

Optimizing Hospital Resource Allocation Using Artificial Intelligence and Predictive Analytics

Executive Presentation Summary

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Executive Overview

This project develops an end-to-end hospital operations decision-support framework. CDC National Healthcare Safety Network weekly data were used to forecast next-week inpatient occupancy. The selected forecasting model was then connected to a linear optimization model that recommends surge-bed activation and supplemental nursing coverage under different demand conditions.

Data Foundation

Measure	Result
Source	CDC/NHSN Weekly Hospital Respiratory Data by Jurisdiction
Original observations	20,770 weekly records
Original variables	322 variables
Modeling panel	17,360 state/territory-week records
Time coverage	August 2020 through July 2026
Primary target	Next-week inpatient occupancy percentage

Forecasting Results

Four forecasting approaches were compared using chronological 70/30, 80/20, and 95/5 train-test partitions. XGBoost achieved the lowest average forecast error and was selected as the leading model.

Model	Mean RMSE	Mean MAE	Mean R ²	Within 3 Points
Persistence Baseline	3.114	1.900	0.891	82.74%
Linear Regression	2.922	1.831	0.905	83.35%
Random Forest	2.899	1.811	0.906	83.81%
XGBoost	2.888	1.805	0.907	83.75%

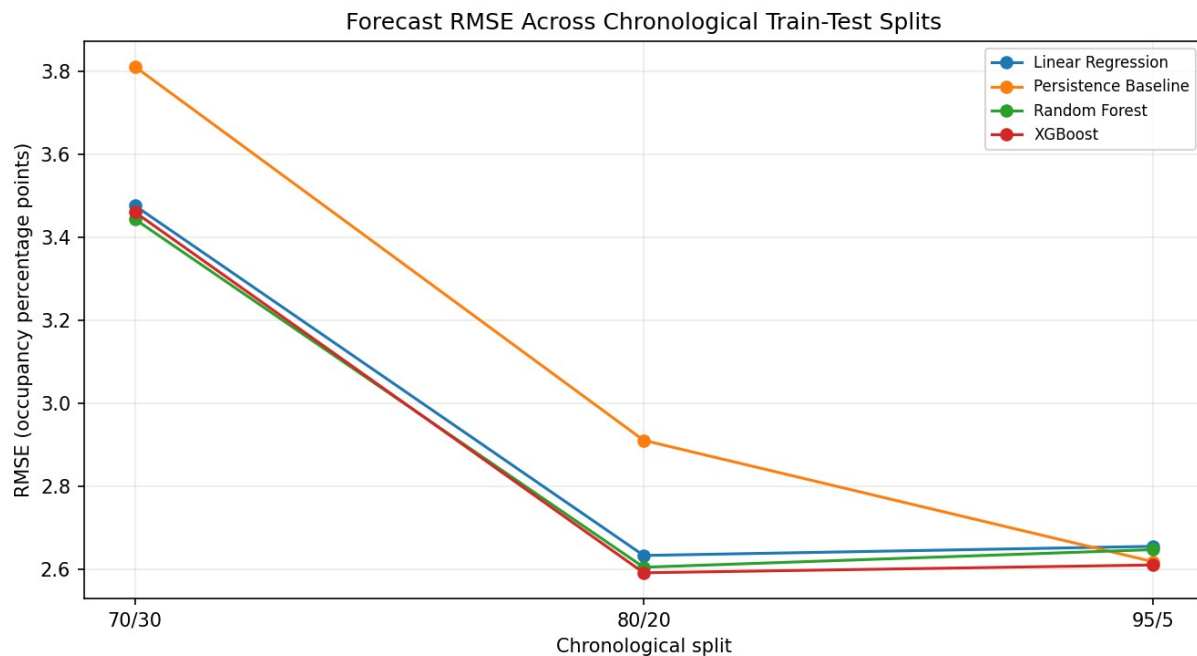


Figure 1. Forecast RMSE across chronological train-test splits.

On the 80/20 test split, XGBoost produced an RMSE of 2.593 occupancy percentage points, an MAE of 1.655, an R² of 0.924, and 85.28% of forecasts within three occupancy points of the observed value.

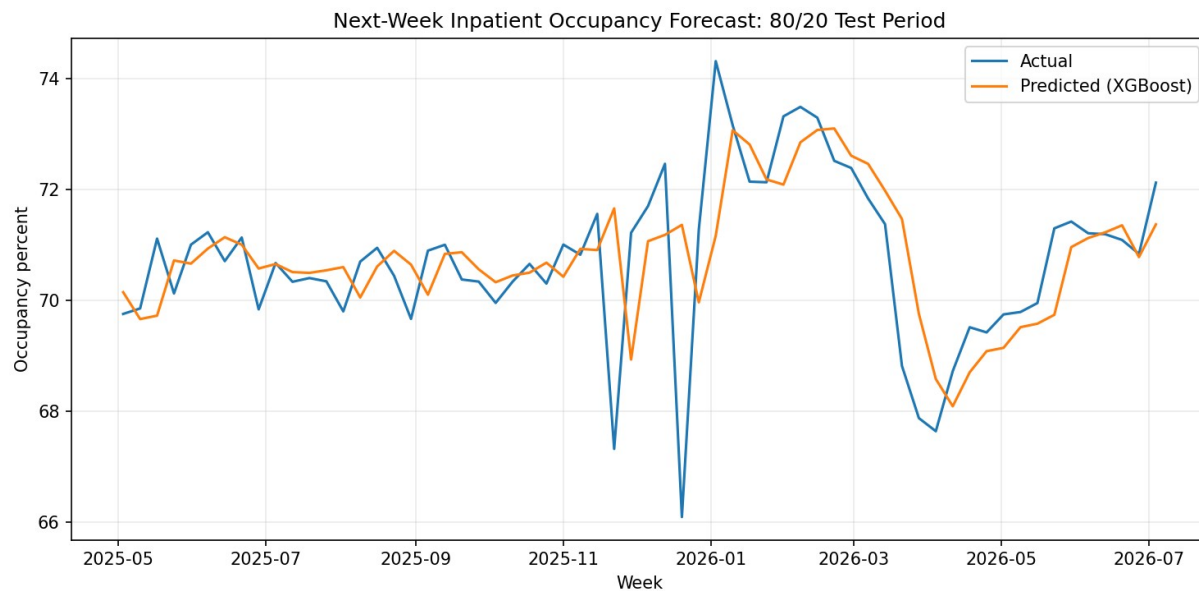


Figure 2. Actual and predicted next-week inpatient occupancy.

Key Predictive Drivers

The most influential signals were current and recent inpatient occupancy, four-week occupancy trends, ICU occupancy, the Operational Stress Index, and respiratory admissions. These findings show that short-term hospital demand is persistent but is also affected by changing clinical and respiratory conditions.

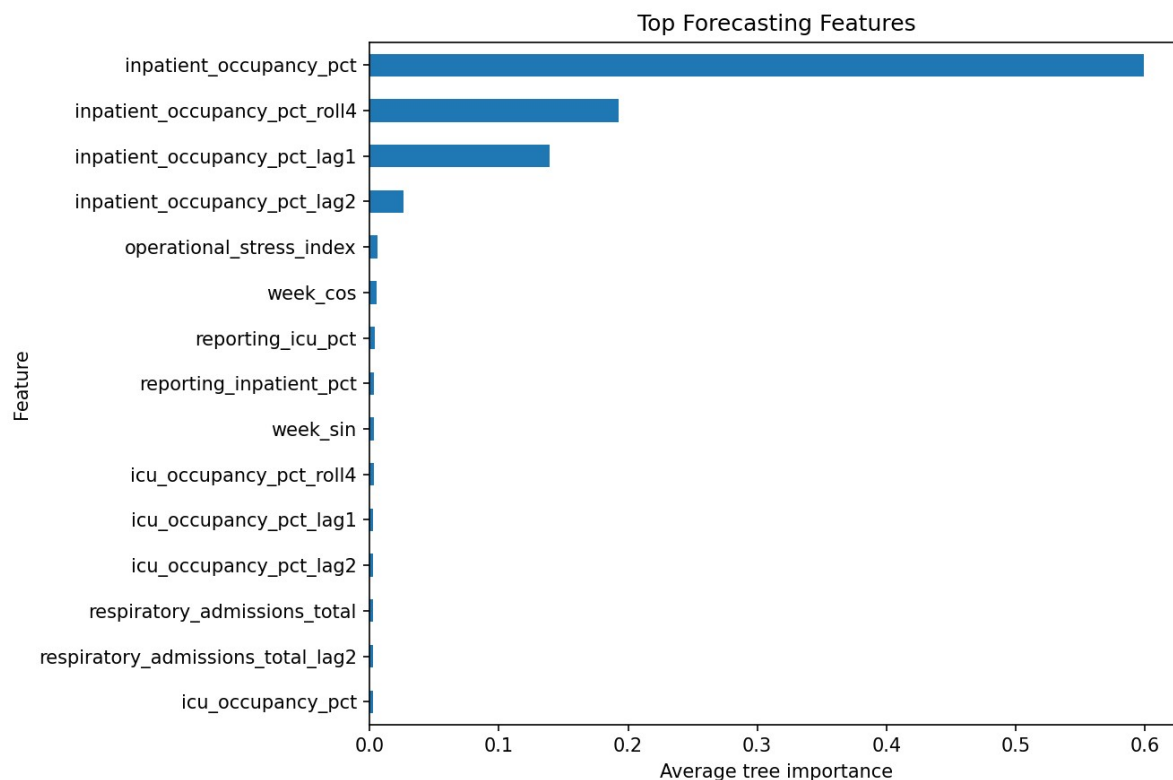


Figure 3. Most influential forecasting features.

Resource Optimization Results

The selected forecast was translated into prescriptive recommendations using a transparent linear-programming model. Because the public CDC dataset does not contain individual hospital staffing costs or licensed-bed details, the

optimization uses a standardized 500-bed reference hospital. These assumptions are illustrative and should be replaced with facility-specific inputs before deployment.

Scenario	Forecast Occupancy	Surge Beds	Additional Nurses/Shift	Unmet Demand
Typical Demand	72.09%	0	0	0
Elevated Demand	76.82%	4	1	0
High Demand	80.63%	24	5	0
Critical Demand	83.07%	37	8	0

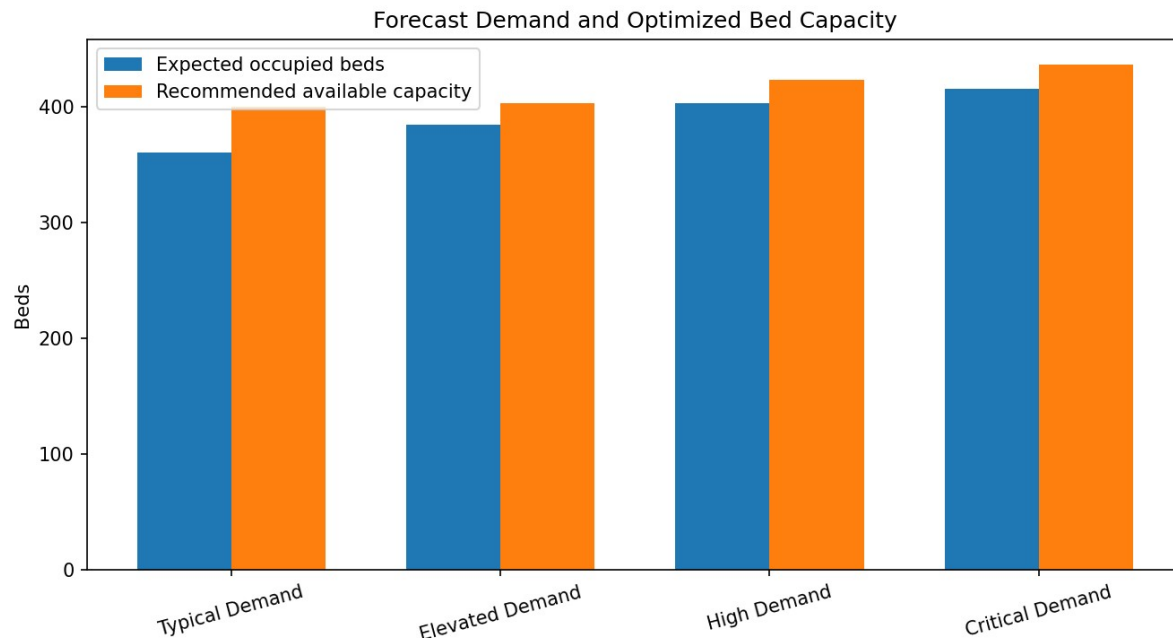


Figure 4. Forecast demand and optimized bed capacity.

Executive Recommendations

- Run the occupancy forecast weekly and distribute results to operations, nursing, and capacity-management leadership.
- Use forecast thresholds to activate flexible staffing and surge capacity before occupancy reaches critical levels.
- Monitor MAE, RMSE, forecast bias, and predictions within three occupancy points to detect model drift.
- Replace the illustrative optimization assumptions with hospital-specific bed, staffing, cost, and safety constraints.
- Keep clinical and operational leadership in the approval loop; the framework should support, not replace, management judgment.

Important Limitations

The source data are aggregated by jurisdiction rather than by individual hospital. The project therefore demonstrates a scalable analytical framework, not a facility-ready staffing standard. Hospital-level deployment requires local census, unit-level capacity, staffing ratios, labor costs, transfer agreements, and governance requirements.

Included Submission Materials

- Phase 1 report and workbook: data understanding, quality assessment, variables, and feature engineering.
- Phase 2 report and workbook: forecasting methods, model comparison, predictions, and feature importance.
- Phase 3 report and workbook: optimization assumptions, resource recommendations, and sensitivity analysis.
- Python scripts: reproducible data preparation, forecasting, and optimization workflow.
- Original and cleaned datasets, supporting CSV tables, and fourteen publication-ready figures.