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ARTIFICIAL INTELLIGENCE ADOPTION, ORGANIZATIONAL READINESS, AND HOSPITAL QUALITY TRAJECTORIES: SECONDARY QUANTITATIVE EVIDENCE FROM THE UNITED STATES HOSPITALS

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Keywords

Artificial Intelligence Adoption, Hospital Performance, Organizational Readiness, Predictive Analytics, Digital Maturity, Healthcare Management, Perceived Risk

ABSTRACT

Within United States hospitals, artificial intelligence has progressed beyond experimental clinical use and is increasingly being incorporated into routine practice; however, the evidence base remains dispersed across clinician acceptance, organizational adoption, and hospital performance. The study sought to determine the relationship between organizational readiness and hospital artificial intelligence adoption, examine how adoption is associated with operating or quality outcomes, and test whether perceived risk serves as a clinician-level mechanism connecting expectations about artificial intelligence with intended use. Evidence was synthesized quantitatively from verified United States studies published through August 2026 that reported hospital-level survey, administrative, financial, or quality data, or clinician-level structural equation estimates. The analytical model combined the technology–organization–environment perspective and the unified theory of acceptance and use of technology. The synthesis covered three complementary quantitative approaches: clinician mediation through structural equation modeling, hospital quality trajectories through longitudinal mixed-effects modeling, and organizational adoption or performance through weighted or endogeneity-aware models. Across national hospital studies, higher adoption was repeatedly associated with

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scale, health-system membership, electronic health record infrastructure, interoperability, and telehealth capacity. In one weighted national analysis, machine-learning adoption was 26.8 percentage points higher for health-system members and 20.6 points higher for hospitals using a leading electronic health record vendor. Several operational and financial indicators showed favorable performance associations, whereas hospital quality trajectories varied and were not consistently beneficial. At the clinician level, intended use declined as perceived risk increased, and perceived risk significantly mediated the effects of expectancy and general artificial-intelligence perception. Overall, the results frame artificial intelligence not as a stand-alone technology but as an organizational capability situated within digital infrastructure, managerial processes, and human acceptance. Accordingly, managerial and policy responses should combine adoption incentives with interoperability, evaluation governance, regional capacity building, and clinician-centered risk management, while refraining from causal interpretations beyond what the observational evidence supports.

1 INTRODUCTION

Artificial intelligence (AI) has become embedded in the digital transformation of United States hospitals through predictive models, decision support, operational applications, ambient documentation, and generative systems. Because the underlying technologies, samples, and definitions are not uniform, national prevalence estimates also vary. An American Hospital Association (AHA) sample showed that 18.7% of hospitals reported at least one AI application in 2022; a subsequent study based on 2024 AHA data identified at least one clinical AI functionality in 68.0% of responding hospitals and at least one operational functionality in 60.7% (Baten, 2024; Vo et al., 2026). In another national study, 31.5% of hospitals reported generative AI integrated with electronic health records in 2024 (Everson et al., 2025). Although these estimates do not constitute a single time series, together they indicate that the managerial issue is no longer simply technical feasibility; it is whether hospitals can implement AI dependably and convert deployment into measurable performance.

Evidence from United States hospitals available through August 2026 provides the setting for this study, which conceptualizes organizational readiness as the managerial capacity through which technology is translated into implementation. The readiness construct encompasses scale, system affiliation, electronic health record capability, interoperability, telehealth intensity, digital maturity, governance, and workforce conditions. Adoption is distributed unevenly: predictive models are used less often by hospitals serving deprived areas, rural institutions commonly face weaker digital infrastructure, and recent spatial work has identified geographically isolated nonadopters, or AI deserts (Chen & Yan, 2025; Hwang et al., 2026; Vo et al., 2026). Evidence concerning outcomes is similarly nonuniform. Observational studies associate AI adoption with revenue, productivity, occupancy, and patient volume, whereas longitudinal quality indicators do not show consistently favorable movement (Aydin et al., 2026; Hwang et al., 2026; Pham et al., 2024).

Integrating quantitative findings on organizational readiness, hospital performance, and clinician acceptance is the central objective of the study. Rather than presuming that an undefined industrial-management construct can be modeled as a mediator using the hospital data currently accessible, the analysis adopts a multilevel framework. For hospitals, the technology–organization–environment perspective describes adoption as being shaped by resources, infrastructure, and external context. For clinicians, the unified theory of acceptance and use of technology explains how expectancy and risk influence willingness to use AI. Mediation is included only where it has actually been estimated in United States healthcare: at a Wisconsin university hospital, structural equation modeling demonstrated that perceived risk mediated the effects of expectancy and general AI perception on

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intention to use an AI-based blood utilization calculator (Choudhury, 2022).

The analysis is structured around three research questions. They address, respectively, the association of organizational and digital readiness with hospital AI maturity; the relationship of AI adoption to operating, financial, and quality performance; and the possibility that perceived risk connects clinician expectancy or AI perception with intended use. The six hypotheses anticipate positive links between readiness and adoption, favorable operating or financial associations, quality trajectories that are heterogeneous rather than uniformly favorable, an inverse relationship between risk and use, and significant indirect effects operating through risk. These issues are relevant to executives, information leaders, clinicians, vendors, regulators, and policymakers because each group can affect a distinct stage of the implementation process.

Theory, empirical findings, and research gaps are brought together in Section 2. The study objective, research questions, and hypotheses are presented in Section 3. Section 4 describes the secondary quantitative design and its three complementary methodological families, followed in Section 5 by the extracted evidence across four tables and four figures. Implications, limitations, and directions for future research are considered in Section 6, while Section 7 closes the article with an integrated readiness–adoption–performance account.

2 LITERATURE REVIEW

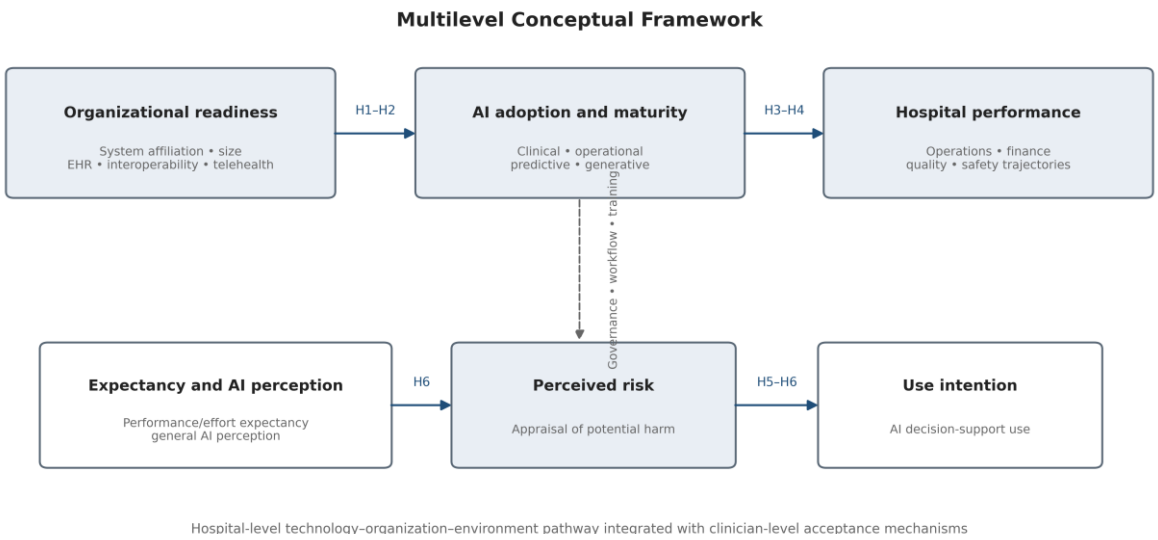
2.1 Theoretical Framework

A two-theory approach is used because no established framework by itself covers both innovation adoption at the hospital level and behavioral acceptance at the clinician level. Under the technology–organization–environment framework, organizational adoption is explained by technological conditions, internal organizational characteristics, and the external environment (Baker, 2011; Tornatzky & Fleischer, 1990). In this analysis, organizational readiness is represented through observed proxies that recur in national hospital studies, including health-system membership, bed size, ownership, teaching status, electronic health record infrastructure, interoperability, telehealth scale, and related digital capability. Reported implementation or maturity across clinical, operational, predictive, machine-learning, or generative AI applications defines AI adoption. Operating volume, revenue, productivity, occupancy, and quality or safety measures constitute hospital performance. The clinician-level mechanism draws on the unified theory of acceptance and use of technology, with particular attention to performance and effort expectancy, while perceived risk is added because decisions involving clinical AI may have consequences for patients (Venkatesh et al., 2012). On this basis, the framework anticipates positive readiness-to-adoption relationships, adoption-to-performance relationships that may be positive but depend on the outcome examined, and a negative risk-to-use relationship. Its main boundary conditions are United States hospital settings, predominantly observational evidence from 2022–2026, inconsistent technology definitions across studies, and clinician mediation evidence derived from one university-hospital application. These constructs and hypothesized directions are depicted in Figure 1.

2.2 Conceptual Framework

The framework in Figure 1 distinguishes the hospital level from the clinician level while connecting both through a shared management and governance context. Organizational readiness comes before AI adoption and maturity at the hospital level, after which adoption and maturity are related to performance. At the clinician level, perceived risk is influenced by expectancy and general AI perception, and intended use is subsequently influenced by perceived risk. The dashed cross-level path expresses the proposition that governance, workflow design, training, and implementation quality may modify the behavioral conditions that allow organizational AI investments to enter routine practice. That cross-level path is conceptual and should not be interpreted as a coefficient newly estimated in this synthesis.

Figure 1. Multilevel conceptual framework linking organizational readiness, AI adoption, hospital performance, and clinician acceptance.



2.3 *Organizational Readiness, Digital Capability, and AI Adoption*

Organizational capacity is becoming a stronger explanation for hospital AI adoption than the simple availability of technology. Evidence from 2022 showed greater adoption among larger, nonprofit, teaching, and system-affiliated hospitals, although just 3.82% fell within the high-adoption category used in that study (Baten, 2024). Subsequent weighted hospital-year models identified particularly large adoption differences associated with health-system membership and leading electronic health record vendors, alongside positive relationships for hospital size and metropolitan location (Huang et al., 2025). Analysis of 2024 data similarly linked system membership, bed capacity, and nurse staffing intensity positively with clinical and operational AI implementation, while rural location and for-profit ownership were negatively associated (Vo et al., 2026). Telehealth also serves as an indicator of readiness: across 6,173 hospitals, telehealth volume emerged as the strongest predictor of AI adoption tiers, and failure to report telehealth was concentrated among hospitals reporting no clinical AI (Liu, 2026). A separate AHA-based analysis estimated operations-related adoption at 27%, with adoption remaining more common in metropolitan and larger hospitals (Goldfarb et al., 2025). Equity-focused evidence reports lower use of predictive models and workforce AI in highly deprived locations (Chen & Yan, 2025), whereas spatial analysis reveals clustered implementation and a lower presence of predictive AI in areas with greater healthcare access needs (Hwang et al., 2026). The broader digital-infrastructure literature reinforces these observations: stronger safety performance is associated with digital maturity (Snowdon et al., 2024), interoperability can be understood in terms of foundational capability and friction (Strawley et al., 2025), and scaling AI depends on interoperable data ecosystems (Mandl et al., 2024). Existing rural–urban differences in electronic health record adoption and interoperability indicate that such constraints existed before AI diffusion (Anzalone et al., 2025). Implementation research also documents persistent gaps between model development and routine deployment (Seneviratne et al., 2020) and highlights leadership, workflow, governance, and local capacity as important within complex health systems (Marwaha et al., 2022). Collectively, the evidence accords with the technology–organization–environment framework (Baker, 2011), innovation-process theory (Tornatzky & Fleischer, 1990), and diffusion theory (Rogers, 2003). Research gap for RQ1: scale, interoperability, telehealth, digital maturity, and geographic disadvantage are seldom combined by existing research into a single managerial readiness construct. H1 and H2 are motivated by this gap.

2.4 AI Adoption and Hospital Performance or Quality

Compared with the relatively consistent evidence on adoption, findings for performance are favorable in some areas but substantially less uniform. In a matched longitudinal study, hospitals adopting AI showed higher outpatient revenue, inpatient revenue, productivity, and occupancy, while the analysis also demonstrated that inference changed materially when endogeneity was controlled (Pham et al., 2024). Another study conducted in 2026 across 2,979 hospitals found positive relationships between a composite AI adoption level and several patient-activity outcomes; at the same time, multiple expense measures increased, and the design did not justify causal interpretation (Aydin et al., 2026). Surveys of health systems reveal broad AI portfolios but inconsistent success, with financial constraints and immature tools limiting the ability to scale (Poon et al., 2025). A similar path dependence is evident for generative AI, because hospitals with greater prior predictive-AI experience were more likely to implement generative AI within electronic health records (Everson et al., 2025). Governance is critical once predictive models are deployed, given the need to evaluate fairness, appropriateness, validity, effectiveness, and safety (Nong et al., 2025). Measurable benefits can occur at the application level, as shown by a real-world deep-learning sepsis model associated with better care processes and survival (Boussina et al., 2024); however, safety research also identifies emerging failure modes when monitoring and organizational learning are inadequate (Singh et al., 2025). Accordingly, reviews separate technical performance from clinical utility (Rajpurkar et al., 2022) and stress evaluation within workflow (Bajwa et al., 2021; Haug & Drazen, 2023). Operations research further shows that, when incorporated into process design, machine learning can assist capacity and resource allocation (Pianykh et al., 2020), while hospital case evidence connects analytics with ethics and change management (Pachamanova et al., 2022). High-stakes contexts likewise increase the importance of interpretable models (Rudin, 2019), evaluation that reflects the decision context (Watson et al., 2019), and implementation choices capable of translating data science into clinical value (Beam & Kohane, 2018). The same conclusion emerges from contemporary clinical reviews: the broad promise of AI must be accompanied by validation, regulation, and responsible integration (Alowais et al., 2023). Research gap for RQ2: studies generally examine operational, financial, and clinical outcomes separately, while definitions of AI differ across predictive, machine-learning, operational, and generative applications. Accordingly, H3 anticipates favorable operating and financial associations, whereas H4 anticipates quality trajectories that differ by outcome rather than a single universal improvement effect.

2.5 Clinician Acceptance, Perceived Risk, and Use Intention

Deploying AI at the hospital level does not guarantee that clinicians will use it, so behavioral acceptance must be treated as a distinct mechanism. The most directly relevant United States evidence analyzed 119 clinicians who used an AI-based blood utilization calculator through structural equation modeling; greater expectancy and a more favorable AI perception were associated with lower perceived risk, whereas higher risk reduced intended use and transmitted significant indirect effects (Choudhury, 2022). This pathway is compatible with the unified theory of acceptance and use of technology, where expectancy and facilitating conditions are central determinants of use behavior (Venkatesh et al., 2012), as well as with the technology acceptance tradition that links usefulness and ease of use with intention (Venkatesh & Davis, 2000). Studies in healthcare indicate that evaluations of AI reflect not only expected performance but also benefit, uncertainty, trust, and risk (Esmaeilzadeh, 2020), while professional acceptance differs according to familiarity, usefulness, organizational setting, and occupational consequences (Turja et al., 2020). Comparable patterns have been documented for AI-enabled service adoption (Gursoy et al., 2019) and for online decisions in which risk and trust shape disclosure or reliance behavior (Bansal & Gefen, 2010). Research on translation identifies human and organizational barriers as crucial when moving AI beyond pilot use (Laï et al., 2020), and clinician-centered reviews draw attention to usability and implications for patient safety (Choudhury & Asan, 2020). Acceptance of intelligent services is also influenced by perceived risk (Gansser & Reich, 2021), which interacts with broader determinants of

technology use (Zhou et al., 2010). Because algorithmic decisions can affect patients, these issues also involve ethical and accountability concerns in medicine (Parikh et al., 2019). Task–technology fit further suggests that acceptance depends on how well system functionality corresponds to work requirements (Goodhue, 1995). Sound measurement is also required before mediation can be interpreted validly: reliability and convergent validity (Hair et al., 2011), discriminant validity (Fornell & Larcker, 1981; Voorhees et al., 2016), and common-method bias control (Podsakoff et al., 2012) need to be established before structural interpretation. Research gap for RQ3: validated latent measures of expectancy, risk, and intention are rarely available in national hospital datasets, which means organizational readiness and clinician acceptance are seldom examined together. H5 specifies a negative risk-to-use relationship, and H6 specifies mediation through perceived risk.

2.6 Problem Statement

The central empirical difficulty is the lack of a bridge connecting hospital-level adoption with human-level use. National surveys identify the organizations that implement AI and the structural characteristics associated with adoption, yet the AHA microdata underlying several recent analyses are licensed and therefore unavailable for open respondent-level re-estimation. Studies of hospital performance also employ different AI definitions, outcome measures, and time windows, preventing a defensible pooled causal estimate. Clinician-acceptance research, meanwhile, offers an empirically tested mediation mechanism but is generally limited to one institution or application. Thus, the principal gap is not an absence of studies on AI outcomes; rather, comparable measures have not been organized into a multilevel evidence structure that connects organizational readiness, adoption maturity, heterogeneous performance, and risk-based clinician acceptance.

3 OBJECTIVE OF THE STUDY

The study aimed to quantify and synthesize relationships linking organizational readiness, artificial intelligence adoption, hospital performance, and clinician acceptance mechanisms within United States healthcare settings.

3.1 Specific Research Questions

RQ1. To quantify how organizational readiness and digital capability have been associated with the adoption and maturity of artificial intelligence across United States hospitals.

RQ2. To evaluate how hospital artificial intelligence adoption has been associated with operating, financial, quality, and safety performance across verified quantitative studies.

RQ3. To assess whether perceived risk has mediated the relationships of expectancy and general artificial-intelligence perception with clinicians' intended use of artificial-intelligence decision support.

3.2 Hypotheses Development

H1. Higher organizational readiness is positively associated with hospital artificial intelligence adoption.

H2. Greater digital capability, including electronic health record infrastructure, interoperability, and telehealth capacity, is positively associated with higher artificial intelligence adoption maturity.

H3. Hospital artificial intelligence adoption is positively associated with operating and financial performance.

H4. Predictive artificial intelligence adoption is associated with heterogeneous, outcome-specific hospital quality trajectories rather than uniformly favorable changes.

H5. Clinicians' perceived risk is negatively associated with their intention to use artificial-intelligence-based clinical decision support.

H6. Perceived risk mediates the relationships of expectancy and general artificial-intelligence perception with clinicians' intention to use artificial-intelligence-based clinical decision support.

4 METHODOLOGY

4.1 Research Design and Evidence Strategy

A post-positivist, deductive secondary quantitative design was adopted for this study. Instead of merging respondent-level datasets that were not compatible, the synthesis used estimates reported directly by verified

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United States studies examining hospital AI adoption, organizational readiness, hospital performance, quality trajectories, or clinician acceptance. Live searches were completed through August 29, 2026, prioritizing peer-reviewed studies from 2022 through 2026 together with seminal theoretical or measurement sources needed for construct interpretation. To qualify for the empirical core, a study had to identify a United States hospital or clinician population, describe its data source and sample, define an AI-related exposure or construct, and provide quantitative findings. Method-free commentary, vendor marketing claims, and studies without traceable numerical evidence were excluded. By following this strategy, the original estimator and unit of analysis used by each study were retained while evidence could still be compared by direction and magnitude across analytical levels.

4.2 Study Context, Population, and Data Sources

Hospital-level evidence was drawn primarily from analyses linking the AHA Annual Survey with the Information Technology Supplement, quality measures from the Centers for Medicare & Medicaid Services, Healthcare Cost Report Information System data, and additional hospital, labor, publication, and digital-maturity sources. The major national samples extended from 2,174 hospitals in the generative-AI survey to 6,173 acute-care hospitals in the telehealth–AI study; Hwang et al. examined 3,560 hospitals and connected predictive-AI status to quarterly quality measures covering 2022 to 2025. Evidence for the clinician mechanism came from 119 verified users of an AI-based blood utilization calculator at a Wisconsin university hospital. Since the AHA survey microdata used in many of the source studies are proprietary, hospital-level case files were not reconstructed and coefficients were not re-estimated in the present study. Published point estimates, confidence intervals, p values, sample sizes, model types, and fit indices were instead extracted from the source articles and their supplementary materials. The structure and analytical contribution of these empirical sources are summarized in Table 1.

Table 1. Empirical Source Architecture and Analytical Contribution

Study		Period		Population / Sample	AI Construct	Method	Role
Baten (2024)	2022	U.S. hospitals; AHA survey	AI adoption maturity	Descriptive + adoption index			National adoption baseline
Pham et al. (2024)	2000–2020	941 AI + 941 matched non-AI hospital-years	AI adoption	Matching/endogeneity-aware models			Operating and financial outcomes
Snowdon et al. (2024)		Cross-sectional		1,026 U.S. hospitals	Digital maturity	Observational modeling	Readiness–quality link
Nong et al. (2025)		2023		U.S. hospitals; AHA IT survey	Predictive AI/models	Survey analysis	Governance/evaluation
Everson et al. (2025)		2024		2,174 U.S. hospitals	Generative AI in EHR	National survey models	Diffusion and prior AI experience
Huang et al. (2025)		2023–2024		2,562 hospitals; 4,055 hospital-years	EHR machine learning	IPW logistic regression	Organizational predictors
Hwang et al. (2026)		2022–2025 quality		3,560 U.S. hospitals	Predictive AI status	Spatial + longitudinal mixed models	Implementation geography and quality
Vo et al. (2026)		2024		2,720 hospitals	Clinical/operational AI	Logistic + spatial analysis	Implementation stages and AI deserts
Liu (2026)		2024		6,173 acute-care hospitals	Clinical/operational AI tiers	Gradient boosting + SHAP	Telehealth readiness
Choudhury (2022)		2021		119 clinician users	AI decision support	CFA + SEM mediation	Clinician acceptance mechanism

Note. AHA = American Hospital Association; EHR = electronic health record; IPW = inverse probability weighting; SEM = structural

4.1 Quantitative Methodologies and Analytical Alignment

The analytical backbone consists of three widely accepted families of quantitative methods. Structural equation modeling (SEM) is used for the mechanism layer because latent constructs and direct and indirect paths can be estimated within the same model. In the published clinician study, SPSS 27 was used for descriptive analysis and bias diagnostics, while confirmatory factor analysis and SEM were estimated in RStudio with the `lavaan` and `psych` packages. SPSS AMOS and SmartPLS are appropriate environments for replication or extension using covariance-based and partial-least-squares SEM, respectively; however, this article attributes no coefficient to AMOS or SmartPLS because the clinician dataset was not reanalyzed. The hospital-quality layer is represented by longitudinal mixed-effects modeling. In the Hwang analysis, quality trajectories across 15 quarters were compared using hospital random intercepts, time, AI-implementation status, time-by-status interactions, covariate adjustment, robust variance estimation, and false-discovery-rate correction. The organizational layer is represented by weighted, endogeneity-aware, and predictive multivariable modeling. Methods in this family include inverse-probability-weighted logistic regression for machine-learning adoption, fixed-effects and decomposition methods for deprivation-related adoption, propensity-score and endogeneity controls in hospital-performance analysis, and gradient-boosted models with Shapley explanations for AI maturity linked to telehealth. Rather than estimating one relationship repeatedly, these complementary approaches address three distinct analytical problems: latent behavioral mechanisms, longitudinal changes in outcomes, and heterogeneous organizational adoption.

4.2 Variable Definitions and Operationalization

Constructs were operationalized using standardized definitions while the measures specific to each study were retained. Organizational readiness included hospital scale, ownership, teaching status, system membership, electronic health record environment, interoperability, telehealth scale, staffing intensity, and community or geographic constraints. Reported use or maturity of clinical, operational, predictive, machine-learning, and generative systems constituted AI adoption. Hospital performance covered operating volume, revenue, productivity, occupancy, and indicators of quality or safety. Clinician expectancy incorporated effort and performance expectancy; perceived risk represented anticipated harm associated with relying on an AI recommendation; and intended use represented willingness to use the decision-support tool. Evidence was evaluated for directional consistency relative to H1–H6. Every numeric estimate was transcribed at exactly the precision used in its source, with no imputation of missing coefficients, no inferred significance values, and no simulated observations.

4.3 Data Screening, Reliability, Validity, and Ethics

Screening focused on the integrity of source-level information rather than individual respondent records. The original articles or their supplementary outputs were used to cross-check sample sizes, study years, definitions, denominators, coefficient signs, confidence intervals, and p-value conventions. Adoption percentages based on different technology definitions or sampling frames were not interpreted as directly comparable observations over time. For quality trajectories, coefficients were read according to the direction assigned to the outcome in the source table, and standardized coefficients were retained for the clinician SEM estimates. Multiple publications derived from the same analysis were not treated as independent evidence. After extraction, evidence was organized according to the relevant research question, and each hypothesis was categorized as supported, partially supported, or supported with qualification. The study recruited no new human participants and analyzed no identifiable patient-level data; ethical and data-use protections were therefore those reported by the original investigators.

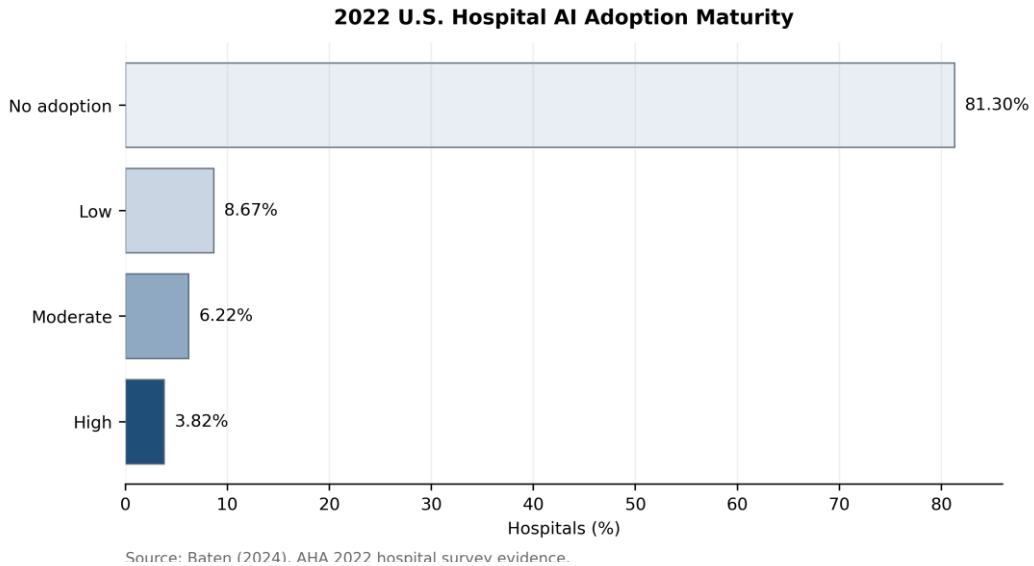
5 RESULTS

5.1 Adoption and Organizational Readiness

Across the empirical literature, adoption broadened while continuing to vary by technology type and organizational setting. Under Baten's 2022 measure, 81.30% of hospitals were classified as nonadopters, 8.67% as low adopters, 6.22% as moderate adopters, and 3.82% as high adopters. Broader diffusion appeared

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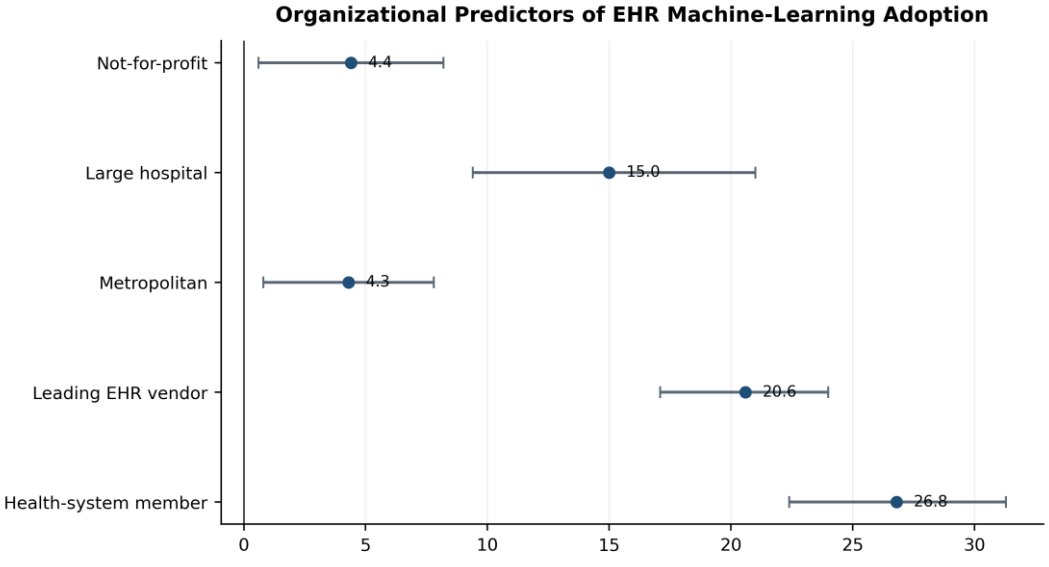
Figure 2. Distribution of U.S. hospital AI adoption maturity in 2022. Percentages are reported by Baten (2024) and sum to approximately 100% subject to rounding.



under later definitions: the AHA measure used by Goldfarb and colleagues showed 27% operations-related AI adoption, whereas Vo and colleagues reported that, among 2,720 responding hospitals, 68.0% had at least one clinical AI functionality and 60.7% had at least one operational functionality in 2024. In 2024, Everson and colleagues identified 31.5% current use of generative AI integrated with electronic health records and another 24.7% planning implementation within one year. Because these percentages represent different constructs, they are described separately and are not combined into a single growth rate. Figure 2 shows the internally consistent maturity distribution for 2022 reported within one study.

Adoption was repeatedly associated with indicators of organizational readiness. In the weighted analysis of 4,055 hospital-year observations, the probability of any electronic-health-record machine-learning adoption was higher by 4.4 percentage points for not-for-profit ownership, 15.0 points for large hospital size, 4.3 points for metropolitan location, 20.6 points for use of a leading electronic health record vendor, and 26.8 points for health-system membership. Each of the five confidence intervals excluded zero, and every reported p value was .02 or lower. These average marginal

Figure 3. Average marginal effects and 95% confidence intervals for selected predictors of any EHR machine-learning adoption. Estimates are from Huang et al. (2025).



Effects and their confidence intervals are shown in Figure 3. Other studies complemented this evidence by identifying lower adoption in deprived and rural settings, strong associations between telehealth and AI maturity, and geographic clustering of implementation. Taken together, these findings support H1 and H2.

5.2 Measurement Model and Clinician Structural Model

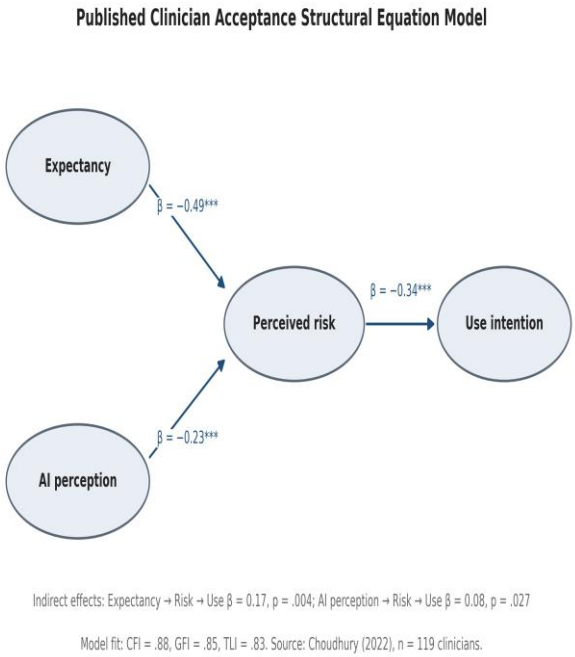
Evidence from the clinician structural-equation model was consistent with the proposed risk mechanism. Strong measurement-model fit was indicated by chi-square 23.56, comparative fit index .99, Tucker–Lewis index .98, root mean square error of approximation .05, and a nonsignificant model p value of .13; in addition, factor loadings exceeded .70, average variance extracted exceeded .50, and the heterotrait–monotrait ratio was .48. For the final structural model, comparative fit index was .88, goodness-of-fit index was .85, and Tucker–Lewis index was .83. Perceived risk was negatively predicted by expectancy ($\beta = -.49$, $p < .001$) and by general AI perception ($\beta = -.23$, $p < .001$), while intended use was negatively predicted by risk ($\beta = -.34$, $p < .001$). A positive indirect effect from expectancy to use through risk was observed ($\beta = .17$, $p = .004$), and the corresponding indirect effect from AI perception to use was also positive ($\beta = .08$, $p = .027$). The estimates are displayed in Table 2 and Figure 4. On the basis of the published model, H5 and H6 are supported.

Table 2. Published Structural-Equation Estimates for Clinician AI Acceptance

Path	β	SE	z	p
Expectancy → Perceived risk	−0.49	0.15	−4.14	< .001
AI perception → Perceived risk	−0.23	0.07	−2.65	< .001
Perceived risk → Use intention	−0.34	0.15	−3.75	< .001
Expectancy → Risk → Use	0.17	0.12	2.87	.004
AI perception → Risk → Use	0.08	0.05	2.21	.027

Note. Standardized estimates reproduced from Choudhury (2022), n = 119. Measurement fit: $\chi^2 = 23.56$, CFI = .99, TLI = .98, RMSEA = .05; structural fit: CFI = .88, GFI = .85, TLI = .83.

Figure 4. Published clinician structural-equation pathway showing the role of perceived risk in intended AI use. Path coefficients are from Choudhury (2022).



5.3 Hospital Performance and Quality Trajectories

Positive hospital-performance findings were observed across several operational areas, although the pattern differed by outcome. After selection and endogeneity were addressed, Pham and colleagues reported higher outpatient revenue, inpatient revenue, productivity, and occupancy among hospitals that had adopted AI. In 2,979 hospitals, Aydin and colleagues likewise identified positive relationships between AI adoption level and each of six operational activity measures, with adjusted admissions showing the largest standardized association; several expense measures, however, increased as well. The longitudinal evidence for quality did not show a single consistent direction. In the 2022–2025 analysis by Hwang and colleagues, hospitals using AI-based predictive models had more favorable adjusted slopes for pneumonia mortality and the total hospital-acquired-condition score, while several readmission, emergency-department, opioid, and sepsis process indicators changed in a less favorable direction. Selected differences in slopes are provided in Table 3.

Frontiers in Applied Engineering and Technology
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Table 3. Selected 2022–2025 Quality-Trajectory Slope Differences for Hospitals with AI Predictive

Quality outcome	A2 vs A0 slope difference	95% CI	Adjusted p	Direction
30-day pneumonia mortality (MORT-30-PN)	−0.32	−0.36 to −0.28	< .0001	Favorable
Total hospital-acquired-condition score	−0.017	−0.028 to −0.006	.011	Favorable
Heart-failure readmission (HRRP)	+0.0023	0.0012 to 0.0034	< .0001	Unfavorable
Pneumonia readmission (HRRP)	+0.00109	0.00002 to 0.00215	.053	Not significant after FDR
Influenza immunization (IMM-3)	+0.57	0.39 to 0.76	< .0001	Favorable
Median ED time to departure (OP-18b)	+0.96	0.63 to 1.30	< .0001	Unfavorable
Safe use of opioids	+0.86	0.70 to 1.02	< .0001	Unfavorable
Excess acute-care days after HF discharge	−0.76	−1.12 to −0.45	.0004	Favorable

Note. Selected estimates from Hwang et al. (2026), Supplementary Table S14. A2 = AI-based predictive models; A0 = no predictive models. Direction follows the source outcome interpretation; p values reflect multiple-testing adjustment where reported.

These findings support H3 for operating and selected financial outcomes, and they support H4 because quality trajectories are heterogeneous and depend on the metric examined.

5.4 Hypothesis Testing and Evidence Synthesis

When considered jointly, the six hypotheses describe an evidence chain that is coherent but requires qualification. The most consistent pattern is the association of readiness and digital capability with adoption. Favorable associations are also present between adoption and operating performance, although financial and quality findings vary according to both the outcome and study design. At the clinician level, the available United States structural model provides statistical support for perceived risk as a mediator of use intention. Table 4 reports the status of the evidence while maintaining the distinction between observational association and causal inference.

Table 4. Evidence Status for the Six Hypotheses

Hypothesis	Relationship	Primary evidence	Status	Quantitative interpretation
H1	Organizational readiness → AI adoption	Baten; Huang; Vo; Hwang	Supported	Size/system affiliation and related capacity consistently predict adoption.
H2	Digital capability → AI maturity	Huang; Liu; Snowdon; Strawley	Supported	EHR environment, telehealth, interoperability, and digital maturity align with higher adoption.
H3	AI adoption → operating/financial performance	Pham; Aydin	Supported with qualification	Positive operational/revenue/productivity evidence; expenses and selection complicate value interpretation.
H4	AI adoption → heterogeneous quality trajectories	Hwang	Supported	Favorable and unfavorable time-by-AI slopes coexist across quality measures.
H5	Perceived risk → use intention	Choudhury	Supported	$\beta = -.34$, $p < .001$.
H6	Risk mediates expectancy/AI perception → use	Choudhury	Supported	Indirect $\beta = .17$ ($p = .004$) and $\beta = .08$ ($p = .027$).

Note. "Supported" denotes consistency with the reported empirical estimates; it does not convert observational associations into experimental causal effects.

6 DISCUSSION

The overall findings characterize hospital AI implementation as a management process operating across multiple levels. At the clinician level, the clearest mechanism is that perceived risk decreases when an AI tool is expected to be useful and easy to use, and lower perceived risk is associated with stronger intention to use the tool. At the organizational level, the hospital evidence similarly depends on enabling conditions. Higher and lower adopters are repeatedly distinguished by system membership, size, electronic health record environment, interoperability, telehealth activity, and geographic resources. From this perspective, AI adoption resembles an organizational capability accumulated through earlier digital investment, coordination, governance, and learning more than it

resembles a one-time capital acquisition. This interpretation addresses RQ1 through the consistent association between readiness indicators and adoption, RQ2 through favorable performance relationships in several operational areas alongside heterogeneous quality findings, and RQ3 through the supported role of perceived risk as a behavioral mediator.

The pattern of hospital performance also shows why generalized statements that AI improves healthcare performance remain premature. Associations involving revenue, productivity, occupancy, admissions, and activity may be economically meaningful, but increases in operating activity or expense do not necessarily represent greater value, and observational designs remain susceptible to selection. Larger, digitally mature, system-affiliated hospitals are simultaneously more likely to adopt AI and more capable of generating favorable performance indicators. Longitudinal quality analysis lessens this concern without removing it, because exact implementation dates are unavailable and time-by-adoption interactions may continue to capture differences in institutional capacity. The coexistence of favorable and unfavorable quality slopes is therefore important in substantive terms: an AI portfolio may improve selected pathways while producing no change in others, or may worsen process measures when monitoring, incentives, or workflow integration are poorly aligned. This pattern is compatible with H4 and favors evaluation by specific outcomes rather than labeling an entire organization as an AI success.

The clinician evidence contributes a mechanism that is usually invisible in hospital-level datasets. Even when a hospital has advanced predictive systems, benefits may remain limited if clinicians distrust recommendations, judge the risk to be excessive, or perceive a poor match between the tool and clinical tasks. By contrast, use can be strengthened by reducing perceived risk through transparent validation, clear accountability, appropriate human oversight, and dependable workflow integration, without making overstated claims about algorithmic autonomy. Caution is warranted because the published clinician study reported marginal structural-model fit, although the indirect effects are directionally consistent with technology-acceptance theory and provide a concrete mechanism for later multilevel investigation. The most informative next step is therefore a linked design rather than another stand-alone adoption survey: organizational readiness would predict implementation quality, implementation quality would shape clinician risk and expectancy, and those behavioral factors would then predict actual use and downstream hospital outcomes.

6.1 Implications of the Study

Theoretically, the technology–organization–environment framework and clinician acceptance theory can be viewed as explaining separate stages within one implementation sequence. Organizational readiness determines a hospital's ability to adopt and govern AI, whereas clinician expectancy and risk influence whether the implemented system becomes integrated into routine practice. Conceptualizing organizational readiness as a higher-level capability helps explain both why identical technologies diffuse differently across hospitals and why technical implementation by itself does not ensure performance. From a managerial perspective, hospital executives should evaluate interoperability, data quality, workflow ownership, evaluation capacity, staff training, and post-deployment monitoring before enlarging AI portfolios. Rather than relying solely on incentives for adoption, policymakers should strengthen shared infrastructure, regional technical capacity, and evaluation resources for hospitals that are rural or resource constrained. Vendors, in turn, should supply evidence packages that facilitate local validation, monitoring, and human-factor integration instead of assuming that model performance will transfer automatically between settings.

6.2 Acknowledgment of Limitations

Interpretation is subject to several limitations. First, because the principal national AHA datasets are proprietary, the synthesis was able to verify published estimates but not independently rebuild hospital-level regression, mixed-effects, or mediation models. Second, AI is defined differently across studies; workforce AI, predictive models, machine learning embedded in electronic health records, generative AI, and composite adoption scores are connected concepts but are not equivalent. Third, the hospital evidence is predominantly observational, and neither extensive adjustment nor endogeneity-control strategies can replicate randomized assignment. Fourth, exact implementation dates for individual predictive systems are unavailable in the longitudinal quality analysis,

which restricts causal timing. Fifth, evidence for clinician mediation comes from 119 users of a single decision-support application in one university hospital and was accompanied by marginal overall structural-model fit. Finally, cross-level relationships between organizational readiness and clinician acceptance cannot be tested in a secondary synthesis because none of the included datasets measures both levels comparably.

6.3 Suggestions for Future Research

Future studies should develop a prospective multilevel panel that connects hospital readiness, exact dates of AI implementation, clinician acceptance constructs, use logs, and standardized performance outcomes. To permit tests of heterogeneity and measurement invariance, sampling should cover variation in system membership, rurality, ownership, and deprivation. Structural equation modeling should be used to estimate the behavioral mechanism, with longitudinal mixed-effects or fixed-effects models used to estimate outcome changes occurring around implementation. Where assumptions are appropriate, SPSS AMOS can support covariance-based replication and SmartPLS can support prediction-oriented robustness analysis; neither should be reported unless the analysis has actually been conducted. Robustness assessment should address alternative readiness definitions, sensitivity to missing data, subgroup invariance, and out-of-sample prediction. One particularly important test is whether interoperability and governance lower perceived risk by improving reliability and workflow fit, thereby linking the hospital and clinician levels represented in Figure 1.

7 CONCLUSION

This study interprets artificial-intelligence implementation in United States hospitals through the capabilities required for adoption to become both usable and valuable. RQ1 is addressed by consistent findings that greater scale, health-system membership, electronic health record environment, interoperability, telehealth capacity, and related organizational resources are associated with higher levels of AI adoption. The answer to RQ2 is necessarily qualified: favorable associations are present for operating and selected financial outcomes, but longitudinal quality changes vary across metrics and do not indicate a universal performance benefit. RQ3 is addressed by structural-equation evidence in which perceived risk is negatively associated with intended use and mediates the effects of expectancy and general AI perception. The study contributes a multilevel readiness–adoption–performance framework without constructing an artificial common dataset or coefficient. Before expanding AI portfolios, managers should strengthen interoperable data infrastructure, governance, local validation, workflow ownership, and clinician risk management. Rather than subsidizing acquisition alone, policymakers should direct technical and evaluation capacity toward hospitals facing geographic or resource constraints. Interpretation remains limited by proprietary source data, heterogeneous definitions of AI, observational study designs, uncertain implementation timing, and mediation evidence from a single site. The next necessary test is a prospective multilevel panel that integrates deployment dates, readiness, clinician constructs, actual use, and standardized outcomes. The central conclusion is that hospital AI performance emerges from an implementation system: technology provides the opportunity, whereas organizational readiness and human acceptance determine whether that opportunity is translated into dependable clinical and operational value.

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