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PREDICTIVE AI ADOPTION AND OPERATIONAL MANAGEMENT IN THE U.S. HOSPITALS: NATIONAL EVIDENCE ON BILLING, SCHEDULING, EVALUATION, AND GOVERNANCE

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ABSTRACT

Artificial intelligence is moving from experimental clinical prediction into the routine administrative and operational infrastructure of hospitals, yet national evidence remains fragmented across adoption, use cases, evaluation, and governance. This quantitative secondary-data study examines predictive artificial intelligence in United States nonfederal acute-care hospitals using weighted national estimates from the 2023 and 2024 American Hospital Association Information Technology Supplement and peer-reviewed multivariable results from the 2023 survey. The present study asks whether adoption increased, whether operational applications expanded, and whether organizational and technology characteristics were associated with evaluation capacity. Predictive artificial intelligence adoption increased from 66 percent in 2023 to 71 percent in 2024. Among hospitals using predictive models, billing simplification increased from 36 percent to 61 percent and scheduling facilitation from 51 percent to 67 percent. Large, urban, system-affiliated, non-critical-access hospitals and hospitals using the market-leading electronic health record vendor reported substantially higher adoption. In 2024, system members reported higher rates than independent hospitals for accuracy evaluation, bias evaluation, and post-implementation monitoring. Published adjusted analysis of the 2023 data further showed that self-developed models were associated with

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greater local evaluation, whereas third-party models were associated with lower local evaluation. Bias evaluation remained less prevalent than accuracy evaluation. The evidence is consistent with a Technology-Organization-Environment interpretation in which digital infrastructure, organizational scale, system affiliation, and model sourcing shape the organizational capacity to deploy and govern predictive tools. The present study contributes a nationally grounded view of hospital artificial intelligence management while avoiding unsupported claims about cost, throughput, or quality outcomes that the public data do not measure. The results identify operational diffusion alongside a persistent organizational digital divide in evaluation and governance capability.

1 INTRODUCTION

Hospital artificial intelligence has shifted from a narrow question of model accuracy to an organizational question of where predictive tools are embedded, who can evaluate them, and which workflows they support. Hospital information-technology research has long shown that digital adoption does not guarantee productivity without complementary organizational capabilities (Dranove et al., 2014). In 2015-2018, fewer than 3% of hospitals in one job-posting study sought artificial-intelligence skills, with demand concentrated in larger organizations (Goldfarb et al., 2020). By 2023-2024, national surveys documented far broader predictive-model use integrated with electronic health records (Chang et al., 2025; Nong et al., 2025). These systems now support scheduling, billing, patient flow, and related operational functions as well as clinical prediction (Grosman-Rimon et al., 2023; Knight et al., 2023; Nunes et al., 2025).

This research investigates predictive artificial intelligence in United States nonfederal acute-care hospitals, emphasizing operational use, evaluation, and governance. This scope is narrower than the preliminary idea of "operational excellence" because the national data measure model use, application, source, accuracy and bias evaluation, and monitoring, but not throughput, labor productivity, cost per case, length of stay, or quality effects attributable to artificial intelligence (Chang et al., 2025; Nong et al., 2025). Operational management is accordingly defined here as deployment into administrative and workflow functions and the organizational capabilities surrounding that deployment. Implementation research supports this distinction: live value depends on integration with information systems, workflows, human judgment, accountability, and monitoring, not development accuracy alone (Kelly et al., 2019; Preti et al., 2024; Rahimi et al., 2024; Wiens et al., 2019).

The central research problem arises from the divergence between rapid diffusion and uneven assurance capacity. Predictive-artificial-intelligence adoption rose from 66% in 2023 to 71% in 2024, yet remained lower in small, rural, independent, government-owned, and critical-access hospitals (Chang et al., 2025). This pattern follows a longer digital divide: disadvantaged hospitals faced electronic-health-record adoption barriers (Jha et al., 2009; Miller et al., 2009), and advanced capabilities still differ between rural and urban hospitals (Anzalone et al., 2026). Artificial intelligence can accordingly produce a second-order divide in both access and local validation. This matters because biased proxies and distribution shifts may preserve aggregate performance while producing inequitable or unstable results across populations and settings (Mullainathan & Obermeyer, 2017; Obermeyer et al., 2019; Wang et al., 2024a; Yang et al., 2024).

The principal objective is to quantify recent national patterns in predictive-artificial-intelligence adoption, operational application, evaluation, and governance and assess variation by hospital and model characteristics. The Technology-Organization-Environment framework anchors the analysis by locating adoption within technological conditions, organizational readiness, and environmental context (Tornatzky et al., 1990). Electronic-health-record vendor and model source represent technology context; size, ownership, rurality, critical-access status, and system affiliation represent organizational context; and contemporary governance expectations form the environment (Caci et

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al., 2025; Food and Drug Administration, 2025; Pulkkinen et al., 2025; Roppelt et al., 2024; Tabassi, 2023; Yang et al., 2022). The contribution is to connect this framework with recent national hospital evidence rather than hypothetical intentions or a single implementation site.

Three research questions ask whether adoption and operational uses changed from 2023 to 2024, whether organizational characteristics are associated with adoption and evaluation, and whether model source is associated with local evaluation. The central proposition is that diffusion and assurance can develop unevenly: administrative applications may scale through established digital platforms, while local evaluation requires expertise, data access, governance routines, and organizational capacity. National evidence is consistent with this proposition: billing and scheduling grew fastest, system-affiliated hospitals exceeded independent hospitals in adoption and evaluation, and adjusted 2023 analysis associated self-development with more local evaluation but third-party sourcing with less (Chang et al., 2025; Nong et al., 2025). The following sections develop the theory and hypotheses, describe the secondary quantitative design, present results, and discuss implications.

2 LITERATURE REVIEW

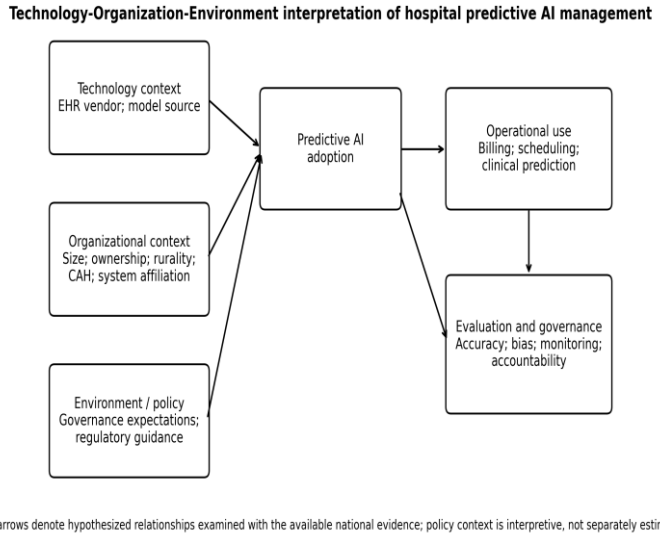
2.1 Theoretical Framework

The Technology-Organization-Environment framework is the most direct theoretical anchor because the empirical variables operate at the hospital level. It proposes that adoption reflects available technologies, internal organizational characteristics and resources, and the external environment (Tornatzky et al., 1990). Healthcare artificial-intelligence reviews likewise emphasize infrastructure, leadership, readiness, stakeholder conditions, risk, and policy (Caci et al., 2025; Li et al., 2023; Pulkkinen et al., 2025; Roppelt et al., 2024; Scipion et al., 2025; Wubineh et al., 2024; Yang et al., 2022). In the present study, model source and electronic-health-record infrastructure represent technology conditions, whereas size, ownership, rurality, critical-access status, and system affiliation proxy organizational resources and integration. The environment is represented conceptually by increasingly formal risk-management and governance expectations. The National Institute of Standards and Technology and sector guidance emphasize risk management, while healthcare governance work stresses accountable roles, validation, monitoring, and lifecycle control (Alami et al., 2026; Food and Drug Administration, 2025; Hassan et al., 2025; Tabassi, 2023).

2.2 Conceptual Framework

Within the conceptual framework, adoption is treated as an intermediate organizational capability rather than a performance outcome. Technology and organizational conditions shape whether a hospital deploys predictive models; adoption then creates opportunities for operational use, while evaluation and governance function as assurance capabilities. This structure reflects evidence that development performance alone does not establish effectiveness in live practice (Kelly et al., 2019; Rahimi et al., 2024). Implementation studies and frameworks repeatedly identify infrastructure, knowledge, culture, stakeholder engagement, leadership, and iterative evaluation as determinants of sustained use (Adnan et al., 2025; Apfelbacher et al., 2024; Powis et al., 2026; Preti et al., 2024; Sendak et al., 2020; van der Vegt et al., 2023). Reporting and deployment frameworks similarly emphasize contextual integration, human interaction, error analysis, and ongoing monitoring (Cruz Rivera et al., 2020; Liu et al., 2020; Wiens et al., 2019). Figure 1 accordingly places technological and organizational context upstream of adoption, operational use downstream, and evaluation/governance as an assurance layer shaped by capacity and sourcing.

Figure 1. Conceptual framework for predictive AI adoption, operational use, evaluation, and governance.



2.3 Predictive AI Diffusion and Operational Use

The first research question addresses diffusion and operational use. Reviews of centralized hospital management, scheduling, and patient-flow prediction suggest that predictive analytics can support coordination, access, and resource allocation, although real-world implementation remains heterogeneous and outcome evidence is uneven (Dranove et al., 2014; Goldfarb et al., 2020; Grosman-Rimon et al., 2023; Knight et al., 2023; Nunes et al., 2025). These studies establish functional plausibility rather than national penetration. National American Hospital Association evidence fills that gap: predictive-artificial-intelligence adoption increased between 2023 and 2024, with billing and scheduling showing the largest growth (Chang et al., 2025). Administrative processes may diffuse faster because they are bounded, high-volume, and integrated into existing electronic-health-record or revenue-cycle platforms. The unresolved question is accordingly which applications are driving national expansion rather than whether isolated tools can support operations. This gap motivates H1 and H2.

2.4 Organizational Context, Digital Divide, and Evaluation Capacity

The second research question examines organizational inequality in adoption and evaluation. Advanced digital capability requires capital, technical staff, complementary systems, and implementation capacity. Early evidence documented electronic-health-record disadvantages among safety-net and resource-constrained hospitals (Jha et al., 2009; Miller et al., 2009), while more recent national evidence shows persistent rural-urban gaps in advanced capabilities despite broad core adoption (Anzalone et al., 2026). Artificial intelligence may deepen this divide because local evaluation requires analytic expertise and representative data. Nong et al. (2025) found that system membership and stronger operating margins were associated with local evaluation and that rural and critical-access hospitals used predictive models less often. The 2024 national estimates likewise show wide descriptive gaps between system-affiliated and independent hospitals in accuracy evaluation, bias evaluation, and monitoring (Chang et al., 2025). Accordingly, the remaining research gap concerns an organizational assurance divide: hospitals may differ not only in adoption but also in their capacity to verify deployed models. The available evidence motivates H3 and H4.

2.5 Model Source, Local Evaluation, and Governance

The third research question considers model source and governance. Externally supplied models can accelerate diffusion but may separate the hospital bearing implementation risk from the organization that designed or trained the model. Local performance cannot be inferred from global validation because populations, workflows, proxies, and data-generating processes differ. Evidence on racial bias, readmission-model fairness, and medical-imaging generalization demonstrates the importance of local subgroup evaluation and distribution-sensitive assessment (Mullainathan & Obermeyer, 2017; Obermeyer et al., 2019; Wang et al., 2024a, 2024b; Yang et al., 2024). Governance frameworks accordingly emphasize accountability, local validation, lifecycle monitoring, and escalation responsibilities (Alami et al., 2026; Hassan et al., 2025; Hussein et al., 2026; Khan et al., 2025; Tabassi, 2023). Nationally, self-developed models were associated with greater local evaluation whereas third-party models were associated with less; hospitals also sourced tools from electronic-health-record developers, third parties, and internal teams (Chang et al., 2025; Nong et al., 2025). An unresolved issue concerns how sourcing strategy relates to assurance practice. H5 addresses that association, while H6 tests whether bias evaluation remains less prevalent than accuracy evaluation.

2.6 Problem Statement

Existing scholarship establishes the promise of predictive tools and the importance of implementation capacity but leaves three connected gaps. Operational studies commonly examine individual tools or local sites rather than national diffusion; adoption studies often stop at whether artificial intelligence is used rather than whether it is evaluated and governed; and sourcing is frequently treated as procurement even though it affects access to development knowledge, training data, and validation assumptions. The 2023-2024 hospital evidence permits these issues to be examined together, though only as repeated cross-sectional associations (Chang et al., 2025; Nong et al., 2025). Accordingly, the

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study addresses the absence of an integrated national account of how predictive artificial intelligence diffuses into hospital operations, how adoption and assurance vary across organizational contexts, and how model source relates to local evaluation.

3 OBJECTIVE OF THE STUDY

The present study aims to quantify national patterns in predictive artificial-intelligence adoption, operational use, evaluation, and governance in United States nonfederal acute-care hospitals and to assess their association with organizational and model-source characteristics.

3.1 Specific Research Questions

RQ1. To determine how predictive artificial-intelligence adoption and operational applications changed between 2023 and 2024 in United States nonfederal acute-care hospitals.

RQ2. To assess how hospital size, ownership, rurality, critical-access status, system affiliation, and electronic-health-record context are associated with predictive artificial-intelligence adoption and evaluation practices.

RQ3. To evaluate whether predictive-model source is associated with local model evaluation and whether hospitals evaluate bias as consistently as model accuracy.

3.2 Hypotheses Development

H1. Predictive artificial-intelligence adoption is higher in 2024 than in 2023 among United States nonfederal acute-care hospitals.

Diffusion theory within the Technology-Organization-Environment perspective predicts increasing adoption as compatible infrastructure, vendor offerings, and organizational experience accumulate.

H2. Use of predictive artificial intelligence for billing simplification and scheduling facilitation is higher in 2024 than in 2023 among hospitals using predictive models.

Administrative applications have bounded workflows and can be integrated with mature revenue-cycle and scheduling systems, making them plausible early targets for scaled operational deployment.

H3. System-affiliated hospitals have higher predictive artificial-intelligence adoption than independent hospitals.

System affiliation can supply shared infrastructure, technical expertise, procurement leverage, and implementation support that increase organizational readiness.

H4. System-affiliated hospitals report higher rates of predictive-model accuracy evaluation, bias evaluation, and post-implementation monitoring than independent hospitals.

Evaluation requires data, analytics personnel, governance routines, and organizational slack, all of which are more likely to be pooled within multi-hospital systems.

H5. Self-developed predictive models are positively associated with local model evaluation, whereas third-party model use is negatively associated with local evaluation.

Internal development and local evaluation draw on overlapping technical knowledge and data access, whereas externally sourced tools can create informational and governance distance between model development and deployment.

H6. Evaluation for model bias is less prevalent than evaluation for model accuracy among hospitals using predictive artificial intelligence.

Accuracy is a conventional technical performance criterion, while bias assessment requires subgroup data, fairness definitions, and governance choices that add analytic and organizational complexity.

4 METHODOLOGY

4.1 Research Design

A quantitative repeated cross-sectional secondary-data design, guided by a deductive theoretical orientation, was employed in this study. The primary empirical source was the 2023 and 2024 American Hospital Association Information Technology Supplement as analyzed and published by the Office of the Assistant Secretary for Technology Policy. The national brief supplies weighted proportions, subgroup comparisons, year-to-year significance tests, and survey methods (Chang et al., 2025). A peer-reviewed analysis of the 2023 survey supplied adjusted relative-risk estimates from weighted multivariable Poisson

regression for local model evaluation (Nong et al., 2025). The design is explanatory in the limited observational sense of testing theoretically specified associations and temporal differences; it does not establish causal effects of artificial intelligence on hospital performance.

4.2 Study Context and Target Population

The present study population comprised United States nonfederal acute-care hospitals, including general medical and surgical, children's general, and cancer hospitals under private nonprofit, investor-owned, or state/local government ownership. The American Hospital Association invited every United States hospital to participate, regardless of association membership. The person most knowledgeable about hospital health information technology, typically the chief information officer, was asked to respond. The 2023 survey was fielded from March through August and obtained 2,547 nonfederal acute-care responses, a 58% response rate. The 2024 survey was fielded from April through September and obtained 2,253 responses, a 51% response rate. For the predictive-artificial-intelligence adoption analysis, informative responses were available from 2,425 hospitals in 2023 and 2,080 in 2024 (Chang et al., 2025). Among hospitals using predictive artificial intelligence, the published use-case analyses included 1,696 hospitals in 2023 and 1,587 in 2024.

4.3 Sampling, Weighting, and Data Sources

Because participation was voluntary rather than a simple random sample with complete response, national estimates used nonresponse adjustment. The Office of the Assistant Secretary for Technology Policy reported a logistic model predicting survey response from hospital size, ownership, teaching status, system membership, cardiac intensive-care capability, urban status, and region; hospital weights were the inverse of predicted response propensity (Chang et al., 2025). The peer-reviewed 2023 analysis used the same national survey and inverse-likelihood weighting approach (Nong et al., 2025). No unrelated datasets were merged to create synthetic hospital records. The present analysis reproduces only published aggregate estimates and regression statistics traceable to these sources.

4.4 4.4 Variables and Operationalization

Predictive-artificial-intelligence adoption was defined by survey-reported use of machine-learning or other predictive models displayed in the electronic health record or in an application embedded in or launched by it. Operational applications included inpatient risk prediction, high-risk outpatient identification, health monitoring, treatment recommendation, billing simplification, and scheduling facilitation. Technology context was represented by electronic-health-record vendor and model source: electronic-health-record developer, third party, or self-developed. Organizational variables included bed-size category, ownership, rurality, critical-access status, and system affiliation. Assurance variables included evaluation for model accuracy and bias and, in 2024, post-implementation evaluation or monitoring. Nong et al. (2025) defined local evaluation as evaluation using hospital or health-system data and modeled whether most or all models were locally evaluated for both accuracy and bias.

Table 1. Data Sources, Variables, and Operationalization

Domain	Observed measure	Operationalization / categories	Primary source
Adoption	Predictive AI use	Machine-learning or other predictive models displayed in, embedded in, or launched by the EHR	Chang et al. (2025); Nong et al. (2025)
Operational use	Use-case indicators	Inpatient risk; high-risk outpatient identification; monitoring; treatment recommendation; billing; scheduling	Chang et al. (2025)
Technology context	Model source	EHR developer; third-party developer; self-developed	Chang et al. (2025); Nong et al. (2025)
Technology context	EHR vendor	Market-leading vendor versus all other vendors	Chang et al. (2025)

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Domain	Observed measure	Operationalization / categories	Primary source
Organization	Hospital characteristics	Bed size; ownership; rurality; critical-access status; system affiliation	Chang et al. (2025)
Assurance	Evaluation	Accuracy; bias; 2024 post-implementation evaluation/monitoring	Chang et al. (2025)
Assurance	Local evaluation	Most/all models evaluated for both accuracy and bias using hospital or health-system data	Nong et al. (2025)
Governance	Accountable entities	Multiple entities; AI committee/task force; departmental leaders; clinical decision support committee; senior executive; IT staff	Chang et al. (2025)

Note. EHR = electronic health record. AI = artificial intelligence. All variables are observed survey items or published derived indicators; no synthetic latent scores were created

4.5 Data Screening and Preparation

The analysis did not reconstruct respondent-level records. Data screening accordingly operated at the published-evidence level. Values were extracted only when the source supplied a clear denominator, year, variable definition, and percentage or regression estimate. The 2023 and 2024 national brief excluded missing and "do not know" responses from the predictive-adoption denominator; for use-case analyses, missing responses were recoded as "No" according to the published method. Evaluation denominators excluded missing responses, and the brief separately reported substantial "do not know" responses in 2024. Cross-year comparisons were retained only where the questionnaire item was comparable. Post-implementation monitoring was not included in the 2023 instrument and was accordingly not treated as a two-year trend. No imputation, winsorization, simulated observations, reverse coding, or invented exclusions were applied by the present study.

4.6 Statistical Analysis

Published weighted proportions and reported significance indicators formed the basis of the primary analysis. published weighted proportions and reported significance indicators for 2023-2024 differences and reference-group comparisons. Percentage-point changes were interpreted directly from the national estimates. For adjusted evidence, the study used the weighted multivariable Poisson regression results reported by Nong et al. (2025), which express associations as relative risks with 95% confidence intervals. Particular attention was given to model-source associations with local evaluation: third-party model use had a reported relative risk of 0.69 (95% confidence interval 0.61-0.78), while self-developed models had a relative risk of 1.54 (95% confidence interval 1.33-1.78). The analysis distinguishes statistical association from causal inference and avoids recomputing standard errors or p values from aggregate percentages.

4.7 Methodological Alternatives and Structural Equation Modeling

Three advanced methods are suitable when respondent-level construct data become available. Covariance-based structural equation modeling in SPSS AMOS could test a confirmatory Technology-Organization-Environment model and indirect pathways from readiness through adoption to evaluation. Partial least squares structural equation modeling in SmartPLS, complemented by necessary-condition analysis, could emphasize prediction and formative capability constructs, while fuzzy-set qualitative comparative analysis could test alternative configurations associated with high evaluation maturity. These methods were not estimated because the public evidence contains weighted aggregate statistics rather than item-level hospital records or a covariance matrix. Estimating latent-variable models from aggregate percentages would create unsupported statistics and an ecological identification problem.

4.8 Reliability, Validity, Robustness, and Ethics

Internal-consistency coefficients such as Cronbach's alpha and composite reliability are not applicable to the observed single survey items used in this secondary analysis. Construct validity instead rests

on the documented American Hospital Association survey wording and the explicit operational definitions published by the national brief and peer-reviewed analysis. Robustness was assessed through triangulation: the 2024 update was compared with the 2023 national baseline, and adjusted model-source findings from the peer-reviewed 2023 analysis were interpreted alongside the later descriptive national patterns. The present study analyzed publicly reported aggregate statistics and did not access patient-level information, identifiable hospital respondent records, or protected health information. No new participant recruitment, intervention, or linkage of identifiable records occurred.

5 RESULTS

5.1 Adoption and Organizational Variation

National adoption increased significantly from 66% in 2023 to 71% in 2024 ($p<.05$ as reported by Chang et al., 2025), supporting H1. The increase was broad but uneven. In 2024, 96% of large hospitals reported predictive-artificial-intelligence use compared with 59% of small hospitals; 81% of urban hospitals used it compared with 56% of rural hospitals; and 80% of non-critical-access hospitals used it compared with 50% of critical-access hospitals. The largest organizational contrast was system affiliation: adoption was 86% among multi-hospital system members and 37% among independent hospitals. Electronic-health-record context also mattered, with 90% adoption among hospitals using the market-leading vendor versus 50% among hospitals using other vendors. The corresponding differences were already present in 2023, indicating persistence rather than a one-year emergence of the organizational divide. These findings support H3.

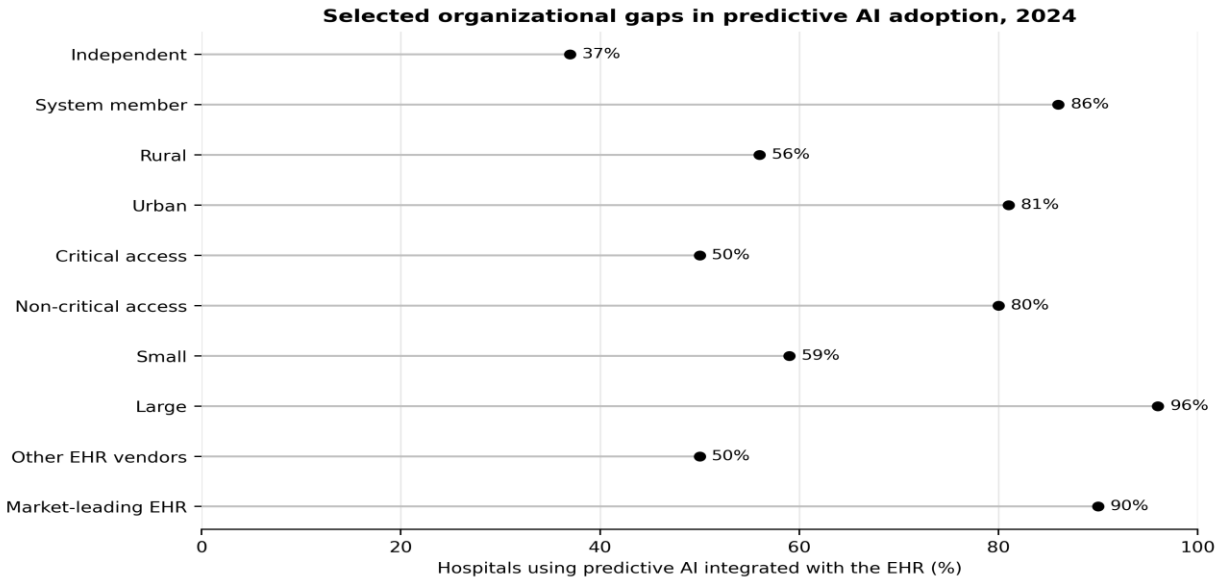
Table 2. Predictive AI Adoption by Hospital Characteristics, 2023-2024

Hospital characteristic	2023	2024
Small (<100 beds)	53%	59%
Medium (100-399 beds)	75%	80%
Large (>400 beds)	90%	96%
Government owned	39%	44%
Nonprofit	75%	80%
For-profit	60%	69%
Rural	48%	56%
Urban	77%	81%
Critical access	46%	50%
Non-critical access	74%	80%
Independent	31%	37%
System member	81%	86%
Market-leading EHR vendor	87%	90%
Other EHR vendors	48%	50%

Note. Weighted national estimates. n = 2,425 (2023) and n = 2,080 (2024) informative responses. Reference-group significance markers are omitted here for visual economy; the source reports p<.05 for marked subgroup

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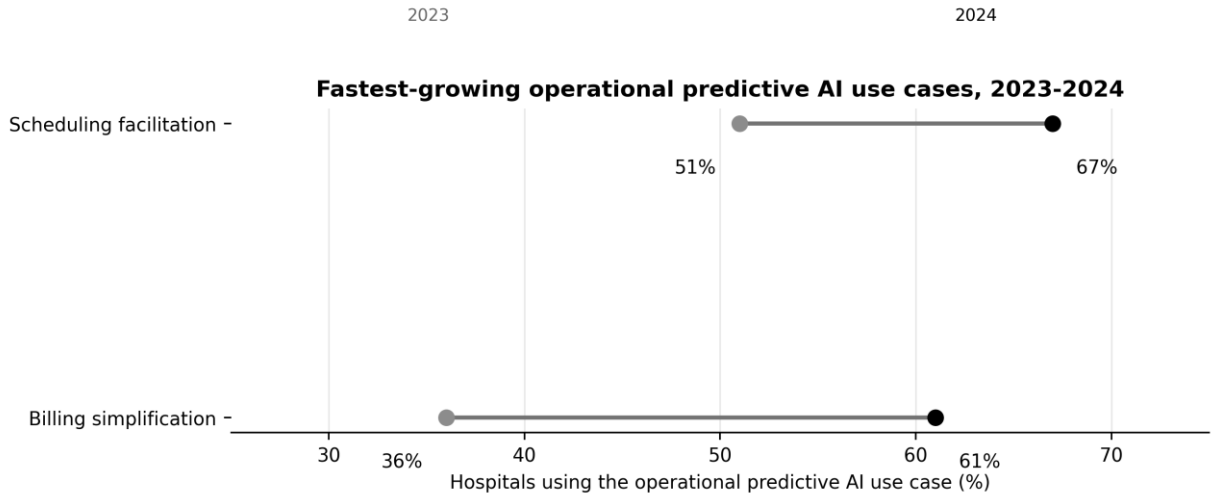
Figure 2. Selected organizational gaps in predictive AI adoption, 2024.



5.2 Operational Use Cases and Model Source

Operational applications expanded faster than several clinical applications. Billing simplification increased from 36% of predictive-artificial-intelligence users in 2023 to 61% in 2024, a 25-percentage-point increase, while scheduling facilitation increased from 51% to 67%, a 16-point increase; both changes were reported as statistically significant (Chang et al., 2025). H2 is accordingly supported. Source-specific patterns suggest multiple diffusion channels. In 2024, 80% of hospitals using predictive artificial intelligence reported models from their electronic-health-record developer, 52% reported third-party models, and 50% reported self-developed models. Billing was reported by 58% of hospitals using electronic-health-record-developed artificial intelligence and 73% of hospitals using other sources only.

Figure 3. Fastest-growing operational predictive AI use cases, 2023-2024.



Note. Billing simplification increased from 36% to 61%; scheduling facilitation increased from 51% to 67%. Both changes were reported as statistically significant at p<.05. Source: Chang et al. (2025).

Scheduling was similar across the two source groups at 67% and 65%, but the reported increase from 2023 was larger for electronic-health-record-developed tools. High-risk outpatient use rose particularly quickly among hospitals using only other sources

Table 3. Predictive AI Use Cases by Model-Source Group, 2024, With Change From 2023

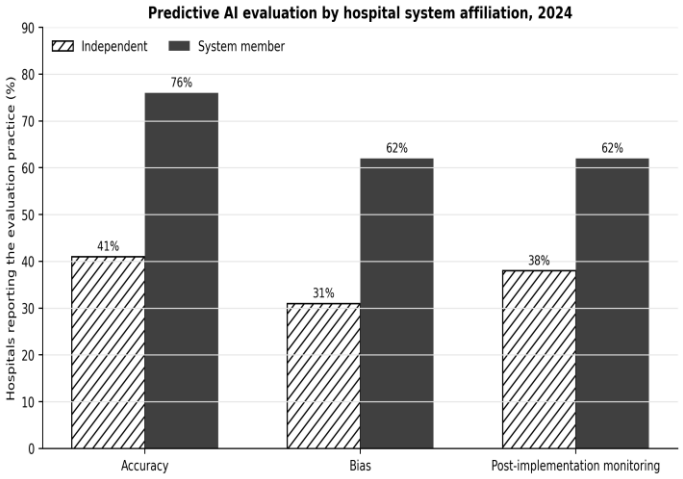
Use case	EHR-developed AI: 2024	Change from 2023	Other sources only: 2024	Change from 2023
Predict inpatient risk	93%	-3 pp	87%	+12 pp
Identify high-risk outpatients	88%	-3 pp	82%	+51 pp
Monitor health	37%	-2 pp	17%	+3 pp
Recommend treatments	53%	+2 pp	16%	-1 pp
Scheduling	67%	+2 pp	65%	+14 pp

Note. Among hospitals using predictive AI. EHR-developed AI represented 80% of hospitals in the 2024 source analysis and "other sources only" 20%. pp = percentage points. Source: Chang et al. (2025), Table 2.

5.3 Evaluation and Governance

Although evaluation was widely reported, it was not universal. In the broader 2024 national measure, 82% of hospitals using predictive artificial intelligence reported evaluation for accuracy, 74% reported evaluation for bias, and 79% reported post-implementation evaluation or monitoring (Chang et al., 2025). A substantial organizational divide accompanied these patterns. Among independent hospitals, 41% reported accuracy evaluation, 31% bias evaluation, and 38% post-implementation monitoring; among system members, the rates were 76%, 62%, and 62%, respectively, with the system-member row significantly different from the independent reference group in the published table. H4 is supported. Governance was distributed across organizational roles: 74% of hospitals reported multiple entities accountable for predictive-artificial-intelligence evaluation, 66% identified a dedicated committee or task force, 60% identified division or department leaders, and 41% identified information-technology staff (Chang et al., 2025). These findings indicate that evaluation is increasingly an organizational governance function rather than a purely technical responsibility.

Figure 4. Predictive AI evaluation by hospital system affiliation, 2024.



Note. Weighted percentages among hospitals in the evaluation analysis. Each system-member value was significantly different from the independent-hospital reference group at p<.05 in the published table. Source: Chang et al. (2025), Appendix Table A3.

5.4 Adjusted Model-Source Associations and Hypothesis Tests

Adjusted evidence relevant to H5 is provided by the peer-reviewed 2023 analysis. After controlling for hospital and technology characteristics in weighted Poisson regression, hospitals using third-party models were less likely to report local evaluation for both accuracy and bias (relative risk 0.69, 95% confidence interval 0.61-0.78), whereas hospitals using self-developed models were more likely to report local evaluation (relative risk 1.54, 95% confidence interval 1.33-1.78) (Nong et al., 2025). The same analysis found that system membership was positively associated with local evaluation and that certain applications had different evaluation profiles. H5 is accordingly supported by adjusted national evidence. H6 is supported descriptively across two published measurement approaches. Nong et al. (2025) reported local accuracy evaluation for 61% of hospitals using models but local bias evaluation for

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44%; the 2024 national brief reported 82% evaluating accuracy and 74% evaluating bias under its broader evaluation definition. Because the sources use related but not identical evaluation definitions, the difference is interpreted as a consistent pattern rather than pooled statistically.

Table 4. Hypothesis Evidence and Decision Summary

Hypothesis	Empirical evidence	Decision
H1	National adoption increased 66% -> 71% from 2023 to 2024; reported p<.05.	Supported
H2	Billing 36% -> 61% (+25 pp) and scheduling 51% -> 67% (+16 pp); both reported p<.05.	Supported
H3	System members vs independent hospitals: 81% vs 31% (2023) and 86% vs 37% (2024); significant reference-group contrasts.	Supported
H4	2024 system members vs independent: accuracy 76% vs 41%; bias 62% vs 31%; monitoring 62% vs 38%; significant reference-group contrasts.	Supported
H5	Adjusted 2023 local evaluation: self-developed RR 1.54 (95% CI 1.33-1.78); third-party RR 0.69 (95% CI 0.61-0.78).	Supported
H6	Accuracy evaluation exceeded bias evaluation in both published measurement approaches (2023 local: 61% vs 44%; 2024 broader: 82% vs 74%).	Supported descriptively

Note. RR = relative risk; CI = confidence interval; pp = percentage points. H1-H4 and H6 use Chang et al. (2025) unless otherwise stated; H5 and the 2023 local-evaluation figures use Nong et al. (2025). H6 is not presented as a new paired significance test because the public sources do not report such a test.

5.5 Robustness and Supplementary Assessment

The principal conclusions remain consistent across the two national publications despite small definitional differences. The peer-reviewed 2023 article reported 65% use under its analytic classification, whereas the later standardized trend brief reported 66% predictive-artificial-intelligence adoption for 2023; this difference does not change the inference of widespread adoption followed by further growth. Both sources identify resource- and system-related variation in adoption or evaluation, while the 2024 survey adds monitoring and accountability measures that complement the 2023 local-evaluation analysis. With no public respondent-level microdata, robustness is limited to cross-source consistency, repeated cross-sectional updating, and adjusted associations already estimated from the underlying 2023 records.

6 DISCUSSION

The findings indicate that predictive artificial intelligence is becoming routine hospital infrastructure while operational and governance maturity remain uneven. Adoption rose during 2023-2024, with the fastest expansion in billing and scheduling rather than the most clinically consequential decision support. These high-volume, repetitive processes offer observable outputs and established digital workflows, making them plausible early targets for scaling. The pattern answers the first research question but does not demonstrate operational excellence; it shows that artificial intelligence is moving into workflows where financial, access, staffing, and throughput effects can later be measured directly.

The second research question reveals a persistent organizational divide. Large, urban, system-affiliated, and non-critical-access hospitals reported higher adoption, while system members also reported stronger evaluation practices. System affiliation can provide shared data infrastructure, analytics staff, procurement standards, legal review, and governance committees that independent hospitals may lack. The resulting inequality is two-stage: some hospitals adopt less often, and some adopters have less capacity to evaluate accuracy and bias. Expanding software

access alone would accordingly not necessarily close the assurance gap.

The third research question adds a technology-governance mechanism. Self-developed models were associated with more local evaluation, while third-party models were associated with less. The likely mechanism is not that internal models are inherently safer. Rather, model development requires access to local data, technical personnel, documentation, and model-performance workflows that also make local evaluation feasible. Third-party procurement can lower the barrier to adoption but may leave hospitals with less visibility into training data, version changes, validation assumptions, or subgroup performance. The result supports lifecycle governance in which procurement, validation, monitoring, and retirement are connected rather than treated as separate administrative steps. The lower prevalence of bias evaluation than accuracy evaluation reinforces this point: conventional performance measurement is easier to institutionalize than fairness analysis, which requires subgroup definitions, sufficient local sample sizes, and explicit choices about acceptable tradeoffs.

6.1 Implications of the Study

Theoretical implications: The findings extend the Technology-Organization-Environment framework from adoption to post-adoption assurance. Technology context matters through electronic-health-record ecosystems and model source; organizational context matters through scale and system affiliation; and the environment increasingly specifies expectations for transparency, monitoring, and risk management. The national evidence suggests that adoption is only the first dependent variable in artificial-intelligence management. Evaluation and governance should be treated as distinct organizational capabilities with their own antecedents. This extension is important because a hospital can be technologically advanced in the sense of deploying many models yet institutionally immature in how those models are validated and monitored. A more complete theory of hospital artificial-intelligence capability should accordingly distinguish access, deployment, evaluation, and governance as sequential but partially independent dimensions.

Practical and policy implications: Hospital leaders should treat predictive artificial intelligence as a managed portfolio rather than a collection of isolated tools. Procurement should require documentation of intended use, training and validation populations, update mechanisms, performance thresholds, subgroup assessment, and responsibilities for post-deployment monitoring. Health systems with centralized expertise can formalize shared evaluation services for member hospitals, while independent and rural hospitals may require external technical assistance, standardized validation tooling, or collaborative regional assurance resources. Governance committees should include clinical, operational, information-technology, analytics, legal, privacy, quality, and equity perspectives because the national data show that accountability already spans multiple organizational entities. For administrative applications such as billing and scheduling, leaders should add outcome measures that the current national survey does not capture, including denials, processing time, appointment access, no-show rates, staff workload, cost, and unintended distributional effects.

Methodological implications: The public evidence cannot support new latent-variable estimates, but it identifies relationships that a future respondent-level survey could test. Multi-item measures of technological readiness, data quality, leadership support, governance maturity, vendor dependence, workforce capability, and regulatory pressure could support confirmatory modeling in SPSS AMOS, prediction-oriented SmartPLS analysis, necessary-condition analysis, and configurational assessment. Such extensions should use genuine item-level observations rather than infer latent scores from aggregate percentages.

6.2 Acknowledgment of Limitations

Acknowledgment of limitations: This analysis is based on self-reported hospital information-technology survey responses, so respondents may not know every model in use or every evaluation activity. Response rates were 58% in 2023 and 51% in 2024; weighting reduces observable nonresponse imbalance but cannot guarantee removal of unobserved selection bias. The survey focuses on predictive models integrated with or launched by electronic health records, so artificial-intelligence tools operating outside that workflow may be missed. The design is repeated cross-sectional, not longitudinal at the hospital level in the public results, and associations cannot establish causality. The operational use variables identify functions but not their effectiveness, cost, safety, or productivity consequences. Evaluation measures also differ across publications: the peer-reviewed 2023 analysis emphasizes local evaluation of most or all models, whereas the 2024 brief reports broader evaluation categories and monitoring. These constraints limit the claims to diffusion, association, and organizational capability patterns.

6.3 Suggestions for Future Research

Suggestions for future research: The next empirical step is to link hospital-level artificial-intelligence use with operational and clinical outcomes while preserving model-source and governance information. Longitudinal data could test whether hospitals that move into billing or scheduling artificial intelligence subsequently experience measurable changes in access, labor requirements, revenue-cycle performance, or patient flow. Multi-level designs could separate hospital effects from health-system effects and examine whether centralized governance produces spillovers across member facilities. Studies should also measure model retirement, version updates, incidents, and performance drift, not only initial evaluation. Finally, research should test whether shared validation infrastructure or policy interventions narrow the evaluation gap for independent, rural, and critical-access hospitals. The most useful future contribution would be evidence that connects organizational assurance practices to patient and operational outcomes rather than assuming that adoption itself is beneficial.

7 CONCLUSION

Predictive artificial intelligence is now widely embedded in United States hospital information systems, but the 2023-2024 national evidence shows that diffusion, operational use, and assurance capacity are developing at different speeds. Adoption increased from 66% to 71%, and the strongest operational growth occurred in billing and scheduling, answering the first research question with evidence of rapid administrative diffusion. The second research question is answered by pronounced organizational inequality: system-affiliated, large, urban, non-critical-access, and technologically advantaged hospitals reported higher adoption, while system members also reported substantially more accuracy evaluation, bias evaluation, and post-implementation monitoring than independent hospitals. The third research question is answered by adjusted evidence that self-developed models are associated with more local evaluation and third-party models with less, alongside a persistent tendency for bias evaluation to trail accuracy evaluation. The study's principal contribution is to separate artificial-intelligence adoption from organizational assurance and to position both within a Technology-Organization-Environment account of hospital digital capability. Hospital leaders should accordingly govern predictive tools as a portfolio, couple procurement with local validation and monitoring, and measure real operational outcomes before labeling deployment as operational excellence. The main constraints are self-report, nonresponse, electronic-health-record-centered scope, repeated cross-sectional design, and the absence of respondent-level public microdata for new latent-variable modeling. Future work should connect hospital-level deployment and governance to cost, access, throughput, quality, and equity outcomes using longitudinal microdata. The

central implication is that scaling artificial intelligence without scaling evaluation capability risks turning a technology divide into a governance divide; responsible operational value depends on both deployment and the organizational capacity to verify what is deployed.

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