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Predictive Risk Analytics and Potentially Preventable Readmissions in Skilled Nursing Facilities

A Real-World Observational Study

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Abstract

Preventable hospitalizations from skilled nursing facilities (SNFs) represent a significant clinical and economic challenge in post-acute care. This study evaluated whether adoption of the Saiva UPT (Unplanned Transfers) application, which is part of a predictive analytics platform is associated with improved performance on the Centers for Medicare & Medicaid Services (CMS) Skilled Nursing Facility Potentially Preventable Readmission (SNFPPR) quality measure. Using publicly reported CMS data from 662 Florida SNFs across two reporting periods (2021–2024), facility-level changes in readmission performance were analyzed comparing facilities adopting Saiva in 2023–2024 with non-adopting controls. Facilities using Saiva were more likely to demonstrate improvement in readmission performance and showed numerically greater reductions in deterioration relative to controls. Exposure-adjusted regression modeling demonstrated a statistically significant association between months of Saiva exposure and improved performance ($p = 0.044$). These findings provide real-world evidence that predictive clinical risk analytics may contribute to reduced preventable hospitalizations in SNF populations.

Background

Preventable hospitalizations represent one of the most consequential adverse events in post-acute care. Transfers from skilled nursing facilities (SNFs) to acute care hospitals are frequently associated with worsened clinical outcomes in frail populations. As noted by the Centers for Medicare & Medicaid Services (CMS), unnecessary hospitalizations are disruptive and expose long-term care residents to additional risks, including hospital-acquired complications and medication errors [1]. These risks contribute to increased morbidity and mortality among older adults receiving post-acute care.

Beyond their clinical consequences, preventable hospitalizations impose substantial financial burdens on the healthcare system. According to the Agency for Healthcare Research and Quality (AHRQ), hospital readmissions for selected high-frequency conditions account for billions of dollars in annual inpatient expenditures across payers. Weiss and Jiang et al report that the average cost per readmission is approximately **$15,200,** and aggregate annual costs associated with readmissions exceed **$26 billion nationally** [2]. These figures underscore the magnitude of potentially avoidable spending tied directly to recurrent hospital use. Reducing preventable readmissions therefore has significant implications for Medicare expenditures, value-based purchasing programs, and overall healthcare resource allocation.
In recognition of their importance, potentially preventable readmissions are measured using standardized, nationally accepted quality metrics developed and maintained by CMS. Within the Skilled Nursing Facility Quality Reporting Program (SNF QRP), 30-day potentially preventable readmissions are reported as a risk-standardized outcome measure derived from Medicare claims data [3, 4, 5].
These measures are publicly reported and widely used by regulators, payers, and providers to benchmark performance, inform quality improvement initiatives, and guide reimbursement decisions [3, 5, 8]. As such, they represent an established and accepted framework for evaluating facility-level performance in post-acute care.

Preventable readmissions are broadly recognized as indicators of care quality and system performance [6, 7]. **Federal** initiatives **such as the Hospital Readmission Reduction Program (HRRP) reinforce the broader policy focus on reducing avoidable hospitalizations across care settings** [8]. At the system level, reductions in readmissions have been associated with improved quality and reduced spending [9].

Saiva's **UPT (Unplanned Transfer) application** is part of a predictive analytics platform designed to identify residents at elevated risk for potentially preventable hospitalization. The product uses clinical Electronic Medical Record (EMR) data to generate resident-level risk stratification and actionable insights for care teams. By flagging high-risk individuals in advance of acute deterioration, the platform aims to support earlier clinical intervention, improved care coordination, and proactive management strategies within SNFs. Additional information about the product and its functionality is available at: https://www.saiva.ai.

The real-world effectiveness of predictive tools depends not only on algorithmic performance but also on adoption and workflow integration. Unlike randomized controlled trials (RCTs), which often rely on strict inclusion and exclusion criteria, tightly monitored protocols, and controlled implementation environments, real-life medical interventions occur across large, heterogeneous populations with varying staffing models, workflows, and operational capacities. In routine practice, the effectiveness of predictive tools depends not only on algorithmic performance but also on facility-level adoption, integration into clinical workflows, and the ability of care teams to act effectively on the information provided. Real-world impact therefore reflects both the intrinsic capability of the intervention and the degree to which it is operationalized in diverse practice settings. Accordingly, the present investigation evaluates whether adoption of Saiva is associated with improved performance on the CMS Hospital-Wide Potentially Preventable Readmission measure in routine SNF practice environments.

Hypothesis

Adoption of the Saiva **UPT application** is associated with a reduction in potentially preventable hospitalizations compared with control facilities, as reflected by improved performance on the CMS Hospital-Wide Potentially Preventable Readmission (PPR) quality measure under real-world Skilled Nursing Facility (SNF) conditions.

Specifically, we hypothesize that facilities adopting Saiva will demonstrate:

- **A higher proportion of facilities exhibiting improvement in readmission performance** and a correspondingly lower proportion of facilities exhibiting performance decline, compared with control facilities.
- **Greater magnitude of performance improvement among improving facilities**, relative to controls.
- **Reduced magnitude of performance deterioration among declining facilities,** suggesting mitigation of downside risk compared with controls.
- **A dose-response relationship,** whereby longer exposure to Saiva within the CMS reporting window is associated with progressively greater improvement in readmission performance.

(Null hypothesis: There is no association between adoption of the Saiva UPT application and changes in CMS potentially preventable readmission performance. Facilities adopting Saiva do not differ from control facilities in the proportion of improving versus declining facilities, the magnitude of improvement, the magnitude of decline, or exposure-duration effects.)

Methods

Study Design

This is a retrospective observational facility-level analysis of publicly reported Skilled Nursing Facility (SNF) quality performance data under real-world operating conditions.

The study evaluates whether adoption of the Saiva **UPT application** is associated with changes in facility-level performance on the CMS Hospital-Wide Potentially Preventable Readmission (PPR) measure **(Measure Code: S_004_01_PPR_PD_RSRR).**

**All analyses were conducted at the facility level.*

Data Source

Facility-level readmission performance data were obtained from publicly reported CMS Skilled Nursing Facility Quality Reporting Program (SNF QRP) datasets covering consecutive two-year reporting periods:

- October 1, 2021 – September 30, 2023
- October 1, 2022 – September 30, 2024

These datasets report risk-standardized 30-day potentially preventable readmission performance for Medicare fee-for-service beneficiaries under the CMS Hospital-Wide PPR measure (S_004_01_PPR_PD_RSRR).

Saiva adoption dates were obtained from internal contract records and matched to facilities using provider identifiers.

Study Population

The study included all Florida SNFs with available readmission performance data for both reporting periods.

Facilities were categorized into:

- Adoption during 2023
- Adoption during 2024
- Adoption during 2025
- No Saiva adoption

For primary comparative analyses:

- Facilities adopting during 2023 or 2024 were designated as the **test group.**
- Facilities adopting in 2025 or never adopting were designated as the **control group.**

Facilities adopting in 2025 were treated as controls because their adoption occurred outside the performance windows evaluated (2021–2024).

PART I

Raw Analysis (Without Accounting for Overlap)

This analysis treated consecutive two-year CMS reporting windows as independent periods. This is done for transparency and presenting the data as is.

Performance Change Calculation

Facility-level change in readmission performance was quantified using **relative period-over-period change (POP), defined as:**

$$POP = \frac{(Score_{Oct2021-Sep2023} - Score_{Oct2022-Sep2024})}{Score_{Oct2021-Sep2023}}$$

Because lower readmission scores indicate better performance, this formulation yields:

- **POP > 0 →** improvement (score decreased)
- **POP < 0 →** worsening (score increased)

Facilities were classified as:

- **Improving facilities:** POP > 0
- **Declining facilities:** POP ≤ 0

No adjustment was made in this section for the 12-month overlap between reporting windows, presenting the data as is.

Outcomes Examined (Raw Analysis)

The following descriptive outcomes were evaluated:

- Mean POP by adoption group
- Proportion of facilities exhibiting improvement (POP > 0)
- Mean magnitude of improvement among improving facilities
- Mean magnitude of decline among declining facilities
- Comparative results between aggregated test and control groups

Descriptive statistics were calculated separately for each adoption cohort and for pooled test versus control groups.

Graphical Analysis

Bar charts were generated to display:

- Proportion of improving facilities by group
- Mean POP among improving facilities
- Mean POP among declining facilities

No inferential correction for serial correlation or overlap was applied in this section.

PART II

Overlap-Adjusted Analysis (Exposure-Weighted Modeling)

Because CMS reports performance using a rolling two-year window updated annually, consecutive reporting periods share 12 months of underlying data (50% overlap). This structural overlap introduces serial correlation and partial exposure within performance windows.
To account for this, an exposure-weighted modeling approach was implemented.

Exposure Definition

Saiva exposure was quantified as the number of months a facility actively used Saiva during the October 1, 2022 – September 30, 2024 reporting window.

Exposure months were calculated as:

Exposure Months=max(0, Sep 30, 2024-max(Adoption Date,Oct 1, 2022))

Facilities adopting after September 30, 2024 were assigned zero exposure months.

This variable captures partial adoption within the rolling performance window and allows modeling of dose-response effects.

Statistical Models

Continuous Change Model

Linear regression modeling POP as a function of Saiva exposure months and baseline readmission score (Oct 2021–Sep 2023):

$$\mathrm{POP}_{\mathrm{i}} = \beta_0 + \beta_{1(\mathrm{exposure_months}_{\mathrm{i}})} + \beta_{2(\mathrm{baseline}_{\mathrm{i}})} + \varepsilon_1$$

The model was fitted on the full cohort without stratification by improvement status (POP > 0 vs. POP ≤ 0), thereby preserving the continuous distribution of performance change and avoiding outcome-conditioned bias.

Robust (heteroskedasticity-consistent) standard errors were applied.

Dose–Response Assessment

A dose–response relationship was evaluated by examining:

- Direction and magnitude of the exposure month coefficient
- Statistical significance (α = 0.05)
- Predicted POP and predicted probability of improvement across exposure duration

Predicted values were calculated while holding baseline performance constant.

Sensitivity Definition of Control

Facilities adopting in 2025 were treated as unexposed in the overlap-adjusted model because their adoption occurred outside the evaluated reporting window. This preserves temporal integrity and prevents contamination of the exposure variable.

Statistical Software

All analyses were conducted using Python (pandas, NumPy, statsmodels, and matplotlib). Robust variance estimators were applied in linear models. Statistical significance was assessed at $\alpha = 0.05$.

Statistical Models

The raw analysis does not account for the structural 50% overlap between reporting windows, partial exposure due to staggered adoption, and the resulting statistical dependence between adjacent CMS reports.

The exposure-weighted modeling approach compensates for these structural features and provides a more conservative and methodologically rigorous estimate of association under real-world implementation conditions.

Results

Study Population

A total of 662 Florida Skilled Nursing Facilities (SNFs) met inclusion criteria, with available readmission performance data for both reporting periods (October 1, 2021 – September 30, 2023 and October 1, 2022 – September 30, 2024).

Facilities were categorized as follows:

- Adopted in 2023: 15 facilities
- Adopted in 2024: 42 facilities
- Adopted in 2025: 40 facilities
- No Saiva adoption: 565 facilities

For comparative purposes:

- **Test group (2023–2024 adopters): 57 facilities**
- **Control group (2025 + non-adopters): 605 facilities**

PART I

Raw Analysis (No Adjustment for Overlap)

Overall Performance Distribution

Across all facilities:

- **Improving facilities: 261 (39%)**
- **Declining facilities: 401 (61%)**

This demonstrates substantial heterogeneity in performance change across the state.

Proportion of Improving Facilities

Table 1: Improvement rates differed between test and control groups:

Group	N total	N improved	% Improving
Adopted 2023	15	8	53.3 %
Adopted 2024	42	21	50.0 %
Adopted 2025	40	16	40.0 %
Non-Saiva	565	216	38.2 %

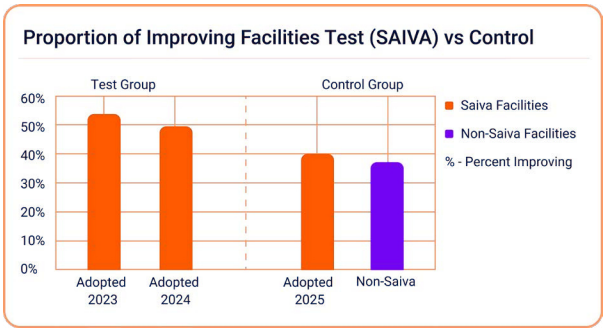

Figure 1: Proportion of improving facilities Saiva adopted 2023-2024 compared to control group (adopted 2025 + non-Saiva facilities)

When pooled:

- **Test group: 50.9% improving**
- **Control group: 38.3% improving**

When pooled, 50.9% of facilities in the test group demonstrated improvement compared with 38.7% in the control group. This corresponds to an absolute difference of 12.2 percentage points in favor of the test group.

Expressed relatively, facilities in the test group were approximately 31% more likely to demonstrate improvement than control facilities.

Magnitude of Improvement

Table 2: Among improving facilities:

Group	Median POP	Mean POP (std)
Adopted 2023	12.55 %	10.14 % (4.7%)
Adopted 2024	6.98 %	7.8 % (5.3%)
Adopted 2025	3.62 %	7.64 % (7.5%)
Non-Saiva	6.34 %	7.49 % (5.4%)

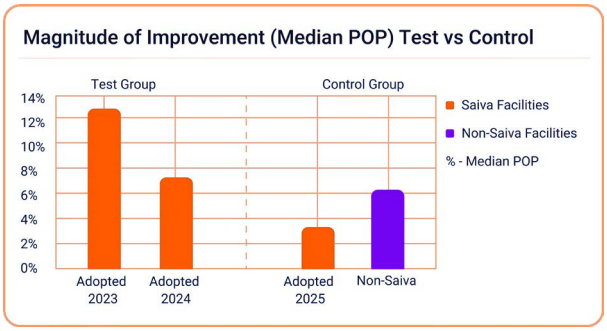

Figure 2: Magnitude of POP improvement between test and control.

Among facilities demonstrating improvement, descriptive statistics (mean, median, and standard deviation of POP) are presented in Table 2.

Among improving facilities, the largest median and mean improvement was observed in the 2023 adoption cohort. Improvement magnitude was numerically greater in early adopters compared with later adopters and control facilities. Variability in improvement magnitude was similar across cohorts.

Magnitude of Decline

Table 3: Among declining facilities:

Group	Median POP	Mean POP (std)
Adopted 2023	-7.8 %	-8.73 % (6.5%)
Adopted 2024	-5.69 %	-7.83 % (7.1%)
Adopted 2025	-8.58 %	-9.85 % (7.3%)
Non-Saiva	-7.83 %	-9.09 % (6.9%)

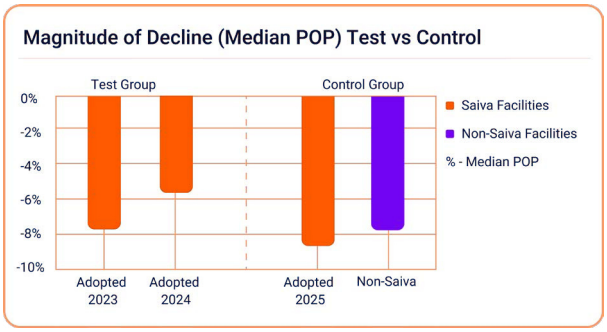

Figure 3: Magnitude of POP decline between test and control.

The smallest median decline was observed in the 2024 adoption cohort. Decline magnitude in the 2023–2024 adoption cohorts was numerically smaller than in the control cohorts (2025 adopters and non-Saiva facilities).

Summary of Raw Findings

Without adjusting for reporting-period overlap:

- Test facilities were more likely to improve.
- Improvement magnitude was numerically greater in early adopters.
- Decline magnitude was attenuated among test facilities.
- The strongest directional signal was observed in 2023 adopters.

PART II

Overlap-Adjusted (Exposure-Weighted) Analysis

To account for the 50% overlap between reporting windows and partial exposure within the performance period, regression models incorporating exposure months were estimated.

Continuous Change Model (POP as Outcome)

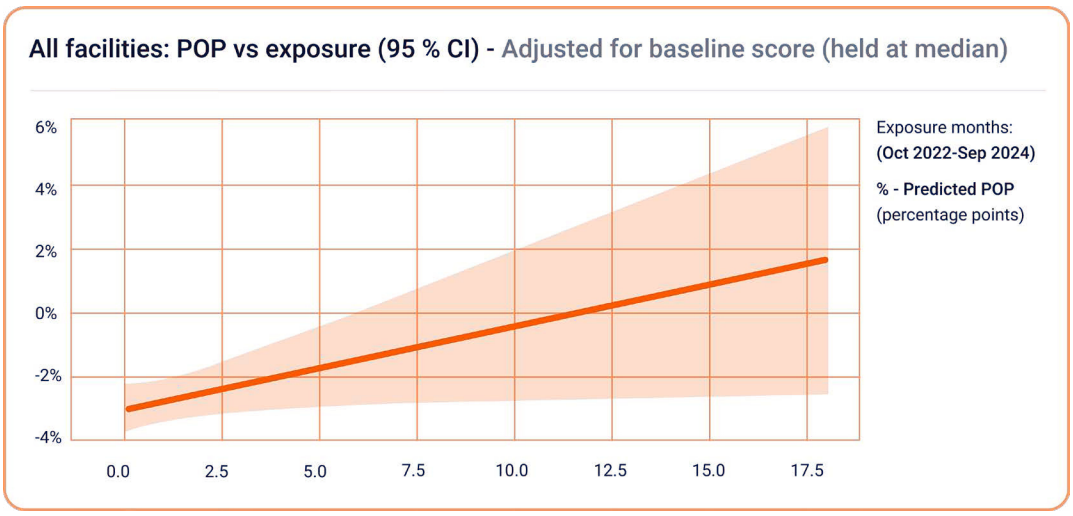

Figure 4: Pop vs exposure (95% CI), adjusted for baseline score.

Linear regression demonstrated:

- **Exposure coefficient:** +0.265 relative improvement units per month
- **p = 0.044**

Interpretation:

Each additional month of Saiva exposure within the reporting window was associated with an incremental improvement in relative performance change. **The model estimates that 12 months of exposure is associated with approximately a 3.2 percentage-point improvement in relative performance change, holding baseline performance constant.**

Discussion

Principal Findings

This analysis evaluated the association between adoption of the Saiva **UPT application** and performance on the CMS Skilled Nursing Facility Quality Reporting Program (QRP) potentially preventable readmission measure (S_004_01_PPR_PD_RSRR) under real-world conditions.

The raw (unadjusted) analysis demonstrated several consistent patterns:

- **A higher proportion of facilities improved** among Saiva adopters compared with control facilities **(Hypothesis 2).**
- **Facilities that improved showed greater magnitude of improvement** within the Saiva cohorts compared with control **(Hypothesis 1).**
- **Facilities that declined exhibited numerically smaller deterioration** when exposed to Saiva during the reporting window **(Hypothesis 4).**
- **Earlier adoption was associated with stronger directional improvement**, consistent with an exposure-duration relationship **(Hypothesis 3).**

Collectively, these findings support the primary hypothesis that Saiva adoption is associated with improved performance on the CMS potentially preventable readmission measure under routine clinical conditions.

Interpretation of the Raw Analysis

The group-level comparisons provide intuitive evidence of association. In pooled analysis, the proportion of improving facilities was higher in the test group (2023–2024 adopters) compared with control facilities (2025 adopters and non-Saiva facilities). This difference was consistent across proportion-based and magnitude-based metrics.

A notable observation emerged when comparing the 2024 adopters: **the proportion-based metric (percentage of facilities improving)** demonstrated a clearer early signal than the **magnitude-based metric (degree of improvement among improvers).**

This pattern suggests that the initial impact of adoption may manifest as a shift in direction of performance (i.e., more facilities crossing from decline to improvement), before larger magnitudes of improvement accumulate. In other words, facilities may first stabilize performance and move into positive territory, with more substantial gains emerging as operational familiarity increases.

Such a pattern is consistent with a **positive learning curve effect,** whereby early implementation produces modest directional improvement, and continued exposure leads to progressive optimization of workflows and clinical response. Under real-world conditions, interventions that require behavioral and organizational integration frequently demonstrate this staged response dynamic.

Importantly, the signal was not driven solely by extreme outliers. Improvement appeared distributed across exposed facilities, with attenuation of deterioration among those that did not improve. This suggests a general shift in performance distribution rather than isolated responder effects.

However, raw comparisons do not account for the structural 50% overlap between CMS reporting periods or partial exposure within rolling windows.

Overlap-Adjusted Modeling

Because CMS reports performance using rolling two-year windows with 12 months of shared data, adjacent reporting periods are structurally dependent. This overlap introduces serial correlation and dilutes the ability of naïve period-over-period comparisons to isolate exposure effects.

To address this, an exposure-weighted regression model was implemented using months of Saiva use within the October 1, 2022–September 30, 2024 reporting window.

In the whole-cohort regression model:

- Exposure duration was positively associated with POP (continuous change).
- Exposure duration was associated with improved follow-up readmission score.
- The exposure coefficient reached statistical significance ($\alpha = 0.05$).
- The direction of effect was consistent with the raw findings.

The adjusted model therefore reinforces — rather than contradicts — the raw group comparisons. Importantly, the exposure-weighted approach provides a more conservative estimate by accounting for partial adoption and structural dependence between reporting windows.

The persistence of association under overlap-adjusted modeling strengthens the internal validity of the observed relationship.

Adoption Timing and Dose–Response Effect

The analysis demonstrates a statistically significant association between months of Saiva exposure and improvement in performance **(Hypothesis 3).** Facilities with longer exposure within the reporting window demonstrated greater relative improvement.

This temporal gradient supports the presence of a dose–response relationship and aligns with the learning curve pattern observed in the raw analysis. While observational data cannot establish causality definitively, the exposure-duration association strengthens causal plausibility beyond simple cross-sectional comparison.

Real-World Implementation Context

Unlike randomized controlled trials (RCTs), real-world implementation does not involve strict protocol adherence, exclusion criteria, or homogeneous patient populations. Skilled Nursing Facilities operate within complex, heterogeneous environments, and intervention impact depends heavily on adoption behavior, workflow integration, and organizational responsiveness.

The observed association under routine operational conditions is therefore meaningful. Demonstrating improvement under non-controlled, real-world conditions provides pragmatic evidence of effectiveness and relevance to operational stakeholders.

Potential Economic Impact

Preventable hospitalizations represent a substantial economic burden in post-acute care. The average cost of a hospital admission in the United States has been estimated at approximately $15,200 per admission (Weiss & Jiang, AHRQ Statistical Brief #278). Even modest reductions in preventable admissions therefore have meaningful financial implications at scale.

To estimate potential national impact, consider the following conservative framework:

- Approximately **15,000 Medicare-certified Skilled Nursing Facilities (SNFs)** operate in the United States.
- A typical SNF manages several hundred Medicare-covered admissions annually.
- Preventable readmission rates commonly range between **15–20%** depending on case mix and payer population.
- The average cost per admission is **$15,200.**

For illustrative purposes:

If a facility experiences 200 annual Medicare discharges and 15% are potentially preventable readmissions:

200 * 0.15 = 30 preventable admissions per year

30 * $15,200 = $456,000 per facility per year

If Saiva adoption were associated with even a

10% relative reduction in preventable readmissions:

30 * 0.10 = 3 admissions avoided

3 * $15,200 = $45,600 per facility annually

Extrapolated nationally:

15,000 SNFs * $45,600 ≈ $684,000,000 annually

Under this conservative scenario, a modest relative improvement translates into **hundreds of millions of dollars in potential national savings annually.**

If the relative reduction were 15–20%, projected national savings would proportionally increase and exceed **$1 billion per year.**

These estimates are illustrative and assume:

- Stable discharge volumes,
- Uniform preventable admission rates,
- Direct cost equivalence per admission.

They do not account for:

- Downstream costs of complications,
- Emergency department utilization,
- Penalty avoidance under value-based purchasing programs,
- Indirect societal costs (e.g., caregiver burden).

Therefore, the true economic impact of reducing preventable hospitalizations may be substantially greater.

Importantly, because the Saiva platform operates within routine clinical workflows and does not require structural infrastructure investment, economic gains from avoided hospitalizations may represent high-value cost containment rather than cost shifting.

Limitations

Several limitations should be acknowledged:

- Observational design — Causality cannot be definitively established.
- Potential residual confounding — Facility-level characteristics not included in the model may influence outcomes.
- Small early-adopter cohort (2023) — Limited sample size reduces precision of subgroup estimates.
- Outcome measure constraints — The CMS rolling window structure inherently introduces temporal dependence.
- State-level dataset — Generalizability beyond the analyzed population requires confirmation.

Additionally, stratification by improvement status in exploratory analyses conditions on the outcome and may attenuate detectable exposure effects.

Future Studies

- Extend analysis to additional CMS reporting cycles.
- Incorporate facility-level covariates.
- Evaluate multi-state datasets.
- Conduct longitudinal trajectory analyses.
- Explore quasi-experimental or matched designs to strengthen causal inference.
- Examine implementation intensity and workflow integration variables to better characterize the learning curve dynamic.

Conclusion

Both raw group-level comparisons and overlap-adjusted exposure modeling demonstrate an association between Saiva adoption and improved performance on the CMS potentially preventable readmission measure.

The findings indicate:

- A higher proportion of improving facilities among adopters (Hypothesis 2),
- Greater magnitude of improvement among exposed facilities (Hypothesis 1),
- Attenuation of decline among adopters (Hypothesis 4),
- A statistically significant exposure-duration effect consistent with a positive learning curve (Hypothesis 3).

Together, these results provide real-world evidence consistent with the hypothesis that Saiva adoption is associated with reduced potentially preventable hospitalizations under routine Skilled Nursing Facility conditions.

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