75%       62434.500000
max      222110.000000
Name: VIS_ER, dtype: float64
```

Feature Exploration

Exploring correlations between variables:

In [81]:
```
# Selecting relevant columns for correlation analysis
correlation_columns = ['PD_HR_ED', 'PRD_HR_ADM', 'VIS_ER', 'BED_LIC', 'BED_AVL', 'BED_STF',
                       'Gross_Patient_Revenue', 'Net_Patient_Revenue',
                       'Expenses_Inpatient', 'Expenses_Outpatient', 'Expenses_EmergencyDept']

# Creating a subset for correlation analysis
correlation_data = data_with_er[correlation_columns]

# Calculating correlation matrix
correlation_matrix = correlation_data.corr()

# Plotting the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Correlation Matrix for ER Visits and Hospital Metrics')
plt.show()
```

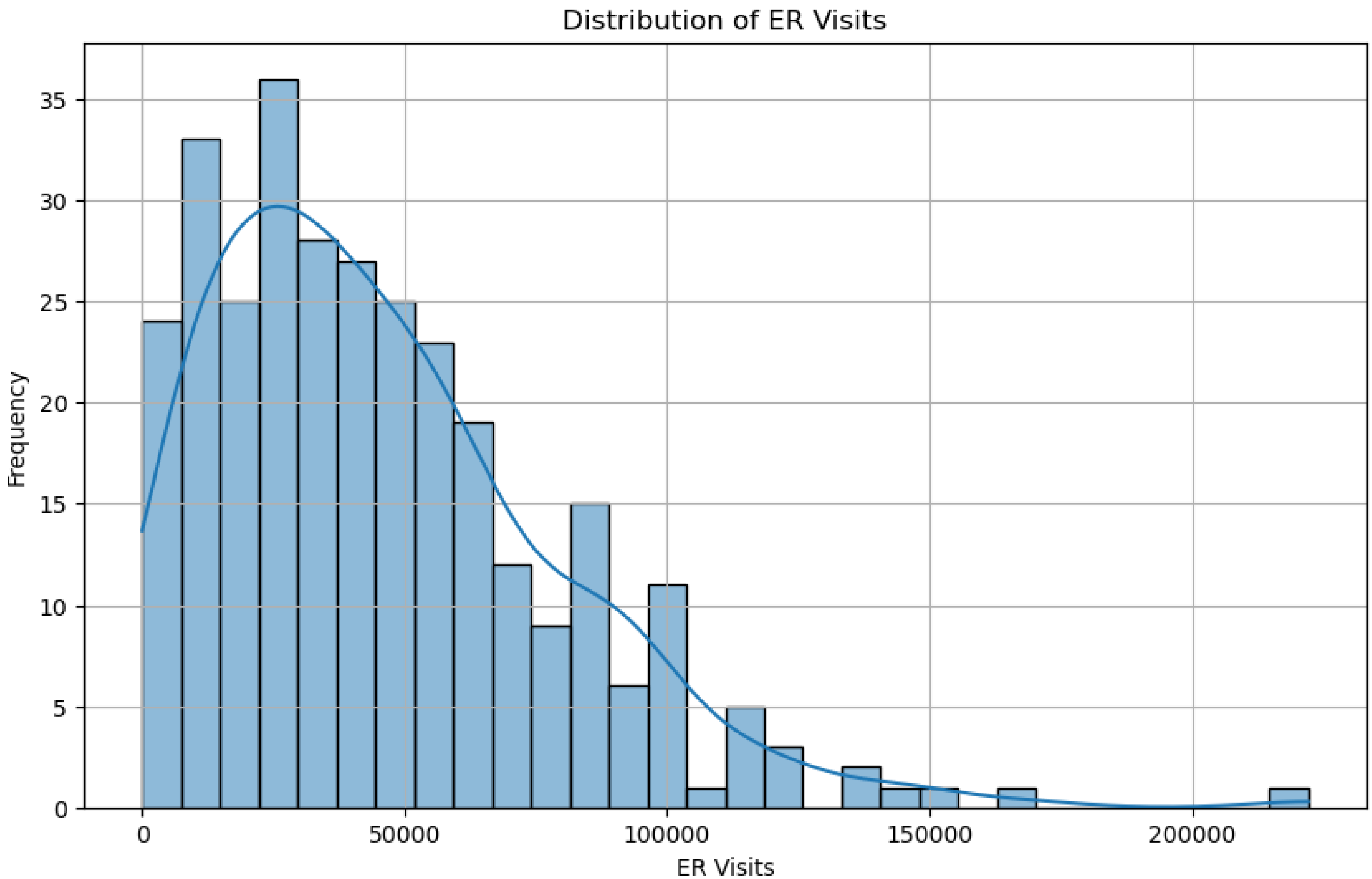

Correlation Matrix for ER Visits and Hospital Metrics
PD_HR_ED
PRD_HR_ADM
VIS_ER
BED_LIC
BED_AVL
BED_STF
Gross_Patient_Revenue
Net_Patient_Revenue
Expenses_Inpatient
Expenses_Outpatient
Expenses_EmergencyDept
1.00 0.78 0.30 0.42 -0.00 0.52 0.68 0.68 -0.03 -0.00 0.87
0.78 1.00 0.54 0.66 -0.01 0.76 0.86 0.88 0.09 0.13 0.65
0.30 0.54 1.00 0.73 -0.05 0.71 0.52 0.56 0.33 0.33 0.35
0.42 0.66 0.73 1.00 0.04 0.93 0.68 0.72 0.18 0.21 0.45
-0.00 -0.01 -0.05 0.04 1.00 0.06 -0.02 -0.01 -0.02 -0.01 -0.01
0.52 0.76 0.71 0.93 0.06 1.00 0.78 0.81 0.12 0.13 0.52
0.68 0.86 0.52 0.68 -0.02 0.78 1.00 0.93 0.07 0.11 0.57
0.68 0.88 0.56 0.72 -0.01 0.81 0.93 1.00 0.18 0.20 0.65
-0.03 0.09 0.33 0.18 -0.02 0.12 0.07 0.18 1.00 0.64 -0.04
-0.00 0.13 0.33 0.21 -0.01 0.13 0.11 0.20 0.64 1.00 -0.01
0.87 0.65 0.35 0.45 -0.01 0.52 0.57 0.65 -0.04 -0.01 1.00
1.0
0.8
0.6
0.4
0.2
0.0

Ext

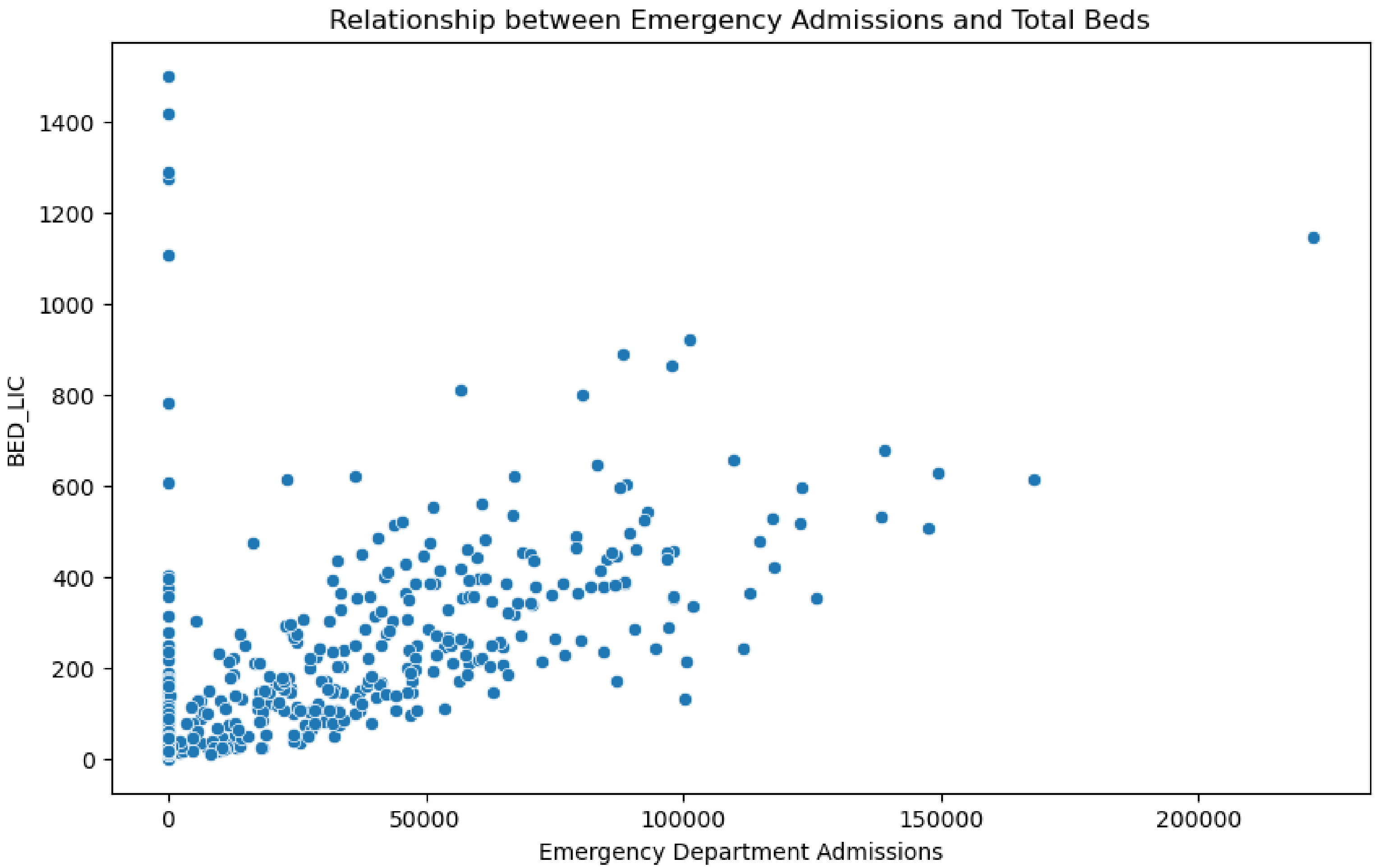
Visualization

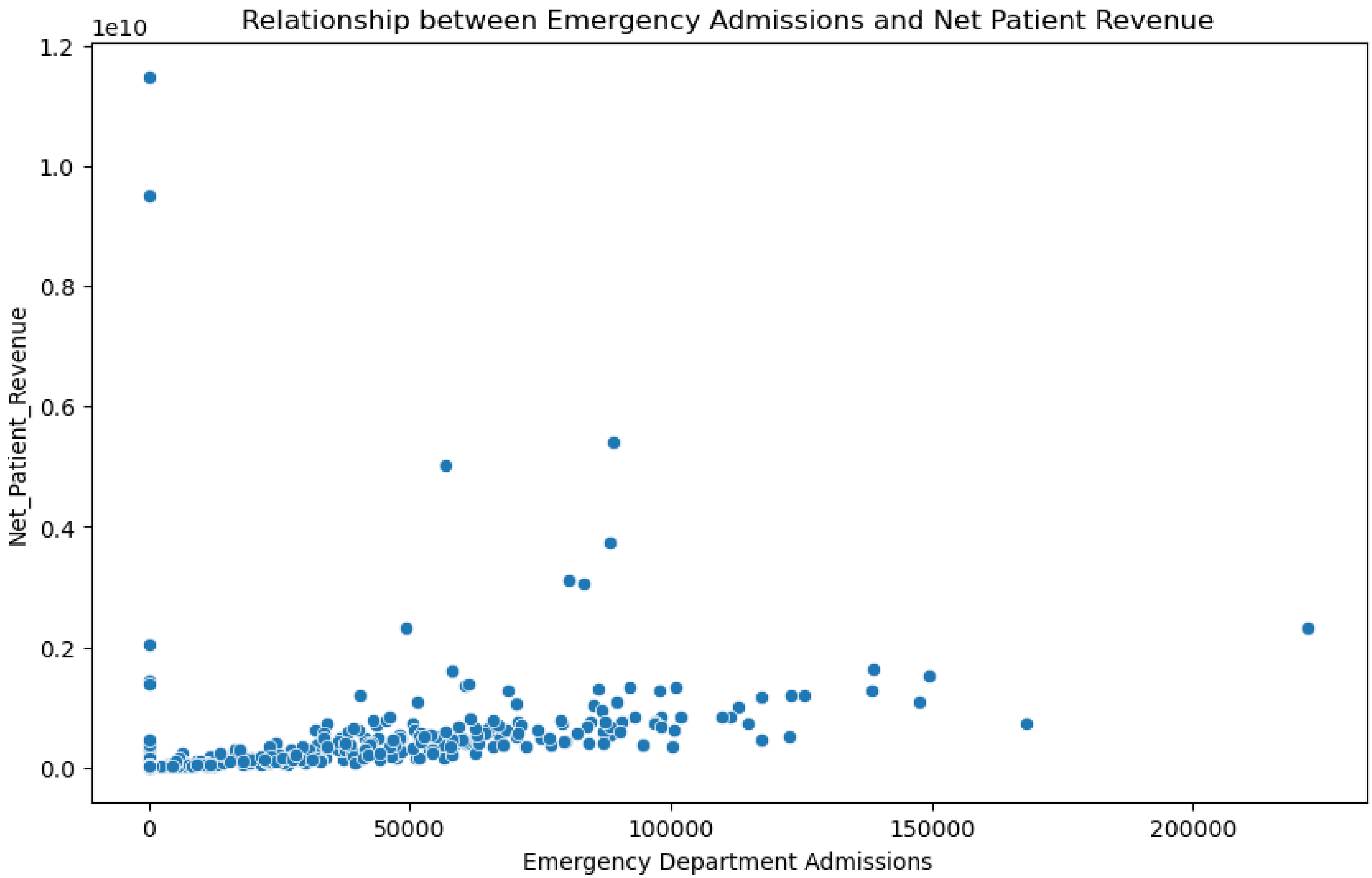
Visualizing the relationships and distributions of data:

In [82]:
```
# Histogram of emergency department admissions
plt.figure(figsize=(10, 6))
sns.histplot(data_with_er['VIS_ER'], bins=30, kde=True)
plt.title('Distribution of ER Visits')
plt.xlabel('ER Visits')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()

# Scatter plot between emergency department admissions and another variable
plt.figure(figsize=(10, 6))
sns.scatterplot(x=data['VIS_ER'], y=data['BED_LIC'])
plt.title('Relationship between Emergency Admissions and Total Beds')
plt.xlabel('Emergency Department Admissions')
plt.ylabel('BED_LIC')

# Scatter plot between emergency department admissions and Net Patient Revenue
plt.figure(figsize=(10, 6))
sns.scatterplot(x=data['VIS_ER'], y=data['Net_Patient_Revenue'])
plt.title('Relationship between Emergency Admissions and Net Patient Revenue')
plt.xlabel('Emergency Department Admissions')
plt.ylabel('Net_Patient_Revenue')
```



Out[82]:
```
Text(0, 0.5, 'Net_Patient_Revenue')
```


Relationship between Emergency Admissions and Total Beds
BED_LIC
Emergency Department Admissions
0
200
400
600
800
1000
1200
1400
0
50000
100000
150000
200000



Data Preparation for Modeling

In [83]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Preparing data for modeling
X = correlation_data.drop(['VIS_ER'], axis=1)
y = correlation_data['VIS_ER']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Randon Forest Model

In [84]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Training Random Forest model
random_forest_model = RandomForestRegressor(n_estimators=100, random_state=42)
random_forest_model.fit(X_train_scaled, y_train)

# Prediction and evaluation
y_pred_test_rf = random_forest_model.predict(X_test_scaled)
mse_test_rf = mean_squared_error(y_test, y_pred_test_rf)
r2_test_rf = r2_score(y_test, y_pred_test_rf)

print(f"MSE Test: {mse_test_rf}, R2 Test: {r2_test_rf}")
```

```
MSE Test: 381931702.5612355, R2 Test: 0.6568538280263421
```

Feature Importance Analysis from Random Forest

In [85]:
```
# Extracting feature importances
feature_importances = random_forest_model.feature_importances_
features_df = pd.DataFrame({'Feature': X.columns, 'Importance': feature_importances}).sort_values(by='Importance', ascending=False)

print(features_df)
```

```
                Feature  Importance
6     Net_Patient_Revenue    0.497804
5   Gross_Patient_Revenue    0.230129
3                BED_AVL    0.068467
2                BED_LIC    0.053595
1             PRD_HR_ADM    0.042668
4                BED_STF    0.041443
7      Expenses_Inpatient    0.020191
9  Expenses_EmergencyDept    0.017056
0              PD_HR_ED    0.015911
8     Expenses_Outpatient    0.012735
```

Suppressing stdout and stderr Output

In [86]:
```
import os
import sys
from contextlib import contextmanager

@contextmanager
def suppress_stdout_stderr():
```

```
    """A context manager that redirects stdout and stderr to devnull"""
    with open(os.devnull, 'w') as fnull:
        old_stdout = sys.stdout
        old_stderr = sys.stderr
        sys.stdout = fnull
        sys.stderr = fnull
        try:
            yield
        finally:
            sys.stdout = old_stdout
            sys.stderr = old_stderr
```

Model Optimization

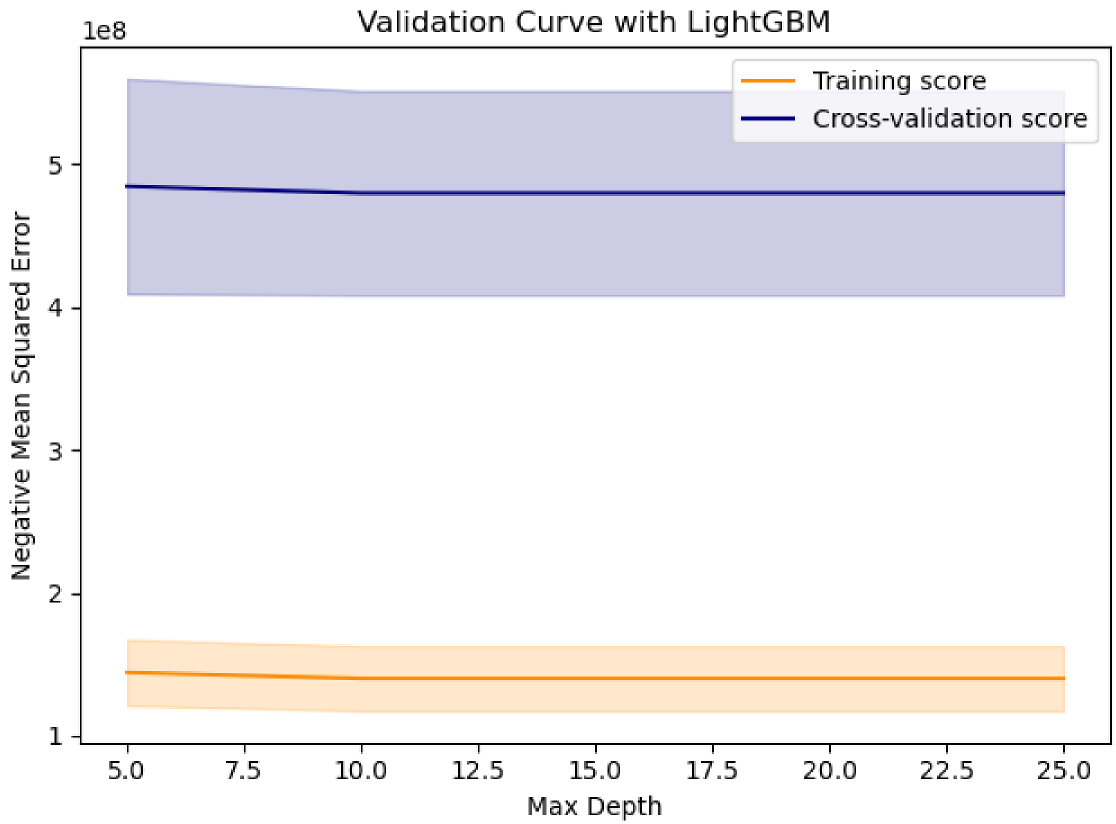
Hyperparameter Tuning with GridSearchCV

In [87]:
```
!pip install lightgbm
from sklearn.model_selection import GridSearchCV
from lightgbm import LGBMRegressor

# Define the parameter grid
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [-1, 5, 10, 20],  # -1 means no limit
    'learning_rate': [0.01, 0.1, 0.2],
    'num_leaves': [31, 50, 100]
}

# Initialize the model
lgbm = LGBMRegressor(random_state=42)

# Initialize the GridSearchCV
grid_search = GridSearchCV(estimator=lgbm, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1, verbose=1)

# Use the suppress_stdout_stderr context manager to mute the fitting process
with suppress_stdout_stderr():
    grid_search.fit(X_train_scaled, y_train)

# Best parameters and score
print("Best parameters found: ", grid_search.best_params_)
print("Best score found: ", grid_search.best_score_)
```

```
Requirement already satisfied: lightgbm in c:\users\salin\anaconda3\lib\site-packages (4.3.0)
Requirement already satisfied: numpy in c:\users\salin\anaconda3\lib\site-packages (from lightgbm) (1.23.5)
Requirement already satisfied: scipy in c:\users\salin\anaconda3\lib\site-packages (from lightgbm) (1.10.0)
Best parameters found:  {'learning_rate': 0.01, 'max_depth': -1, 'n_estimators': 200, 'num_leaves': 31}
Best score found:  -419703446.35472023
```

Validation Curves

In [88]:
```
from sklearn.model_selection import validation_curve

# Define the range of the parameter
param_range = [5, 10, 15, 20, 25]

# Calculate scores for training and test sets
train_scores, test_scores = validation_curve(
    LGBMRegressor(n_estimators=100, learning_rate=0.1, num_leaves=31, random_state=42),
    X_train_scaled, y_train, param_name="max_depth", param_range=param_range,
    cv=5, scoring="neg_mean_squared_error", n_jobs=-1)

# Calculate mean and standard deviation for training set scores
train_mean = -np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)

# Calculate mean and standard deviation for test set scores
test_mean = -np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Plotting the validation curve
plt.plot(param_range, train_mean, label="Training score", color="darkorange")
plt.fill_between(param_range, train_mean - train_std, train_mean + train_std, color="darkorange", alpha=0.2)
plt.plot(param_range, test_mean, label="Cross-validation score", color="navy")
plt.fill_between(param_range, test_mean - test_std, test_mean + test_std, color="navy", alpha=0.2)

plt.title("Validation Curve with LightGBM")
plt.xlabel("Max Depth")
plt.ylabel("Negative Mean Squared Error")
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```



Model Validation

Hold-out Test Set

In [89]:

```python
# Predicting on the test set
y_pred = grid_search.best_estimator_.predict(X_test_scaled)

# Calculating metrics
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Test MSE: {mse}")
print(f"Test MAE: {mae}")
print(f"Test R2: {r2}")
```

```
Test MSE: 361674983.19146454
Test MAE: 13629.47091262214
Test R2: 0.675053458122163
```

Cross-Validation

In [90]:
```python
from sklearn.model_selection import cross_val_score

# Use the suppress_stdout_stderr context manager to mute the cross-validation process
with suppress_stdout_stderr():

    # Perform cross-validation
    scores = cross_val_score(grid_search.best_estimator_, X_train_scaled, y_train, cv=5, scoring='neg_mean_squared_error')

# Compute the average MSE
average_mse = -scores.mean()
print(f"Average MSE from cross-validation: {average_mse}")
```

```
Average MSE from cross-validation: 419703446.35472023
```

Feature Selection

In [91]:
```python
# Selecting relevant features based on the correlation analysis
features = ['BED_LIC', 'BED_AVL', 'BED_STF','Gross_Patient_Revenue', 'Net_Patient_Revenue',
                       'Expenses_Inpatient', 'Expenses_Outpatient', 'Expenses_EmergencyDept']
target = 'VIS_ER'

# Creating the feature matrix (X) and target vector (y)
X = data[features]
y = data[target]

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardizing the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

#X_train_scaled and X_test_scaled are ready for modeling
```

LightGBM model

In [92]:
```python
from lightgbm import LGBMRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

```python
# Initialize the LightGBM model with verbosity set to -1 to suppress LightGBM warnings
lgbm_model = LGBMRegressor(random_state=42, verbosity=-1)

# Train the model with the scaled training data
lgbm_model.fit(X_train_scaled, y_train)

# Predict on the testing set
y_pred = lgbm_model.predict(X_test_scaled)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error (MSE): {mse}')
print(f'R-squared (R2): {r2}')
```

```
Mean Squared Error (MSE): 210694167.46182555
R-squared (R2): 0.6967957293273033
```

Model Ensemble with Stacking

In [93]:

```python
from sklearn.ensemble import StackingRegressor, RandomForestRegressor
from lightgbm import LGBMRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Define the base models with LGBMRegressor's verbosity set to -1
base_models = [
    ('rf', RandomForestRegressor(n_estimators=100, random_state=42)),
    ('lgbm', LGBMRegressor(random_state=42, verbosity=-1))  # Setting verbosity to -1 to suppress warnings
]

# Define the meta-model
meta_model = LinearRegression()

# Create the stacking ensemble
stacked_model = StackingRegressor(estimators=base_models, final_estimator=meta_model, cv=5)

# Fit the model on the training data
stacked_model.fit(X_train_scaled, y_train)

# Predict and evaluate on the test data
y_pred_stack = stacked_model.predict(X_test_scaled)
mse_stack = mean_squared_error(y_test, y_pred_stack)
r2_stack = r2_score(y_test, y_pred_stack)

print(f'Stacked Model MSE: {mse_stack}, R2: {r2_stack}')
```

```
Stacked Model MSE: 165694071.68841383, R2: 0.7615541485258361
```

Cross-Validation

For cross-validation with the original LightGBM model:

In [94]:
```
# Reinitialize the LightGBM model for cross-validation
lgbm_cv = LGBMRegressor(random_state=42)

with suppress_stdout_stderr():
    # Perform cross-validation
    cv_scores = cross_val_score(lgbm_cv, X_train_scaled, y_train, cv=5, scoring='neg_mean_squared_error')

# Calculate average MSE
avg_mse_cv = -cv_scores.mean()

print(f'Average MSE from CV: {avg_mse_cv}')
```

```
Average MSE from CV: 419941972.8879991
```

Hyperparameter tuning for a StackingRegressor model using GridSearchCV

The StackingRegressor combines three base models (RandomForestRegressor, LGBMRegressor, and GradientBoostingRegressor) with a LinearRegression model as the final estimator

In [95]:
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV

# Adding GradientBoostingRegressor for diversity
base_models = [
    ('rf', RandomForestRegressor(random_state=42)),
    ('lgbm', LGBMRegressor(random_state=42)),
    ('gbr', GradientBoostingRegressor(random_state=42))
]

# Stacking ensemble setup
stacked_model = StackingRegressor(estimators=base_models, final_estimator=LinearRegression(), cv=5)

# Define a grid of hyperparameters to search
param_grid = {
    'rf__n_estimators': [100, 200],
    'rf__max_depth': [None, 10, 20],
    'lgbm__num_leaves': [31, 50],
    'lgbm__learning_rate': [0.1, 0.01],
    'gbr__n_estimators': [100, 200],
    'gbr__learning_rate': [0.1, 0.01]
}
```

```
with suppress_stdout_stderr():
    # Initialize GridSearchCV
    grid_search = GridSearchCV(estimator=stacked_model, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error', verbose=1, n_jot
    # Fit GridSearchCV
    grid_search.fit(X_train_scaled, y_train)

# Best parameters and score
print("Best parameters:", grid_search.best_params_)
print("Best score:", -grid_search.best_score_)
```

```
Best parameters: {'gbr__learning_rate': 0.01, 'gbr__n_estimators': 200, 'lgbm__learning_rate': 0.1, 'lgbm__num_leaves': 31, 'rf__max_d
epth': 10, 'rf__n_estimators': 100}
Best score: 377519278.44106954
```

Evaluate the Performance of the Optimized Stacking Regressor Model on Test Dataset

In [96]:

```
# Predicting on the test set
y_pred = grid_search.best_estimator_.predict(X_test_scaled)

# Calculating metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Output the results
print(f"Test MSE: {mse}")
print(f"Test R2: {r2}")
```

```
Test MSE: 148943417.71257594
Test R2: 0.7856595610449314
```