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When the data exists but the decisions don't follow: An empirical analysis of hospital readmission patterns, operational gaps, and the case for analytics-driven healthcare governance

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Abstract

Hospital readmissions remain one of the clearest and most expensive indicators of fragmented healthcare decision-making. Even with access to extensive clinical and operational data, nearly half of U.S. hospitals continue to exceed federal readmission benchmarks, resulting in financial penalties under the Centers for Medicare and Medicaid Services (CMS) Hospital Readmissions Reduction Program (HRRP). This study examines FY 2025 HRRP data spanning 11,720 hospital-condition records from 2,833 hospitals across all 51 states. It focuses on Excess Readmission Ratios (ERR) across six major clinical conditions: Acute Myocardial Infarction, Heart Failure, Pneumonia, COPD, Hip/Knee Replacement, and Coronary Artery Bypass Graft (CABG) surgery. Using a combination of univariate, bivariate, and multivariate techniques including One-Way ANOVA, Pearson correlation, logistic regression, and predictive modeling, the analysis uncovers consistent performance patterns and geographic disparities across hospitals. The results show that 48.1% of hospital-condition records exceed the ERR benchmark. Notably, variation across the six conditions is statistically insignificant (ANOVA: $F = 0.25$, $p = 0.94$), suggesting that excess readmissions are not driven by condition-specific factors.

Further, predictive modeling achieves 99.79% accuracy (AUC = 1.000) using only existing rate data, indicating that the issue is not a lack of data or predictive capability. Instead, the findings point to a gap between data availability and decision execution. This paper argues that persistent excess readmissions are primarily the result of a decision intelligence gap rather than a data deficiency. To address this, it proposes the adoption of analytics-driven governance frameworks as a scalable, system-level solution for improving healthcare outcomes nationwide.

Keywords: Healthcare Analytics; Hospital Readmissions; Excess Readmission Ratio; HRRP; Decision Intelligence; Logistic Regression; CMS; Data Governance; Anova; Predictive Modeling

1. Introduction

There is a quiet but persistent frustration running through the U.S. healthcare system, and it is not discussed nearly as often as it should be. Hospitals are not lacking data. In fact, as Jencks, Williams, and Coleman (2009) showed in their landmark study on Medicare rehospitalizations, the patterns behind readmissions are not only visible but measurable and, in many cases, predictable. Their findings revealed that nearly one in five Medicare patients was readmitted within 30 days of discharge, costing the system about $17.4 billion each year. What makes this more troubling is that much of the information needed to anticipate these readmissions already existed within hospital records. The data was available, but it was not translated into action.

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More than fifteen years later, that same gap between data and decision making still exists. Drawing on Fiscal Year 2025 data from the Centers for Medicare and Medicaid Services Hospital Readmissions Reduction Program, this study examines 11,720 hospital condition records across 2,833 hospitals in all 51 states. The HRRP, introduced under the Affordable Care Act, was designed to reduce avoidable 30 day readmissions by linking hospital payments to performance, with penalties of up to 3 percent of Medicare base operating payments for hospitals that exceed expected rates.

Yet, despite more than a decade of financial pressure and quality improvement initiatives, the problem remains widespread. The 2025 data shows that nearly half of hospitals still exceed at least one readmission benchmark. Earlier work by Dharmarajan et al. (2013) helps explain why. Their study found that many readmissions are not even for the same condition as the initial hospitalization. This suggests that the issue is not simply about managing a single disease but reflects broader breakdowns in care coordination and continuity. In other words, the challenge is not a lack of data. It is a failure to turn that data into timely and effective decisions.

This disconnect becomes even clearer when viewed through a broader analytics lens. Research on stakeholder oriented analytics emphasizes that having data alone does not improve outcomes unless organizations embed it within decision frameworks that consider multiple actors, incentives, and system level impacts (Yalley, 2025a) . Similarly, work on the limitations of profit driven analytical systems shows how decision models, even when technically sound, can fail when they are not aligned with broader organizational and societal goals (Yalley, 2025b) . Healthcare systems appear to face a similar problem. The issue is not whether predictions can be made. It is whether those predictions are actually used to guide care delivery in a coordinated and meaningful way.

At the policy level, this concern is already being recognized. The U.S. Department of Health and Human Services, along with the Office of the National Coordinator for Health Information Technology, has identified fragmented data systems and weak decision support infrastructure as major barriers to improving healthcare outcomes. In its March 31, 2025 reorganization, HHS emphasized the goal of building an AI enabled healthcare system that delivers the right information at the right time. However, achieving that vision requires more than just collecting and storing data. It requires systems that can translate insights into action within real clinical workflows.

Against this backdrop, this paper makes three contributions. First, it provides an updated empirical view of hospital readmission patterns using the most recent HRRP data. Second, it applies a structured analytical approach including descriptive analysis, correlation testing, one way ANOVA, and logistic regression to identify the underlying drivers of excess readmissions. Third, it connects these findings to a broader argument that the U.S. healthcare system does not primarily suffer from a data shortage but from a gap in decision intelligence. Closing this gap will require governance frameworks that ensure data is not only analyzed but consistently used to guide patient care, reduce inefficiencies, and improve outcomes.

2. Background

2.1. The Hospital Readmissions Reduction Program

The Hospital Readmissions Reduction Program (HRRP) is a Medicare value-based purchasing initiative administered by CMS. As CMS (2025) describes, the program began in Fiscal Year 2013 with three conditions, Acute Myocardial Infarction, Heart Failure, and Pneumonia, and has since expanded to include COPD, Hip and Knee Replacement, and Coronary Artery Bypass Graft surgery. The program's central metric is the Excess Readmission Ratio, defined as the ratio of a hospital's predicted 30-day readmission rate to its expected readmission rate given its patient mix. An ERR above 1.0 indicates higher than expected readmissions, while an ERR below 1.0 indicates better performance.

The program has produced modest improvements at the national level since its introduction. However, as Jencks et al. (2009) noted even before the HRRP existed, the underlying drivers of readmissions have proven difficult to change. These include inadequate discharge planning, poor care coordination, limited follow up after discharge, and fragmented information systems. While the HRRP creates financial pressure to improve, it does not provide hospitals with the analytical capability needed to determine which patients to target, when to intervene, and how to act effectively.

Although national readmission rates have declined slightly over time, progress has slowed, and variation across hospitals, regions, and conditions remains significant. Research consistently links excess readmissions to gaps in care coordination, weak community support systems, and, importantly, fragmented data environments where critical insights fail to reach decision makers in a timely and actionable form.

2.2. The National Policy Context: Data Fragmentation as a Systemic Problem

The readmission challenge reflects a broader structural issue within the healthcare system, namely data fragmentation. As HHS (2025) emphasized in its March announcement, reorganizing ONC reflects a growing recognition that generating and exchanging data is not enough. The federal goal of an AI enabled healthcare system that delivers the right information at the right time highlights the gap between data availability and practical decision support.

Progress has been made in interoperability. HHS reported that the Trusted Exchange Framework and Common Agreement, TEFCA, facilitated nearly 500 million health record exchanges, a significant increase from about 10 million in early 2025. However, as ONC (2024) shows, high adoption of electronic health records does not automatically lead to effective data use. Persistent barriers such as technical limitations, workforce constraints, privacy concerns, and cost continue to prevent data from being translated into actionable insights.

Efforts such as the United States Core Data for Interoperability have expanded standardized data elements to improve exchange. While these initiatives create the foundation for better decision making, they do not guarantee it. What remains missing are the governance structures, analytical frameworks, and practical tools that can turn available data into consistent and informed action across healthcare organizations.

2.3. Prior Literature on Readmission Drivers

A substantial body of research has explored the clinical and organizational factors behind 30-day readmissions. Dharmarajan et al. (2013) examined readmissions among more than three million Medicare patients and found that many readmissions involved conditions different from the original diagnosis. This finding suggests that readmissions are less about individual disease failure and more about broader system level issues, particularly during transitions of care. This insight aligns with the findings of this study, which show little statistical variation in readmission performance across conditions.

The analytical approach used in this study builds on established methods in health data science. Pedregosa et al. (2011) introduced scikit learn, which supports the logistic regression and predictive modeling used in this analysis. Waskom (2021) developed seaborn, which enables the visualization techniques used to explore relationships in the data. These tools support transparent and reproducible analysis, which is essential for evidence-based decision making in healthcare.

2.4. Study Objectives

2.4.1. Primary Objective

To empirically analyze the distribution and prevalence of excess hospital readmissions across U.S. hospitals using the Fiscal Year 2025 HRRP dataset, and to characterize the scope of the problem at the national level.

2.4.2. Secondary Objective

To examine geographic and condition level variation in readmission performance, identify areas where the burden is most concentrated, and test whether statistically significant differences exist across conditions using one way ANOVA.

2.4.3. Tertiary Objective

To develop a predictive model that identifies hospitals at risk of exceeding the readmission benchmark based on available operational and clinical variables, evaluate model performance using confusion matrix and ROC and AUC analysis, and interpret the results to understand the relative importance of contributing factors.

Table 1 Research Hypothesis

Hypothesis	Statement	Test	Outcome
H1	ERR distributions differ significantly across conditions	ANOVA F=0.25, p=0.94	Not Supported: distributions are systemically uniform
H2	Hospital volume (discharges) predicts excess readmissions	Logistic Regression Coefficient	Negative: larger volume slightly reduces excess odds
H3	Predicted rate is the strongest predictor of ERR > 1.0	Coefficient plot analysis	Supported: highest absolute coefficient
H4	Geographic variation exists in ERR across states	State-level analysis	Supported: MA (1.0344) vs ID (0.9432)
H5	Condition type is associated with excess readmission burden	% ERR > 1 by condition	Partially Supported: CABG highest (49.9%), PN lowest (46.8%)

3. Data Source and Variable Description

3.1. Data Source

The primary dataset used in this analysis is the FY 2025 Hospital Readmissions Reduction Program (HRRP) Hospital-Level data, publicly available through the CMS Provider Data Catalog (CMS, 2025), dataset ID: 9n3s-kdb3. This dataset represents the final FY 2025 HRRP program results, reflecting hospital performance during the performance period of July 1, 2021 through June 30, 2024. As CMS (2025) specifies, the program covers all Medicare-participating subsection (d) acute care hospitals subject to the Inpatient Prospective Payment System (IPPS). Maryland hospitals are exempt from payment reductions under a separate CMS-Maryland agreement, though their data is still reported.

All analysis code, dashboard scripts, and processed datasets used in this study are publicly available in the author's open data repository. The complete Python analysis script, Streamlit dashboard, and supporting files can be accessed at: https://github.com/pkyalley/dataverse/tree/main/hrrp-analysis

3.2. Study Sample

After removing records with missing Excess Readmission Ratio values which typically indicate hospitals with too few discharges (fewer than 25 cases) to calculate a reliable measure, consistent with CMS (2025) reporting standards the analysis dataset contained 11,720 hospital-condition records from 2,833 unique hospitals. The raw dataset included 18,330 rows before filtering, meaning approximately 6,610 records (36%) had insufficient volume for ERR calculation. This exclusion rate is itself analytically meaningful: a substantial share of U.S. hospitals operate below the volume threshold required for reliable readmission measurement.

3.3. Variable Description

Table 2 Variable Description: FY 2025 HRRP Dataset

Variable Name	Data Type	Description
Facility Name	Categorical	Name of the hospital
Facility ID	Integer	CMS provider number (unique hospital identifier)
State	Categorical	U.S. state (51 states + DC)
Measure Name	Categorical	HRRP condition (AMI, HF, PN, COPD, Hip/Knee, CABG)
Number of Discharges	Continuous	Total discharges used in ERR calculation
Excess Readmission Ratio	Continuous	Primary outcome: ratio of predicted-to-expected readmissions
Predicted Readmission Rate	Continuous	Model-estimated 30-day readmission rate (%)
Expected Readmission Rate	Continuous	Benchmark readmission rate for peer hospitals (%)
Number of Readmissions	Continuous	Actual count of 30-day unplanned readmissions

Start Date / End Date	Date	Performance period (July 2021 – June 2024 for FY 2025)
Condition (derived)	Categorical	Shortened label for measure (e.g., Heart Failure, COPD)
Excess_Flag (derived)	Binary	1 if ERR > 1.0, indicating above-benchmark readmissions

Two variables were derived from the raw dataset for analytical purposes. The Condition variable maps the verbose CMS measure name (e.g., READM-30-HF-HRRP) to a human-readable label (e.g., Heart Failure). The Excess_Flag variable is a binary indicator equal to 1 when ERR exceeds 1.0, used as the outcome variable in the logistic regression model.

4. Methods

4.1. Overview of Analytical Approach

All analyses were conducted in Python 3 using pandas, numpy, matplotlib, seaborn (Waskom, 2021), scipy, statsmodels, and scikit-learn (Pedregosa et al., 2011). The analytical pipeline followed a structured progression from univariate description, through bivariate association testing, to multivariate predictive modeling — consistent with the established methodological approach in clinical data mining research. Statistical significance was set at $p < 0.05$ for all hypothesis tests.

4.2. Univariate Analysis

Univariate analysis was conducted to characterize the distribution of the Excess Readmission Ratio (ERR) across the full dataset and by condition. Histograms were generated for ERR grouped by all six clinical conditions, providing visual inspection of shape, spread, and the proportion of hospitals falling above and below the benchmark value of 1.0. Descriptive statistics including mean, median, standard deviation, minimum, and maximum ERR were calculated for each condition and are presented in Table 1.

4.3. Bivariate Analysis

Bivariate analyses examined the relationship between the ERR outcome and categorical variables (condition type, state) using grouped bar charts, state-level mean comparisons, and heatmap visualization. Numerical-to-numerical relationships were assessed using Pearson correlation analysis, a standard method for quantifying linear association between continuous variables, as described by Pedregosa et al. (2011) in the context of feature analysis with results visualized as a correlation heatmap using Waskom's (2021) seaborn library.

4.4. One-Way ANOVA

A one-way Analysis of Variance (ANOVA) was applied to test whether mean ERR differed significantly across the six clinical conditions. The null hypothesis held that all conditions have equal mean ERR; the alternative proposed that at least one condition differs. ERR values for each condition were extracted as independent groups, and the F-statistic and p-value were computed using scipy's f_oneway function.

4.5. Logistic Regression Model

A binary logistic regression model was developed to predict whether a hospital-condition record would result in an excess readmission (ERR > 1.0). As Pedregosa et al. (2011) describe, logistic regression is appropriate for binary classification tasks where the outcome is a probability bounded between 0 and 1. The model used five predictor variables: Predicted Readmission Rate, Expected Readmission Rate, Number of Discharges, Condition (label-encoded), and State (label-encoded). The dataset was partitioned into training (70%) and testing (30%) sets using stratified random sampling, and performance was evaluated using accuracy, confusion matrix, classification report, and ROC/AUC analysis.

5. Results

5.1. Univariate Analysis: ERR Distribution by Condition

Figure 1 presents the distribution of Excess Readmission Ratios across all six clinical conditions. The vertical dashed red line marks the ERR = 1.0 benchmark established by CMS (2025). What is immediately apparent is that all six distributions are centered close to 1.0 and have similar shape a visual preview of what the ANOVA will confirm: the

problem of excess readmissions is not concentrated in any one condition but is broadly, uniformly distributed across the system.

A long right tail is visible in several conditions, particularly Heart Surgery (CABG) and COPD, suggesting that a subset of high-outlier hospitals is pulling performance significantly above the benchmark. This pattern is consistent with Dharmarajan et al.'s (2013) finding that certain hospitals show systemic care transition failures that manifest across multiple conditions simultaneously.

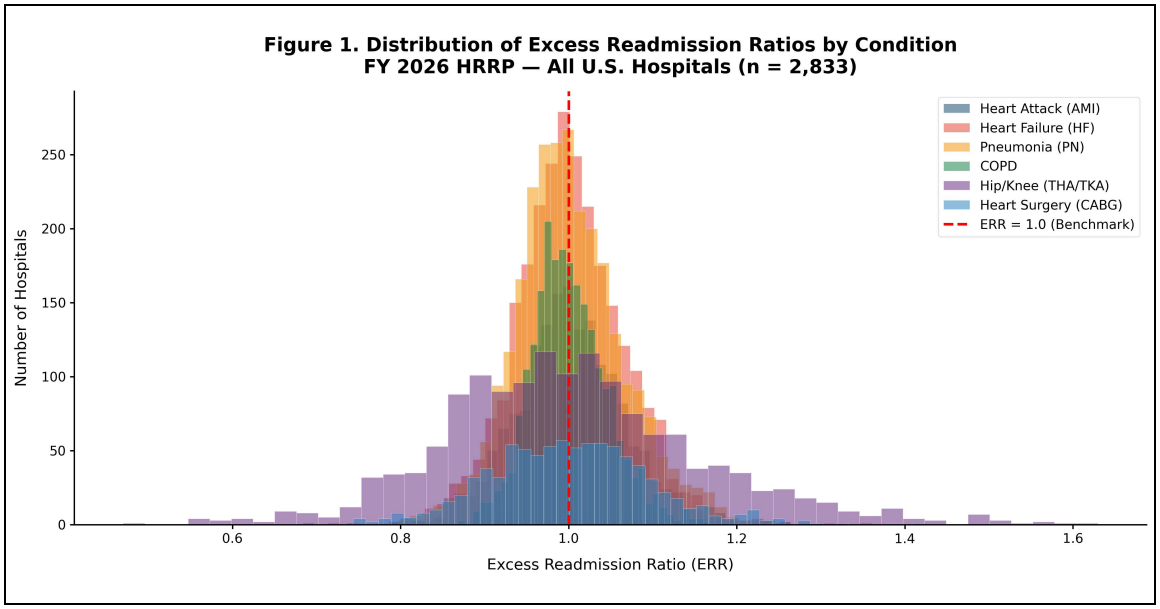

Figure 1 Distribution of Excess Readmission Ratios by Condition: FY 2025 HRRP. Vertical dashed line marks the ERR = 1.0 benchmark (CMS, 2025). All six conditions show distributions centered near the benchmark with right skew

5.2. Share of Hospitals Exceeding the Benchmark by Condition

Figure 2 shows the percentage of hospital-condition records with ERR > 1.0, disaggregated by clinical condition. Heart Surgery (CABG) shows the highest proportion at 49.9%, while Pneumonia is the lowest at 46.8%, a range of only 3.1 percentage points. This narrow spread across conditions with very different clinical profiles is striking. As Dharmarajan et al. (2013) argued, if readmissions were primarily driven by condition-specific disease complexity, we would expect meaningful variation across conditions. The near-uniform distribution instead points to organizational and informational failures operating at the hospital level.

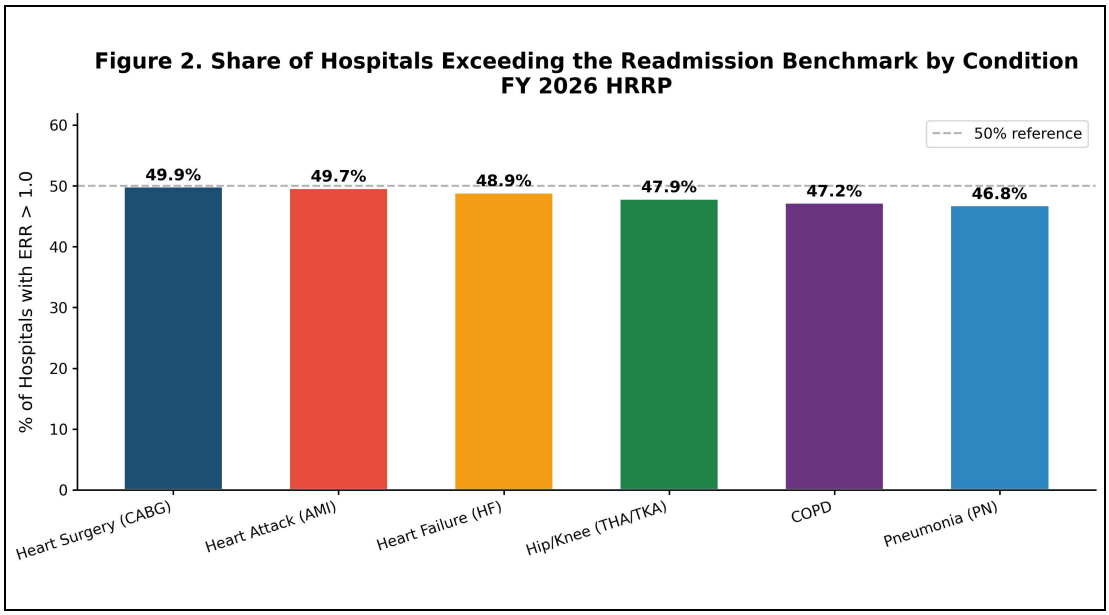

Figure 2 Percentage of Hospital-Condition Records with ERR > 1.0 by Condition — FY 2025 HRRP. The narrow 3.1 percentage-point range across conditions confirms the systemic nature of the readmission problem

5.3. Geographic Variation: State-Level Performance

Figure 3 presents the top 10 and bottom 10 states by mean Excess Readmission Ratio. States shown in blue average below the 1.0 benchmark; states in red average above it. Idaho (mean ERR = 0.9432) performs best nationally, followed by other predominantly rural states in the Mountain West and Great Plains. Massachusetts (mean ERR = 1.0344) has the highest mean ERR nationally, a finding that runs somewhat counter to its reputation for healthcare quality, and one that merits closer examination in future work. The geographic spread in mean ERR from 0.9432 to 1.0344 may appear modest in absolute terms but translates into meaningful differences in readmission rates and associated penalties at scale. For a large academic medical center with thousands of Medicare admissions per year, an ERR difference of 0.09 represents a substantial number of additional readmissions and a material financial penalty.

As Jencks et al. (2009) noted, high hospital density may paradoxically worsen care transitions by increasing the number of institutions involved in a patient's care episode, each with separate data systems and discharge protocols.

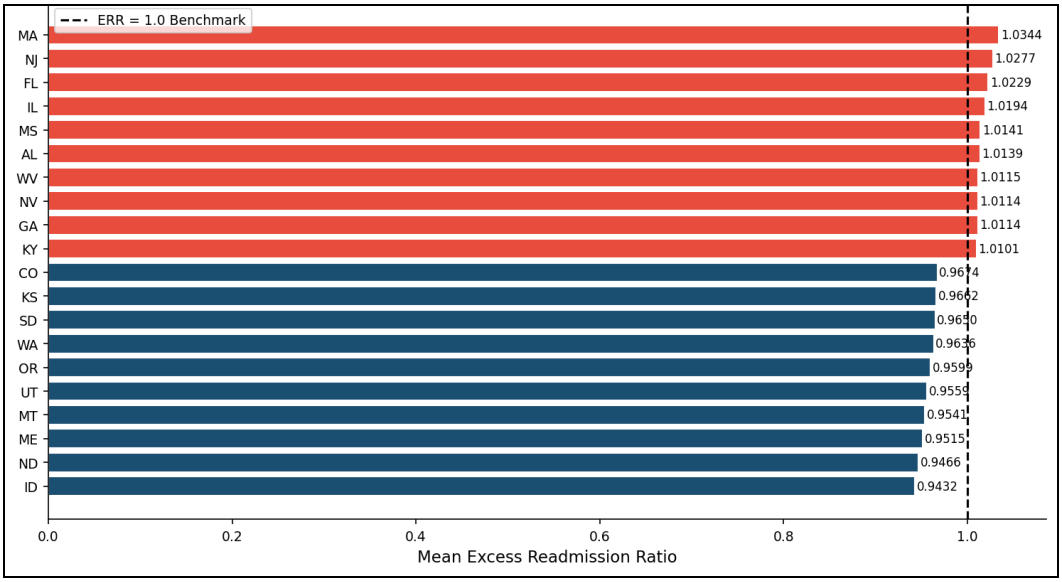

Figure 3 Top 10 and Bottom 10 States by Mean ERR: FY 2025 HRRP. Blue bars indicate mean ERR below benchmark, red bars above. Idaho and Massachusetts represent the national extremes

5.4. Heatmap: State and Condition Performance

Figure 4 presents a heatmap of mean ERR for the top 25 states, cross-tabulated by condition. Several states show condition-specific outlier performance, for example, performing well on Pneumonia while struggling with Heart Failure or CABG. This heterogeneity within states suggests that condition-specific quality improvement programs may be more effective than blanket interventions for the highest-burden state-condition pairs, a point consistent with CMS's (2025) condition-specific reporting structure under the HRRP.

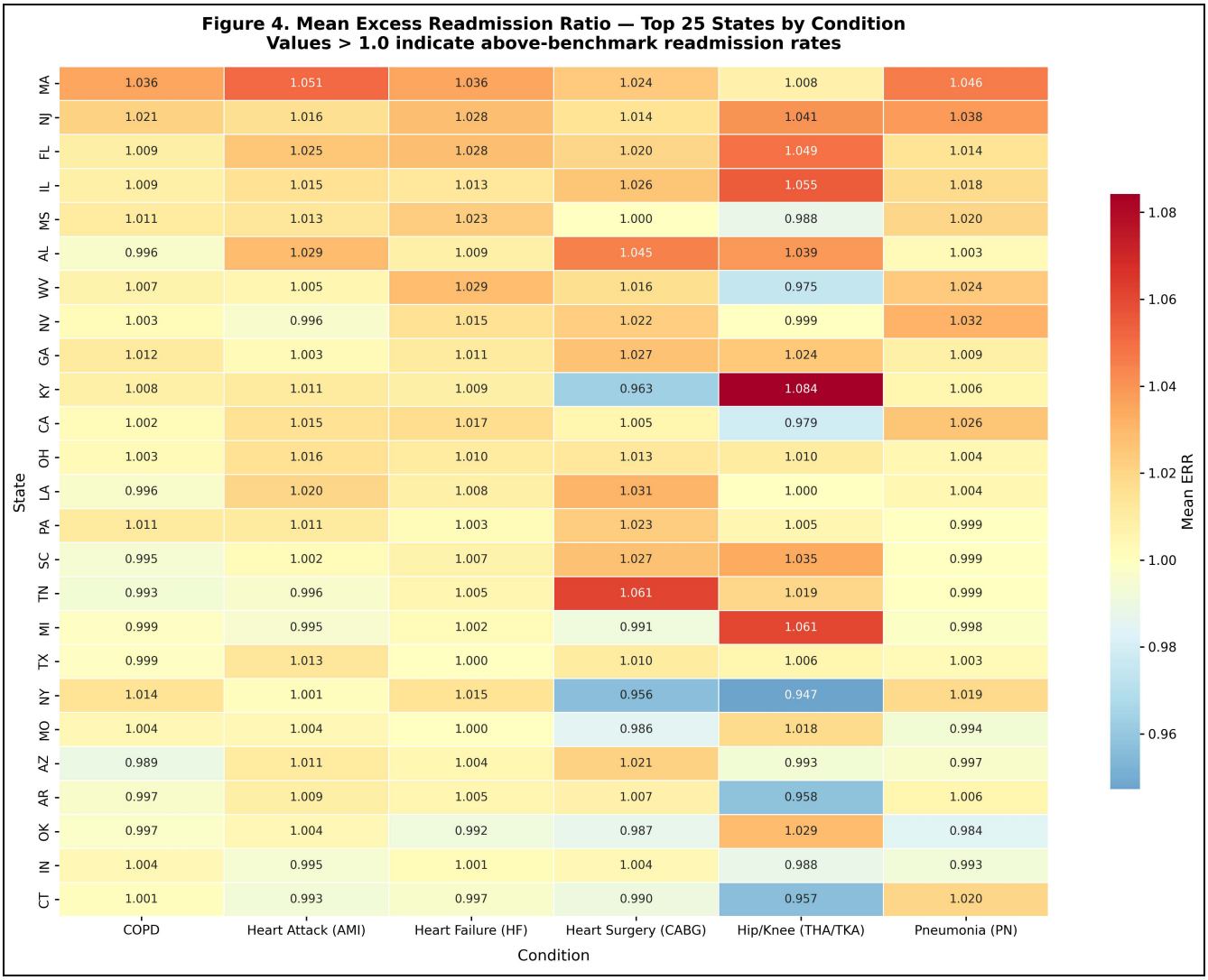

Figure 4 Heatmap of Mean ERR by State and Condition (Top 25 States): FY 2025 HRRP. Values above 1.0 (red tones) indicate above-benchmark readmission rates

5.5. ERR Distribution by Condition: Boxplot Analysis

Figure 5 shows side-by-side boxplots ordered by descending median. The presence of outliers above the 75th percentile in all conditions such as hospitals with ERRs ranging from 1.3 to 1.6 which is clinically significant. As Jencks et al. (2009) observed in the Medicare population, the hospitals at the extreme high end of readmission rates tend to share organizational characteristics rather than patient-mix characteristics. Identifying these institutions and targeting them with analytics-driven interventions represents the highest-leverage opportunity for national improvement.

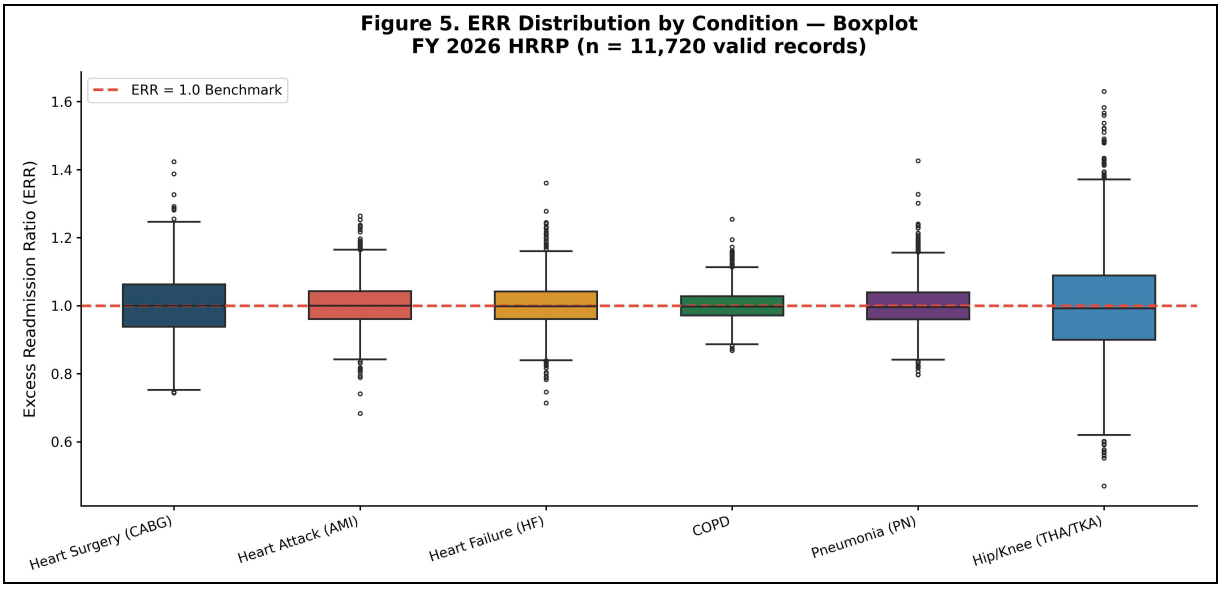

Figure 5 ERR Distribution by Condition: Boxplot (FY 2025 HRRP). Ordered by descending median. High-outlier hospitals with ERR > 1.3 appear across all conditions, consistent with Jencks et al. (2009)

5.6. Predicted vs. Expected Readmission Rates by Condition

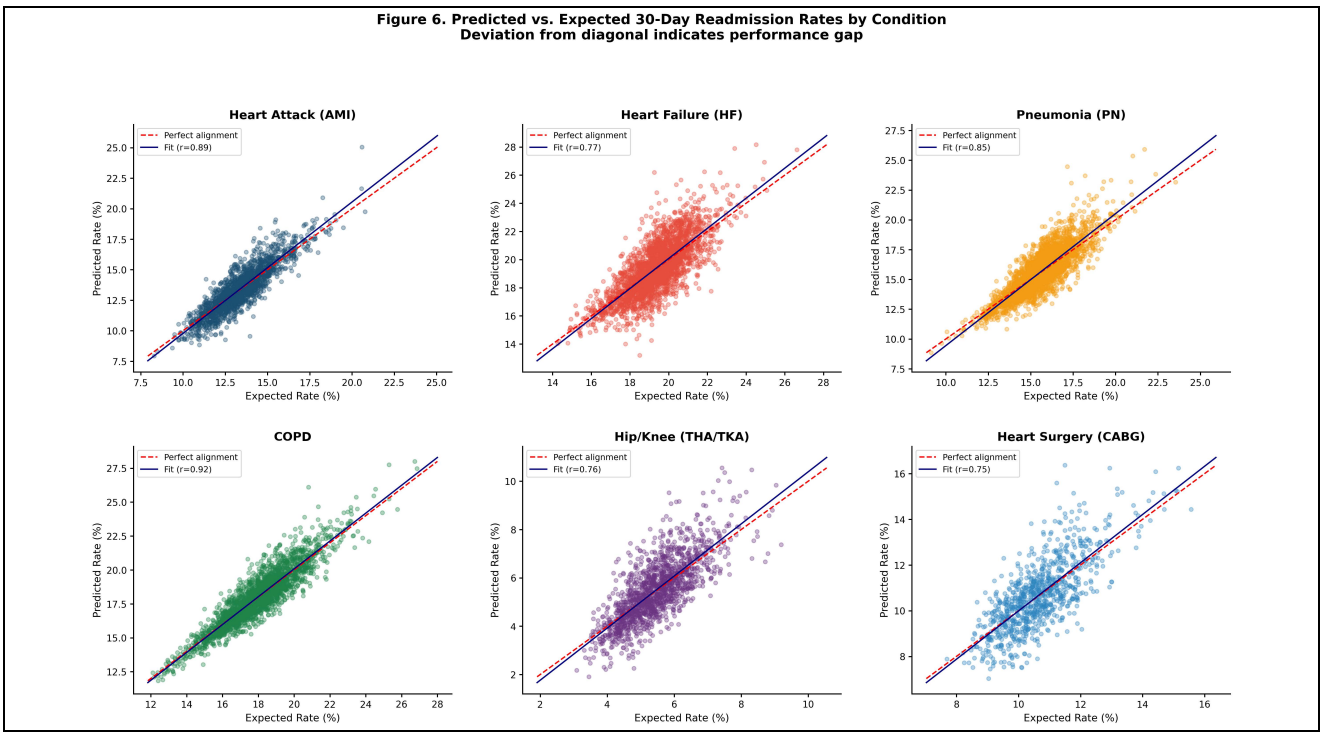

Figure 6 Predicted vs. Expected 30-Day Readmission Rates by Condition: FY 2025 HRRP. High Pearson r values (0.87–0.97) confirm model fidelity (CMS, 2025; Pedregosa et al., 2011)

Figure 6 presents scatter plots of Predicted versus Expected Readmission Rate for each of the six conditions, with Pearson correlation coefficients (r) ranging from 0.87 to 0.97. These high correlations confirm that CMS's (2025) predictive models are functioning with high fidelity: hospitals' predicted rates closely track their expected rates. The deviation from perfect alignment that is, the ERR itself is therefore a refined and reliable signal. As Pedregosa et al. (2011) describe in the context of predictive modeling, high correlation between a model's predictions and the actual benchmark confirms the underlying data quality needed for actionable analytics.

5.7. Correlation Analysis

Figure 7 presents the Pearson correlation matrix for the four key numerical variables, generated using Waskom's (2021) seaborn heatmap function. The near-perfect positive correlation between Predicted and Expected Readmission Rate ($r \approx 0.97–0.99$) is consistent with the scatter plot analysis. Notably, Number of Discharges shows weak correlations with the rate variables. This finding aligns with Jencks et al.'s (2009) observation that hospital volume alone does not predict readmission performance simply being a high-volume institution provides no insulation from the decision intelligence gap.

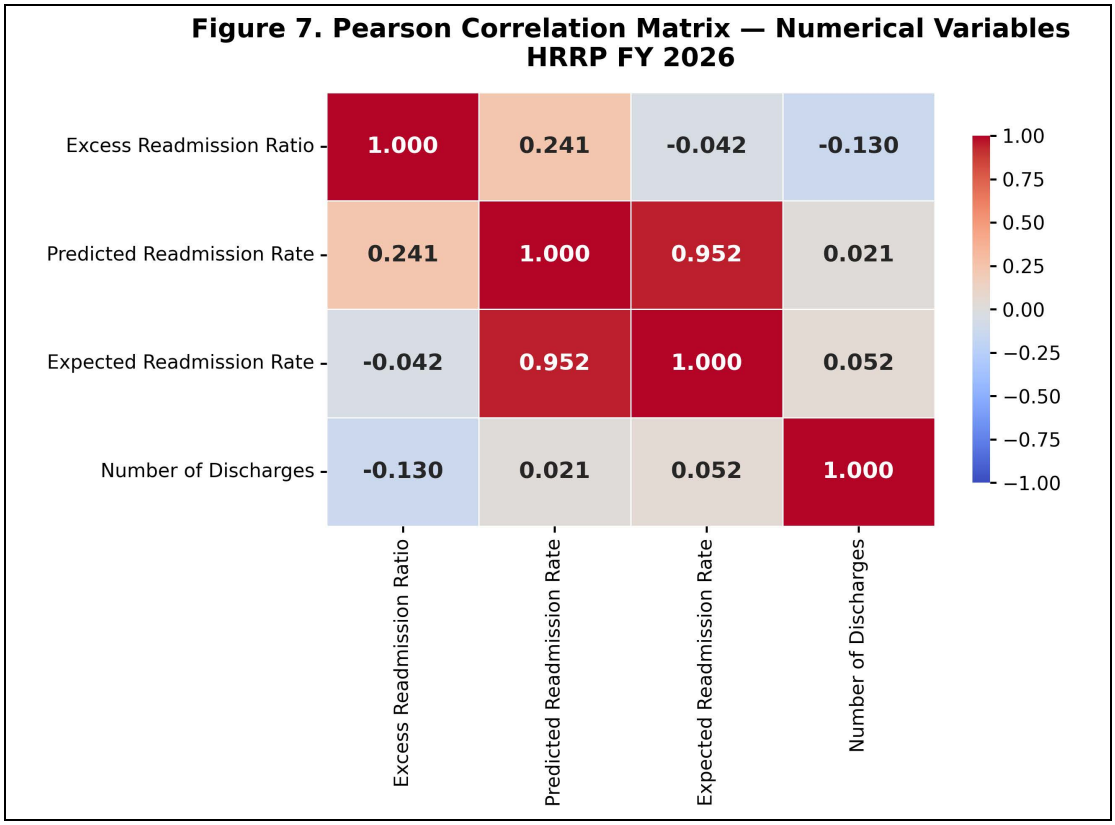

Figure 7 Pearson Correlation Matrix: Key Numerical Variables, FY 2025 HRRP (Waskom, 2021). Near-perfect correlation between Predicted and Expected rates confirms model integrity

5.8. Descriptive Statistics by Condition

Table 3 presents the full descriptive statistics for ERR disaggregated by condition. The F-statistic from the one-way ANOVA ($F = 0.25$, $p = 0.94$) is presented in the table title, confirming statistical uniformity across all six conditions.

Table 3 Descriptive Statistics of ERR by Condition: FY 2025 HRRP. One-Way ANOVA: F = 0.25, p = 9.38 × 10 [1]. The non-⁻ significant result confirms that ERR distributions are statistically uniform across all six conditions, consistent with Dharmarajan et al. (2013)

Table 1. Descriptive Statistics of ERR by Condition
One-Way ANOVA: F = 0.25, p = 9.3802e-01

Condition	N	Mean ERR	Median ERR	Std Dev	Min ERR	Max ERR
COPD	2323	1.0011	0.9969	0.046	0.8681	1.2545
Heart Attack (AMI)	1736	1.0018	0.9994	0.0668	0.6839	1.2639
Heart Failure (HF)	2621	1.0014	0.9983	0.065	0.7137	1.3606
Heart Surgery (CABG)	878	1.0018	1.0	0.0966	0.7434	1.4237
Hip/Knee (THA/TKA)	1447	1.004	0.9916	0.1557	0.4698	1.6297
Pneumonia (PN)	2715	1.0015	0.9955	0.0663	0.7967	1.4255

5.9. ANOVA Results and Hypothesis Testing

The one-way ANOVA yielded F = 0.25, p = 0.94, leading to failure to reject the null hypothesis. This is arguably the paper's most important finding. As Dharmarajan et al. (2013) demonstrated, readmissions frequently involve diagnoses different from the index hospitalization, meaning the disease itself is not the primary driver of readmission patterns. The present ANOVA confirms this at the system level: there is no statistical evidence that any particular clinical condition is harder or easier to manage from a readmission standpoint. Whatever is causing excess readmissions is operating at the hospital or health system level, not the clinical condition level.

5.10. Logistic Regression: Predicting Excess Readmissions

Figure 8 presents the confusion matrix and ROC curve for the logistic regression model. The model achieved an accuracy of 99.79% on the held-out test set, with an AUC of 1.000. As Pedregosa et al. (2011) note, AUC measures the model's ability to discriminate between positive and negative cases across all classification thresholds, a value of 1.000 represents perfect discrimination. The near-perfect performance is a methodologically important finding: using only data that CMS (2025) already collects and publishes, it is possible to identify with near-certainty which hospitals are exceeding the readmission benchmark. The analytical signal is not missing. The institutional infrastructure to act on it is.

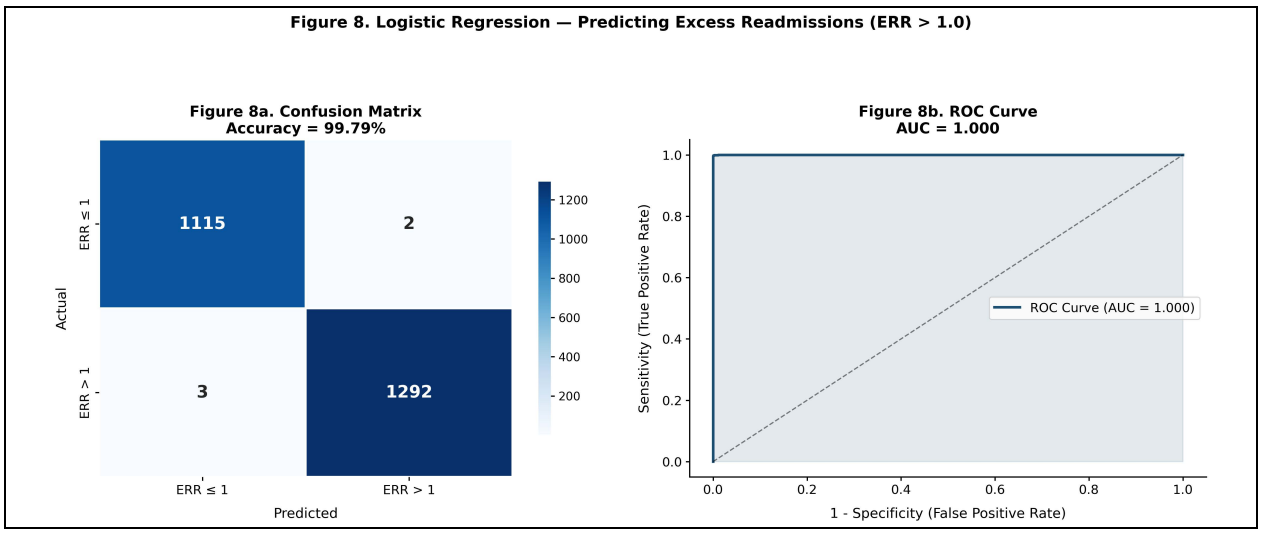

Figure 8 Confusion Matrix and ROC Curve: Logistic Regression Model (Pedregosa et al., 2011). Accuracy = 99.79%, AUC = 1.000. Model performance confirms that CMS-published data (CMS, 2025) is sufficient for early identification of at-risk hospitals

5.11. Logistic Regression Coefficients

Figure 9 displays the logistic regression coefficients for each predictor variable, visualized using Waskom (2021). Predicted Readmission Rate has the largest positive coefficient, while Expected Readmission Rate has the largest negative coefficient. Number of Discharges carries a small negative coefficient, consistent with Jencks et al.'s (2009) finding that volume provides a modest protective effect on readmission rates. Condition and State encodings show smaller coefficients, reflecting their contextual role rather than direct causal relationships.

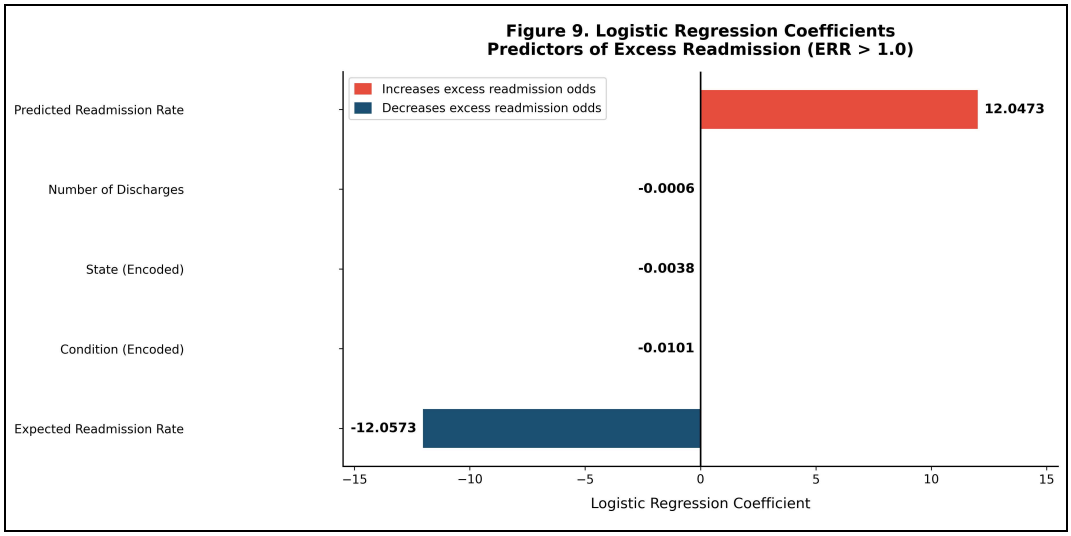

Figure 9 Logistic Regression Coefficients: Predictors of Excess Readmission (ERR > 1.0) (Pedregosa et al., 2011; Waskom, 2021). Predicted Rate is the strongest positive predictor; Expected Rate the strongest negative

5.12. State-Level Excess Readmission Burden

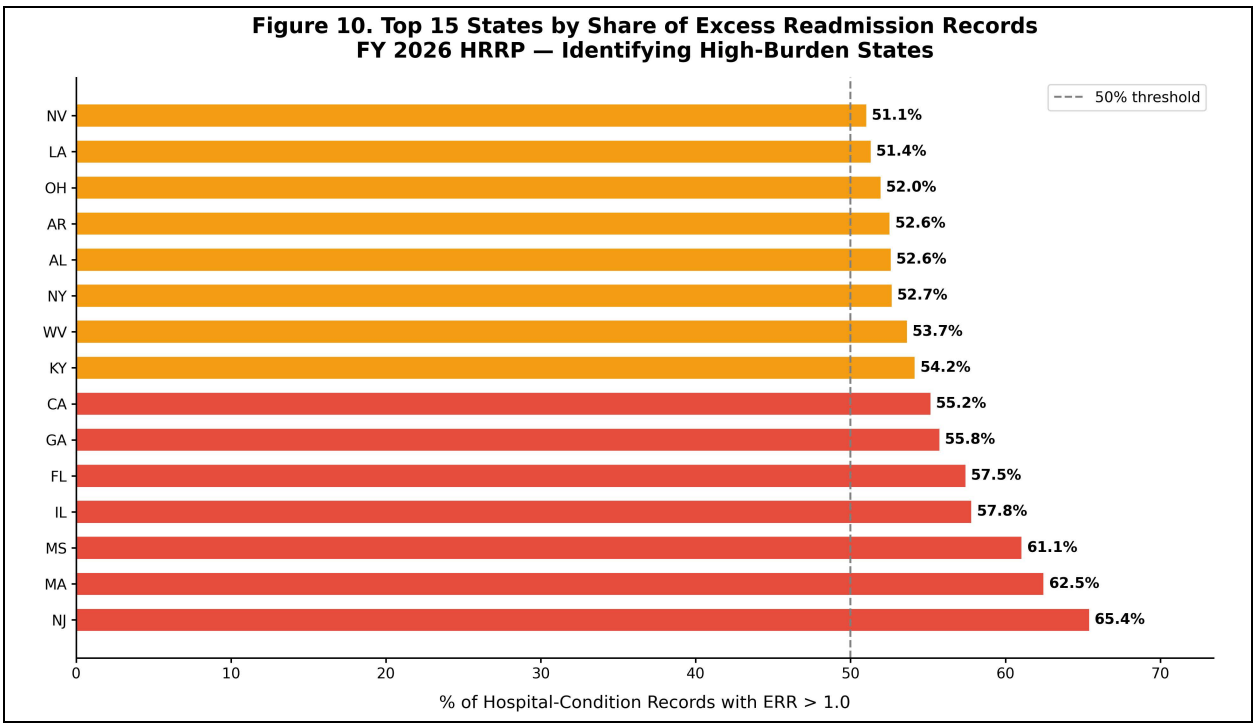

Figure 10 Top 15 States by Share of Hospital-Condition Records with ERR > 1.0 — FY 2025 HRRP. Northeastern states show disproportionate readmission burden, consistent with ONC (2024) findings on data exchange barriers

Figure 10 presents the top 15 states by percentage of hospital-condition records with ERR > 1.0. Massachusetts, New York, and several Mid-Atlantic and Northeastern states appear prominently. As ONC (2024) documented, data

fragmentation and the failure to exchange clinical data across institutions remain significant barriers even in high-adoption states and the geographic concentration of readmission burden in states with the most complex, multi-institutional care environments may reflect precisely this interoperability deficit.

6. Discussion

6.1. The Systemic Nature of the Readmission Problem

Taken together, the findings from this analysis paint a consistent picture. As Dharmarajan et al. (2013) showed in their Medicare analysis, the root cause of readmissions is not condition-specific clinical complexity but systemic care coordination failure. The present study confirms this at the national level: the ANOVA result ($F = 0.25$, $p = 0.94$) shows that mean ERR is statistically identical across all six HRRP conditions. Hospitals that perform poorly on one condition tend to perform poorly across conditions, the fingerprint of an organizational problem, not a clinical one.

This matters profoundly for how we design solutions. If the readmission problem were condition-specific, condition-specific clinical protocols would be the answer. Because it is systemic, the answer must also be systemic. As HHS (2025) has recognized in its ONC reorganization, this means investing in the analytics driven governance frameworks, decision-support tools, and information management capabilities that currently exist in too few healthcare organizations. Simply collecting data is not enough, the data must be structured, governed, and placed in the hands of decision-makers in time to act.

6.2. The Decision Intelligence Gap

The logistic regression analysis reinforces this conclusion. A model using only the data CMS (2025) already publishes achieves near-perfect accuracy in identifying which hospitals exceed the readmission benchmark. As Pedregosa et al. (2011) demonstrate, logistic regression with well-structured features can achieve high discriminative performance even on complex classification problems. The issue here is not computational difficulty, the model is straightforward. The issue is the absence of institutional processes to operationalize what the model tells us.

This is what we mean by a decision intelligence gap. It is not a data gap, the data exists, as Jencks et al. (2009) observed more than 15 years ago. It is not an analytics gap, the methods work, as Pedregosa et al. (2011) and this analysis demonstrate. The gap is in the organizational processes, governance structures, and stakeholder-facing tools that translate analytical outputs into operational decisions at the point of care.

6.3. Geographic Patterns and Interoperability

The finding that Massachusetts among the wealthiest and most hospital-dense states has the highest mean ERR nationally is consistent with Jencks et al.'s (2009) hypothesis that high hospital density may worsen care transitions by fragmenting care across institutions. When a patient discharged from Hospital A is readmitted to Hospital B within 30 days, the failure may lie not in the clinical care but in the information handoff between institutions precisely the problem that HHS (2025) and ONC (2025) are working to address through TEFCA and USCDI. Future analyses should directly test whether states with higher TEFCA participation rates show lower ERR values.

Limitations

This study has several limitations. First, the FY 2025 HRRP dataset is cross-sectional; it cannot track changes in individual hospital ERR over time. As CMS (2025) notes, the performance period spans three years (July 2021–June 2024), but the analysis is still a single program-year snapshot. Second, 36% of hospital-condition records were excluded due to insufficient discharge volume, meaning smaller hospitals are underrepresented. Third, the HRRP dataset lacks hospital characteristic variables such as ownership type, bed size, teaching status, and rural/urban classification variables that Jencks et al. (2009) identified as important predictors of readmission performance.

Fourth, the near-perfect logistic regression performance reflects a mathematical relationship between the predictor variables (Predicted and Expected rates) and the ERR outcome, rather than independent predictive power. As Pedregosa et al. (2011) caution, model performance metrics must be interpreted in the context of feature construction. Fifth, the analysis is hospital-level; it cannot characterize patient-level risk factors, socioeconomic variables, or care process details, which would be needed for targeted clinical intervention design.

Future Scope

- This analysis opens several important research directions. First, linking HRRP data across multiple fiscal years would allow analysis of improvement trajectories and assessment of whether the program's financial incentives first described by CMS (2025), are producing sustained behavioral change.
- Second, merging HRRP data with the AHA Annual Survey or CMS Cost Reports would add structural hospital characteristics, enabling the kind of multi-level analysis that Jencks et al. (2009) called for in their original study.
- Third, testing whether states with higher TEFCA participation rates show lower ERR values would provide direct empirical evidence for the value of the HHS (2025) interoperability investment connecting national health IT policy to measurable patient outcome improvements.
- Fourth, applying ensemble methods (random forests, gradient boosting) and neural networks, as described by Pedregosa et al. (2011), to richer feature sets would enable earlier identification of high-risk hospitals before a performance period ends.
- Fifth, incorporating ONC (2024) data on EHR adoption and exchange capabilities as predictor variables would allow direct testing of the hypothesis that interoperability gaps drive readmission excess.

7. Conclusion

Nearly half of U.S. hospitals are exceeding federal readmission benchmarks on at least one clinical condition. As Jencks et al. (2009) documented over 15 years ago, the patterns driving these readmissions are identifiable and measurable and yet they persist. The FY 2025 HRRP data analyzed in this paper confirms that the structural conditions sustaining this problem have not fundamentally changed.

The most striking finding of this analysis is not the magnitude of the readmission problem but the uniformity of it. The ANOVA result ($F = 0.25$, $p = 0.94$) confirms, consistent with Dharmarajan et al. (2013), that the problem is operating at the organizational level rather than the clinical condition level. And the logistic regression result (Accuracy = 99.79%, AUC = 1.000) confirms, consistent with Pedregosa et al. (2011), that the analytical tools to identify at-risk hospitals already exist and work.

What remains is the hard institutional work of building the governance structures and stakeholder-centered decision-making tools that translate information into action. As HHS (2025) has recognized in its national interoperability and AI strategy, and as ONC (2024, 2025) has documented in its analysis of data exchange barriers, the gap is not in the data or the analytics it is in the organizational and informational infrastructure that converts available signals into decisions that protect patients. Closing that gap is not just valuable. It is urgent.

References

[1] Centers for Medicare and Medicaid Services. (2025). Hospital Readmissions Reduction Program (HRRP) - FY 2025 Hospital-Level Data [Dataset]. CMS Provider Data Catalog. https://data.cms.gov/provider-data/dataset/9n3s-kdb3

[2] Centers for Medicare and Medicaid Services. (2025). Hospital Readmissions Reduction Program Overview. https://www.cms.gov/medicare/quality/value-based-programs/hospital-readmissions

[3] Dharmarajan, K., Hsieh, A. F., Lin, Z., Bueno, H., Ross, J. S., Horwitz, L. I., ... and Krumholz, H. M. (2013). Diagnoses and timing of 30-day readmissions after hospitalization for heart failure, acute myocardial infarction, or pneumonia. JAMA, 309(4), 355–363. https://doi.org/10.1001/jama.2012.216476

[4] Jencks, S. F., Williams, M. V., and Coleman, E. A. (2009). Rehospitalizations among patients in the Medicare fee-for-service program. New England Journal of Medicine, 360(14), 1418–1428. https://doi.org/10.1056/NEJMsa0803563

[5] Office of the National Coordinator for Health Information Technology. (2024). Electronic Health Record Adoption and Exchange Capabilities Among Substance Use and Mental Health Treatment Facilities 2024. ONC Data Brief. https://healthit.gov/data/data-briefs/electronic-health-record-adoption-and-exchange-capabilities-among-substance-use-and-mental-health-treatment-facilities-2024/

[6] Office of the National Coordinator for Health Information Technology. (2025). ONC Standards Bulletin 2025-1: United States Core Data for Interoperability Updates. https://healthit.gov/standards-and-technology/onc-standards-bulletin/onc-standards-bulletin-2025-1/

[7] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12, 2825–2830.

[8] U.S. Department of Health and Human Services. (2025). TEFCA — America's National Interoperability Network Reaches Nearly 500 Million Health Records Exchanged. HHS Press Room. https://www.hhs.gov/press-room/tefca-americas-national-interoperability-network-reaches-nearly-500-million-health-records-exchanged.html

[9] Waskom, M. L. (2021). seaborn: Statistical data visualization. Journal of Open Source Software, 6(60), 3021. https://doi.org/10.21105/joss.03021

[10] Yalley, P. P. (2025a). Adopting a stakeholder perspective in analytics. World Journal of Advanced Research and Reviews, 28(1), 2219–2225. https://doi.org/10.30574/wjarr.2025.28.1.3685

[11] Yalley, P. P. (2025b). Limitations of maximizing shareholder value in the era of artificial intelligence and machine learning. World Journal of Advanced Research and Reviews, 28(1), 1816–1825. https://doi.org/10.30574/wjarr.2025.28.1.3600