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Adoption Barriers for Artificial Intelligence-Assisted Clinical Decision Support in Public Hospitals: A Policy and Management Perspective

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ABSTRACT

Background: Artificial intelligence-assisted clinical decision support (AI-CDSS) has been proposed as a tool to improve diagnostic accuracy, reduce clinical variation, and extend specialist expertise in resource-constrained public hospitals, yet documented deployments in these settings remain sparse relative to the volume of published feasibility and validation studies. Objective: To synthesize the peer-reviewed literature on barriers to AI-CDSS adoption in hospitals, with particular attention to organizational and workforce factors, clinician trust and workflow integration, regulatory and liability uncertainty, data infrastructure and interoperability, and the funding and procurement constraints distinctive to publicly financed hospital systems, and to draw implications for health policy and hospital management. Methods: A narrative review of systematic reviews, scoping reviews, mixed-methods studies, technology-acceptance surveys, and health-policy analyses addressing AI-CDSS and broader clinical AI implementation, with each source individually verified against its primary bibliographic record. Findings: Implementation barriers cluster into six recurring domains: workforce and organizational readiness, clinician trust and automation bias, workflow and interoperability friction, regulatory and liability ambiguity, data governance and infrastructure gaps, and funding or procurement constraints. Clinician trust in AI-CDSS is shaped less by algorithmic accuracy than by explainability, perceived clinical relevance, and integration into existing workflows rather than disruptive alerts. Regulatory frameworks for AI-enabled medical devices remain unsettled regarding post-deployment monitoring of adaptive algorithms, and liability allocation between clinicians, hospitals, and developers is legally unresolved in most jurisdictions. Public hospitals face compounding constraints from fragmented electronic health record infrastructure, procurement processes not designed for iteratively updated software, and capital budgets that rarely accommodate recurring model-monitoring costs; evidence from low- and middle-income country settings shows pilot AI programs frequently fail to scale into routine public-sector practice absent sustained institutional investment and governance structures. Conclusions: Durable AI-CDSS adoption in public hospitals requires coordinated management strategies-phased, risk-tiered governance; procurement models suited to iterative software; interoperability investment; and workflow-embedded implementation-rather than reliance on technical performance alone.

Keywords: *artificial intelligence; clinical decision support; public hospitals; health policy; technology adoption*

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Abstract

Background: Artificial intelligence-assisted clinical decision support (AI-CDSS) has been proposed as a tool to improve diagnostic accuracy, reduce clinical variation, and extend specialist expertise in resource-constrained public hospitals, yet documented deployments in these settings remain sparse relative to the volume of published feasibility and validation studies. Objective: To synthesize the peer-reviewed literature on barriers to AI-CDSS adoption in hospitals, with particular attention to organizational and workforce factors, clinician trust and workflow integration, regulatory and liability uncertainty, data infrastructure and interoperability, and the funding and procurement constraints distinctive to publicly financed hospital systems, and to draw implications for health policy and hospital management. Methods: A narrative review of systematic reviews, scoping reviews, mixed-methods studies, technology-acceptance surveys, and health-policy analyses addressing AI-CDSS and broader clinical AI implementation, with each source individually

verified against its primary bibliographic record (PubMed, journal platform, or Crossref/OpenAlex metadata). Findings: Across settings, implementation barriers cluster into six recurring domains: workforce and organizational readiness, clinician trust and automation bias, workflow and interoperability friction, regulatory and liability ambiguity, data governance and infrastructure gaps, and funding or procurement constraints. Clinician trust in AI-CDSS is shaped less by algorithmic accuracy than by explainability, perceived clinical relevance, and the degree to which recommendations are integrated into existing workflows rather than added as disruptive alerts. Regulatory frameworks for AI-enabled medical devices remain unsettled with respect to post-deployment monitoring of adaptive algorithms, and liability allocation between clinicians, hospitals, and developers is legally unresolved in most jurisdictions. Public hospitals face compounding constraints: fragmented electronic health record infrastructure and limited interoperability, procurement processes not designed for iteratively updated software, and capital budgets that rarely accommodate the recurring costs of model monitoring and revalidation. Evidence from low- and middle-income country settings shows that pilot AI programs frequently fail to scale into routine public-sector practice absent sustained institutional investment and governance structures. Conclusions: Durable AI-CDSS adoption in public hospitals requires coordinated management strategies--phased, risk-tiered governance; procurement models suited to iterative software; interoperability investment; and workflow-embedded implementation--rather than reliance on technical performance alone.

Introduction

Artificial intelligence-assisted clinical decision support systems (AI-CDSS) apply machine learning or other AI methods to patient-level data to generate diagnostic suggestions, risk stratifications, or treatment recommendations at the point of care. Interest in AI-CDSS has grown rapidly across high-, middle-, and low-income health systems, driven by the promise of improved diagnostic accuracy, reduced clinical variation, and extension of scarce specialist expertise to under-resourced settings [1]. Yet a persistent gap separates the volume of published AI model development and validation studies from the number of AI-CDSS tools embedded in routine hospital practice, particularly in publicly financed hospitals operating under tight capital and operating budgets [2,3].

This gap has prompted a distinct and growing literature on implementation barriers, as opposed to algorithmic performance. Reviews of this literature converge on a small number of recurring barrier domains, spanning workforce and organizational readiness, clinician trust and workflow integration, regulatory and liability uncertainty, data infrastructure and interoperability, and funding and procurement constraints [4,5,3]. These barriers are not independent: for example, procurement rules that assume a static, one-time software purchase interact poorly with AI models that require ongoing monitoring and periodic retraining, and regulatory ambiguity about liability compounds clinician reluctance to rely on system outputs [6,7]. For public hospitals in particular, adoption barriers are shaped by budgetary cycles, civil-service procurement rules, and health system governance structures that differ materially from those of private or academic medical centers, yet much of the AI-CDSS implementation literature does not disaggregate public-sector experience from the broader hospital literature.

This review addresses that gap by synthesizing published evidence on AI-CDSS adoption barriers from an explicitly policy and management perspective, with attention to how organizational, clinical, legal, technical, and fiscal barriers interact in public hospital settings, and by identifying management strategies that health systems have used, or been advised to use, to address them.

Methods

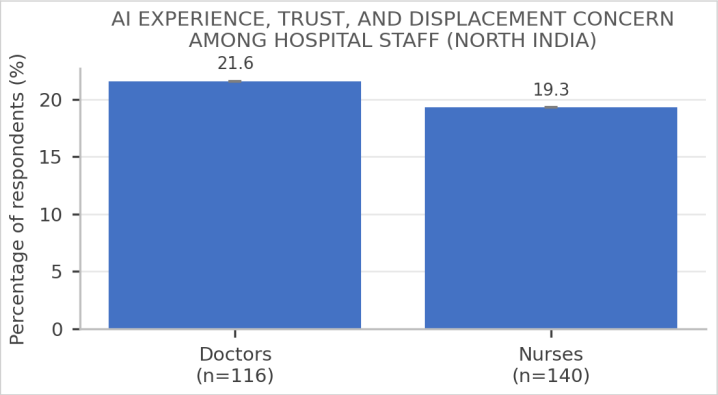
This is a narrative review rather than a systematic review or meta-analysis, reflecting the objective of synthesizing a heterogeneous literature--spanning systematic and scoping reviews, cross-sectional surveys using technology-acceptance frameworks, health-policy and legal analyses, and implementation case reports--into a policy-relevant thematic structure rather than pooling quantitative effect estimates. Candidate literature was identified through structured searches for terms combining "artificial intelligence," "clinical decision support," "adoption," "implementation," "barriers," "trust," "liability," "interoperability," "procurement," and "public hospital" or "low- and middle-income countries," conducted across bibliographic and full-text sources including PubMed, journal publisher platforms, and preprint or protocol registries. Eligible sources addressed barriers to, or facilitators of, AI or AI-CDSS adoption in hospital or health-system settings, including organizational, clinical, regulatory, technical, or financial dimensions of implementation; conceptual and legal analyses of liability and governance were included given their direct relevance to a policy and management synthesis. Sources describing only algorithmic development or diagnostic performance without an implementation or adoption dimension were excluded. Each candidate reference was individually verified against its primary bibliographic record--journal platform, PubMed, or Crossref/OpenAlex metadata--to confirm authorship, publication venue, and identifying details before inclusion; sources that could not be independently verified were excluded rather than retained on the basis of a search-engine snippet alone. The resulting evidence base was organized into five thematic domains that recur across the literature: organizational and workforce barriers, clinician trust and workflow integration, regulatory and liability considerations, data infrastructure and interoperability, and public-sector funding and procurement constraints, with a final section synthesizing cross-cutting health systems management strategies.

Organizational and Workforce Barriers

Systematic and scoping reviews of AI implementation in healthcare consistently identify organizational readiness and workforce capacity as primary, rather than secondary, barriers to adoption. A review organizing 92 studies of provider-reported AI adoption challenges around a human-organization-technology framework identified sixteen recurring barriers spanning all three domains, with organizational obstacles--insufficient infrastructure, unclear implementation roadmaps, and weak institutional backing--interacting with human factors such as staff workload and resistance to change [3]. A mixed-methods synthesis of barriers and facilitators similarly found that organizational-level factors, including leadership engagement, resource allocation, and change-management capacity, moderated whether technical AI capabilities translated into sustained clinical use [5]. A scoping review of the broader adoption literature reached comparable conclusions, emphasizing that facilitators such as early stakeholder engagement and

iterative evaluation of end-user needs were as strongly associated with successful adoption as any property of the algorithm itself [4].

Prior AI experience, trust in AI recommendations, and reported job-displacement concern among doctors and nurses in a tertiary care public hospital in North India, based on a UTAUT-framed survey of 256 respondents (Kataria, 2026).



Workforce-specific barriers include limited AI literacy among clinicians and administrators, absence of AI content in medical and nursing curricula, and uncertainty among staff about how AI-CDSS tools alter professional roles and accountability. A UTAUT-based survey of doctors and nurses in a tertiary care hospital in North India found that only about one-fifth of respondents in either profession reported prior AI experience in healthcare, and that trust, medico-legal concern, and limited awareness were the dominant reported barriers, with nurses additionally citing concern about job displacement [8]. An integrative review of AI acceptance among healthcare professionals in hospitals similarly concluded that perceived usefulness and organizational support, more than technical sophistication, predicted willingness to adopt AI tools into practice [9]. These findings indicate that workforce-directed interventions--profession-specific training, transparent communication about role change, and visible institutional commitment--are necessary complements to technical deployment.

Organizational change-management models developed for AI-enabled technology implementation in hospital settings reinforce this point. A transformational change management model developed for AI-enabled technology introduction in the operating room emphasized structured phases of awareness-building, stakeholder engagement, workflow redesign, and sustained monitoring, arguing that treating AI deployment as a discrete technology rollout rather than an organizational change process was a principal cause of implementation failure [10]. Comparable emphasis on multi-stakeholder governance recurs in frameworks for AI governance in healthcare organizations, which call for structured mechanisms--covering role definition, oversight committees, and escalation pathways--to enable, rather than merely regulate, AI adoption [11].

Clinician Trust and Workflow Integration

A substantial and rapidly growing literature examines clinician trust in AI-CDSS as a distinct determinant of adoption, separate from measured algorithmic accuracy. A systematic review of trust in AI-based clinical decision support systems among health care workers found that trust was shaped by perceived explainability, alignment with clinical reasoning, and prior experience with the specific tool, rather than by validation statistics alone, and that low trust was associated with reduced or inconsistent use even when systems performed well in retrospective evaluation [1]. A legal and clinical perspectives analysis similarly distinguished between clinicians' trust in AI-CDSS as a technical artifact and their assessment of its trustworthiness as a basis for clinical action, arguing that this distinction has direct implications for how liability should be allocated when AI-informed decisions lead to adverse outcomes [12].

Representative evidence on clinician trust and workflow-integration barriers to AI-CDSS adoption and their reported effect on sustained clinical use.

Barrier	Study population/design	Reported effect on adoption	Key reference
Low explainability / poor alignment with clinical reasoning	Systematic review of trust in AI-CDSS among health care workers	Reduced or inconsistent use even when validated accuracy was high	Tun et al. 2025
Misalignment with existing clinical workflow	Scoping review of real-world AI-CDSS implementation barriers	Identified as a primary obstacle to sustained use alongside data-quality and interpretability concerns	Bogner et al. 2026
Alert placement/timing within EHR order sets	Case study of AI-CDSS implementation in a hospital EHR system	Alert design affected clinician engagement independent of underlying model accuracy	Finkelstein et al. 2024
Unresolved accountability for AI-informed recommendations	Technology acceptance model survey, gynecologic oncology physicians	Persisted as a barrier to intended adoption despite high perceived usefulness/ease of use	Stalp et al. 2026
Automation bias / algorithm aversion	Cross-disciplinary UTAUT analysis, fracture-detection AI	Performance expectancy and institutional support predicted acceptance more than effort expectancy	Breitwieser et al. 2025

Workflow integration is a closely related and frequently cited barrier. A scoping review of real-world barriers to and facilitators of implementing AI-based clinical decision support systems identified misalignment with existing clinical workflows, alongside algorithm interpretability and data-quality management challenges, as primary obstacles to sustained use, while early and ongoing assessment of end-user needs, stakeholder engagement, and peer endorsement were identified as enabling factors [13]. A case study identifying facilitators and barriers to implementing AI-assisted clinical decision support within an electronic health record system likewise found that technical accuracy was necessary but insufficient, and that alert placement, timing, and integration with existing order sets substantially affected whether clinicians engaged with system recommendations [14]. Where AI-CDSS outputs are delivered as additional pop-up alerts layered onto already alert-dense electronic health record interfaces, clinicians report the tool as

contributing to alert fatigue rather than reducing cognitive burden, undermining the efficiency rationale for adoption.

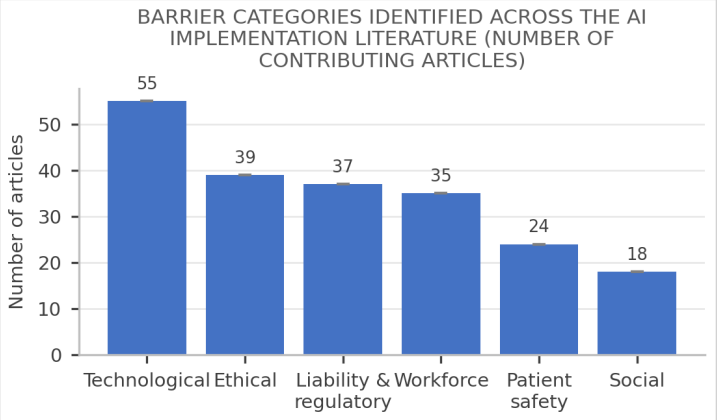
Automation bias--the tendency to over-rely on system recommendations without independent verification--and its inverse, algorithm aversion, represent a second trust-related tension documented in this literature. Reviews of AI implementation barriers identify both risks as clinically significant: automation bias can propagate systematic errors when training data diverge from local patient populations, while excessive skepticism can cause clinicians to disregard genuinely useful decision support, and both outcomes are more common where clinicians lack adequate time or training to critically evaluate AI outputs [2,8]. Technology-acceptance model studies in specific clinical domains illustrate how these dynamics play out empirically: a technology acceptance model study of physicians' acceptance of large language model-based clinical decision support in gynecologic oncology found that perceived usefulness and perceived ease of use were strong predictors of intended adoption but that concerns about accountability for AI-informed recommendations persisted independent of measured usability [15], and a cross-disciplinary UTAUT analysis of physician acceptance of AI in fracture detection found that performance expectancy and facilitating institutional conditions were significant predictors of acceptance, while effort expectancy mattered less once radiologists trusted the underlying detection accuracy [16].

Regulatory and Liability Considerations

Regulatory frameworks for AI-enabled clinical decision support remain in active development in most jurisdictions, and the literature identifies persistent gaps between the pace of AI-CDSS deployment and the maturity of regulatory oversight, particularly for adaptive algorithms that continue to learn or update after initial deployment. A systematic review of barriers to AI implementation in healthcare identified liability and regulatory uncertainty as one of six major barrier categories, noting that accountability for AI-related adverse outcomes remains contested and that regulatory frameworks for oversight of deployed, updating algorithms are underdeveloped relative to those governing static medical devices [2].

Liability allocation is a recurring and unresolved theme in the legal and health-policy literature specifically. An early analysis of AI decision support systems and liability for medical injuries argued that existing negligence and products-liability doctrines were not well suited to systems in which a clinician's judgment and an algorithm's recommendation are jointly implicated in a decision, and called for clearer allocation rules distinguishing developer, institutional, and clinician responsibility [17]. A more recent analysis characterized clinical decision support systems as functioning as "co-decision makers" rather than passive information tools, and warned against physicians becoming a de facto liability absorber for AI-attributable errors, particularly where workflow constraints leave insufficient time for clinicians to meaningfully evaluate system outputs before acting on them; the authors emphasized that effective human oversight, and any associated liability framework, depends on adequate training and adequate time for review, not merely the formal requirement that a clinician remain "in the loop" [7]. Clinicians' own perspectives on trust, trustworthiness, and liability further indicate that unresolved liability allocation itself functions as an adoption barrier: uncertainty about legal exposure discourages reliance on AI-CDSS recommendations independent of clinicians' assessment of the tool's clinical validity [12].

Relative frequency of six major barrier categories identified across the reviewed systematic-review literature on artificial intelligence implementation in healthcare, by number of contributing articles (Ahmed et al., 2023).



For public hospitals, regulatory and liability uncertainty compounds pre-existing institutional risk aversion. Public hospital administrators and legal counsel, often operating under sovereign or government indemnity arrangements with limited precedent for AI-related claims, face difficulty assessing institutional risk exposure when approving AI-CDSS deployment, and this uncertainty can slow or block adoption even where clinical evidence for a tool is favorable. Reviews addressing barriers to AI adoption in low-resource settings note that regulatory frameworks originally developed in high-income jurisdictions are frequently unavailable, inconsistently enforced, or absent altogether in the public health systems of many low- and middle-income countries, creating an additional layer of ambiguity for public hospital decision-makers in those settings [18].

Data Infrastructure, Interoperability, and Public-Sector Funding and Procurement Constraints

AI-CDSS tools depend on timely access to structured, interoperable clinical data, and gaps in electronic health record infrastructure represent a widely documented technical barrier to adoption, particularly in publicly financed hospital systems that have historically received lower capital investment in health information technology than private counterparts. A scoping review of machine-learning-enabled clinical information systems built on Fast Healthcare Interoperability Resources (FHIR) data standards found that interoperability remains an active technical and organizational challenge even where standards exist, because inconsistent implementation of those standards across vendors and institutions limits the portability of AI models validated in one health information environment to another [19]. Reviews of implementation barriers more broadly identify fragmented data, inconsistent data quality, and limited data governance capacity as central obstacles to AI adoption, noting that an algorithm's outputs are only as reliable as the data infrastructure feeding it, and that this dependency is especially acute in health systems with heterogeneous or paper-based legacy records [2,5].

Public hospitals face compounding constraints beyond data infrastructure. Frameworks for procurement, integration, monitoring, and evaluation of AI tools in clinical settings, synthesized from a systematic review of published implementation frameworks, found that most existing frameworks were developed with well-resourced academic

medical centers in mind and did not adequately address the procurement rules, budget cycles, and governance capacity typical of publicly financed hospital systems, where software procurement is often structured around one-time capital purchases rather than the recurring licensing, monitoring, and revalidation costs that AI-CDSS tools require over their operational lifespan [6]. A review of hospital-level AI adoption challenges similarly noted that financial constraints--encompassing both upfront acquisition costs and the less visible ongoing costs of model monitoring, retraining, and technical support--were reported as a top-tier barrier by healthcare providers and administrators across settings [3].

These constraints are most visible in the literature on AI implementation in low- and middle-income country public health systems, where the gap between pilot demonstration and sustained routine use is a recurring finding. A perspective on AI implementation in medical imaging in low- and middle-income countries identified infrastructure limitations, workforce shortages, and the absence of sustainable financing mechanisms as central challenges distinguishing implementation in these settings from high-income contexts, and called for context-specific deployment strategies rather than direct transfer of models and workflows validated elsewhere [20]. An analysis of why AI health interventions frequently fail to scale from pilot to policy in developing countries argued that donor-funded pilot projects often lack the sustained institutional financing, governance structures, and local technical capacity needed to transition into permanent components of public health system infrastructure, resulting in a persistent "pilotitis" in which promising tools are repeatedly piloted but rarely institutionalized [21]. A systematic review protocol assessing organizational and technological readiness for AI implementation in the Ghana health service similarly framed readiness assessment--covering infrastructure, workforce capacity, governance, and financing--as a necessary precursor to public-sector AI adoption rather than an afterthought to technology selection [22]. A broader scoping review of ethical, regulatory, and implementation barriers to AI in low-resource health settings reached a parallel conclusion, arguing that inclusive digital health strategies require simultaneous attention to infrastructure investment, regulatory capacity-building, and financing mechanisms tailored to public health system budget cycles, rather than treating any single barrier domain in isolation [18].

Discussion

The literature reviewed here indicates that AI-CDSS adoption barriers in hospitals, and particularly in publicly financed hospitals, are best understood as a set of interacting organizational, clinical, legal, technical, and fiscal constraints rather than as a single dominant obstacle. Organizational readiness and workforce trust are necessary but insufficient without workflow-embedded design, since even well-trusted tools that add friction to existing clinical workflows see limited sustained use [13,14]. Regulatory and liability uncertainty compounds clinician-level trust barriers by adding institutional risk-aversion on top of individual reluctance to rely on algorithmic recommendations, and this compounding effect appears most acute where legal precedent for AI-related clinical liability is thin [17,7]. Data infrastructure and procurement constraints, finally, determine whether an otherwise well-designed and well-trusted AI-CDSS tool can be deployed and sustained at all, independent of clinician acceptance [6,19].

Health systems management strategies for AI-CDSS adoption in public hospitals, principal mechanism, and reported constraints on effectiveness.

Management lever	Principal mechanism	Reported constraint or contingency	Key reference(s)
Procurement models suited to iterative software	Aligns budgeting and contracting with recurring monitoring/retraining costs of AI tools	Existing frameworks largely developed for well-resourced academic centers, not public-sector procurement rules	Khan et al. 2024
Risk-tiered AI governance structures	Differentiates oversight intensity by clinical stakes and algorithm autonomy	Requires institutional governance capacity that many public hospitals lack at baseline	Hassan et al. 2024b
Workforce AI-literacy training and role transparency	Builds clinician trust and reduces displacement-related resistance	Effectiveness contingent on sustained investment, not one-time training events	Kataria 2026; Lambert et al. 2023
Workflow-embedded implementation design	Integrates AI recommendations into existing order sets/alerts rather than adding disruptive interfaces	Requires iterative end-user evaluation during and after deployment	Bogner et al. 2026; Finkelstein et al. 2024
Sustained institutional financing and readiness assessment	Converts donor-funded pilots into permanent public health system infrastructure	Absent sustained financing, pilots recur without institutionalization ("pilotitis")	Joseph 2026; Dzramado et al. 2026; Marey et al. 2025

For health policy and hospital management, several implications follow. First, procurement frameworks for public hospitals need updating to reflect the recurring-cost, iteratively-updated nature of AI software, rather than treating AI-CDSS as a one-time capital purchase; this is a policy lever distinct from, and complementary to, clinical validation requirements [6]. Second, risk-tiered governance structures--differentiating oversight requirements by the clinical stakes and autonomy level of a given AI-CDSS tool--offer a more proportionate regulatory approach than uniform requirements applied regardless of risk, and several governance frameworks reviewed here explicitly recommend this structure [11]. Third, workforce-directed investment, including profession-specific AI literacy training and transparent communication about how AI-CDSS changes clinical accountability, addresses a barrier that purely technical interventions cannot resolve [8,9]. Fourth, the low- and middle-income country evidence on "pilotitis" suggests that public hospital systems should treat sustained institutional financing and governance capacity as adoption prerequisites, not later-stage implementation details, when planning AI-CDSS programs [21,22].

This review has limitations inherent to a narrative rather than systematic approach: source selection, while guided by structured search terms and individual verification of every included reference, was not exhaustive, and the evidence base itself is

uneven, with substantially more published literature addressing high-income hospital settings than public hospitals in low- and middle-income countries. Much of the technology-acceptance survey literature is also cross-sectional and drawn from single institutions, limiting generalizability of specific quantitative findings even where the qualitative barrier themes recur consistently across studies.

Conclusions

Adoption of AI-assisted clinical decision support in public hospitals is constrained by a recurring set of organizational, clinical-trust, regulatory-liability, data-infrastructure, and public-sector funding and procurement barriers that interact rather than operate independently. No single intervention addresses all of these barriers simultaneously: workflow-embedded design and clinician trust-building address clinical adoption but not procurement or liability barriers, while updated procurement and risk-tiered governance frameworks address institutional adoption but not clinician-level trust. Health systems seeking durable AI-CDSS adoption in public hospitals should therefore pursue coordinated, multi-domain management strategies--combining workforce training, workflow-integrated implementation, risk-proportionate governance, interoperability investment, and procurement models suited to iteratively updated software--rather than relying on algorithmic performance or isolated pilot demonstrations alone.

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