# Operational Artificial Intelligence Adoption in U.S. Specialty Hospitals: Evidence from Long-Term Acute Care Hospitals and Inpatient Rehabilitation Facilities, 2021-2023

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## ABSTRACT

**Importance:** Long-term acute care hospitals (LTACHs) and inpatient rehabilitation facilities (IRFs) face distinct operational pressures shaped by different Medicare payment rules and patient populations. No prior research has documented operational artificial intelligence (AI) adoption in either sector, leaving administrators and policymakers without an evidence base.

**Objective:** To document AI adoption trends and domain-specific patterns among U.S. LTACHs and IRFs from 2021 to 2023, and to examine organizational predictors of adoption.

**Design:** Descriptive analysis and preliminary linear probability models using national panel data from the American Hospital Association (AHA) Annual Survey Information Technology (IT) Supplement, 2021-2023.

**Setting:** U.S. LTACHs and IRFs responding to the AHA Annual Survey IT Supplement.

**Participants:** 425 LTAC hospital-year observations (376 non-adopters, 49 adopters) and 604 IRF hospital-year observations (528 non-adopters, 76 adopters), restricted to facilities responding in at least two of three survey years.

**Main Outcomes:** AI use across five operational domains: predicting patient demand, predicting staffing needs, staff scheduling, automating routine tasks, and optimizing administrative and clinical workflows.

**Results:** AI adoption in LTACHs rose from 12.7% in 2021 to 15.7% in 2022, then declined to 11.7% in 2023. Staff scheduling was the dominant LTAC domain, peaking at 12.7% in

2022. IRF adoption grew steadily from 8.7% in 2021 to 15.0% in 2023, with workflow optimization as the leading and fastest-growing domain at 12.5% in 2023. In both sectors, AI adopters were more likely to be non-profit and carried worse operating margins than non-adopters. Preliminary multivariate analysis confirms these associations after controlling for facility size and region.

**Conclusions and Relevance:** Facility-specific regulatory environments shape which AI domains each sector adopts. LTACHs prioritize scheduling tools to maintain workforce continuity for medically complex, long-stay patients. IRFs prioritize workflow optimization to address documentation demands from the Medicare 60% rule and IRF Patient Assessment Instrument (IRF-PAI) requirements. Worse operating margins associate with AI adoption in both sectors, suggesting that financial pressure drives operational AI investment in post-acute settings.

**Keywords:** artificial intelligence; long-term acute care hospitals; inpatient rehabilitation facilities; staff scheduling; workflow optimization; post-acute care; health information technology adoption

## 1. INTRODUCTION

The U.S. post-acute care system allocates patients recovering from serious illness or injury across a spectrum of specialized facilities. Two of the most resource-intensive are long-term acute care hospitals (LTACHs) and inpatient rehabilitation facilities (IRFs). LTACHs treat medically complex patients requiring extended stays of 25 days or more, providing ventilator weaning, complex wound care, and intensive medical management for patients transitioning out of intensive care units [1,2]. IRFs deliver intensive multidisciplinary rehabilitation therapy to patients recovering from stroke, spinal cord injury, traumatic brain injury, and major joint replacement, coordinating physical therapy, occupational therapy, and speech-language pathology under a structured daily regimen [3,4]. Together, these two facility types serve Medicare's highest-acuity post-acute beneficiaries and account for a disproportionate share of program expenditure.

Despite their shared position in the post-acute continuum, LTACHs and IRFs operate under fundamentally different regulatory environments that generate distinct operational challenges. LTACHs face the Centers for Medicare and Medicaid Services (CMS) site-neutral payment policy, which reimburses at lower rates when patients do not meet strict clinical criteria for LTAC-level care [5]. Implemented in stages since 2016, this policy has compressed margins, reduced facility counts through consolidation and closure, and created pressure to document medical necessity for every admission [6,7]. The central operational challenge is maintaining specialized workforce continuity for patients whose clinical recovery unfolds over weeks or months.

IRFs face a different constraint through the Medicare 60% rule, which requires that at least 60% of a facility's admissions meet qualifying condition criteria from a list of 13

approved diagnoses [8]. The IRF-PAI, which all facilities must complete within 72 hours of admission, documents functional status, medical complexity, and therapy needs, directly determining payment rates under the IRF Prospective Payment System (IRF PPS) [9]. The operational burden falls on documentation accuracy, assessment timeliness, and throughput efficiency. A facility that falls below the 60% threshold risks reclassification as a general acute care hospital at lower reimbursement.

AI tools for hospital operations promise efficiency gains through scheduling optimization, demand forecasting, task automation, and workflow improvement [10,11]. A growing evidence base documents AI adoption in general acute care hospitals, where health system membership, financial strength, and facility size predict adoption [12,13]. Electronic health record (EHR) adoption followed a similar diffusion pattern a decade earlier [14,15]. It remains unknown whether operational AI has reached post-acute care, as no prior study has documented adoption rates, domain priorities, or organizational predictors in either LTACHs or IRFs. This gap leaves administrators without benchmarks, vendors without market data, and policymakers without the evidence base needed to evaluate whether payment constraints affect technology investment in post-acute care.

This paper provides the first national comparative analysis of operational AI adoption across LTACHs and IRFs, using three years of survey data to document adoption trajectories, domain-specific patterns, and organizational correlates. The comparative design is central to the contribution: two facility types facing similar pressures of workforce constraints and payment reform but under different regulatory regimes allow us to examine whether the specific operational environment shapes technology adoption priorities.

### *1.1 Technology Adoption in Healthcare Settings*

The economics of health IT adoption identifies consistent predictors. Hospital size, health system membership, non-profit ownership, and teaching status positively predict adoption of EHRs and clinical decision support systems [14,15,16]. In general acute care, stronger margins predict earlier adoption, consistent with the organizational slack hypothesis that technology investment requires financial resources [12]. This pattern aligns with diffusion of innovation theory, in which early adopters tend to be larger, wealthier, and better connected to professional networks [17].

Post-acute care facilities differ from general acute care along dimensions relevant to technology adoption. They are smaller on average, more likely to be for-profit, and operate under tighter Medicare payment constraints [6,18]. They lack the academic medical center affiliations that accelerate technology diffusion in teaching hospitals [19]. They face workforce challenges specific to their patient populations, including specialized clinical skill requirements and high turnover [20,21]. These structural differences suggest that AI adoption patterns in post-acute care may diverge from the general acute care literature, but no data have previously existed to test this.

### *1.2 Operational Pressures in LTACHs and IRFs*

LTACHs have faced sustained financial pressure since CMS implemented site-neutral payment rates [5,6]. The number of LTAC facilities declined from roughly 435 in 2016 to approximately 400 by 2023, reflecting closures and consolidations among financially marginal facilities [7]. The specialized workforce required to care for ventilator-dependent patients is expensive and difficult to retain [20,21]. The LTAC market is concentrated

among large for-profit chains, including Select Medical and Kindred Healthcare, that operate centralized IT infrastructure across their networks.

IRFs face a more stable but equally binding regulatory constraint. The 60% rule has been in effect since 2004 and creates a continuous imperative to classify admissions correctly and document qualifying conditions thoroughly [8]. The IRF-PAI assessment requires trained clinicians to complete multi-domain functional evaluations within tight timeframes [9]. Payment rates under IRF PPS adjust for case mix complexity, creating incentives to document patient acuity accurately [22]. The IRF market is similarly concentrated, with Encompass Health as the dominant chain alongside smaller regional systems.

### *1.3 AI in Hospital Operations*

Operational AI applications span functional domains relevant to post-acute care. Demand forecasting tools use historical admission patterns to predict bed utilization and enable proactive capacity management [10,23]. Staff scheduling tools generate optimized shift assignments balancing coverage requirements, clinician preferences, and certification constraints [24]. Task automation tools reduce administrative burden in prior authorization, billing, and clinical documentation [25,26]. Workflow optimization tools identify bottlenecks in patient transitions and discharge planning [27,28]. Administrative costs account for nearly 35% of total U.S. hospital expenditure, making the potential returns to these tools large [29]. Evidence on returns in post-acute settings does not exist, and generalizability from general acute care to facilities with different patient populations and regulatory constraints is unclear.

## 2. METHODS

### *2.1 Data Source and Sample*

We analyzed data from the AHA Annual Survey IT Supplement for 2021, 2022, and 2023. The IT Supplement is a voluntary annual survey asking hospitals whether they use AI or machine learning tools for specific operational functions. We restricted the sample to LTACHs (AHA service code 13) and IRFs (AHA service code 33) present in at least two of three survey years with complete responses to AI questions. This restriction reduces attrition bias from facilities responding in some years and not others. The final sample includes 425 LTAC hospital-year observations (376 non-adopters, 49 adopters) representing approximately 190 unique facilities, and 604 IRF hospital-year observations (528 non-adopters, 76 adopters) representing approximately 260 unique facilities.

### *2.2 Measures*

The IT Supplement asks hospitals to report AI or machine learning use across five operational domains: (1) predicting patient demand; (2) predicting staffing needs; (3) staff scheduling; (4) automating routine tasks; and (5) optimizing administrative and clinical workflows. We construct domain-specific binary adoption indicators and a binary indicator for any AI use.

Hospital characteristics include health system membership, teaching status, ownership type (government, non-profit, for-profit), size (adjusted admissions and FTE, both lagged one year to reduce reverse causality), and three-year average operating margin. Market characteristics include county-level Herfindahl-Hirschman Index (HHI) measuring market

concentration, median household income, share with a bachelor's degree or higher, and share without health insurance.

### *2.3 Analysis*

We calculate adoption rates by domain and year for each facility type. We compare characteristics of AI adopters versus non-adopters using two-sample t-tests for continuous variables and chi-square tests for categorical variables. As a preliminary multivariate step, we estimate linear probability models (LPMs) regressing each domain-specific AI adoption indicator on governance characteristics (system membership, non-profit ownership), facility size (log FTE), operating margin, and region and year fixed effects. We report LPM coefficients as marginal effects on the probability of adoption. Given the modest adopter counts, particularly for LTACHs (n=49), we treat these multivariate results as preliminary and interpret them descriptively. The multivariate sample is smaller than the bivariate sample (LTAC n=355, IRF n=494) due to covariate missingness on lagged size variables. All analyses use the facility-year as the unit of observation. This study is exempt from IRB review as it uses hospital-level administrative data without human subjects involvement.

## 3. RESULTS

### *3.1 Overall Adoption Trends*

Figure 1 displays overall AI adoption rates for both facility types from 2021 to 2023. The two sectors follow divergent trajectories that converge by year-end. In LTACHs, adoption rose from 12.7% in 2021 to 15.7% in 2022, then declined to 11.7% in 2023. In IRFs, adoption grew steadily from 8.7% in 2021 to 13.8% in 2022 to 15.0% in 2023. IRF growth of 72% over three years exceeds the LTAC trajectory over the same period. The LTAC decline between 2022 and 2023 is unusual relative to general acute care hospitals, where adoption grew steadily across the same period [12], and coincides with continued CMS site-neutral payment pressure and facility consolidation [7].

### *3.2 Domain-Specific Adoption Patterns*

Figures 2 and 3 display domain-specific adoption rates for LTACHs and IRFs. The domain hierarchies differ sharply, revealing how sector-specific regulatory constraints translate into distinct AI investment priorities.

In LTACHs (Figure 2), staff scheduling was the most widely adopted domain, peaking at 12.7% in 2022 before declining to 7.8% in 2023. Automating routine tasks held at 5.9 to 6.9% and workflow optimization held at 4.9 to 5.9% across all three years. Predicting patient demand and predicting staffing needs remained below 4% throughout. The sharp rise and fall of scheduling adoption, against the relative stability of automation and workflow tools, suggests that scheduling systems face sustainability challenges specific to the LTAC workforce environment.

In IRFs (Figure 3), workflow optimization dominated and grew throughout the study period, reaching 12.5% in 2023 from 6.2% in 2021. Automating routine tasks rose from 5.0% to 9.4%. Staff scheduling held stable at 7.5%. The continuous growth of workflow optimization in IRFs contrasts with the LTAC scheduling reversal, suggesting that tools addressing a stable regulatory constraint embed more durably than tools requiring ongoing workforce-specific reconfiguration.

### *3.3 Bivariate Characteristics of Adopters*

Tables 1 and 2 present bivariate comparisons of AI adopters and non-adopters for LTACHs and IRFs. Several patterns appear consistently across both sectors.

Non-profit ownership is the strongest predictor of adoption in both sectors. Non-profit facilities make up 51% of adopters in both LTACHs and IRFs, compared to 20% and 14% of non-adopters respectively (both $p<0.01$). The for-profit share among non-adopters exceeds 77% in LTACHs and 85% in IRFs. Both markets are dominated by large for-profit chains, yet non-profit facilities drive adoption. System membership rates are similar across adopters and non-adopters in both sectors, indicating that nominal chain affiliation alone does not predict adoption.

Operating margins are worse among AI adopters in both sectors. LTAC adopters carry average margins of -5.9% versus 1.6% for non-adopters ($p<0.01$). IRF adopters show margins of -1.4% versus 7.5% for non-adopters ($p<0.01$). This pattern inverts the relationship in general acute care, where stronger financial performance predicts adoption [12].

Size effects differ across sectors. In LTACHs, adopters have larger adjusted admissions (1,143 vs. 527, $p<0.01$), while FTE differences do not reach statistical significance at the $p<0.05$ threshold. In IRFs, adjusted admissions are similar across groups, but adopters have more FTE (424 vs. 278, $p<0.01$). LTAC adopters operate in more concentrated markets (county HHI 9.2 vs. 8.0 thousand, $p<0.01$). IRF adopters operate in more concentrated, higher-income, and more educated counties, suggesting stronger private payer mixes among IRF adopters.

### *3.4 Preliminary Multivariate Analysis*

Table 3 presents preliminary LPM estimates of domain-specific AI adoption for both facility types, with region and year fixed effects.

For LTACHs (Panel A), non-profit ownership is the most consistent predictor, with positive and statistically significant associations for staff scheduling (0.168, $p<0.01$), automating routine tasks (0.143, $p<0.05$), and workflow optimization (0.157, $p<0.05$). System membership associates positively with task automation (0.114, $p<0.05$) but is not significant for other domains. Worse operating margins associate with workflow optimization adoption (-0.004, $p<0.05$), consistent with financially distressed LTACHs targeting AI tools that address administrative costs. Log (FTE) and operating margin are not significant predictors for the remaining domains.

For IRFs (Panel B), system membership is a positive predictor across most domains, reaching significance for staff scheduling (0.108, $p<0.01$), workflow optimization (0.122, $p<0.05$), predicting patient demand (0.077, $p<0.05$), and predicting staffing needs (0.113, $p<0.01$). This pattern diverges from LTACHs and suggests that IRF chains actively deploy

AI capabilities network wide. Non-profit ownership predicts task automation (0.215, $p<0.01$) and workflow optimization (0.193, $p<0.05$). Log (FTE) and operating margin do not reach statistical significance in IRF models at the $p<0.05$ threshold. These results should be interpreted with caution given the modest adopter sample and cross-sectional design.

## 4. DISCUSSION

This paper provides the first national evidence on operational AI adoption in U.S. LTACHs and IRFs. The central finding is that facility-specific regulatory environments shape which AI domains get adopted, even when facilities face similar pressures of workforce constraints and payment reform. This extends the diffusion of innovation literature to a new sector and raises questions about adoption sustainability, governance, and the financial dynamics of technology investment in payment-constrained settings.

### *4.1 Regulatory Environment as an Adoption Driver*

The domain hierarchies in LTACHs and IRFs map directly onto regulatory constraints. LTAC patients require specialized care over extended stays. Consistent nursing assignments improve care quality when caregiver relationships develop over weeks [30,31]. Scheduling AI that maintains caregiver continuity while managing shift coverage addresses LTACHs' most visible operational challenge, and the 12.7% scheduling adoption rate in 2022 reflects genuine and widespread demand for this capability.

The decline in LTAC scheduling adoption from 12.7% to 7.8% between 2022 and 2023 raises a sustainability question the existing health IT adoption literature has not addressed. EHR adoption, once initiated, rarely reverses [15]. Scheduling AI may behave differently. Workforce composition in LTACHs shifts continuously under high turnover and a specialized labor market for critical care nursing. Scheduling algorithms calibrated to a specific workforce mix require reconfiguration as that mix changes, generating ongoing maintenance demands that facilities under margin pressure may not sustain. Vendors targeting the LTAC market should design adaptive systems that reconfigure dynamically,

as tools requiring manual recalibration may face discontinuation before delivering efficiency gains.

IRFs present a contrasting durability story. Workflow optimization adoption grew continuously to 12.5% in 2023 without reversal. The 60% rule and IRF-PAI mandates are stable regulatory features unlikely to change in the near term. Tools that address a persistent, well-defined compliance constraint generate recurring value without requiring ongoing justification against shifting operational conditions. This contrast between LTAC scheduling reversibility and IRF workflow durability is itself an empirical finding with implications for how administrators and vendors evaluate AI sustainability in each sector.

Preliminary multivariate results add an important dimension. In IRFs, chain or system membership predicts adoption across most domains, suggesting IRF chains actively deploy AI capabilities network wide. This system-level coordination appears absent in LTACHs, where chain membership is not significant in any domain model. The difference may reflect the more strategically coordinated IRF market, where non-profit health systems operate multiple facilities and spread implementation costs across networks, versus the LTAC market, where chain structures are predominantly for-profit and may face governance constraints on upfront IT investment.

### *4.2 The Financial Distress Pattern*

The consistent negative association between operating margins and AI adoption in both sectors, in bivariate comparisons and in the multivariate workflow optimization model for LTACHs, inverts the relationship in general acute care [12]. Two mechanisms may explain this. First, financially distressed facilities may turn to operational AI as a

turnaround strategy, seeking efficiency gains to restore margin viability. This is consistent with evidence from other industries that firms facing margin pressure accelerate automation investments to reduce labor costs [34]. Second, AI investment may create short-term implementation costs that depress margins before efficiency gains materialize.

These mechanisms carry different policy implications. If financial distress drives adoption, CMS payment constraints may concentrate AI investment among struggling facilities while better-resourced facilities stay on the sideline. If AI investment depresses short-term margins, the question becomes whether reimbursement structures should account for transition costs of operational technology investment. Longitudinal facility-level margin analysis before and after adoption would distinguish these mechanisms. The cross-sectional design cannot resolve this, and we flag it as a priority for future research.

### *4.3 The For-Profit Governance Gap*

Non-profit facilities adopt AI at higher rates in both sectors despite for-profit chains dominating both markets. Chains including Encompass Health, Select Medical, and Kindred Healthcare operate centralized IT infrastructure and employ corporate IT teams capable of facility-level deployment at scale [6,7]. Yet for-profit facilities dominate the non-adopter group, and preliminary multivariate analysis confirms the non-profit ownership association after controlling for facility size and region.

For-profit chains face short-term earnings pressure from investors that may deter upfront IT investment even when the long-term operational case is clear [35]. Non-profit governance structures, accountable to boards with longer investment horizons, may be more willing to absorb short-term implementation costs. Government-owned facilities may

access public infrastructure support. The HITECH Act demonstrated that financial incentives accelerate health IT adoption across facility types including for-profit chains that had lagged in EHR adoption [15]. A targeted policy lever for operational AI in post-acute care could address this governance gap while channeling diffusion through chain infrastructure that already reaches most LTAC and IRF beds.

### *4.4 Implications for Stakeholders*

For LTAC administrators, staff scheduling is the highest-priority AI investment domain, with the evidence supporting adoption at meaningful scale. Scheduling tools that adapt dynamically to workforce changes will prove more durable under high-turnover conditions. Tracking whether adoption translates into measurable reductions in nursing turnover, overtime costs, and adverse patient events is essential for building and sustaining the business case.

For IRF administrators, workflow optimization tools tied directly to IRF-PAI completion and 60% rule compliance represent the clearest return-on-investment case. Facilities near the 60% threshold or subject to focused medical review from CMS have the strongest financial incentive to adopt documentation tools that reduce compliance errors. Preliminary evidence suggests that system or chain affiliation accelerates IRF adoption network-wide, so independent IRFs may benefit from consortium arrangements that replicate the coordination advantages available to system members.

For AI vendors, the post-acute market requires differentiated products. The constraints driving IRF adoption, IRF-PAI documentation and 60% rule compliance, are specific enough that general hospital documentation tools provide limited value. LTAC scheduling

needs differ from general hospital scheduling because of extended patient stays, specialized certification requirements, and the centrality of caregiver continuity. Vendors that invest in facility-type-specific design will find more receptive markets than those offering generic operational AI platforms.

For policymakers at CMS and the Medicare Payment Advisory Commission (MedPAC), the negative margin pattern across both sectors raises questions about whether payment constraints concentrate AI investment among financially distressed facilities and whether the tools these facilities adopt deliver the efficiency gains needed to restore viability. Linking adoption data to patient outcomes and financial performance longitudinally would clarify whether current investment patterns generate social returns warranting expanded policy support.

### *4.5 Limitations*

This analysis has several limitations. The AHA IT Supplement relies on self-reported data, and facilities may report pilot programs as operational AI use, overstating adoption. The survey does not capture which specific AI products facilities use, the scale of deployment, or implementation quality. The modest adopter counts, particularly for LTACHs (n=49), limit statistical power and preclude more granular subgroup analysis. Facilities that exited the market or stopped responding to the survey are unobserved, which may bias adoption estimates.

The most significant limitation is the absence of chain-level ownership identifiers. The AHA system membership variable captures nominal affiliation but does not identify which facilities belong to Encompass Health, Select Medical, Kindred Healthcare, or other

chains. Chain affiliation almost certainly predicts adoption through centralized IT infrastructure and corporate mandates, but this analysis cannot test that directly. Future research with chain-level ownership data and longitudinal facility tracking would advance understanding of these mechanisms. The cross-sectional design precludes causal inference throughout.

## 5. CONCLUSION

This paper provides the first national documentation of operational AI adoption in U.S. LTACHs and IRFs. Adoption reached comparable levels of approximately 12 to 15% by 2023, but the domain mix and trajectory differ between sectors. LTACHs prioritize staff scheduling to maintain caregiver continuity for medically complex, long-stay patients, though sustainability challenges caused adoption to decline between 2022 and 2023. IRFs prioritize workflow optimization to address documentation burdens from the Medicare 60% rule and IRF-PAI requirements, with adoption growing continuously throughout the study period. Preliminary multivariate analysis suggests non-profit ownership robustly predicts adoption in both sectors, while chain or system membership specifically predicts IRF adoption network wide. Worse operating margins associate with adoption in both sectors, a pattern that contrasts with the organizational slack hypothesis and points toward financial pressure as a driver of operational technology investment in post-acute care.

For administrators, domain-specific evidence provides a clear signal: invest in AI tools that address your facility type's most binding operational constraint, which differs meaningfully between LTACHs and IRFs. For vendors, post-acute care requires facility-type-specific product design. For policymakers, the concentration of AI adoption among financially distressed non-profit facilities raises questions about whether payment constraints shape technology diffusion in ways that affect post-acute capacity and care quality over time. For the research community, the productive next step is causal: identifying plausibly exogenous variation in AI adoption to estimate the effects of operational AI on facility financial performance and patient welfare in post-acute care.

## REFERENCES


[1] Kahn JM, Benson NM, Appleby D, Carson SS, Iwashyna TJ. Long-term acute care hospital utilization after critical illness. JAMA. 2010;303(22):2253-2259.
https://doi.org/10.1001/jama.2010.761
PMid:20530778 PMCid:PMC3094575

[2] Scheinhorn DJ, Hassenpflug MS, Votto JJ, et al. Post-ICU mechanical ventilation at 23 long-term care hospitals: a multicenter outcomes study. Chest. 2007;131(1):85-93.
https://doi.org/10.1378/chest.06-1081
PMid:17218560

[3] DeJong G, Horn SD, Smout RJ, Tian W, Putman K, Gassaway J. Joint replacement rehabilitation outcomes on discharge from skilled nursing facilities and inpatient rehabilitation facilities. Arch Phys Med Rehabil. 2009;90(8):1284-1296.
https://doi.org/10.1016/j.apmr.2009.02.009
https://doi.org/10.1016/j.apmr.2008.12.029
https://doi.org/10.1016/j.apmr.2008.11.021
https://doi.org/10.1016/j.apmr.2009.04.003

[4] Ottenbacher KJ, Graham JE, Ottenbacher AJ, et al. Current trends and challenges in inpatient rehabilitation. PM R. 2010;2(2):114-121.

[5] Centers for Medicare and Medicaid Services. Medicare Program: Prospective Payment System for Long-Term Care Hospitals. Federal Register. 2023;88(155):52262-52516.

[6] Liu K, Wissoker D, Rimes C. Determinants of nursing home closures. Health Services Research. 2017;52(S1):309-329.

[7] Medicare Payment Advisory Commission. Healthcare Spending and the Medicare Program: A Data Book. Washington, DC: MedPAC; 2023.

[8] Medicare Payment Advisory Commission. Report to the Congress: Medicare Payment Policy. Washington, DC: MedPAC; 2023.

[9] Centers for Medicare and Medicaid Services. Medicare Program: Inpatient Rehabilitation Facility Prospective Payment System for Federal Fiscal Year 2024. Federal Register. 2023;88(149):47754-47906.

[10] Matheny ME, Whicher D, Thadaney Israni S. Artificial intelligence in health care: a report from the National Academy of Medicine. JAMA. 2020;323(6):509-510.
https://doi.org/10.1001/jama.2019.21579
PMid:31845963

[11] Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine. 2019;25(1):44-56.
https://doi.org/10.1038/s41591-018-0300-7
PMid:30617339

[12] Adler-Milstein J, DesRoches CM, Kralovec P, et al. Electronic health record adoption in US hospitals: progress continues, but challenges persist. Health Affairs. 2015;34(12):2174-2180.
https://doi.org/10.1377/hlthaff.2015.0992
PMid:26561387

[13] Obermeyer Z, Emanuel EJ. Predicting the future: big data, machine learning, and clinical medicine. New England Journal of Medicine. 2016;375(13):1216-1219.

https://doi.org/10.1056/NEJMp1606181
PMid:27682033 PMCid:PMC5070532

[14] Jha AK, DesRoches CM, Campbell EG, et al. Use of electronic health records in U.S. hospitals. New England Journal of Medicine. 2009;360(16):1628-1638.
https://doi.org/10.1056/NEJMsa0900592
PMid:19321858

[15] Adler-Milstein J, Jha AK. HITECH Act drove large gains in hospital electronic health record adoption. Health Affairs. 2017;36(8):1416-1422.
https://doi.org/10.1377/hlthaff.2016.1651
PMid:28784734

[16] Ye J, Ren N, Wang J, Zheng Z. Health information technology adoption in small hospitals and rural health care. Journal of Rural Health. 2022;38(1):52-60.

[17] Rogers EM. Diffusion of Innovations. 5th ed. New York: Free Press; 2003.

[18] Buntin MB, Colla CH, Deb P, Sood N, Escarce JJ. Medicare spending and outcomes after postacute care for stroke and hip fracture. Medical Care. 2010;48(9):776-784.
https://doi.org/10.1097/MLR.0b013e3181e359df
PMid:20706167 PMCid:PMC3627731

[19] Blumenthal D, Tavenner M. The meaningful use regulation for electronic health records. New England Journal of Medicine. 2010;363(6):501-504.
https://doi.org/10.1056/NEJMp1006114
PMid:20647183

[20] Hanrahan NP, Aiken LH, McClaine L, Hanlon AL. Relationship between psychiatric nurse work environments and nurse burnout in acute care general hospitals. Issues in Mental Health Nursing. 2010;31(3):198-207.
https://doi.org/10.3109/01612840903200068
PMid:20144031 PMCid:PMC2856615

[21] American Hospital Association. Massive Growth in Expenses and Rising Inflation Fuel Continued Financial Challenges for America's Hospitals and Health Systems. Chicago: AHA; 2023.

[22] Jette DU, Warren RL, Wirtalla C. The relation between therapy intensity and outcomes of rehabilitation in skilled nursing facilities. Arch Phys Med Rehabil. 2005;86(3):373-379.
https://doi.org/10.1016/j.apmr.2004.10.018
PMid:15759214

[23] Bates DW, Saria S, Ohno-Machado L, Shah A, Escobar G. Big data in health care: using analytics to identify and manage high-risk and high-cost patients. Health Affairs. 2014;33(7):1123-1131.
https://doi.org/10.1377/hlthaff.2014.0041
PMid:25006137

[24] Shortliffe EH, Sepulveda MJ. Clinical decision support in the era of artificial intelligence. JAMA. 2018;320(21):2199-2200.
https://doi.org/10.1001/jama.2018.17163
PMid:30398550

[25] Shanafelt TD, Dyrbye LN, Sinsky C, et al. Relationship between clerical burden and characteristics of the electronic environment with physician burnout and professional satisfaction. Mayo Clinic Proceedings. 2016;91(7):836-848.
https://doi.org/10.1016/j.mayocp.2016.05.007
PMid:27313121

[26] Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. Nature Medicine. 2022;28(1):31-38.
https://doi.org/10.1038/s41591-021-01614-0
PMid:35058619

[27] Adler-Milstein J, Zhao W, Willard-Grace R, Knox M, Grumbach K. Electronic health records and burnout: time spent on the electronic health record after hours and message volume associated with exhaustion but not cynicism. JAMIA. 2020;27(4):531-538.
https://doi.org/10.1093/jamia/ocz220
PMid:32016375 PMCid:PMC7647261

[28] Maddox KEJ, Reidhead M, Hu J, et al. Adjusting for social risk factors affects provider assessments of care coordination quality. Health Affairs. 2019;38(6):938-945.

[29] Himmelstein DU, Woolhandler S. The current and projected taxpayer shares of U.S. health costs. American Journal of Public Health. 2017;107(3):449-452.
https://doi.org/10.2105/AJPH.2015.302997
PMid:26794173 PMCid:PMC4880216

[30] Kalisch BJ, Lee KH. Nurse staffing levels and teamwork: a cross-sectional study of patient care units in acute care hospitals. Journal of Nursing Scholarship. 2011;43(1):82-88.
https://doi.org/10.1111/j.1547-5069.2010.01375.x
PMid:21342428

[31] Dobson A, DaVanzo J, Doherty J, Tanamor M. Analysis of Payment and Quality Trends in Inpatient Rehabilitation Facilities Under the Prospective Payment System. Falls Church, VA: Dobson DaVanzo and Associates; 2018.

[32] Burns LR, Pauly MV. Transformation of the health care industry: curb your enthusiasm? Milbank Quarterly. 2018;96(1):57-109.
https://doi.org/10.1111/1468-0009.12312
PMid:29504199 PMCid:PMC5835686

[33] Bazzoli GJ, Chan B, Shortell SM, D'Aunno T. The financial performance of hospitals belonging to health networks and systems. Inquiry. 2000;37(3):234-252.

[34] Acemoglu D, Restrepo P. Robots and jobs: evidence from U.S. labor markets. Journal of Political Economy. 2020;128(6):2188-2244.
https://doi.org/10.1086/705716
PMCid:PMC11006199

[35] Freedman S, Golberstein E, Huang TY, Satin DJ, Burns LR. Disability and distress: the effect of disability laws on workers with disabilities. Journal of Human Resources. 2015;50(3):763-800.

**TABLE 1. Characteristics of AI Adopters vs. Non-Adopters Among U.S. Long-Term Acute Care Hospitals, 2021-2023**

| Characteristic | Non-Adopters (n=376) | Adopters (n=49) | Difference |
|---|---|---|---|
| System Member | 0.86 | 0.92 | 0.05 |
| | *(0.34)* | *(0.28)* | *(0.05)* |
| Teaching Hospital | 0.00 | 0.00 | 0.00 |
| Government Owned | 0.03 | 0.10 | 0.07** |
| | *(0.18)* | *(0.31)* | *(0.03)* |
| Non-Profit | 0.20 | 0.51 | 0.31*** |
| | *(0.40)* | *(0.51)* | *(0.06)* |
| For-Profit | 0.77 | 0.39 | -0.38*** |
| | *(0.42)* | *(0.49)* | *(0.07)* |
| Rural | 0.01 | 0.00 | -0.01 |
| | *(0.07)* | *(0.00)* | *(0.01)* |
| Adjusted Admissions (mean) | 527 | 1,143 | 616*** |
| | *(411.6)* | *(3,048.8)* | *(178.0)* |
| FTE (mean) | 164 | 217 | 53 |
| | *(148.8)* | *(340.5)* | *(28.7)* |
| Operating Margin, 3-yr avg. (%) | 1.6 | -5.9 | -7.6*** |
| | *(12.74)* | *(17.40)* | *(2.09)* |
| County HHI (000s) | 8.0 | 9.2 | 1.2*** |
| | *(2.85)* | *(1.70)* | *(0.42)* |
| County Median Income ($) | 69,209 | 72,207 | 2,998 |
| | *(16,152)* | *(21,254)* | *(2,553)* |
| % Bachelor's Degree+, County | 32.6 | 34.5 | 1.9 |
| | *(10.10)* | *(12.48)* | *(1.58)* |
| % Uninsured, County | 12.0 | 12.1 | 0.1 |
| | *(5.95)* | *(4.44)* | *(0.88)* |

*Note: ** p<0.05; *** p<0.01. Standard deviations in parentheses for continuous variables; standard errors in parentheses for differences. P-values from two-sample t-tests (continuous) or chi-square tests (categorical). HHI = Herfindahl-Hirschman Index. FTE = Full-Time Equivalents. Sample restricted to facilities responding in at least two of three survey years.*

**TABLE 2. Characteristics of AI Adopters vs. Non-Adopters Among U.S. Inpatient Rehabilitation Facilities, 2021-2023**

| Characteristic | Non-Adopters (n=528) | Adopters (n=76) | Difference |
|---|---|---|---|
| System Member | 0.86 | 0.84 | -0.02 |
| | *(0.35)* | *(0.37)* | *(0.04)* |
| Teaching Hospital | 0.00 | 0.01 | 0.01 |
| | *(0.04)* | *(0.11)* | *(0.01)* |
| Government Owned | 0.01 | 0.01 | 0.00 |
| | *(0.11)* | *(0.11)* | *(0.01)* |
| Non-Profit | 0.14 | 0.51 | 0.37*** |
| | *(0.35)* | *(0.50)* | *(0.05)* |
| For-Profit | 0.85 | 0.47 | -0.38*** |
| | *(0.36)* | *(0.50)* | *(0.05)* |
| Rural | 0.01 | 0.00 | -0.01 |
| | *(0.08)* | *(0.00)* | *(0.01)* |
| Adjusted Admissions (mean) | 1,886 | 1,907 | 21 |
| | *(1,466.2)* | *(1,316.0)* | *(186.0)* |
| FTE (mean) | 278 | 424 | 146*** |
| | *(298.7)* | *(416.0)* | *(40.7)* |
| Operating Margin, 3-yr avg. (%) | 7.5 | -1.4 | -8.9*** |
| | *(13.67)* | *(14.27)* | *(1.83)* |
| County HHI (000s) | 7.6 | 8.4 | 0.8** |
| | *(3.10)* | *(2.86)* | *(0.38)* |
| County Median Income ($) | 74,541 | 80,855 | 6,314*** |
| | *(17,671)* | *(19,709)* | *(2,201)* |
| % Bachelor's Degree+, County | 35.4 | 38.6 | 3.2** |
| | *(10.16)* | *(12.21)* | *(1.28)* |
| % Uninsured, County | 11.0 | 10.1 | -0.9 |
| | *(5.37)* | *(5.16)* | *(0.66)* |

*Note: ** p<0.05; *** p<0.01. Standard deviations in parentheses for continuous variables; standard errors in parentheses for differences. P-values from two-sample t-tests (continuous) or chi-square tests (categorical). HHI = Herfindahl-Hirschman Index. FTE = Full-Time Equivalents. Sample restricted to facilities responding in at least two of three survey years.*

**TABLE 3. Preliminary Linear Probability Models of Domain-Specific AI Adoption: Long-Term Acute Care Hospitals and Inpatient Rehabilitation Facilities, 2021-2023**

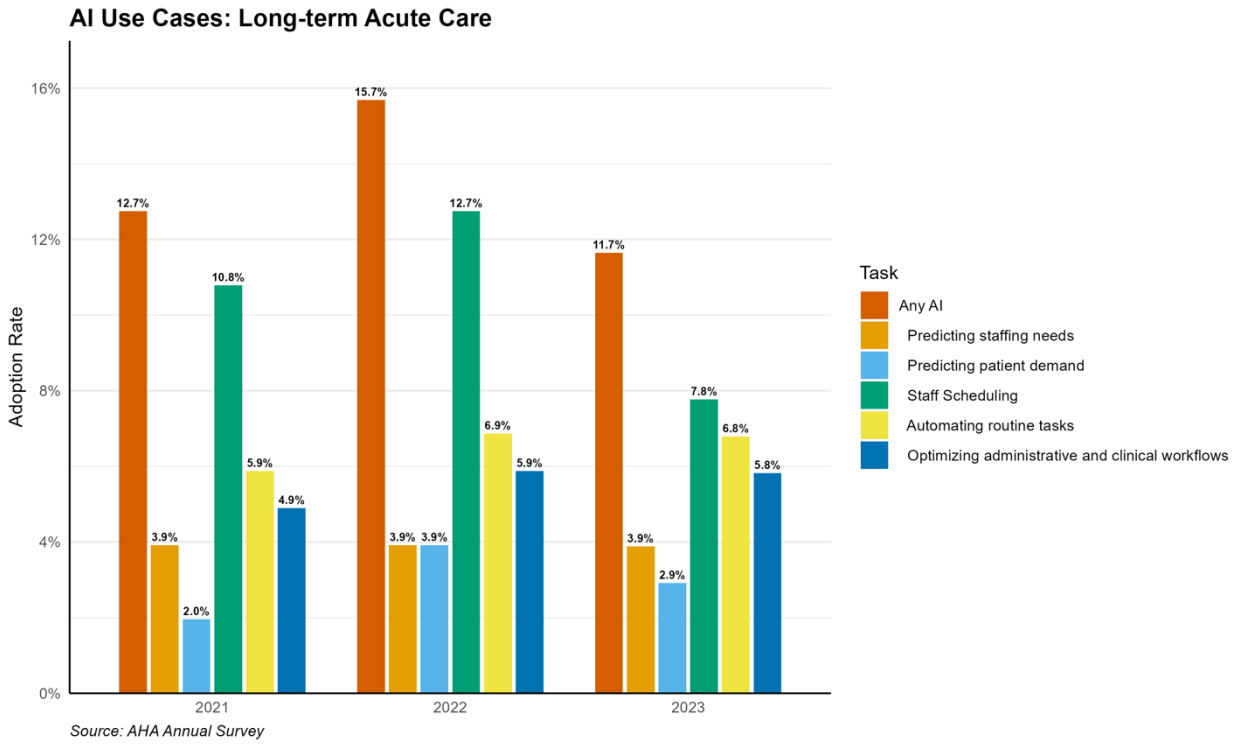
| | Staff Scheduling | Automate Tasks | Optimize Workflows | Predict Demand | Predict Staffing |
|---|---|---|---|---|---|
| ***Panel A: Long-Term Acute Care Hospitals (n = 355 facility-year observations)*** | | | | | |
| System Member | 0.058 | 0.114** | 0.064 | 0.057 | 0.065 |
| | *(0.055)* | *(0.042)* | *(0.048)* | *(0.031)* | *(0.032)* |
| Non-Profit | 0.168*** | 0.143** | 0.157** | 0.075 | 0.074 |
| | *(0.053)* | *(0.067)* | *(0.064)* | *(0.042)* | *(0.045)* |
| Log(FTE) | 0.008 | 0.026 | 0.010 | 0.063 | 0.084 |
| | *(0.060)* | *(0.069)* | *(0.071)* | *(0.060)* | *(0.059)* |
| Operating Margin | 0.001 | -0.003 | -0.004** | 0.000 | 0.001 |
| | *(0.001)* | *(0.002)* | *(0.002)* | *(0.001)* | *(0.001)* |
| Region FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.047 | 0.152 | 0.199 | 0.082 | 0.062 |
| ***Panel B: Inpatient Rehabilitation Facilities (n = 494 facility-year observations)*** | | | | | |
| System Member | 0.108*** | 0.009 | 0.122** | 0.077** | 0.113*** |
| | *(0.034)* | *(0.075)* | *(0.051)* | *(0.030)* | *(0.039)* |
| Non-Profit | 0.117 | 0.215*** | 0.193** | 0.102 | 0.154 |
| | *(0.077)* | *(0.077)* | *(0.082)* | *(0.061)* | *(0.081)* |
| Log(FTE) | -0.021 | -0.025 | 0.002 | -0.004 | -0.015 |
| | *(0.025)* | *(0.046)* | *(0.044)* | *(0.025)* | *(0.026)* |
| Operating Margin | 0.000 | -0.001 | -0.002 | 0.000 | 0.000 |
| | *(0.001)* | *(0.001)* | *(0.001)* | *(0.000)* | *(0.001)* |
| Region FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.022 | 0.110 | 0.102 | 0.033 | 0.053 |

*Note: Coefficients are marginal effects on the probability of adoption from linear probability models. All specifications include region and year fixed effects. Standard errors in parentheses. ** p<0.05; *** p<0.01. Operating Margin is the three-year facility average. Log (FTE) is lagged one year. Multivariate sample is smaller than bivariate sample due to covariate missingness on lagged size variables (LTAC n=355; IRF n=494). Adjusted admissions (lagged), county median income, percentage uninsured, county HHI, percentage 65+, and percentage bachelor's degree were included in extended specifications but were not statistically significant at p<0.05 and are excluded here for clarity.*

**FIGURE 1. AI Adoption Rates in U.S. LTACHs and IRFs, 2021-2023**

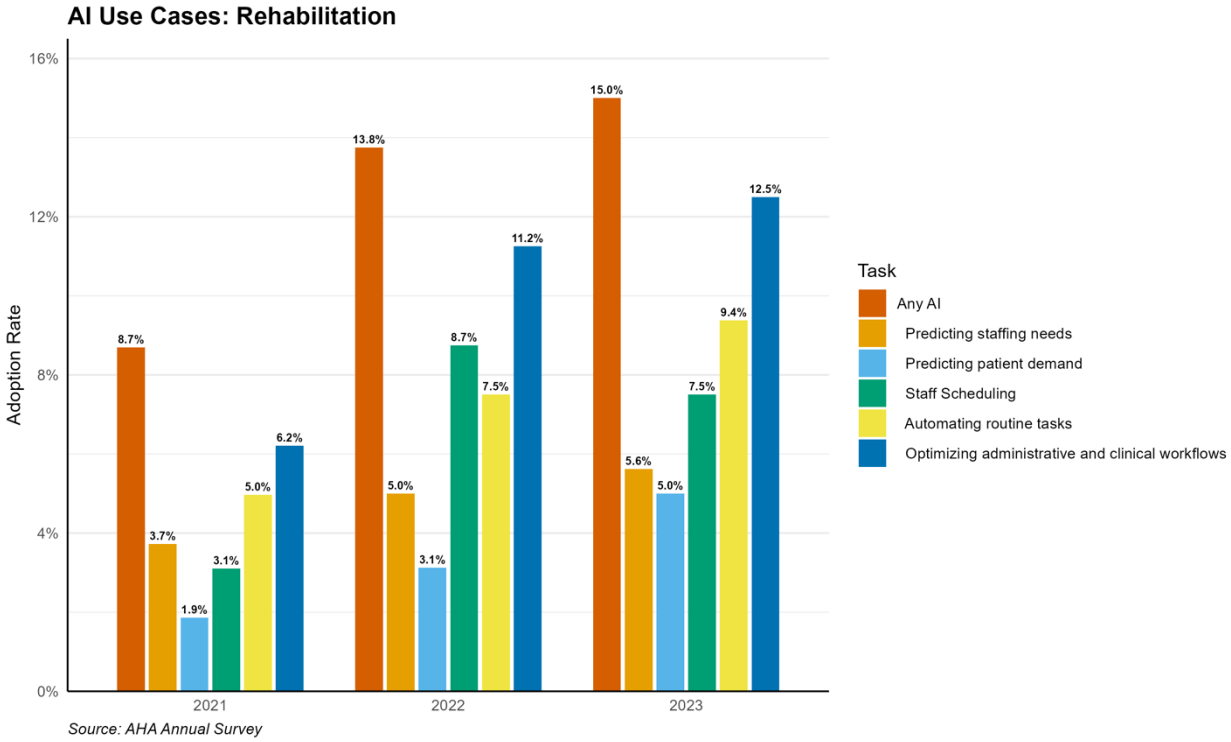
*Source: AHA Annual Survey IT Supplement, 2021-2023.*

**FIGURE 2. Domain-Specific AI Adoption in U.S. Long-Term Acute Care Hospitals, 2021-2023**




*Source: AHA Annual Survey IT Supplement, 2021-2023.*

**FIGURE 3. Domain-Specific AI Adoption in U.S. Inpatient Rehabilitation Facilities, 2021-2023**




*Source: AHA Annual Survey IT Supplement, 2021-2023.*