Title: Adoption of Operational AI in U.S. General Acute Care Hospitals: Market, State, and Domain Patterns, 2021-2023

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Abstract

Importance: General acute care (GAC) hospitals in the United States (U.S.) are rapidly adopting artificial intelligence to improve operational efficiency and manage costs. National evidence on which hospitals adopt AI, and how adoption varies across domains and geographic regions, remains limited.

Objective: To examine hospital, market, and state characteristics associated with AI adoption among U.S. GAC hospitals, focusing on heterogeneity across states, five operational domains, and breadth of AI adoption.

Design, Setting, and Participants: National panel of GAC hospitals responding to the American Hospital Association Annual Survey IT Supplement, 2021 to 2023 (8,511 hospital-years).

Main Outcomes and Measures: AI use, domain-specific use including predicting patient demand, predicting staffing needs, staff scheduling, automating routine tasks, optimizing workflows, and breadth of adoption measured as count of domains, 0-5.

Results: Any AI use grew from 23.4% in 2021 to 27.4% in 2023. Workflow optimization and routine task automation were the most widely adopted domains; staff scheduling remained the least adopted and showed minimal growth over the study period (13.1% to 13.4%). Hospitals using AI were larger (277 vs. 150 beds), more likely to be health system members (89% vs. 64%), and more often located in urban areas than non-users. Using linear probability models with region and year fixed effects, system membership, teaching status, and non-profit ownership showed the largest associations with any AI use, increasing adoption probabilities by 19.6, 14.8, and 26.9 percentage points, respectively.

Conclusions and Relevance: AI use concentrates among hospitals with greater organizational capacity, raising the risk that productivity gains widen existing gaps in financial performance and patient access within and across states, and accelerate market consolidation. Extending AI-related operational gains to smaller, independent, and rural hospitals will require targeted financing and shared infrastructure. Domain-specific barriers, particularly for staffing tools, call for governance frameworks that build trust among clinicians and hospital leaders.

Keywords: artificial intelligence, hospital operations, health IT diffusion, staffing, workflow optimization, technology adoption

1. Introduction

The United States (U.S.) has more than 3,000 general acute care (GAC) hospitals that together account for over 33 million admissions per year [1, 2]. Between 2021 and 2023, hospital labor costs rose by over $42 billion, driven by persistent workforce shortages, rising wages, and heavier reliance on contract staff [3, 4], with the deepest gaps in rural and nonmetropolitan areas [5]. At the same time, many hospitals still operate with margins below pre pandemic levels, and Medicare reimburses roughly 83 cents for every dollar hospitals spend on patient care [3, 6]. Under these pressures, hospitals are turning to artificial intelligence (AI) tools to manage operations, contain costs, and stabilize capacity.

Early AI applications in health care focused on clinical decision support, imaging, and risk prediction [7, 8]. A growing share of deployment now targets hospital operations [9]. The American Hospital Association (AHA) Annual Survey IT Supplement captures hospital-reported AI use across five operational domains. Predicting patient demand uses AI to forecast inpatient census, emergency department volume, or service-line use, allowing hospitals to anticipate surges, allocate beds, and reduce bottlenecks [10, 11]. Predicting staffing needs estimates the number and skill mix of personnel required for upcoming shifts, addressing the core problem of matching labor supply to variable patient volumes [12]. Staff scheduling generates or optimizes work schedules for nurses, physicians, and support staff, balancing coverage requirements against employee preferences, labor regulations, and fatigue constraints [13]. Automating routine tasks applies AI to repetitive administrative processes such as prior authorization, claims processing, and documentation [14, 15]. Optimizing administrative and clinical workflows identifies

inefficiencies in care delivery and patient transitions and recommends process improvements [16].

These five domains differ in implementation complexity. Automating routine tasks and optimizing workflows build on existing electronic health record (EHR) and revenue cycle infrastructure. AI tools for staffing and scheduling require integration with human resources systems, clinician buy-in, and governance over labor allocation decisions [17, 18]. These organizational differences, combined with variation in state policy and payment environments, likely shape which AI tools hospitals adopt first, how fast they spread, and where adoption stalls.

Prior literature on hospital technology diffusion shows that uptake is uneven and strongly related to hospital size, ownership, system affiliation, and market structure [19-22]. Recent work using AHA 2022 data provides a cross-sectional baseline: fewer than one in five U.S. hospitals reported operational AI use, and adopters were more likely to be larger, not-for-profit, and system-affiliated [23]. That analysis pools all hospital types and a single survey year, and does not examine geographic variation, trends over time, breadth of adoption across domains, or market-level predictors. Other studies document widespread use of predictive models embedded in EHR systems and describe governance and oversight challenges [24, 25]. This literature addresses hospital-level any-AI adoption but does not distinguish across operational domains or geographic regions.

Understanding AI adoption in healthcare is critical for several reasons. First, AI deployment is not homogenous technology shock and reflects selection into it by hospitals. Leaders decide whether to invest, which domains to target, and how deeply to integrate tools into everyday operations. Those choices reflect organizational capacity,

governance structures, and strategic priorities [26, 27]. Second, if AI use concentrates in hospitals with more resources, operational AI may widen existing gaps between hospitals and regions in financial stability, workforce resilience, and access to timely care [28]. Third, policy discussions increasingly assume that AI will raise efficiency and strengthen hospital resilience. Those gains will depend on where and how hospitals adopt AI, and whether adoption reaches departments, institutions, and regions that face the most acute operational strain [29]. State-level variation in AI use, which this study documents for the first time, shapes whether those gains distribute broadly or compound existing geographic inequalities in hospital capacity and patient access.

This paper studies operational AI use among U.S. GAC hospitals between 2021 and 2023. We describe which hospitals report any operational AI use in each year, examine use across the five operational domains, measure breadth of adoption as the count of domains used, and describe state-level patterns and changes between 2021 and 2023. We relate any use, domain-specific use, and breadth to hospital, market, and state characteristics. We consider operational AI use as a strategic organizational decision shaped by expected benefits, implementation costs, and institutional constraints. Our empirical approach follows prior work on hospital participation in complex organizational arrangements [30, 31]. We estimate linear probability models relating AI use at both the extensive margin (any use) and the intensive margin (breadth across domains) to hospital structure, ownership, system affiliation, and market context.

This study provides the first national, state- and domain-specific panel analysis of operational AI use among GAC hospitals, extending prior cross-sectional work by adding three survey years, restriction to GAC hospitals, state-level geographic analysis, a

breadth-of-adoption measure, and market-level covariates. The findings describe where AI is in use, how adoption differs across domains and states, which organizational environments support broader diffusion, and where structural barriers limit spread.

2. Conceptual Framework and Hypotheses

2.1 Organizational Capacity, Governance, and Financial Resources

Larger GAC hospitals face higher fixed operational demands and can spread the fixed costs of AI over more patients and encounters [19, 20, 34, 42]. System-affiliated hospitals draw on shared IT infrastructure, centralized analytics teams, and prior experience deploying complex technologies [19, 22, 44]. Teaching hospitals maintain research infrastructure, data science expertise, and governance structures that lower informational and implementation costs [20, 45-48]. Not-for-profit hospitals and hospitals with stronger financial performance have more flexibility to invest in long-horizon projects and can absorb the initial costs of AI adoption [19, 20, 49-53]. Based on this literature, we expect capacity and resources to shape AI use at each margin of interest. Hospitals with more organizational capacity and stronger financial performance should be more likely to adopt any operational AI, to use AI in a broader set of domains, and to expand use between 2021 and 2023.

Hypothesis 1: Hospitals with greater organizational capacity and stronger financial performance are more likely to adopt operational AI, to use it across more domains, and to increase use over time.

2.2 Market and State Context

Hospitals make technology decisions within local markets and state policy environments. Competition can raise the return to AI if hospitals use operational gains to improve access, reduce wait times, or stabilize staffing [54-57]. Urban markets offer deeper labor pools, more vendor presence, and stronger peer effects, which can all support AI deployment

[19, 58-60]. Community characteristics such as income, education, and insurance coverage shape payer mix and revenue, which in turn affect the feasibility of new investments [61-63]. States also differ in payment policy, regulatory oversight, and broader digital infrastructure, which can support or slow AI diffusion [64-67, 78]. We expect AI use to cluster in more competitive, urban, and economically advantaged markets and in states with environments that support health IT and operational innovation. These contextual factors should shape both whether hospitals use operational AI at all and how rapidly use grows between 2021 and 2023.

Hypothesis 2: Hospitals in more competitive, urban, and economically advantaged markets are more likely to adopt operational AI and to use it across more domains.

2.3 Domain-Specific Heterogeneity and Breadth of Use

The five operational AI domains differ in implementation requirements and organizational touchpoints. Workflow optimization and routine task automation build on existing EHR and revenue cycle infrastructure. Demand prediction and staffing-need prediction require integration with bed-management, throughput, and finance functions. Staffing and scheduling tools move labor allocation decisions into algorithmic systems and require strong governance and trust from clinicians and managers [17, 18, 34-39].

Hypothesis 3: Among hospitals that use AI, adoption concentrates in workflow optimization and routine task automation. Staffing-related domains lag. The same organizational and contextual characteristics that predict any use also predict greater breadth of adoption across domains.

3. Methods

3.1 Data Sources

Hospital-level data on AI use are drawn from the AHA Annual Survey IT Supplement for 2021 through 2023. The AHA IT Supplement is the first nationally representative data source to systematically collect information on hospital-reported use of AI and machine-learning tools across operational and clinical domains. Hospital characteristics, including ownership status, service type, teaching status, rural-urban location, system affiliation, and bed size, are obtained from the corresponding AHA Annual Survey files and linked to the IT Supplement using unique hospital identifiers.

County-level market characteristics, including median household income, average educational attainment, age distribution, and uninsurance rates, are obtained from the American Community Survey [72]. Hospital market concentration is calculated from AHA admissions data. Standardized Medicare spending per capita at the county level is obtained from the Centers for Medicare and Medicaid Services (CMS) Geographic Variation Public Use File [73]. This study was exempt from institutional review board review because it relies exclusively on secondary hospital data and does not use any individual-level patient information.

We restrict the sample to GAC hospitals, defined as nonfederal, short-term, general medical and surgical hospitals (AHA service code 10). We exclude federal hospitals, psychiatric facilities, long-term care hospitals, rehabilitation hospitals, children's specialty hospitals, and other specialty facilities because these hospitals face different operational environments and are unlikely candidates for the same AI tools [30]. Hospitals must

appear in both the AHA Annual Survey and the IT Supplement in at least one study year and have complete data for the variables examined. The final analytic sample for regression analyses consists of 8,511 hospital-year observations; lagged variable construction reduces this from the full descriptive sample of 9,371 observations.

3.2 AI Use Measures

The AHA IT Supplement asks hospitals whether they use AI or machine-learning tools for each of the following operational functions: (1) predicting patient demand, (2) predicting staffing needs, (3) staff scheduling, (4) automating routine tasks, and (5) optimizing administrative and clinical workflows. From these items, we construct three sets of outcome measures.

Any AI use. A binary indicator equal to 1 if a hospital reports using AI or machine learning in at least one of the five operational domains in a given year, and 0 otherwise. This measure captures the extensive margin of AI use.

Breadth of AI use. A count variable (ranging from 0 to 5) equal to the number of operational domains in which a hospital reports AI use in a given year. This measure captures the intensive margin i.e., the breadth of AI integration across operational functions.

Domain-specific AI use. Five separate binary indicators, one for each operational domain, equal to 1 if the hospital reports AI use in that domain and 0 otherwise. These measures allow us to assess whether predictors of AI use vary across domains with different implementation requirements and organizational implications.

3.3 Hospital and Market Characteristics

We include hospital-level and market-level variables that correspond to the hypotheses described in the conceptual framework. Hospital-level variables include: log of total staffed beds (size), log of admission rate, teaching status (membership in the Council of Teaching Hospitals), ownership type (not-for-profit, for-profit, government), health system membership, rural-urban location, case mix index, full-time equivalent total personnel, and three-year average operating margin (measured as the mean operating margin over the current and two preceding years to smooth short-term fluctuations). Market-level variables are measured at the county level and include: the Herfindahl-Hirschman Index (HHI) of hospital market concentration, calculated as the sum of squared market shares based on hospital admissions within the county [75]; median household income; percentage of the population aged 65 and older; percentage of adults with a bachelor's degree or higher; percentage uninsured; and standardized, risk-adjusted Medicare spending per capita. We also include a binary indicator for whether the hospital's state adopted Medicaid expansion prior to 2016, which captures state-level policy environments that may affect hospital finances and patient populations [74].

3.4 Descriptive Analyses

We conduct four sets of descriptive analyses. First, we examine national trends in AI use from 2021 to 2023 by plotting bed-weighted use rates for any AI and for each of the five operational domains. Second, we assess state-level geographic variation in AI use by mapping bed-weighted use rates across states for each survey year. Third, we plot the change in state-level AI use against 2021 baseline levels to examine diffusion dynamics. Fourth, we compare hospital and market characteristics of AI users and non-users in the pooled sample using two-sample t-tests with unequal variances.

3.5 Regression Analyses

We estimate the association between hospital and market characteristics and AI use, adjusting for potential confounders and accounting for secular trends and time-invariant regional factors. Regression models adjust for log(admissions) to treat each hospital-year observation equally and descriptive figures use bed-weighted rates to reflect the share of inpatient capacity exposed to AI-enabled systems. We use linear probability models as the primary specification because coefficients represent percentage-point changes that are directly comparable across all six outcome columns and across domains, which is central to the policy interpretation of the results. We assessed robustness using multi-level logistic regression for binary outcomes and Poisson regression for the breadth count outcome, with results reported in the supplementary appendix Tables A1 and A2.

Extensive margin. We estimate the probability that a hospital reports any operational AI use using a linear probability model:

$$AnyAI_{i,s,t} = \alpha + \gamma' X_{i,t} + \delta_t + \theta_s + \varepsilon_{i,s,t}$$

where AnyAI_{i,s,t} is a binary indicator equal to 1 if hospital i in state s reports AI use in at least one operational domain in year t. The vector X_{i,t} includes the hospital-level and market-level covariates described above. Year fixed effects (δ_t) absorb common trends in AI availability, vendor marketing, and survey awareness. Region fixed effects (θ_s) absorb time-invariant differences across states in regulatory environment, technology infrastructure, and health care market structure. Standard errors are clustered at the hospital level to account for within-hospital serial correlation across survey years [76]. We use a linear probability model as the primary specification for ease of interpretation:

coefficients represent percentage point changes in the probability of AI use associated with a one-unit change in the covariate. We assess robustness using logistic regression and report odds ratios in supplementary analyses.

Breadth. We model breadth of AI use by estimating the count of operational domains (0-5) using ordinary least squares. Coefficients represent changes in the number of domains in which AI is used.

Domain-specific models: To test whether the same characteristics predict AI use across all five operational domains, we estimate:

$$DomainAI^k_{i,s,t} = \alpha_k + \gamma_k' X_{i,t} + \delta_t + \theta_s + \varepsilon_{i,s,t}^k$$

where k indexes each of the five domains. Comparing coefficients across domains reveals whether domains involving workforce decisions respond to different organizational characteristics than domains involving administrative automation. All regression models include the full set of covariates simultaneously.

4. Results

4.1 Trends in Operational AI Use

Figure 1 shows that any AI use among U.S. GAC hospitals increased from 23.4% in 2021 to 27.4% in 2023. Use varied across the five operational domains. In 2023, the most commonly used domain was optimizing administrative and clinical workflows (21.3%), followed by automating routine tasks (19.2%), predicting patient demand (16.1%), predicting staffing needs (15.6%), and staff scheduling (13.4%). The ordering of domains was stable over the study period: workflow optimization and task automation led in each year, while the three staffing-related domains consistently lagged. Between 2021 and 2023, workflow optimization grew from 15.6% to 21.3% (5.7 percentage points), and automating routine tasks grew from 14.4% to 19.2% (4.8 percentage points). Staff scheduling grew from 13.1% to 13.4% (0.3 percentage points), the slowest-growing domain over the study period. AI tools that build on existing EHR and revenue cycle infrastructure spread readily. Tools that require integration with human resources systems and governance over labor allocation decisions spread more slowly. This pattern is consistent with hypothesis three that AI applications that build on existing EHR and revenue-cycle infrastructure spread more readily than those that involve labor allocation decisions with workforce governance implications.

4.2 Geographic Variation

Figure 2 shows substantial state-level heterogeneity in AI use. These rates are bed-weighted, reflecting the share of inpatient capacity in each state exposed to AI-enabled systems. Between 2021 and 2023, states in the Northeast and upper Midwest tended to

have higher use rates, while several Southern and Mountain West states remained below 20%. Several states with low 2021 use rates experienced rapid gains: Vermont (+61 percentage points), New Jersey (+46 percentage points), and Idaho (+44 percentage points) each moved from low baselines to substantially higher use by 2023. Connecticut, Pennsylvania, and Washington also showed large gains. States with the highest 2021 use rates, including Utah, the District of Columbia, and Missouri, exhibited flat or declining trajectories, consistent with a ceiling effect. North Dakota, Rhode Island, and South Dakota each saw declines of 20 percentage points or more, suggesting instability among early adopters or changes in survey response composition. The overall pattern shows growth concentrating among states that started from lower baselines. These geographic patterns likely reflect differences in state regulatory environments, health system consolidation, vendor market penetration, and workforce pressures, which we investigate through the regression analyses below.

4.3 Characteristics of AI Users and Non-Users

Table 1 compares hospital and market characteristics of AI users and non-users across the pooled 2021-2023 sample. The two groups differ significantly on every measured dimension. AI users were substantially larger, with a mean adjusted admissions of 16,659 compared with 7,332 among non-users ($p < 0.01$). Users employed roughly twice as many full-time equivalent personnel (1,022 vs. 470, $p < 0.01$). Users were more likely to be health system members (89% vs. 64%, $p < 0.01$), teaching hospitals (14% vs. 4%, $p < 0.01$), and not-for-profit institutions (97% vs. 86%, $p < 0.01$). Users were predominantly urban: 10% were located in rural areas compared with 26% of non-users ($p < 0.01$). Users had higher three-year average operating margins (-2.34% vs. -5.11%, $p < 0.01$), though

both groups reported negative average margins. Market-level differences mirror the hospital-level patterns. Users operated in counties with lower hospital market concentration (HHI of 5,280 vs. 6,880, $p < 0.01$), indicating more competitive markets. Their counties had higher median household incomes ($73,683 vs. $66,686, $p < 0.01$), more educated populations, younger age profiles, and lower uninsurance rates. These descriptive differences are consistent with Hypotheses 1 and 2. The regression analyses that follow isolate the independent association of each characteristic with AI use.

4.4 Predictors of AI Use - Any AI and Breadth of Adoption

Table 2 reports linear probability models for any operational AI use and for breadth of adoption. System membership, teaching status, and non-profit ownership show the strongest associations with AI use. System-member hospitals are 19.6 percentage points more likely to report any AI use than independent hospitals [0.196, $p < 0.01$]. Teaching hospitals are 14.8 percentage points more likely to use AI than non-teaching hospitals [0.148, $p < 0.01$]. Non-profit hospitals are 26.9 percentage points more likely to adopt than for-profit hospitals [0.269, $p < 0.01$]. These three coefficients align with Hypothesis 1 about organizational capacity and governance.

Operating margin shows a small, positive, and statistically significant association with any AI use [0.002, $p < 0.05$]: hospitals with stronger financial performance are more likely to adopt. Adjusted admissions are positively associated at conventional significance levels [0.037, $p < 0.10$]. After accounting for size, structure, and market characteristics, rural location and FTE show small, statistically imprecise associations.

Market context plays a limited independent role after conditioning on organizational characteristics. County HHI, county median income, age structure, and educational attainment show small, statistically imprecise coefficients. The percentage uninsured is positively associated with any AI use [0.006, $p < 0.05$], a pattern consistent with greater administrative burden in high-uninsurance markets raising the return to automation. Organizational structure and governance explain substantially more variation in any AI use than local market or state characteristics.

For breadth of adoption, the associations follow the same pattern with larger magnitudes. System-member hospitals use AI in 0.785 more operational domains than independent hospitals [0.785, $p < 0.01$]. Teaching hospitals use AI in 0.612 more domains [0.612, $p < 0.01$]. Non-profit hospitals use AI in 0.912 more domains than for-profit hospitals [0.912, $p < 0.01$]. Operating margin is positively associated with breadth [0.005, $p < 0.10$], and standardized Medicare spending per capita shows a positive association [0.049, $p < 0.10$], suggesting that hospitals in higher-spending markets adopt AI across a broader range of functions. The breadth model adjusted R-squared is 0.159.

4.5 Domain Specific Predictors

Table 2 reports separate models for each operational domain. System membership, teaching status, and non-profit ownership show large positive associations across all five domains, with magnitudes that vary systematically by task.

System-member hospitals are 13.8 to 17.5 percentage points more likely to use AI in each domain. The coefficients range from 0.138 for staff scheduling to 0.175 for predicting

staffing needs. This pattern indicates that system infrastructure and shared IT capacity support AI deployment across a wide range of hospital operations.

Teaching status shows a clear gradient across domains. For optimizing workflows, teaching hospitals are 19.0 percentage points more likely to use AI [0.190, $p < 0.01$]. For automating routine tasks the gap is 16.1 percentage points [0.161, $p < 0.01$]. For predicting patient demand the gap is 12.3 percentage points [0.123, $p < 0.01$]. For predicting staffing needs the coefficient is 7.7 percentage points [0.077, $p < 0.01$]. For staff scheduling the coefficient is 6.0 percentage points and marginally significant [0.060, $p < 0.05$].

Non-profit hospitals show the same gradient. They are 23.0 percentage points more likely to use AI for workflow optimization [0.230, $p < 0.01$], 21.9 percentage points more likely for automating routine tasks [0.219, $p < 0.01$], 17.7 percentage points more likely for predicting staffing needs [0.177, $p < 0.01$], 17.6 percentage points more likely for predicting patient demand [0.176, $p < 0.01$], and 11.0 percentage points more likely for staff scheduling [0.110, $p < 0.01$]. Organizational capacity advantages translate most strongly into automation and workflow domains. The staffing-related gap, while statistically significant, is meaningfully smaller. This gradient is consistent with Hypothesis 3.

Among market-level and demographic covariates, several domain-specific patterns emerge. The share of adults aged 65 and older is negatively associated with predicting patient demand [-0.005, $p < 0.10$] and staff scheduling [-0.004, $p < 0.05$], indicating lower adoption of these tools in older communities. The share of adults with a bachelor's degree or higher is positively associated with predicting patient demand [0.002, $p < 0.05$] and

workflow optimization [0.002, $p < 0.05$]. Operating margin is positively associated with workflow optimization [0.002, $p < 0.05$]. The percentage uninsured is positively associated with automating routine tasks [0.006, $p < 0.01$] and workflow optimization [0.004, $p < 0.10$], consistent with greater administrative burden in high-uninsurance markets driving demand for these tools. Standardized Medicare spending per capita is positively associated with predicting staffing needs [0.018, $p < 0.01$], suggesting that hospitals in higher-spending markets face greater pressure to optimize labor through AI. County HHI and county median income show small, statistically imprecise coefficients across all five domains.

Taken together, the domain-specific models show two main patterns. First, structural features that support any AI adoption, specifically system membership, teaching missions, and non-profit ownership, predict AI use across all domains. Second, staffing-related domains show smaller ownership and teaching gradients, indicating distinct organizational and policy frictions that persist regardless of broader AI adoption status.

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5. Discussion

This study provides a national, state and domain-specific analysis of AI use among U.S. GAC hospitals. We document three main findings.

5.1 AI Use Is Growing and Concentrated

As of 2023, more than one in four GAC hospitals reported using AI in at least one operational domain, up from 23.4% two years earlier. Growth slowed between 2022 and 2023, raising an important question about whether diffusion will extend to a broader set of hospitals or remain confined to early movers. If that gap persists, hospitals without AI risk falling further behind on operating margins and workforce stability, deepening existing inequalities in operational performance and patient access. Larger, system-affiliated, teaching, and not-for-profit hospitals in wealthier and more competitive markets are more likely to use operational AI. These patterns follow the trajectory of EHR adoption, where large system-affiliated hospitals led and smaller, independent, and rural hospitals lagged by years [19, 22, 64]. The parallel suggests that AI diffusion follows the same industrial and organizational dynamics that governed prior waves of hospital health IT [27, 71].

System membership is the critical organizational lever. Systems reduce per-hospital implementation costs through shared infrastructure, centralized analytics teams, and the ability to pilot a tool at one facility and roll it out to others at low marginal cost [37, 38]. This advantage is likely more pronounced for AI than for earlier health IT: AI tools require specialized data engineering and governance capacity that few independent hospitals maintain [35, 36]. Independent hospitals, especially smaller and rural ones, risk falling further behind as health system consolidation continues.

5.2 Domains Tell Different Stories

Workflow optimization and task automation are the most widely used AI applications. Staffing prediction and staff scheduling lag, and staff scheduling barely grew over the three-year period (13.1% to 13.4%). The gap reflects differences in what each domain asks of the organization. Automating prior authorizations or coding builds on existing EHR and revenue cycle systems, requiring no changes to clinical staffing patterns. AI for staffing and scheduling relocates labor allocation decisions into algorithmic systems, intersecting with collective bargaining, clinical autonomy, scheduling norms, and human resources governance [13, 70].

This domain-level variation carries direct implications for multiple stakeholders. For hospital leaders, it signals that deploying AI for workflow automation involves a fundamentally different organizational load than deploying AI for staffing and scheduling: different infrastructure, different governance, different change management. For vendors, it suggests that product design and implementation support should address the workforce governance challenges that slow uptake of staffing tools. For policymakers, aggregate AI use rates will obscure whether hospitals are deploying tools most relevant to their operational bottlenecks. For researchers, domain-level measurement in future surveys and evaluations is essential to connect specific AI applications to specific operational outcomes.

5.3 Geography Adds Another Layer of Heterogeneity

State-level AI use varied substantially, and hospital composition explains only part of the differences. Several small states with low baseline use experienced rapid gains (Vermont, New Jersey, Idaho), while some high-baseline states saw declines (North Dakota, South Dakota). These swings partly reflect small-sample dynamics: in states with few large hospitals, a single system's decision to deploy or discontinue a tool can shift the state average meaningfully.

The remaining variation is consistent with factors described in prior literature, including vendor market entry, state health IT incentive programs, workforce pressures, and shifts in system-level strategy [79]. These forces are not directly measured in our models, and future work with richer state-level data could test these mechanisms explicitly. The partial convergence pattern, growth concentrating among lower-baseline states and plateauing among higher-baseline states, is a common feature of technology diffusion and suggests that the initial wave of use was driven by a small number of large systems concentrated in certain states [71].

5.4 Comparison to Prior Literature

Our findings align with the technology diffusion literature on several dimensions and diverge on one. The positive associations between AI use and hospital size, system membership, teaching status, and not-for-profit ownership are consistent with decades of work on health IT uptake [19, 20, 41, 48]. They also align with Baten (2024), who documents similar patterns in a cross-sectional analysis of 2022 AHA data [23]. The present study extends that baseline by tracking adoption across three years, isolating GAC hospitals, incorporating market-level covariates, and introducing a breadth measure that captures how deeply AI embeds across operational domains. The economic

mechanism suggests that fixed costs of implementation are spread across more patients in larger hospitals [42], and systems provide shared infrastructure that lowers marginal deployment costs [37].

The finding that hospitals in more competitive markets are more likely to use AI aligns with models of nonprice competition, where hospitals invest in technology to differentiate on quality and efficiency [54, 55]. This contrasts with earlier findings that hospitals in less competitive markets were more likely to join affiliation networks [30]. The difference reflects how each organizational strategy works: affiliation networks provide brand recognition and external expertise, more valuable in less contested markets. Operational AI targets internal efficiency, and those gains yield greater returns under competitive pressure and leaner operations.

5.5 Limitations

This study has some limitations. First, the AHA IT Supplement relies on hospital self-report. Respondents may interpret 'artificial intelligence' and 'machine learning' differently, and some may include any algorithmic decision support while others apply a stricter definition [24]. Future surveys could improve measurement by providing standardized definitions and examples for each domain. Second, the survey captures whether a hospital uses AI in a given domain; it does not capture depth of use within that domain. Our breadth measure reflects the number of domains used, with depth within any one domain remaining unmeasured. Third, the three-year observation window limits our ability to observe longer-term diffusion patterns; the period also covers the aftermath of COVID-19, which may have independently shifted technology investment timelines [3, 80]. Fourth, market-level variables are measured at the county level, which may not align with

hospitals' metropolitan service areas [75]. Fifth, our models identify associations between hospital characteristics and AI use. Measuring the downstream effects of operational AI on efficiency, costs, quality, and patient care is an important next step.

5.6 Implications

The concentration of AI use among larger, better-resourced hospitals has practical consequences. If AI tools deliver the operational efficiencies, early adopters will compound advantages in cost management, staff retention, and patient throughput [9, 34]. Rural hospitals and financially constrained institutions, disproportionately represented among non-users, risk falling further behind, deepening existing disparities in operational performance and, over time, in patient access to efficiently delivered care [60, 61].

This gap suggests a role for policy interventions that lower the fixed costs of AI deployment for hospitals outside large systems. Targeted subsidies, shared-services models, regional health IT cooperatives, and vendor procurement assistance could help smaller hospitals access tools that are currently available primarily through system-level infrastructure [81, 82]. The HITECH Act demonstrated that federal investment could accelerate health IT diffusion broadly. A similar approach, adapted to the specific barriers facing AI deployment, could close the technology gap from widening further.

The slow uptake of AI for staffing and scheduling suggests that the domains where workforce shortages create the most urgent need are precisely the domains where organizational barriers slow deployment most. Closing this gap will require hospital leaders, labor organizations, and policymakers to work together on governance

frameworks that make AI-assisted workforce management feasible and trusted [13, 70]. Economic evaluations of early deployments, and clinician engagement in tool design could help build the organizational capacity that staffing-related AI currently lacks.

6. Conclusion

AI in U.S. GAC hospitals is following the same diffusion path as earlier waves of health IT: concentrated first among larger, better-resourced, system-affiliated institutions, spreading unevenly across states, and advancing most slowly in the domains where operational need is greatest. The hospitals with the most to gain from AI tools for staffing and scheduling face the steepest organizational barriers to deploying them. If this pattern holds, AI will compound existing advantages, widening the performance gap between well-resourced and resource-constrained hospitals and accelerating consolidation. Closing that gap requires more policy intervention. It requires financing structures that lower adoption costs for independent and rural hospitals, governance frameworks that make AI-assisted workforce management trusted by clinicians and labor, and a research agenda that connects specific AI tools to concrete operational outcomes. The central question going forward is whether the reshaping of hospital operations through AI reaches the institutions and patients who stand to benefit most.

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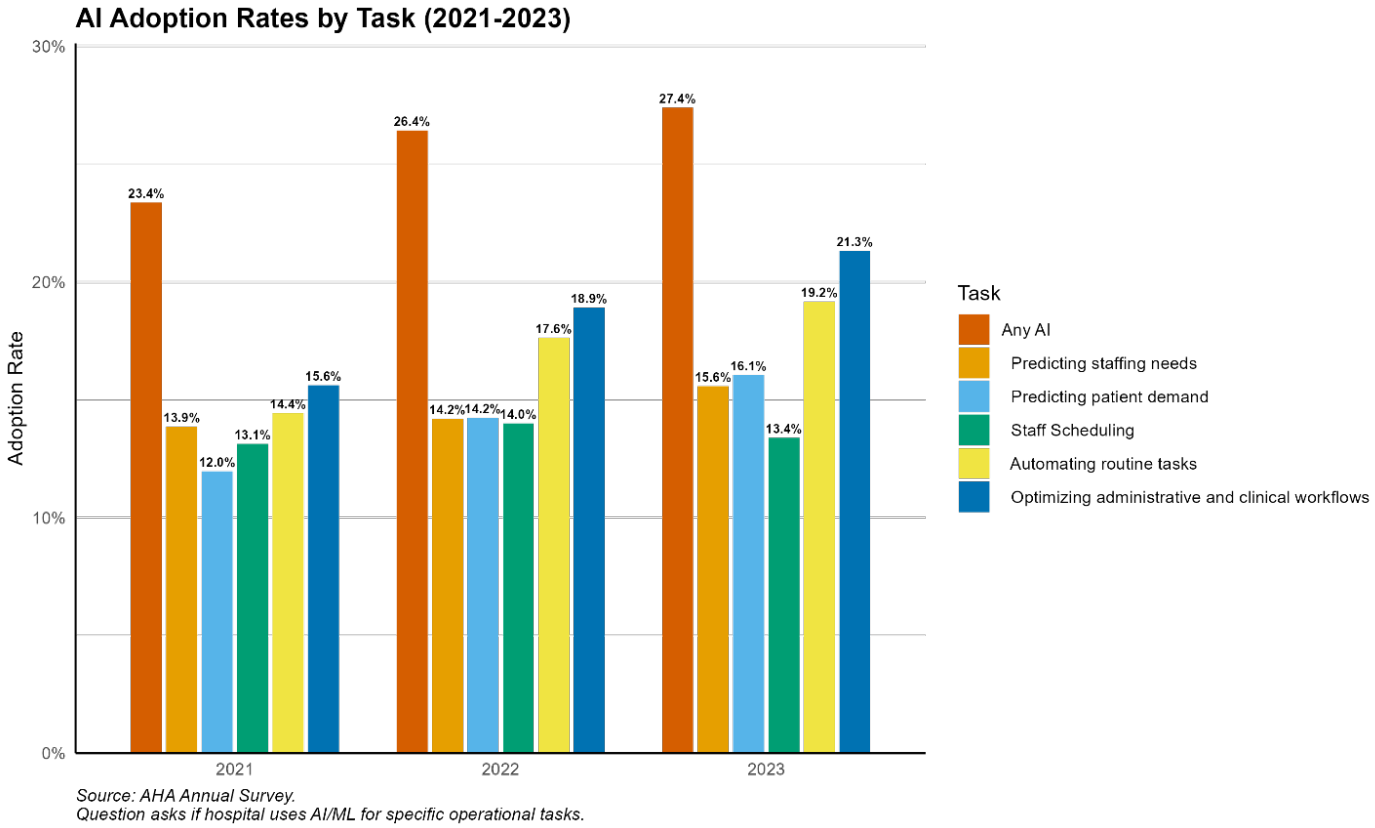
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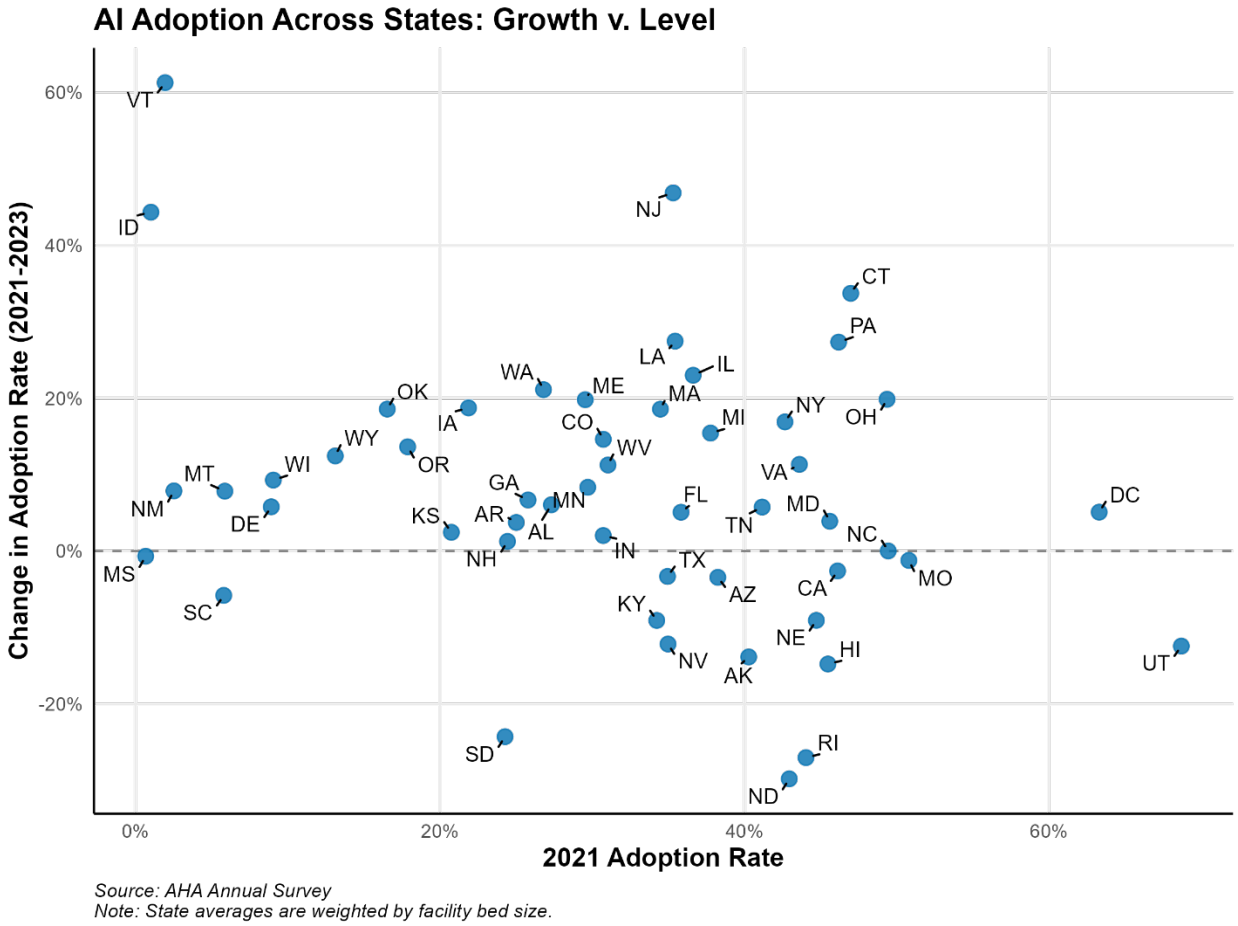
Figures

Figure 1: Growth of AI Adoption Across GAC Hospitals by Operational Domain, 2021 to 2023



Notes: Bed-weighted use rates plotted for any AI and for each of the five operational domains. Sample restricted to GAC hospitals responding to the AHA IT Supplement in the relevant survey year. Any AI reflects use in at least one of the five domains.

Figure 2: State variation in AI Adoption



Notes: Scatter plot showing change in bed-weighted state-level AI use rate (2021 to 2023) against 2021 baseline. States labeled. States in the upper-left quadrant represent those with low 2021 use and large subsequent gains (e.g., Vermont, New Jersey, Idaho). States in the lower-right quadrant reflect high 2021 use and flat or declining trajectories (e.g., Utah, Missouri, North Dakota).

Tables

Table 1: Comparison of AI Adopters and Non-Adopters

Variable	(1) Non-Adopters	(2) Adopters	(3) Difference
Hospital-level			
System member	0.64 (0.48)	0.89 (0.31)	0.25***
Teaching	0.04 (0.19)	0.14 (0.35)	0.10***
Non-profit	0.86 (0.34)	0.97 (0.18)	0.10***
Rural	0.26 (0.44)	0.10 (0.30)	-0.16***
Log(Adjusted Admissions)	8.90 (1.29)	9.72 (1.09)	0.82***
Log(Full-Time Equivalent Personnel)	6.15 (1.21)	6.93 (1.28)	0.77***
Three-year avg. operating margin	-5.11 (13.79)	-2.34 (12.55)	2.77***
Area-level			
HHI (county, 1000s)	6.88 (3.38)	5.28 (3.48)	-1.60***
Log(county median income)	11.10 (0.25)	11.21 (0.25)	0.11***
Percent age 65+ (county)	18.42 (4.53)	16.98 (3.88)	-1.44***
Percent bachelor's+ (county)	27.79 (11.42)	33.62 (11.61)	5.82***
Percent uninsured (county)	9.29 (4.91)	8.43 (4.51)	-0.86***
Std. Medicare payment per capita ($1k)	11.26 (1.83)	11.33 (1.63)	0.07*
Region			
North	0.09 (0.29)	0.19 (0.39)	0.10***
South	0.39 (0.49)	0.31 (0.46)	-0.08***

Midwest	0.32 (0.47)	0.30 (0.46)	-0.02**
West	0.19 (0.39)	0.20 (0.40)	0.00
Observations	6,710	2,703	9,413

*Notes: Values represent means with standard deviations in parentheses. Sample consists of N = 9,371 hospital-year observations, stratified into AI adopters and non-adopters. The adopter column (N = 2,697) and non-adopter column (N = 6,674) sum to the full sample. Column 3 displays the unconditional mean difference between the two groups. Statistical significance determined using two-tailed t-tests assuming unequal variances. * p < 0.10, ** p < 0.05, *** p < 0.01.*

Table 2: Predictors of AI Adoption (Linear Probability Models)

Variable	Any AI	Predict Staffing Need	Predict Patient Demand	Staff Scheduling	Automate Routine Tasks	Optimize Workflows	AI Breadth
System member	0.196***	0.175***	0.164***	0.138***	0.165***	0.142***	0.785***
	(0.026)	*(0.023)*	*(0.023)*	*(0.021)*	*(0.025)*	*(0.024)*	*(0.102)*
Teaching	0.148***	0.077***	0.123***	0.060**	0.161***	0.190***	0.612***
	(0.035)	*(0.032)*	*(0.033)*	*(0.029)*	*(0.034)*	*(0.034)*	*(0.135)*
Non-profit	0.269***	0.177***	0.176***	0.110***	0.219***	0.230***	0.912***
	(0.037)	*(0.028)*	*(0.031)*	*(0.027)*	*(0.036)*	*(0.035)*	*(0.129)*
Rural	0.001	0.003	0.021	0.016	-0.000	0.006	0.046
	(0.024)	*(0.023)*	*(0.023)*	*(0.019)*	*(0.024)*	*(0.023)*	*(0.101)*
Adj. admissions (log, lag 1yr)	0.037*	0.036**	0.030*	0.024*	0.021	0.020	0.131*
	(0.021)	*(0.018)*	*(0.018)*	*(0.014)*	*(0.021)*	*(0.019)*	*(0.078)*
FTE (log, lag 1yr)	0.007	-0.017	-0.014	-0.007	0.003	0.011	-0.024
	(0.025)	*(0.021)*	*(0.021)*	*(0.017)*	*(0.025)*	*(0.023)*	*(0.095)*
Op. margin (3-yr avg)	0.002**	0.001	0.001	0.001	0.001	0.002**	0.005*
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.003)*
HHI (1000s)	-0.002	-0.004	-0.000	0.001	-0.001	-0.002	-0.007
	(0.004)	*(0.004)*	*(0.004)*	*(0.003)*	*(0.004)*	*(0.004)*	*(0.015)*
Log(county median income)	0.054	0.059	0.026	0.025	0.054	0.010	0.174
	(0.059)	*(0.061)*	*(0.049)*	*(0.063)*	*(0.058)*	*(0.058)*	*(0.227)*
% age 65+ (county)	-0.005	-0.004	-0.005*	-0.004**	-0.003	-0.005	-0.020*

Variable	Any AI	Predict Staffing Need	Predict Patient Demand	Staff Scheduling	Automate Routine Tasks	Optimize Workflows	AI Breadth
	(0.003)	*(0.003)*	*(0.003)*	*(0.002)*	*(0.003)*	*(0.003)*	*(0.012)*
% bachelor's+ (county)	0.002	-0.000	0.002*	0.001	0.002	0.002*	0.006
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.004)*
% uninsured (county)	0.006**	0.003	0.001	0.003	0.006***	0.004*	0.017**
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.009)*
Medicare payment per capita ($1k)	0.010	0.018***	0.011	0.010	0.004	0.006	0.049*
	(0.007)	*(0.007)*	*(0.007)*	*(0.006)*	*(0.007)*	*(0.007)*	*(0.028)*
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,511	8,511	8,511	8,511	8,511	8,511	8,511
Adj. R^2	0.167	0.117	0.113	0.072	0.131	0.143	0.159

*Notes: All models estimated using ordinary least squares (OLS) with region and year fixed effects. Standard errors clustered at the hospital level. Sample restricted to GAC hospitals with complete data for all covariates; N = 8,511 hospital-year observations (some observation loss due to lagged variable construction relative to the full descriptive sample of N = 9,371). Coefficients for any AI and domain-specific models represent percentage-point changes in the probability of AI use associated with a one-unit change in the covariate. The AI Breadth coefficient represents the change in the count of operational domains (0-5) in which AI is used. Adj. admissions and FTE are lagged one year. Operating margin is a three-year rolling average. For-profit ownership is the omitted ownership category. * p < 0.10, ** p < 0.05, *** p < 0.01.*

SUPPLEMENTARY APPENDIX

Appendix Table A1: Robustness Check - Multi-level Logistic and Poisson Regression Models

This appendix reports multi-level logistic regression (for binary outcomes) and Poisson regression (for the AI breadth count outcome) as robustness checks for the primary OLS results reported in Table 2. Values for binary outcomes are odds ratios; the AI Breadth column reports incidence rate ratios (IRR). 95% confidence intervals are reported in brackets. Region and year fixed effects are included in all models. Sample size is 8,511 hospital-year observations. Convergence required 6 to 8 iterations across models.

The odds ratios for system membership, teaching status, and non-profit ownership are large (e.g., system membership OR = 34.664 for any AI), reflecting strong organizational selection into AI adoption. These magnitudes are consistent with the primary LPM findings but are expressed on a multiplicative scale. The LPM coefficients in Table 2 provide the more interpretable marginal effect estimates for policy purposes. The direction and ordering of effects across domains are consistent across both specifications.

Variable	Any AI	Predict Staffing Need	Predict Patient Demand	Staff Scheduling	Automate Routine Tasks	Optimize Workflows	AI Breadth (IRR)
System member	34.664***	171.581***	118.222***	55.077***	58.535***	23.340***	7.014***
	[16.224,74.061]	*[52.427,561.545]*	*[39.401,354.724]*	*[18.415,164.723]*	*[23.498,145.814]*	*[10.753,50.663]*	*[5.005,9.829]*
Teaching	3.164***	2.038**	2.440***	1.685	4.171***	3.491***	1.394***
	[1.691,5.919]	*[1.048,3.961]*	*[1.333,4.465]*	*[0.829,3.425]*	*[2.260,7.696]*	*[1.951,6.249]*	*[1.128,1.722]*
Non-profit	4.425***	4.819**	6.740**	1.560	15.922***	7.100***	2.175***
	[1.489,13.150]	*[1.100,21.111]*	*[1.507,30.139]*	*[0.387,6.281]*	*[4.305,58.883]*	*[2.239,22.517]*	*[1.297,3.648]*
Rural	1.039	1.210	1.240	1.253	0.971	1.065	0.974
	[0.611,1.766]	*[0.637,2.299]*	*[0.675,2.279]*	*[0.655,2.396]*	*[0.551,1.710]*	*[0.613,1.852]*	*[0.792,1.197]*

Variable	Any AI	Predict Staffing Need	Predict Patient Demand	Staff Scheduling	Automate Routine Tasks	Optimize Workflows	AI Breadth (IRR)
Adj. admissions (log, lag 1yr)	1.551**	1.247	1.303	1.747**	1.297	1.422*	1.119*
	[1.073,2.243]	*[0.801,1.942]*	*[0.855,1.986]*	*[1.122,2.719]*	*[0.867,1.941]*	*[0.962,2.101]*	*[0.979,1.280]*
FTE (log, lag 1yr)	1.109	1.175	1.122	0.846	1.049	1.121	1.069
	[0.781,1.575]	*[0.779,1.772]*	*[0.759,1.658]*	*[0.564,1.270]*	*[0.719,1.531]*	*[0.778,1.616]*	*[0.944,1.211]*
Op. margin (3-yr avg)	1.007	1.003	0.999	1.004	1.004	1.004	0.999
	[0.994,1.021]	*[0.988,1.017]*	*[0.985,1.013]*	*[0.989,1.020]*	*[0.990,1.017]*	*[0.992,1.018]*	*[0.995,1.004]*
HHI (1000s)	0.980	0.925**	0.965	1.004	0.970	0.959	0.979*
	[0.921,1.042]	*[0.861,0.993]*	*[0.904,1.031]*	*[0.934,1.080]*	*[0.909,1.034]*	*[0.902,1.019]*	*[0.957,1.001]*
Log(county median income)	1.377	5.008**	3.555**	1.139	1.568	0.847	1.331
	[0.461,4.112]	*[1.401,17.896]*	*[1.099,11.499]*	*[0.314,4.131]*	*[0.502,4.901]*	*[0.291,2.460]*	*[0.878,2.017]*
% age 65+ (county)	0.917***	0.878***	0.909***	0.902***	0.929***	0.930***	0.960***
	[0.872,0.964]	*[0.827,0.934]*	*[0.858,0.962]*	*[0.848,0.959]*	*[0.881,0.979]*	*[0.885,0.978]*	*[0.941,0.979]*
% bachelor's+ (county)	1.011	0.969**	0.995	1.012	1.007	1.008	1.000
	[0.988,1.036]	*[0.943,0.997]*	*[0.970,1.021]*	*[0.984,1.040]*	*[0.983,1.033]*	*[0.985,1.032]*	*[0.992,1.009]*
% uninsured (county)	1.042	1.092***	1.057*	1.071**	1.075**	1.013	1.029***
	[0.990,1.097]	*[1.028,1.160]*	*[0.996,1.122]*	*[1.008,1.138]*	*[1.016,1.138]*	*[0.961,1.068]*	*[1.008,1.050]*

Variable	Any AI	Predict Staffing Need	Predict Patient Demand	Staff Scheduling	Automate Routine Tasks	Optimize Workflows	AI Breadth (IRR)
Medicare payment per capita ($1k)	1.037	1.056	1.042	0.980	1.002	1.055	0.997
	[0.914,1.178]	*[0.908,1.228]*	*[0.904,1.202]*	*[0.844,1.138]*	*[0.873,1.151]*	*[0.929,1.198]*	*[0.952,1.044]*
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,511	8,511	8,511	8,511	8,511	8,511	8,511

*Notes: Binary outcome models estimated using multi-level logistic regression; AI Breadth estimated using Poisson regression. Values are odds ratios (binary outcomes) or incidence rate ratios (AI Breadth). 95% confidence intervals in brackets. Region and year fixed effects included. Standard errors clustered at the hospital level. * p < 0.10, ** p < 0.05, *** p < 0.01.*

Appendix Table A2: Robustness Check - Multi-level Logistic and Poisson Models, Average Marginal Effects

This table reports average marginal effects (AMEs) derived from the multi-level logistic and Poisson models. AMEs represent the average change in the probability of AI use (or number of domains for breadth) associated with a one-unit change in each predictor, evaluated at observed covariate values. 95% confidence intervals in brackets. Region and year fixed effects included in all models. N = 8,511 hospital-year observations.

Variable	Any AI	Pred. Staffing Need	Pred. Patient Demand	Staff Scheduling	Automating Routine Tasks	Optimizing Workflows	AI Breadth
System member	0.228*** [0.181, 0.276]	0.194*** [0.149, 0.239]	0.190*** [0.146, 0.233]	0.150*** [0.109, 0.192]	0.198*** [0.154, 0.243]	0.178*** [0.133, 0.223]	3.353*** [1.772, 4.934]
Teaching	0.074*** [0.034, 0.114]	0.027** [0.002, 0.052]	0.035*** [0.011, 0.060]	0.020 [-0.007, 0.046]	0.070*** [0.039, 0.100]	0.071*** [0.037, 0.104]	0.572*** [0.162, 0.982]
Non-profit	0.096*** [0.026, 0.166]	0.059** [0.004, 0.115]	0.076** [0.017, 0.135]	0.017 [-0.035, 0.069]	0.135*** [0.071, 0.198]	0.111*** [0.046, 0.176]	1.338*** [0.366, 2.309]
Rural	0.002 [-0.032, 0.037]	0.007 [-0.017, 0.031]	0.009 [-0.016, 0.033]	0.008 [-0.016, 0.033]	-0.001 [-0.029, 0.026]	0.004 [-0.028, 0.035]	-0.046 [-0.402, 0.310]
Log(Adjusted Admissions)	0.028** [0.004, 0.052]	0.008 [-0.008, 0.025]	0.011 [-0.006, 0.027]	0.021** [0.004, 0.038]	0.013 [-0.007, 0.032]	0.020* [-0.002, 0.042]	0.194 [-0.043, 0.432]
Log(FTE)	0.007 [-0.016, 0.029]	0.006 [-0.009, 0.021]	0.005 [-0.011, 0.020]	-0.006 [-0.022, 0.009]	0.002 [-0.016, 0.021]	0.006 [-0.014, 0.027]	0.115 [-0.104, 0.333]
Operating Margin (3yr avg.)	0.000 [-0.000, 0.001]	0.000 [-0.000, 0.001]	-0.000 [-0.001, 0.001]	0.000 [-0.000, 0.001]	0.000 [-0.000, 0.001]	0.000 [-0.000, 0.001]	-0.001 [-0.009, 0.007]
HHI (1000s)	-0.001 [-0.005, 0.003]	-0.003** [-0.006, -0.000]	-0.001 [-0.004, 0.001]	0.000 [-0.003, 0.003]	-0.002 [-0.005, 0.002]	-0.002 [-0.006, 0.001]	-0.037* [-0.078, 0.003]

Log(County Median Income)	0.021 [-0.050, 0.091]	0.061** [0.013, 0.109]	0.050** [0.004, 0.097]	0.005 [-0.043, 0.053]	0.022 [-0.034, 0.078]	-0.009 [-0.070, 0.051]	0.492 [-0.240, 1.224]
% Age 65+	-0.006*** [-0.009, -0.002]	-0.005*** [-0.007, -0.003]	-0.004*** [-0.006, -0.002]	-0.004*** [-0.006, -0.002]	-0.004*** [-0.006, -0.001]	-0.004*** [-0.007, -0.001]	-0.070*** [-0.113, -0.028]
% Bachelor's+	0.001 [-0.001, 0.002]	-0.001** [-0.002, -0.000]	-0.000 [-0.001, 0.001]	0.000 [-0.001, 0.001]	0.000 [-0.001, 0.002]	0.000 [-0.001, 0.002]	0.001 [-0.014, 0.016]
% Uninsured	0.003 [-0.001, 0.006]	0.003*** [0.001, 0.006]	0.002* [-0.000, 0.005]	0.003*** [0.000, 0.005]	0.004** [0.001, 0.006]	0.001 [-0.002, 0.004]	0.049** [0.010, 0.088]
Medicare Payment per Capita ($1k)	0.002 [-0.006, 0.011]	0.002 [-0.004, 0.008]	0.002 [-0.004, 0.007]	-0.001 [-0.006, 0.005]	0.000 [-0.007, 0.007]	0.003 [-0.004, 0.010]	-0.005 [-0.085, 0.075]
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,511	8,511	8,511	8,511	8,511	8,511	8,511

*Notes: AMEs derived from multi-level logistic regression (binary outcomes) and Poisson regression (AI Breadth). 95% confidence intervals in brackets. Region and year fixed effects included. * p < 0.10, ** p < 0.05, *** p < 0.01.*