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AI Adoption and Hospital Performance: Evidence from 2,979 U.S. Hospitals

Serdar Aydin, Gokhan Agac, Ramshah Mona Eliza, Tomia Sheares, Zachary Roberts, Chad Kuchvalek, Institute of Health Administration, J. Mack Robinson College of Business, Georgia State University

Corresponding Author: saydin@gsu.edu

Abstract

What is the message? Hospital-level artificial intelligence adoption is positively associated with operational efficiency and patient volume, while its association with financial performance varies across revenue- and expense-based outcomes.

What is the evidence? Using data from 2,979 U.S. hospitals in the 2022 American Hospital Association Annual Survey, multiple regression models show that AI Adoption Level is positively associated with higher admissions and inpatient volume, as well as with higher operating expenses and payroll.

Keywords: Artificial Intelligence, Hospital Operations, Administrative Costs

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Introduction

Artificial intelligence (AI) is a new force in healthcare optimization, with the potential to drive improved clinical decision making, more accurate economic forecasting and cost allocation, and impactful workforce support mechanisms (1). AI tools can improving time allocation for clinicians by completing redundant and routine responsibilities and allowing doctors to spend more time with their patients, thereby improving wait times and physician workloads (2). Administrative systems using AI have the opportunity to shift from reactive to proactive and predictive infrastructures, which disrupts traditional clinical operations. It was estimated that implementation of healthcare AI programs could create 5% to 10% percent cost saving of overall U.S. healthcare spending (3).

As staffing shortages and rising healthcare costs place increasing pressure on health systems, artificial intelligence has emerged as a potential means of addressing these challenges. Many health systems are working toward becoming Learning Health Systems (LHS) – organizations that continuously generate and apply evidence from their own data to improve care – with artificial intelligence serving as a central enabler of this model (4,5). However, AI adoption across U.S. health providers remains limited. Only 38% of hospitals have implemented AI into their processes, and when implementation happens, it is often limited to an individual unit or department and is not implemented throughout the whole healthcare facility (6).

Many studies do a good job of showing what kind of effect the implementation of AI has on the workflows of individuals or departments, but few focus on what kind of effect AI adoption is having on whole-hospital operational performance. This shortcoming leaves a gap in the ability of healthcare administrators to assess AI's value at the organizational level. Addressing the gap ensures informed decisions on investment translate into operational success. The purpose of this study is to address the following research question:

Research Question. What is the adoption level of AI in hospitals, and how is it associated with hospital operational and financial performance?

This paper provides a statistical analysis of data from the American Hospital Association (AHA) database and an empirical examination of the relationship between hospital AI adoptions levels and operational efficiency, comparing data outcomes across various U.S. hospitals. There are

limited studies that link AI adoption to total hospital expenses, which are examined alongside our database findings on operational performance measures. This approach examines the broader organizational impacts of AI, moving beyond departmental analyses. It offers insights for healthcare administrators and policymakers. The findings provide evidence on the associations between AI adoption and hospital performance that may inform healthcare decision making. This article contributes to the literature by:

1. Providing organization-level evidence on AI adoption and hospital performance across a large sample of U.S. hospitals.
2. Connecting hospital-level AI adoption to financial performance under value-based payment models, specifically risk-based and capitated revenue.
3. Offering managerial implications regarding the association between AI adoption and hospital performance.

Literature Review

The picture of AI use in healthcare, it seems, is mostly drawn from statistical modelling and national survey data. For example, a short report that looked at the 2022 American Hospital Association survey said about 18.7% of U.S. hospitals had at least one AI tool that year (7). That number may mean adoption is still early, but it also could just reflect how the survey asked the question. Other researchers have taken the same AHA data and paired it with the Area Deprivation Index. By running state-level models, they tried to see if poorer regions adopt AI less often (8). The approach sounds solid, yet the fixed-effect trick might hide local quirks. Beyond raw percentages, people have been scanning published papers to catch what hospitals think about AI. Those literature reviews keep coming back with a theme: health systems treat AI like a trial toy, not a finished product (9). Roppelt et al. (10) added a list of roadblocks – high costs, privacy worries, hard-to-link systems, and not enough tech staff. Those hurdles feel real, though some folks argue they're overstated.

Discussions of AI's impact on hospital staff and department operations focus on the benefits, but most evidence comes from small pilots, clinical trials, or technology reviews. While some argue that tools like "ambient" AI note-taking ease clinical workloads – with pilot data supporting this, such as a difference-in-differences study of an AI scribe over 300,000 visits (11) – these results may overlook hidden costs like extra training. When it comes to staffing and scheduling,

researchers took the historical-narrative route, compiling 11 real-world studies. A qualitative review was chosen because the original papers varied significantly in their findings (2). That way, they could still discuss the mix of methods without forcing everything into one tidy model.

In actual wards, people rely on quasi-experimental or full-on experiments to determine if operations improve. One study, for example, found that human reviewers of Early Warning Scores caught patient decline more often when the score got an AI boost. That work employed a retrospective cohort with a regression-discontinuity design, aiming to tease out cause and effect (12). Still, you could argue that a retrospective look isn't as clean as a true random test. The operating room story underwent a systematic review that followed PRISMA guidelines, drawing on 22 recent papers that examined aspects such as surgery duration and post-anesthesia care (13). Overall, the evidence suggests beneficial effects, but the methods aren't perfect, and the picture may shift as more varied data become available.

The financial effects of AI were analyzed through specialized tools developed by researchers, economic modeling, and regression analysis. Economic modeling, in turn, leads to the broader hypothesis that significant cost savings could be realized if AI were to be widely adopted. A NBER Working Paper estimated that healthcare leaders could save 5% to 10% by leveraging national healthcare spending data and case studies (3). However, this methodology only distills the latter's observations rather than randomized control trials. At the hospital level, one study found that AI adoption is linked to improved facility revenue and productivity in U.S. hospitals and utilized both logit and Ordinary Least Squares (OLS) regression models to test hypotheses (14). However, the same study did not analyze how AI adoption affects operating costs (14). Another study developed an "AI return on investment (ROI) calculator" to address the problem that many hospital leaders are unclear about how to measure returns from their AI investments (15). Based on interviews with department staff and a literature review, the study developed a multidimensional calculator for use in hospitals (16).

Even though AI can drive significant healthcare transformation, evidence linking the intensity of AI adoption to hospitals' overall financial performance is still limited. The literature relies on national surveys to track adoption, clinical trials, and pilot programs to assess operational and workforce impacts, as well as economic modeling to estimate potential savings. Few studies have quantified the financial return on AI investments across entire organizations using empirical data. Available studies have examined AI adoption levels, workforce optimization, and

operational efficiency, but few combine all three with total hospital expenses. This gap highlights the need for comprehensive, quantitative research to create a clear model for healthcare leaders to understand how AI adoption could improve organizational performance.

Methodology

Data Collection

Data for this study were obtained from the 2022 American Hospital Association (AHA) Annual Survey Database. This dataset includes information from 6,193 hospitals across the United States. After excluding entries with missing data for AI adoption indicators or key financial variables, the final analytic sample consisted of 2,979 hospitals.

AI adoption was measured using five binary indicators (1 = yes, 0 = no): automating routine tasks in patient care and treatment (WFAIART), optimizing administrative and clinical workflows (WFAIOACW), predicting patient demand for population health management (WFAIPPD), supporting patient safety and nursing operations (WFAIPSN), and staff scheduling (WFAISS).

The response (dependent) variables captured two domains of hospital performance. Operational efficiency was measured using six variables: adjusted admissions (ADJADM), an aggregate measure reflecting inpatient admissions adjusted for outpatient utilization; adjusted patient days (ADJPD), an aggregate measure of inpatient days adjusted for outpatient activity; total facility admissions (ADMTOT); average daily census (ADC), defined as inpatient days divided by days in the reporting period; adjusted average daily census (ADJADC); and total facility inpatient days (IPDTOT). Financial performance was captured through ten variables: on the revenue side, percent of patient revenue from ACO contracts (ACOCN), percent of patient revenue from bundled payment arrangements (BNDPCT), percent of net patient revenue paid on a shared risk basis (CAPRSK), and percent of patient revenue paid on a capitated basis (CPPCT); on the expense side, total facility expenses excluding bad debt (EXPTOT), hospital unit total expenses excluding bad debt (EXPTHA), total facility payroll expenses (PAYTOT), hospital unit payroll expenses (PAYTOTH), pharmacy expenses (PHREXA), and supply expenses (SUPEXA).

The primary control variable was hospital bed size category (BSC), a categorical variable ranging from 1 (fewer than 25 beds) to 8 (500 or more beds), serving as a proxy for overall hospital size

and resource capacity. Full variable definitions are provided in Appendix 1.

Data Analysis

To address the potential multicollinearity identified among the five individual AI adoption indicators, a composite AI Adoption Level index was constructed as the arithmetic average of the five binary indicators. This single composite variable was used as the primary independent variable in all regression models in place of the individual indicators. Prior to regression analysis, a logarithmic transformation was applied to all response variables to address skewed distributions. Separate multiple regression models were estimated for each of the 16 outcome variables, with the AI Adoption Level index and BSC as independent variables. Models were organized into three groups: six operational efficiency models, four revenue-based financial models, and six expense-based financial models. Model fit was evaluated using R^2, adjusted R^2, RMSE, and F statistics. Regression coefficients, standard errors, standardized coefficients, t statistics, p values, and variance inflation factors (VIF) are reported for each model. Models for which the overall F test did not reach statistical significance ($p > .05$) were excluded from the regression coefficient tables.

Findings

This study examines the association between the level of AI adoption in U.S. hospitals and measures of operational and financial performance. Multiple regression analyses were conducted using a composite AI Adoption Level index and hospital bed size as predictors. Separate models were estimated for operational efficiency outcomes, revenue-based financial measures, and expense-based financial measures. The findings are organized accordingly in the sections that follow.

Descriptive Statistics

Table 1 presents the descriptive statistics for all variables in their original, untransformed form. The six operational efficiency outcome variables – ADJADM, ADJPD, ADMTOT, ADC, ADJADC, and IPDTOT – display substantially large standard deviations relative to their means, alongside wide ranges between minimum and maximum values.

Table 1. Descriptive Statistics of Variables

Variable	Descriptive Statistics				
	N*	Mean	Standard Deviation	Minimum	Maximum
ADJADM	2979	16440.8	21030.3	3	251335
ADJPD	2979	98269.6	133235	36	$2.004\times10^{+6}$
ADMTOT	2979	7334.14	10780.4	2	147344
ADC	2979	123.628	181.75	0	2292
ADJADC	2979	269.298	364.992	0	5492
IPDTOT	2979	45125.2	66338.1	4	836510
ACOCN	740	10.297	13.072	0	85
BNDPCT	621	2.744	8.336	0	75
CAPRSK	2572	2.211	7.816	0	98
CPPCT	2764	1.639	8.782	0	95
EXPTOT	2979	$3.155\times10^{+8}$	$6.021\times10^{+8}$	$2.659\times10^{+6}$	$7.574\times10^{+9}$
EXPTHA	309	$2.783\times10^{+8}$	$4.928\times10^{+8}$	$4.985\times10^{+6}$	$3.740\times10^{+9}$
PAYTOT	2979	$1.175\times10^{+8}$	$2.279\times10^{+8}$	$1.044\times10^{+6}$	$3.772\times10^{+9}$
PAYTOTH	309	$1.057\times10^{+8}$	$1.886\times10^{+8}$	57595	$1.862\times10^{+9}$
PHREXA	2757	$2.743\times10^{+7}$	$8.003\times10^{+7}$	1483	$1.412\times10^{+9}$
SUPEXA	2747	$4.024\times10^{+7}$	$8.659\times10^{+7}$	4739	$1.965\times10^{+9}$
WFAIART	2979	0.241	0.428	0	1
WFAIOACW	2979	0.259	0.438	0	1
WFAIPPD	2979	0.195	0.396	0	1
WFAIPSN	2979	0.195	0.396	0	1
WFAISS	2979	0.192	0.394	0	1
AI Adoption Level	2979	0.216	0.330	0	1
BSC	2979	3.712	2.045	1	8

**Note: Number of valid observations*

Among the financial outcome variables, the revenue-based measures – ACOCN, BNDPCT, CAPRSK, and CPPCT – show relatively low mean values, with minimum values of zero across all four measures, reflecting the limited and uneven penetration of alternative payment models such as accountable care organization contracts, bundled payments, and capitation arrangements among U.S. hospitals. The expense-based outcomes display considerably higher variability. Total facility expenses (EXPTOT) and total payroll expenses (PAYTOT) in particular span several orders of magnitude across hospitals, reflecting the wide range of organizational sizes represented in the sample.

Regarding the independent variables, the five binary AI adoption indicators – WFAIART, WFAIOACW, WFAIPPD, WFAIPSN, and WFAISS – have means ranging from 0.192 to 0.259, indicating that between approximately 19% and 26% of the 2,979 hospitals in the sample had adopted each respective AI application at the time of the survey. The composite AI Adoption Level index, computed as the arithmetic average of these five binary indicators, has a mean of 0.216 (SD = 0.330, min = 0, max = 1), reflecting that on average hospitals in the sample had adopted approximately one in five of the AI applications examined. The control variable, hospital bed size category (BSC), has a mean of 3.712 on its 1 to 8 ordinal scale, with values ranging from the smallest category (fewer than 25 beds) to the largest (500 or more beds), indicating that the sample spans the full range of hospital sizes represented in the AHA database.

Model Summary

Table 2 presents the overall fit statistics for all 16 regression models, including correlation coefficients (R), variance explained (R^2 and adjusted R^2), root mean square error (RMSE), F statistics, and associated significance levels. Each row in the table represents a separate regression model estimated with a distinct dependent variable. All 16 models share the same set of independent variables: the AI Adoption Level composite index and hospital bed size category (BSC). Differences in sample sizes across models reflect variations in data completeness across the outcome variables in the AHA database.

Table 2. Model Summary of Dependent Variables

Variable	R	R^2	Adjusted R^2	RMSE	F	p
ADJADM	0.709	0.503	0.503	1.070	1505.910	< .001
ADJPD	0.864	0.747	0.747	0.647	4401.503	< .001
ADMTOT	0.842	0.709	0.708	0.917	3617.811	< .001
ADC	0.919	0.844	0.844	0.602	8076.126	< .001
ADJADC	0.873	0.762	0.761	0.613	4752.342	< .001
IPDTOT	0.900	0.811	0.811	0.714	6378.901	< .001
ACOCN	0.089	0.008	0.005	1.253	2.955	0.053
BNDPCT	0.031	0.001	-0.002	0.864	0.294	0.746
CAPRSK	0.291	0.085	0.084	0.858	118.852	< .001
CPPCT	0.198	0.039	0.039	0.735	56.366	< .001
EXPTOT	0.854	0.730	0.730	0.769	4026.042	< .001
EXPTHA	0.785	0.616	0.614	0.900	245.570	< .001
PAYTOT	0.863	0.746	0.745	0.722	4360.974	< .001
PAYTOTH	0.717	0.514	0.511	1.044	161.982	< .001
PHREXA	0.766	0.587	0.587	1.274	1960.589	< .001
SUPEXA	0.785	0.616	0.616	1.175	2201.767	< .001

The six operational efficiency models all achieve high levels of statistical significance (F $p <$ .001). R^2 values range from 0.503 for ADJADM to 0.844 for ADC, with the remaining four outcomes falling between these values. These results indicate that the predictor set accounts for a substantial proportion of variance in operational efficiency outcomes across the sample. Among the financial models, a notable difference in explanatory power is observed between expense-based and revenue-based outcomes. The models for EXPTOT, PAYTOT, and PHREXA explain between 59% and 75% of variance, while those for PAYTOTH and EXPTHA explain

approximately 51% and 62%, respectively. In contrast, the revenue-based models for CAPRSK and CPPCT explain considerably less variance (R^2 = 0.085 and 0.039, respectively), indicating that the predictor set has limited explanatory coverage of alternative payment model revenue. The models for ACOCN (F p = .053) and BNDPCT (F p = .746) did not achieve statistical significance and are therefore excluded from the regression coefficient tables that follow.

AI Adoption and Operational Efficiency

Table 3 presents the unstandardized coefficients (B), standard errors, standardized coefficients (β), t statistics, p values, and VIF values for the association between AI Adoption Level and each of the six operational efficiency outcomes, controlling for hospital bed size category. AI Adoption Level is positively and significantly associated with all six operational efficiency outcomes, though the magnitude of these associations varies across metrics.

Table 3. Linear Regression Coefficients of AI Adoption Level for Various Operational Efficiency Response Variables

Response Variable	B	Standard error	β	t	p	VIF
ADJADM	0.682	0.061	0.148	11.133	< .001	1.062
ADJPD	0.294	0.037	0.075	7.932	< .001	1.062
ADMTOT	0.489	0.052	0.095	9.324	< .001	1.062
ADC	0.087	0.034	0.019	2.529	0.011	1.062
ADJADC	0.287	0.035	0.075	8.166	< .001	1.062
IPDTOT	0.102	0.041	0.020	2.493	0.013	1.062

Note. B = unstandardized coefficient; β = standardized coefficient for AI Adoption Level. All models control for BSC. VIF values indicate no multicollinearity concern.

The strongest association is observed for ADJADM (B = 0.682, β = 0.148, p < .001), indicating that hospitals with higher overall AI adoption are associated with higher adjusted admissions.

Positive and statistically significant associations of similar direction are also found for ADMTOT (B = 0.489, β = 0.095, p < .001), ADJPD (B = 0.294, β = 0.075, p < .001), and ADJADC (B = 0.287, β = 0.075, p < .001), consistently indicating that AI adoption is associated with greater overall patient activity across multiple operationalization approaches. The associations for ADC (B = 0.087, β = 0.019, p = .011) and IPDTOT (B = 0.102, β = 0.020, p = .013) are statistically significant but smaller in magnitude relative to the other operational outcomes. Across all six models, VIF values of 1.062 confirm the absence of multicollinearity concerns between AI Adoption Level and BSC.

AI Adoption and Financial Efficiency: Revenue

Table 4 displays the regression coefficients for the association between AI Adoption Level and the revenue-based financial outcome variables. As noted in Section 4.2, ACOCN and BNDPCT were excluded from this table as their overall regression models did not reach statistical significance (F p > .05), indicating no meaningful association between AI Adoption Level and these two revenue outcomes in the present sample.

Table 4. Linear Regression Coefficients of AI Adoption Level for Various Financial Efficiency – Revenue Response Variables

Response Variable	B	Standard error	β	t	p	VIF
CAPRSK	0.779	0.053	0.286	14.692	< .001	1.063
CPPCT	0.364	0.044	0.160	8.319	< .001	1.062

Note. B = unstandardized coefficient; β = standardized coefficient for AI Adoption Level. All models control for BSC. VIF values indicate no multicollinearity concern. ACOCN and BNDPCT were excluded as the overall regression models for these outcomes were not statistically significant (F-test p > .05).

Among the remaining revenue outcomes, AI Adoption Level shows a positive and significant association with both CAPRSK (B = 0.779, β = 0.286, p < .001) and CPPCT (B = 0.364, β = 0.160, p < .001). The standardized coefficient for CAPRSK is notably larger than that for CPPCT, indicating a relatively stronger association between AI adoption and the proportion of net

patient revenue paid on a shared risk basis compared to the proportion paid on a capitated basis. As reported in Table 2, the overall R^2 values for these two models are 0.085 and 0.039, respectively, reflecting the limited explanatory coverage of the predictor set for revenue-based financial outcomes.

AI Adoption and Financial Efficiency: Expenses

Table 5 presents the regression coefficients for the association between AI Adoption Level and the six expense-based financial outcome variables, controlling for hospital bed size. AI Adoption Level is positively and significantly associated with four of the six expense outcomes. The largest standardized coefficient is observed for PHREXA (B = 0.792, β = 0.131, p < .001), followed by EXPTOT (B = 0.483, β = 0.108, p < .001), SUPEXA (B = 0.608, β = 0.106, p < .001), and PAYTOT (B = 0.432, β = 0.100, p < .001). These results indicate that hospitals with higher AI adoption levels are associated with higher total facility expenses, payroll expenses, pharmacy expenses, and supply expenses. The associations with EXPTHA (B = 0.311, β = 0.068, p = .065) and PAYTOTH (B = 0.348, β = 0.073, p = .075) do not reach conventional significance thresholds, suggesting that the association between AI adoption and expenses at the hospital unit level is less consistent than at the total facility level.

Table 5. Linear Regression Coefficients of AI Adoption Level for Various Financial Efficiency – Expenses Response Variables

Response Variable	B	Standard error	β	t	p	VIF
EXPTOT	0.483	0.044	0.108	10.984	< .001	1.062
EXPTHA	0.311	0.168	0.068	1.853	0.065	1.059
PAYTOT	0.432	0.041	0.100	10.468	< .001	1.062
PAYTOTH	0.348	0.195	0.073	1.787	0.075	1.059
PHREXA	0.792	0.076	0.131	10.431	< .001	1.057
SUPEXA	0.608	0.07	0.106	8.682	< .001	1.056

Note. B = unstandardized coefficient; β = standardized coefficient for AI Adoption Level. All models control for BSC. VIF values indicate no multicollinearity concern.

Discussion

This study examines how the level of artificial intelligence (AI) adoption in hospitals is associated with measures of operational and financial performance using data from the AHA Annual Survey. Multiple regression models were estimated using a composite AI Adoption Level index, computed as the average of five binary AI adoption indicators (WFAIART, WFAIOACW, WFAIPPD, WFAIPSN, WFAISS), as the primary predictor, controlling for hospital bed size category (BSC).

Referring to the research question: "*What is the adoption level of AI in hospitals, and how is it associated with hospital operational and financial performance?",* the findings indicate two main patterns. First, AI adoption levels remain relatively low across the sample, with mean values for the five individual AI indicators ranging from 0.192 to 0.259, indicating that approximately 19% to 26% of hospitals reported using each respective application. This pattern is consistent with prior research identifying financial and technical barriers to AI integration in healthcare settings (17). Second, AI Adoption Level is positively and significantly associated with all six operational efficiency outcomes (Table 3), with the strongest associations observed for ADJADM, ADMTOT, ADJPD, and ADJADC. These associations are consistent with prior literature suggesting that AI-enabled tools may be linked to improvements in operational throughput (17,18). However, as this is a cross-sectional study, these associations do not permit causal conclusions. Hospitals with higher AI adoption also tend to be larger institutions with greater patient volumes, as reflected in the consistently significant role of BSC across all models, and it is not possible to determine from these data whether AI adoption is associated with higher patient throughput because of the technology itself, or whether larger, higher-capacity hospitals are simply more likely to have adopted a broader range of AI applications.

From a financial efficiency perspective, AI Adoption Level is positively associated with several expense-based outcomes, including total facility expenses (EXPTOT), total payroll expenses (PAYTOT), pharmacy expenses (PHREXA), and supply expenses (SUPEXA) (Table 5), with weaker and non-significant associations for EXPTHA and PAYTOTH. As with the operational findings, this positive association with higher expenses does not necessarily indicate that AI adoption leads to increased costs; it is equally consistent with the interpretation that larger, more resource-

intensive hospitals, which naturally incur higher operating expenses, are also more likely to have adopted AI applications across multiple domains, again pointing to hospital size as a potential underlying factor in both AI adoption and expense levels.

In contrast, AI Adoption Level shows weaker associations with revenue-based outcomes. AI Adoption Level is positively associated with CAPRSK and CPPCT (Table 4), though the overall explanatory power of these models is low ($R^2 = 0.085$ and 0.039, respectively). This may suggest that operational changes associated with AI adoption are not strongly linked to revenue from alternative payment models (20).

These findings may be of interest to healthcare administrators considering AI adoption. The composite AI Adoption Level index, which reflects the breadth of AI use across automating routine tasks, workflow optimization, predictive analytics, patient safety applications, and staffing/scheduling, was associated with higher operational activity across all six efficiency measures. At the same time, administrators should note that AI adoption is associated with higher expenses across several categories in this sample. This pattern is broadly consistent with literature identifying the substantial infrastructure, training, and resource requirements that constitute key organizational antecedents of AI adoption in healthcare settings (10). As BSC was included as a control variable in all models, organizational context, particularly hospital size, may be an important factor to consider when interpreting the relationship between AI adoption and performance.

This study has several limitations that should be acknowledged. First, the data are cross-sectional, coming from the 2022 AHA Annual Survey, which limits the ability to draw conclusions about the direction of the relationships between AI adoption and hospital performance. AI adoption was not randomly assigned, and the observed associations may reflect a range of underlying factors, including hospital size, resource availability, and organizational capacity, rather than a direct effect of AI adoption itself. Second, AI adoption is measured using five binary indicators combined into a single composite index, which may not capture the full extent or quality of AI integration in hospital processes. Third, the study focuses only on U.S. hospitals, so the findings may not generalize to healthcare systems in other countries with different structures, resources, or regulatory environments. Fourth, while bed size is included as a control variable, other factors such as hospital ownership type, staff skill levels, and patient case mix are not considered and could influence both AI adoption and the outcomes examined. Finally,

associations between AI adoption and outcomes vary across measures; for example, AI Adoption Level shows a positive association with CAPRSK but a comparatively weaker association with CPPCT (Table 4), and the overall models for ACOCN and BNDPCT were not statistically significant (Table 2), suggesting that unmeasured factors such as implementation strategy, payer mix, or contracting arrangements may influence these relationships.

Future studies could draw on data from multiple years to examine how AI adoption and hospital performance measures change over time, which would allow for stronger inferences about the direction and stability of the associations identified here. Future research could also examine which specific AI applications are most consistently associated with particular operational or financial outcomes across different hospital types. Additionally, future research should consider how smaller, rural, or resource-limited hospitals are associated with AI adoption and performance relative to larger urban facilities. It is also recommended that future research use more granular measures of AI adoption, rather than binary indicators, to better capture the extent and intensity of AI implementation. These studies can provide guidance on how AI can be effectively integrated into hospital operations to support broader healthcare goals.

Conclusion

This study examined the association between hospital-level AI adoption and measures of operational and financial performance using cross-sectional data from 2,979 U.S. hospitals. Multiple regression models, using a composite AI Adoption Level index and hospital bed size as predictors, indicate that AI Adoption Level is positively associated with all six operational efficiency outcomes examined, as well as with several expense-based financial outcomes, while showing weaker associations with revenue-based outcomes. These cross-sectional associations should not be interpreted as evidence that AI adoption causes changes in hospital performance: hospital bed size was a significant covariate across all models, and it is plausible that larger, more resource-intensive hospitals are both more likely to adopt AI and more likely to exhibit higher operational volumes and expenses. Institutions considering AI adoption are advised to pursue contextually appropriate planning that aligns with organizational goals and resources.

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Appendix 1. Variables and Their Descriptions

Note. Descriptions are condensed from the 2022 American Hospital Association Annual Survey Database field definitions.

	Variable	Field	Description
Dependent – Operational Efficiency	ADC	Average daily census	Average number of inpatients per day, calculated as inpatient days divided by the number of days in the reporting period.
	ADJADC	Adjusted average daily census	Estimated average number of inpatients and outpatients receiving care per day, derived from adjusted inpatient days.
	ADJADM	Adjusted admissions	Inpatient admissions plus an estimate of equivalent admissions attributable to outpatient services, based on the outpatient-to-inpatient revenue ratio.
	ADJPD	Adjusted patient days	Inpatient days plus an estimate of equivalent patient days attributable to outpatient services, based on the outpatient-to-inpatient revenue ratio.
	ADMTOT	Total facility admissions	Number of patients (excluding newborns) admitted for inpatient care during the reporting period, including ED admissions.
	IPDTOT	Total facility inpatient days	Total adult and pediatric inpatient days of care provided during the reporting period, excluding newborn days.
Dependent – Financial Efficiency – Revenue	ACOCN	ACO contract revenue (%)	Percent of hospital/system patient revenue from accountable care organization (ACO) contracts in 2022.
	BNDPCT	Bundled payment revenue (%)	Percent of patient revenue paid through bundled payment arrangements.
	CAPRSK	Shared-risk revenue (%)	Percent of net patient revenue paid on a shared-risk basis (e.g., capitation with refunds/bonuses tied to expenditure targets).
	CPPCT	Capitated revenue (%)	Percent of net patient revenue paid on a capitated basis, where a fixed prearranged payment covers all medically necessary care for enrollees.
Dependent – Financial Efficiency – Expenses	EXPTOT	Total facility expenses (excl. bad debt)	All payroll, non-payroll, and operating expenses for the reporting period; bad debt is excluded per AICPA guidance.
	EXPTHA	Hospital unit total expenses (excl. bad debt)	Total facility expenses less nursing home unit expenses.
	PAYTOT	Total facility payroll expenses	Total salaries and wages for all facility personnel, including residents, interns, and trainees.
	PAYTOTH	Hospital unit payroll expenses	Total facility payroll expenses less nursing home unit payroll expenses.
	PHREXA	Pharmacy expense	Total pharmacy expense.
	SUPEXA	Supply expense	Net cost of expensed tangible items (incl. freight and taxes, net of rebates), excluding labor and labor-related costs.
Independent – Artificial Intelligence	WFAIART	AI – automating routine tasks	Hospital uses AI/machine learning to automate routine tasks.
	WFAIOACW	AI – optimizing workflows	Hospital uses AI/machine learning to optimize administrative and clinical workflows.
	WFAIPPD	AI – predicting patient demand	Hospital uses AI/machine learning to predict patient demand.
	WFAIPSN	AI – predicting staffing needs	Hospital uses AI/machine learning to predict staffing needs.
	WFAISS	AI – staff scheduling	Hospital uses AI/machine learning for staff scheduling.
Control Variable	BSC	Bed size category	Categorical variable indicating hospital bed size: 1 = 6-24 beds, 2 = 25-49, 3 = 50-99, 4 = 100-199, 5 = 200-299, 6 = 300-399, 7 = 400-499, 8 = 500 or more beds.

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