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Building AI-Ready Infrastructure for U.S. Healthcare: A Product Management Perspective

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Abstract

U.S. public and safety-net hospitals widely view AI as a path to better outcomes, lighter clinician workload, and lower costs, but most are not yet “AI-ready” due to immature governance, uneven data infrastructure, and chronic resource constraints. This policy perspective outlines a practical roadmap for building AI-ready infrastructure from a product management lens. We synthesize evidence on five pillars: (1) modernizing legacy IT and enforcing interoperability to unlock data liquidity; (2) raising data quality and governance standards to reduce bias and protect privacy; (3) provisioning compute, storage, and resilient networks via hybrid on-prem/cloud architectures; (4) developing an AI-literate workforce and co-design practices that integrate tools into real clinical workflows; and (5) adopting disciplined procurement, validation, and post-deployment monitoring to ensure safety and value. We translate global lessons from the NHS, Canada, and Singapore into actionable steps for U.S. public systems, emphasizing standards like FHIR, privacy-preserving approaches such as federated learning, and guideline-aligned evaluation (e.g., DECIDE-AI). The result is a sequenced, governance-anchored playbook that helps executives and product leaders move from pilot-itis to sustainable scale. Implemented well, this approach can accelerate equitable AI adoption in safety-net settings, reduce clinician burden, and improve patient outcomes while maintaining transparency, accountability, and trust.

Keywords: AI readiness; Health IT interoperability; Data governance; Federated learning; Clinical decision support; Product management

1. Introduction

Artificial intelligence (AI) is crossing from promise to practice in health care, yet clinical impact remains patchy because most hospitals lack the foundations to deploy it safely, equitably, and at scale. Reporting frameworks such as DECIDE-AI underscore a persistent “AI chasm”: strong in-silico performance, but limited benefits at the bedside without rigorous early-stage evaluation, human-factors attention, and transparent reporting (Vasey et al., 2022). In U.S. public hospitals, the gap is magnified by aging infrastructure, fragmented data, and constrained resources—conditions that turn otherwise powerful tools into brittle, untrusted add-ons rather than embedded decision support.

Interoperability is a first-order dependency. Without consistent data models and open interfaces, AI cannot see enough high-quality, context-rich data to be useful. Fast Healthcare Interoperability Resources (FHIR) has emerged as the lingua franca for clinical data exchange in research and operational settings, easing integration across EHRs, imaging, and ancillary systems (Vorisek et al., 2022). Even with pipes in place, however, model performance is only as good as the underlying data. Systematic reviews show that EHR data quality—completeness, correctness, plausibility, and conformance—varies widely and lacks standardized assessment practices, making data governance and continuous quality improvement essential prerequisites for AI (Lewis et al., 2023).

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Infrastructure choices also matter. Many clinical AI workloads benefit from hybrid architectures that pair on-premises GPU capacity (for performance, cost predictability, and PHI control) with cloud elasticity for development and bursty tasks (Sachdeva et al., 2024). Privacy-preserving techniques—especially federated learning—can enable multi-institution model training while minimizing data movement and strengthening compliance (Teo et al., 2024).

Technology alone is insufficient. Large-scale clinician adoption hinges on aligning tools to workflow, building AI literacy, and demonstrating net time savings and safety in real settings (Scott et al., 2024). Implementation frameworks such as SALIENT help teams move end-to-end—from problem definition to monitoring—so AI augments clinical work rather than disrupting it (van der Vegt et al., 2023). Governance completes the picture: bias audits, dataset transparency, and lifecycle monitoring are now recommended norms to prevent the amplification of inequities and to maintain trust (Alderman et al., 2025; Kolbinger et al., 2024).

This article synthesizes these strands into a product-management-ready roadmap for U.S. public hospitals. We detail a staged plan—modernize and integrate systems; elevate data quality and governance; provision scalable compute and networks; invest in workforce readiness and co-design; and institutionalize evidence-based procurement and monitoring—drawing practical lessons from the NHS, Canada, and Singapore. Our aim is to help safety-net systems move beyond pilots to durable, responsible AI that measurably improves care

2. The Promise and the Imperative for AI-Ready Health Systems

Artificial intelligence (AI) holds tremendous promise for transforming healthcare delivery, from automating tedious administrative tasks to enhancing clinical decision-making (Chustecki, 2024; Varnosfaderani & Forouzanfar, 2024). Studies estimate that up to 36% of activities in health and social care could be automated using AI, which would help mitigate the projected workforce shortages by 2030 (Chustecki, 2024). AI can unlock value from the vast troves of health data (an estimated 97% of which currently go unused in decision-making) by surfacing critical insights for providers (Sedlakova et al., 2023). Early applications have already saved lives, for example, by detecting disease patterns and speeding vaccine development during COVID-19 (El Arab et al., 2025). The potential benefits – including improved patient outcomes, reduced clinician workload, and lower costs – make a compelling case for U.S. public hospitals to adopt AI (Varnosfaderani & Forouzanfar, 2024; Chustecki, 2024).

Yet realizing these gains is not automatic. Public hospital systems in the United States face unique challenges in becoming "AI-ready." Many are burdened by aging IT infrastructure, siloed data systems, and limited resources, which impede AI integration (Ahmed et al., 2023). Without deliberate action to modernize infrastructure and governance, there are risks that AI's deployment could backfire, producing biased results due to poor data, leaking sensitive information, or further straining an already-stretched workforce (Ahmed et al., 2023). Indeed, there are significant risks not only from using AI improperly, but also from failing to take action to create the conditions for AI to be used responsibly. This policy perspective examines how U.S. public hospitals can build AI-ready infrastructure from a product management perspective – aligning technology, processes, data governance, and people – and draws lessons from global leaders (the UK's National Health Service, Canada, Singapore, and others). The goal is to outline a roadmap for public hospital systems to harness AI's potential safely, ethically, and effectively.

3. Legacy Systems and Integration Challenges

The first reality facing public hospitals is the prevalence of legacy systems and fragmented health IT environments. Many hospitals still run on outdated hardware and software that struggle to handle basic tasks, let alone AI algorithms. In the UK's NHS, for example, it's estimated that 10–50% of technology systems need to be modernized, as staff in some trusts report "crumbling" computers that crash frequently and run on obsolete operating systems. The situation is similar in many U.S. public hospitals that have historically underinvested in IT upgrades. Old PCs on the ward and unstable networks directly hamper AI adoption – clinicians cannot leverage AI tools if their devices won't even reliably run a web browser. Ensuring adequate computing devices and connectivity for every clinician is an essential foundation. Hospitals should budget for regular hardware refresh cycles and high-bandwidth, secure internet connections enterprise-wide. Without these basics, even the most sophisticated AI will remain out of reach (Ahmed et al., 2023).

Legacy electronic health record (EHR) systems and data silos pose an equally daunting challenge. Public hospitals often use a patchwork of EHR, radiology, lab, and billing systems – many of them proprietary and not designed for interoperability. An AI algorithm is only as good as the data it can access, yet hospitals frequently find their critical data trapped in closed systems. A common frustration voiced in the NHS is the "lack of conformity when it comes to standards" for health IT systems, and that some vendors make it difficult (or expensive) to extract data or integrate new tools. In practice, hospitals encounter EHR vendors that either don't allow third-party AI plugins, allow them but offer no support, or charge prohibitive fees to enable data access. This vendor lock-in creates a hidden cost for innovation: hospitals must spend extra on middleware or staff workarounds just to get at their own data before AI development can even begin. As one clinician put it, "If you are in a closed proprietary system…the data belongs to you, but the database belongs to the company. …They say you can get it out, but we're not going to help you, or we will help you, but we will charge you." Such barriers stifle AI experimentation in public hospitals (Walker et al., 2023).

Interoperability, therefore, is a critical priority. Hospitals need to modernize interfaces and adopt common data standards so that systems can communicate and share data fluidly. The lack of standardized formats today leads to data fragmentation and inefficiency. U.S. policymakers are taking note – the Office of the National Coordinator for Health IT (ONC) recently finalized a rule to boost data interoperability in certified health software, requiring adoption of the latest US Core Data for Interoperability (USCDI v3) standard by 2026. This update will expand the classes of data that can be exchanged (e.g., social determinants of health, genomics), supporting more comprehensive and equitable datasets for AI models. Equally important, ONC's rule establishes Trusted Exchange Framework and Common Agreement (TEFCA) networks to enable nationwide health information exchange without fear of violating information-blocking rules. For public hospitals, participating in such interoperability frameworks will be key to accessing broader data (e.g. community-wide records) and external AI services (Walker et al., 2023).

On a technical level, embracing modern data standards like HL7 FHIR (Fast Healthcare Interoperability Resources) and standard terminologies (ICD-10, SNOMED CT) will make integration of AI smoother. These standards ensure that, for example, a diagnosis or lab result is coded uniformly across systems, so an AI model trained in one hospital can interpret data from another. When hospitals cling to bespoke legacy interfaces, adding AI is "like fitting a jet engine onto a biplane." By updating interface engines and APIs to modern web services and FHIR-based data exchange, public hospitals create a more "pluggable" architecture for AI modules. Indeed, experts note that difficulty integrating AI with legacy systems is one of the major technical barriers in healthcare – many institutions still use outdated tech that makes implementing AI solutions hard (Torab-Miandoab et al., 2023; Ahmed et al., 2023). The future of an AI-ready hospital is one with a connected IT ecosystem, where EHRs, imaging systems, and other platforms all speak the same language. This connectivity lays the groundwork for real-time data flow between clinical workflows and AI decision support tools.

4. Data Governance, Quality, and Standards Compliance

Upgrading system infrastructure solves only part of the puzzle – data governance and quality are equally vital. AI algorithms thrive on abundant, high-quality data. If the data going in is poor (biased, inconsistent, or error-laden), the output will be questionable at best and dangerously wrong at worst. Unfortunately, real-world healthcare data, especially in large public systems, are often incomplete or messy. Frontline anecdotes and studies reveal many issues: missing values in patient records, miscoded entries, and idiosyncratic data quirks that can confuse an algorithm. For example, a UK AI specialist described how imaging metadata can be misleading – a file labeled as a "chest" X-ray might actually be an abdominal film where an extra view was appended but not relabeled. Such inconsistencies occur "every day for every patient" and would easily throw off an AI that expects cleanly labeled inputs. Thus, making hospital data AI-ready requires systematic data cleaning, standardization, and validation processes (Lewis et al., 2023; Roberts et al., 2021).

A product management approach would treat data as a critical asset that needs continuous quality improvement. This involves establishing tools and workflows for data profiling, error checking, and curation. Hospitals might implement automated validators that flag implausible values or use natural language processing to help normalize free-text entries into standard codes. Dedicated data engineering teams or "data stewards" may be needed to prepare and maintain datasets for AI model training and monitoring. Crucially, improving data quality should be built into routine operations (not a one-off project) – for instance, adjusting clinical documentation processes or training staff in better data entry practices, with feedback loops when data issues are found. National and local health leaders should create an environment that incentivizes data quality improvements, by providing tools (e.g. the UK's open-source CogStack platform for data extraction) and developing workforce skills to use them. By embedding data quality initiatives into everyday care delivery (and not simply adding more work for clinicians), hospitals can gradually elevate the fidelity of their data without alienating staff (Lewis et al., 2023; Yeung et al., 2024; Noor et al., 2022).

Another pillar of data governance is ensuring consistent data standards and accessibility across the enterprise. As noted, adopting interoperability standards (FHIR, HL7 v2/v3, DICOM for images, etc.) and medical vocabularies (SNOMED CT, LOINC, RxNorm) is essential so that data from different departments or facilities can be integrated for AI analysis. In Canada, a recent interoperability task force highlighted that a lack of integration between record systems and inconsistency in data exchange formats are major barriers in modernizing healthcare. The task force recommended mandating common data and technology standards for clinical data exchange nationwide, as part of a Pan-Canadian Health Data Charter. The U.S. could draw a parallel: public hospitals, perhaps with federal support, should coalesce around shared data standards to enable AI at scale. Encouragingly, legislation and funding agreements are starting to push in this direction – for instance, Canada's Bill C-72 will require vendors of digital health services to adopt common interoperability standards. U.S. public hospitals can leverage federal programs (like ONC's certification criteria and TEFCA networks) to demand standards compliance from their IT vendors and achieve data liquidity. Every procurement of a new system or AI solution should include requirements for standards support and open APIs to prevent the creation of new data silos (Vorisek et al., 2022; Park, 2024; El Sabawy et al., 2024; Walker et al., 2023; Tenenbaum et al., 2025).

Data governance also entails protecting privacy and ensuring proper use of data, especially when repurposing clinical data for AI development. Patient data in public hospitals is subject to strict laws (HIPAA in the U.S.) that place the patient in control of who accesses identifiable information. This contrasts with places like Singapore, where public healthcare institutions operate within frameworks such as the Personal Data Protection Act (PDPA) and the Human Biomedical Research Act, which together shape data sharing for research and innovation. To reconcile innovation with privacy, techniques like de-identification and federated learning can allow model training on patient data without exposing identities. Singapore's experience and European initiatives highlight robust de-identification practices and privacy-preserving infrastructures that enable AI research while minimizing re-identification risks. Secure data sandboxes and trusted environments, combined with strong governance processes, can allow cross-institutional analysis while keeping raw data locked down. U.S. public hospitals should adopt similar privacy-by-design principles – whether by creating in-house "safe havens" for data analysis or partnering with academic data enclaves – to ensure AI development complies with privacy regulations and maintains public trust (Teo et al., 2024; Kondylakis et al., 2024; Lysaght et al., 2023).

Finally, an often overlooked aspect of data governance for AI is information governance and legal clarity around data use. Under current rules, clinicians can freely view patient records for treatment, but if those same data are to be used to train or validate an AI tool, hospitals need to ensure an appropriate legal basis (e.g. research consent or waiver) and often separate data-sharing agreements. Many healthcare innovators lament that traditional information governance is seen as a blocker – but it is critical for maintaining trust. Clear national guidance can help here. For example, the UK is considering a Data (Use and Access) Bill that would clarify mechanisms for health data sharing in the public interest. Hospitals, for their part, should establish internal governance committees to vet AI data use proposals and ensure compliance with laws and ethics. The bottom line is that high-quality, well-governed data is the fuel of healthcare AI. Investing in cleaning up legacy data, standardizing formats, protecting privacy, and clarifying usage policies will pay off in AI tools that are accurate, fair, and trustworthy (Kerasidou et al., 2023; STANDING Together Consortium, 2025).

5. Technical Infrastructure: Computing, Cloud, and Connectivity

With data and integration issues addressed, attention must turn to the technical infrastructure required to develop and deploy AI solutions. Many public hospitals currently lack the computing horsepower and architecture needed for machine learning workloads. Training modern AI models (like deep neural networks) is computationally intensive – it often relies on GPUs or specialized AI accelerators rather than standard CPUs. For example, a company whitepaper checklist for AI readiness emphasizes that "AI model training demands GPU-optimized systems capable of parallel processing, not general-purpose CPUs". Public hospitals will need to plan for how to access such computing resources. Broadly, there are two strategies: invest in on-premises infrastructure or leverage cloud services (or a hybrid of both) (Kirimtat et al., 2024).

On-premises AI infrastructure gives hospitals direct control over hardware and data locality. This can be advantageous for ensuring compliance with data security (keeping sensitive health data within hospital firewalls) and for potentially lower ongoing costs at scale. Singapore's NUHS opted to build its own private AI supercomputing cluster (Discovery AI platform running NVIDIA DGX A100 systems) to support its ambitious AI programs. By doing so, NUHS can train models on site and handle heavy analytics without dependency on external networks. Similarly, the U.S. Department of Veterans Affairs – which operates a nationwide public health system – has invested in high-performance computing for its AI research, recognizing that as the largest integrated system it has massive data to harness. Public hospital consortia or state hospital systems might consider shared AI compute resources that multiple hospitals can use, which would be cost-effective compared to each hospital building its own. However, on-premises solutions require up-front capital expenditure and skilled IT personnel to maintain, which can be challenging for underfunded hospitals (Chew & Ngiam, 2025; Justice et al., 2024).

Cloud-based AI services offer an alternative: major cloud providers (AWS, Google Cloud, Azure) now provide ready-made machine learning platforms, from data storage to pre-trained models. For many use cases, cloud can expedite AI adoption – hospitals can spin up scalable compute on demand and take advantage of advanced AI toolkits without managing the infrastructure. For instance, Google Cloud's partnership with Mayo Clinic created an enterprise AI platform that allowed Mayo to perform complex analytics (like calculating kidney disease progression or running a breast cancer risk model) more quickly. Cloud is well-suited for natural language processing tasks (e.g. transcribing and summarizing doctor-patient conversations with AI "scribes") and for bridging multiple data sources. That said, there are trade-offs. Cloud costs can accumulate ("pay-as-you-go" might become expensive for constant use), and not all data is easily movable to the cloud due to bandwidth or regulatory constraints. Additionally, some AI applications require real-time response (e.g. an AI analyzing images in the ER), where latency and connectivity matter – an internet outage shouldn't halt critical AI functions (Ryu et al., 2021; Farrugia, 2024; Sachdeva & Maheshwari, 2024; Tierney et al., 2024).

A balanced approach – hybrid cloud architecture – is increasingly seen as optimal. Less sensitive or batch-processing tasks can run in the cloud, while latency-sensitive or highly confidential workloads run on-prem. Indeed, a key decision for product managers is which AI workloads belong at the edge, on-prem datacenter, or cloud. The IT Medical checklist noted that "while cloud services work for general AI, healthcare-specific AI often benefits from on-premises systems due to performance, cost efficiency, and compliance requirements". For example, training a large image recognition model on millions of X-rays might be cost-efficient on a hospital's GPU cluster, but deploying a small model to run inference on an edge device in the ICU (e.g. an AI on a patient monitor detecting early sepsis signs) avoids reliance on internet connectivity. Public hospitals should evaluate their use cases and consider building a flexible infrastructure that can span on-prem and cloud, with robust networking between them (Sachdeva & Maheshwari, 2024; Rancea et al., 2024).

Network connectivity is indeed the backbone of AI-ready infrastructure. High-speed, high-reliability networks (including Wi-Fi and wired connections within the hospital, and broadband to cloud) must be in place. As the King's Fund analysis succinctly put it, "for AI to work, connectivity is really important… a fast, high-capacity, stable internet connection is essential". However, many hospital facilities – especially older public hospitals – suffer from dead Wi-Fi zones, aging network gear, and insufficient bandwidth. These bottlenecks can cripple AI applications (e.g. timeouts in fetching large imaging studies for analysis). Upgrading network infrastructure is therefore a critical investment: hospitals should extend secure Wi-Fi across all clinical areas, ensure redundant connections for uptime, and consider edge computing setups where needed. Even basics like adequate power and cooling for new IT equipment need attention; a hospital cannot be AI-ready if a power surge or overheated server closet takes systems down (Rancea et al., 2024).

Another infrastructural element is data storage and pipelines. AI requires aggregating data from multiple sources into formats suitable for analysis – often a data lake or warehouse architecture. Hospitals will need to integrate EHR data (structured data like lab results, plus clinical notes), imaging archives, pathology slides, real-time waveform data, etc. into a unified platform for AI model development. For example, an AI-driven early warning system for patient deterioration might need to pull data from vitals monitors, nurse notes, and lab systems simultaneously. Product managers should map out data flows and ensure the infrastructure supports smooth data movement (via interfaces or HL7/FHIR feeds) without breaking data integrity. One best practice is to maintain a secondary copy of key operational databases specifically for analytics/AI, so that running heavy queries or model training won't disrupt the primary clinical systems. This could be an internal analytics warehouse or a cloud data lake, depending on strategy (Rajagopal et al., 2024; Dey et al., 2023).

Security and resilience must be built into all infrastructure components. As healthcare becomes more digital and AI-driven, it also becomes a bigger target for cyberattacks. The OECD warns that global cyber losses in health could reach $10.5 trillion by 2025, with attackers even leveraging AI to find system vulnerabilities. Public hospitals, which often have fewer resources for cybersecurity, must prioritize practices like network segmentation, encryption, and continuous monitoring to protect patient data and AI systems. Interestingly, AI can also be part of the solution – e.g. using AI tools to detect anomalies that indicate a security breach. In any case, downtime is deadly in healthcare, so infrastructure should be designed with redundancy and disaster recovery plans. If an AI tool becomes embedded in care (say an algorithm that flags critical results), the hospital needs procedures for failover or manual fallback if the tool or its data pipeline goes down. The product management mindset here is proactive risk mitigation: identify single points of failure in the AI tech stack and address them before they cause patient harm (Abouk et al., 2024; Ji et al., 2024).

In summary, becoming AI-ready requires that public hospitals treat IT infrastructure as strategic, not incidental. Just as new medical equipment requires planning (space, power, training), AI infrastructure demands forward-looking design. Health IT leaders should secure C-suite buy-in for multi-year investments in scalable infrastructure and not assume existing setups can magically handle AI. Investing in modern devices for clinicians, strong networks, hybrid cloud capabilities, and robust security will create an environment where AI systems can actually function and grow over time.

As a bonus, these upgrades often improve overall system performance for current uses too – for example, clinicians will welcome faster logins and fewer crashes, which in turn makes them more receptive to new digital tools like AI.

6. Workforce Readiness and AI Literacy

Even with the best technology and data, AI adoption can stumble if the people in the system are not ready or willing. Workforce readiness and AI literacy are thus central to an AI strategy (Scott et al., 2024). Front-line healthcare workers – doctors, nurses, technicians – need at least a baseline understanding of what AI is (and isn't), how it can assist them, and how to interpret its outputs. Equally, the broader organization (from C-suite to support staff) must cultivate a culture that views AI as a tool to enhance care, not a threat. In many public hospitals, there is a notable knowledge gap: clinicians hear buzzwords about AI but may not grasp practical applications, leading to skepticism or fear (Hassan et al., 2024). "Front-line teams communicate daily with patients and miss 90% of what AI has to offer, but it's not their fault – they are clinicians, not technologists," observes Dr. Peter Chang of Tampa General Hospital. Tampa General, a large public academic hospital, recognized this dichotomy and focused on AI literacy as a foundation for transformation.

One effective approach is fostering structured collaboration between technologists and clinicians. Tampa General's transformation officer emphasized the "marriage" of IT experts who know what's technically possible with clinicians who know the workflows – "to put those two pieces together is super important." In practice, before deploying any AI tool, Tampa General embeds its IT and data science team with front-line staff to shadow their workflow and pain points. By seeing real-world challenges, the tech team can tailor AI solutions that clinicians actually need. Conversely, clinicians start to learn how these tools work and how they could make their jobs easier. The result at Tampa General was that once staff saw the benefits firsthand, enthusiasm exploded – "as soon as frontline workers learn about the benefits of AI in their work, excitement blows up and requests follow like tidal waves," Dr. Chang noted. This highlights a key lesson: hands-on exposure and education can flip the mindset from AI-aversion to AI-advocacy on the front lines. Product managers should facilitate workshops, pilot programs, and demos that let clinicians experiment with AI in a low-risk setting, ask questions, and even critique the tool's outputs. This not only builds understanding but often yields valuable feedback to improve the AI (van der Vegt et al., 2023; Scott et al., 2024).

Addressing the fear of automation is also crucial for workforce buy-in. A major hurdle in AI adoption is the concern among healthcare workers that "the robots will take our jobs." Public hospitals, many of which serve as essential employment hubs in their communities, cannot ignore these anxieties. The leadership at Tampa General confronted this head-on by framing AI as a workforce enhancement, not a replacement. They consistently message to staff that AI will offload drudgery and empower them to practice at the top of their license – "augmenting, not displacing" human clinicians (Hassan et al., 2024). For example, AI might handle the rote task of pulling up relevant prior records (a task that consumed physicians' time) while the physician focuses on nuanced patient communication. Indeed, experiences from TidalHealth (the Maryland health system mentioned earlier) show that when AI was introduced to automatically gather patient info from the record, doctors celebrated the time saved and did not feel usurped. In that case, integrating an AI clinical decision support tool into the EHR workflow made it easier to use, and time studies revealed 73% of AI-assisted searches provided answers in under one minute – saving up to 3 minutes per search compared to manual methods. Clinicians quickly appreciated that this meant more minutes back for patient care. Sharing such success stories internally can help dispel myths and build trust that AI is genuinely there to help them (Tierney et al., 2024; Labkoff et al., 2024).

Developing AI literacy programs is becoming a recognized need worldwide. The European Union's draft AI Act even includes provisions that high-risk AI (like many healthcare applications) must be accompanied by training so users understand its appropriate use, limitations, and how to interpret results (van Kolfschooten & van Oirschot, 2024). In healthcare, this means hospitals should ensure their workforce can at least interpret AI outputs and spot when something seems off. Training should cover basic concepts (e.g., what is machine learning vs. rules-based algorithms), the importance of data quality (so clinicians grasp why, say, proper charting matters to the AI's accuracy), and how to critically appraise AI recommendations. Professional societies and educators are beginning to respond – for instance, nursing journals have started publishing AI literacy guides for nurses, and medical schools are experimenting with curricula that include AI fundamentals and ethics (Glauberman et al., 2023; Ng et al., 2023). Public hospital leadership, however, should not wait for generational turnover; they can organize continuing education sessions and leverage online courses to upskill current staff. Interdisciplinary "lunch and learn" sessions with clinicians, data scientists, and informaticists can break down jargon barriers. The goal is not to turn doctors into coders, but to give them confidence in working alongside AI – knowing when to trust it, when to question it, and how to integrate it into clinical reasoning. Hospitals might designate clinician "AI champions" (perhaps tech-savvy physicians or nurses) who receive deeper training and can serve as liaisons or trainers for their peers (Scott et al., 2024).

Another aspect of workforce readiness is ensuring sufficient IT and data science talent within public hospital systems. The best AI roadmap will flounder if there are no skilled professionals to implement and maintain the systems. Historically, many hospitals (especially smaller public ones) underfunded their IT departments – as one NHS digital director quipped, “Nobody wants to fund IT what it’s actually worth”. Budget cuts and centralized IT pools have left teams overstretched and with high turnover. This leads to loss of institutional knowledge and slower progress in setting up new technologies (every time a new person comes, they must relearn basic tasks). To be AI-ready, hospitals must invest in growing their IT and informatics teams, providing them with training in AI infrastructure and analytics. Upskilling existing IT staff in areas like data engineering, machine learning ops, and cybersecurity for AI will pay dividends. Also, product management should foster a closer collaboration between IT and clinical operations, reducing the “us vs. them” dynamic. Embedding IT personnel in clinical units (as was done in the past) helps IT better understand real needs and builds trust with clinicians. In turn, clinicians who see responsive IT support are more likely to embrace new digital tools (Doll et al., 2024; Scott et al., 2024).

Finally, empowering the workforce includes culture change and leadership engagement. Frontline enthusiasm can fizzle if middle management or senior clinicians are resistant. It’s important to have physician and nurse leaders visibly championing AI efforts – for example, by participating in pilot projects and sharing their positive experiences. Hospitals might create interdisciplinary AI committees including clinicians, IT, administration, and even patient representatives, to guide implementation and address concerns early. Tampa General’s experience shows that success is “not only a matter of technical training, but also a process of cultural change”. They focus on emotional resonance – communicating how AI can enhance patient care experiences – and on long-term development of internal expertise, even teaching clinicians how they can contribute to AI development (such as co-designing an ambient documentation AI). This inclusive approach turns users into collaborators. When clinicians feel they have a say in shaping the AI tools and that their values (like patient-centered care) are being respected, they will more readily trust and adopt the technology. As one TidalHealth physician advisor noted, “AI will establish more trust with physicians when it solves the challenges we’re actually struggling with”. By listening to clinicians’ needs and incorporating their feedback, product teams can ensure AI initiatives address real pain points, thereby accelerating clinical adoption and building a virtuous cycle of trust (Scott et al., 2024).

7. Procurement and Vendor Strategy for AI Solutions

Selecting and procuring AI solutions is a non-trivial task for public hospitals – the marketplace is crowded with startups and established vendors offering AI tools for everything from imaging diagnostics to revenue cycle optimization. A strategic procurement approach is required to cut through the hype and identify solutions that truly fit the hospital’s needs and infrastructure. Many providers report being inundated by AI vendors. In response, some leading health systems have developed internal frameworks to sift and evaluate AI tools methodically. For example, NHS hospitals have outlined staged assessment processes – moving from initial awareness, to matching solutions to needs, to retrospective testing on local data, to piloting in clinical workflow, and finally scaling up if results are positive. U.S. public hospitals would benefit from adopting a similar disciplined funnel (Blake & Das, 2024; Khan et al., 2024; Shelmerdine et al., 2024).

A product management perspective on procurement means start with the problem, not the product. Hospitals should first identify high-impact problems or gaps in care where AI might help (e.g., a high readmission rate for heart failure patients, or a bottleneck in radiology turnaround times). Multi-disciplinary input is key here: a group including clinicians, nurses, IT staff, and even patients should define the problem and the desired outcomes. This ensures any AI tool considered addresses a genuine need and aligns with organizational priorities, rather than being a shiny novelty. As the King’s Fund reported, some hospitals convene clinicians and patients to ask whether a proposed AI provides a clear improvement or solves a pressing problem before even looking at its specs. This needs-driven selection will filter out many “nice to have” AI tools that don’t justify the effort (Scott et al., 2024; Brady et al., 2024).

Once a candidate solution is identified, the hospital must perform due diligence on several fronts: technical integration, data requirements, validation evidence, regulatory compliance, and vendor support. A thorough RFP (request for proposal) or evaluation checklist can structure this. Key questions include:

- Infrastructure & Integration: What are the infrastructure requirements of the AI tool? Does it integrate with the existing EHR or IT systems? For instance, does a radiology AI need a certain Picture Archiving and Communication System (PACS) version or GPU hardware? Compatibility is crucial – one NHS hospital found a promising AI imaging tool failed on 25% of their scans because it was too strict about patient positioning, indicating a mismatch with real-world imaging variability. Checking how well the AI can ingest and output data through standards (FHIR, DICOM) is also vital to avoid extensive custom interfacing. Procurement should favor vendors that support interoperability standards, which will ease integration and reduce vendor lock-in (Shelmerdine et al., 2024; Brady et al., 2024; Blake & Das, 2024).

- Data & Privacy: What data does the AI need, and can the hospital provide it? If a tool requires years of high-quality annotated data for training, does the hospital have it, or will the vendor supply pre-trained models? Also, is the data flow compliant with privacy laws – e.g., will patient data leave the hospital for cloud processing, and if so, is there a Business Associate Agreement in place? Hospitals must ensure any AI handling PHI (protected health info) meets HIPAA requirements (e.g., encryption, access controls) and ideally that the vendor has experience with healthcare data governance (Labkoff et al., 2024).
- Evidence of Effectiveness: What validation and clinical evidence backs the AI's claims? Vendors should provide results of trials or studies, preferably peer-reviewed or at least robust internal tests. Procurement teams should ask: How was the algorithm trained and tested? On what population? Were results benchmarked against standard care? For example, if an AI sepsis predictor is 90% sensitive in literature, was that in an ICU academic center or a general ward environment? If the vendor only has a small study, the hospital might conduct a limited retrospective validation using its own historical data (with appropriate approvals) to see how the AI would have performed on its patients. Indeed, doing a retrospective evaluation on local data is a best practice: it familiarizes staff with the tool and can catch issues (like the aforementioned imaging mismatch) before patient care is involved (Vasey et al., 2022; Mahmood et al., 2024).
- Workflow and User Experience: How will the AI fit into clinicians' workflow? A great algorithm that isn't accessible within the clinical workflow will not be used. Procurement should involve end-users in evaluating the user interface and integration points. Does the AI output appear in the EHR screen that clinicians already use, or do they have to log into a separate app? Tampa General's approach of embedding IT with clinical staff prior to rollout helps identify the optimal integration point. The easier and more intuitive the AI tool, the higher the adoption. Some hospitals now insist that AI solutions launch via single sign-on and context-aware links within their main EHR, to reduce disruption (Scott et al., 2024).
- Vendor transparency and support: Given the novelty of many AI tools, hospitals should partner with vendors who are committed to algorithm transparency, monitoring, and co-development. ONC's new transparency requirements (part of the HTI-1 rule) are pushing in this direction – developers of certified clinical decision support or predictive AI must disclose information on the model's intended use, its underlying logic or value, known risks, and how it is maintained. Hospitals should leverage this and demand access to such "algorithmic accountability" information. Additionally, contract terms should include ongoing vendor support for updates (since models may need re-training or tweaks over time) and the ability for the hospital to audit or get explanations of the AI's recommendations. Ideally, vendors will agree to provisions around post-deployment monitoring – for instance, assisting the hospital in reviewing the model's performance periodically and addressing issues like drift or adverse events. Leading institutions are starting to bake in these requirements; the NHS has recommended that procurement processes include requirements for post-deployment monitoring to comply with clinical safety standards (Labkoff et al., 2024; Brady et al., 2024; van der Vegt et al., 2023).
- Cost and ROI: Finally, a pragmatic look at total cost of ownership and return on investment is necessary, especially for resource-constrained public hospitals. Beyond licensing fees, consider infrastructure costs (does it need a new server or cloud instance?), implementation costs (project management, training, workflow redesign), and maintenance (software updates, data storage). Some innovative procurement models involve outcome-based pricing or pilots where the tool is free initially and paid for later upon success – but as a hospital director in the NHS cautioned, even a "free" proof-of-concept can consume significant staff time and resources to implement properly. Thus, an internal cost-benefit analysis should be done: if the AI aims to, say, reduce length of stay, what value does each day avoided bring, and does that outweigh the investment? Public hospitals might seek grant funding or public-private partnerships for initial AI projects to offset costs. Moreover, collaborative purchasing (multiple hospitals or a network buying together) could negotiate better deals and share the risk (Brady et al., 2024; Kamel Rahimi et al., 2024).

In summary, procurement of AI in healthcare must be evidence-driven and context-sensitive. A hospital should establish an AI evaluation committee or taskforce that brings all stakeholders to the table and uses a standardized rubric to assess potential tools. By doing the homework upfront – ensuring an AI is a good technical and clinical fit – public hospitals can avoid costly misadventures and pick solutions that deliver real value. Furthermore, sharing lessons learned between institutions is valuable. If one public hospital system successfully vetted and implemented an AI for, say, diabetic retinopathy screening, that knowledge (what criteria they used, what challenges they hit) can serve as a template for others. Health systems in the UK and Canada are already encouraging such knowledge exchange on AI assessment. U.S. public hospitals could similarly collaborate (through associations or regional health information exchanges) to develop best-practice procurement guidelines for AI – a collective effort that individual hospitals with limited means would find beneficial (Khan et al., 2024; Brady et al., 2024).

8. Governance, Regulation, and Ethical Considerations

Implementing AI in public hospitals is not just a technical endeavor; it is also a socio-ethical one. Strong governance and ethical oversight are essential to ensure AI is used responsibly and garners public trust. On the regulatory front, the landscape is evolving. In the U.S., the Food and Drug Administration (FDA) regulates many AI-based medical devices (for example, AI that reads medical images for diagnostics) and has issued guidelines on “Good Machine Learning Practice” for AI in healthcare, alongside work on adaptive AI/ML software as a medical device (SaMD) and predetermined change control plans (Palaniappan et al., 2024; Mashar et al., 2023). The FDA is grappling with how to oversee adaptive algorithms that learn over time, with proposed frameworks for periodic re-evaluation of algorithmic performance (Palaniappan et al., 2024). Public hospital leaders must keep abreast of these regulations to ensure any AI tools they deploy either have appropriate FDA clearance or fall under enforcement discretion or research use only, as applicable. Additionally, liability and accountability need clarification – if an AI provides a faulty recommendation that leads to harm, who is responsible? Most legal frameworks still place responsibility on the clinician end-user, but as AI becomes more autonomous this may be tested (Mello & Guha, 2024). Hospitals should work with their risk management and legal teams to update policies on use of decision support: e.g., making clear that clinicians must verify AI outputs and that AI is there to assist, not substitute clinical judgment (Mello & Guha, 2024).

A critical emerging requirement is algorithmic transparency and auditability. Front-line clinicians and patients will trust AI decisions only if they sense the process is not a “black box” or, at least, that it’s been vetted by experts. Recent informatics guidance emphasizes documenting logic, intended use, maintenance, risks, and monitoring plans for clinical AI/predictive tools to support safe deployment and oversight (Labkoff et al., 2024). This push for transparency aligns with broader calls for explainable, interpretable AI to support clinician trust (Rosenbäck et al., 2024). Hospitals deploying AI should consider building an “algorithm registry” or documentation hub where details about each AI tool (intended use, validation results, data used in training, performance metrics, etc.) are recorded and available to clinicians; early proposals argue that such registries can enhance trust and safety (van Genderen et al., 2024). Some large hospitals have internal AI ethics boards that review algorithms before they go live, examining for biases or potential harm. This is a prudent step – for example, a biased training dataset could cause an AI to perform worse for certain racial or ethnic groups, exacerbating disparities. A randomized study showed that when clinicians were exposed to systematically biased AI, their diagnostic accuracy dropped by more than 11 percentage points, and explanations did not mitigate the harm—underscoring the need for rigorous bias assessment and oversight (Jabbour et al., 2023).

Ethical frameworks provide guiding principles. The recent literature synthesizes common pillars—human oversight, safety and well-being, transparency, accountability, privacy, equity and inclusion, and sustainability—and highlights practical implications for clinical settings (Ning et al., 2024; Mennella et al., 2024). Comparable governance discussions in Canada likewise stress equity, accountability, and public trust as foundations for “responsible AI” in health systems (Attard-Frost, 2024). Public hospital systems should adopt or adapt such high-level principles into their own governance charters. For instance, a hospital might have a policy that any AI used in patient care must be monitored for performance and safety on an ongoing basis, and there must be a clear path to intervene or shut it off if it malfunctions. Another policy could require that patients are informed when AI is being used in their care (transparency to the public). Indeed, trust is paramount – as Canadian governance analyses note, trust is a key enabler of AI adoption in health, and maintaining it requires engaging stakeholders, including patients, in how AI is implemented (Attard-Frost, 2024).

One concrete governance mechanism is to establish an AI oversight committee at the hospital or health system level. This interdisciplinary committee (involving clinicians, data scientists, ethicists, legal, and patient advocates) would review proposed AI deployments for ethical and safety concerns, set guidelines for use, and monitor outcomes. Multi-society recommendations in imaging similarly call for structured evaluation, implementation, and post-deployment monitoring to ensure clinical safety and effectiveness (Brady et al., 2024). In a U.S. public hospital, such a committee might also evaluate compliance with federal regulations (e.g., ensuring any research use of AI has IRB approval) and track any patient complaints or incidents involving AI. Having a formal governance body signals to staff that AI is being handled responsibly and not just dropped in without oversight.

Another important governance aspect is post-market surveillance – analogous to pharmacovigilance for drugs. AI performance can drift over time; patient populations or care processes may change, or the AI’s predictive power may wane as it encounters new data. Therefore, hospitals should plan for regular re-validation of AI tools and fairness monitoring, with feedback channels for frontline users (Feng et al., 2022; Andersen et al., 2024). Some systems are exploring real-time monitoring dashboards for AI, which track metrics like usage rates, alert overrides, calibration, and outcome correlations to catch issues early (Feng et al., 2022). Product managers should incorporate monitoring capabilities when designing or buying AI solutions and ensure processes exist to recalibrate, retrain, or retire models when performance shifts (Andersen et al., 2024).

We should also consider equity and access from a governance lens. Public hospitals serve vulnerable populations, and AI should ideally help reduce health disparities, not widen them. This means governance should ask: Is the AI equally effective for different demographic groups? Are there any biases in how it's deployed (e.g., only available in certain clinics or languages)? The methodological literature now provides practical equity guidance for dataset representativeness, bias assessment, and reporting to reduce downstream harm (STANDING Together Collaboration, 2025; Ueda et al., 2023). Proactive governance policies—such as requiring diverse representation in AI training data and conducting impact assessments on health equity—can help fulfill the ethical mandate of public healthcare (Ueda et al., 2023).

In sum, robust governance and ethical oversight transform AI from a high-risk venture to a high-reward benefit. Public hospital systems should not view governance as red tape but as an enabling framework that builds trust and sustainability for AI innovations. By putting in place transparency measures, accountability structures, and ethical guidelines, hospitals signal to patients and staff that they are using AI thoughtfully. This helps cultivate the social license to innovate – the public's acceptance of AI in care – which is just as important as the technical capability. As one leader noted, healthcare is ultimately about people, and AI must be introduced in a human-centered way that enhances care experiences rather than detracting from them. Good governance ensures the focus stays on improved patient outcomes and safety, aligning technology with the core mission of public healthcare.

9. Global Lessons: NHS, Canada, and Singapore as AI-Ready Exemplars

9.1. Why Global Examples Matter Now:

The United States has unmatched innovation capacity in AI and digital health, yet many of its public hospitals remain structurally unprepared to benefit from these advances. By contrast, countries like the UK, Canada, and Singapore have made deliberate, system-wide investments to modernize infrastructure, unify data standards, and embed ethical oversight — not because their systems are perfect, but because coordinated action accelerates AI readiness (Varnosfaderani & Forouzanfar, 2024). These global exemplars demonstrate what is possible when public health policy aligns around a shared digital vision. For U.S. policymakers, they offer not a roadmap to replicate, but a compelling case for bold, unified action to equip public hospitals with the tools, governance, and workforce capacity to safely and effectively deploy AI.

Looking abroad provides valuable insights into how large public health systems are gearing up for AI. The United Kingdom's National Health Service (NHS), for example, has launched an AI Lab and multiple initiatives to foster innovation, but a recurring theme has been the need to shore up basic infrastructure and digital maturity first. A 2025 analysis by the King's Fund bluntly noted that "basic infrastructure challenges are holding back the potential for AI" in the NHS – front-line staff are enthusiastic but are hampered by crashing computers and "outdated technology unable to support AI". The NHS experience highlights that national investment in health IT is a prerequisite for the effective implementation of AI. The UK government has begun to address this by funding hospitals to eliminate fax machines, upgrade devices, and ensure every staff member has access to a digital device. They've also emphasized auditing of IT equipment age and functionality, with the Department of Health tracking these metrics to better target funding for modernization. The lesson for U.S. public hospitals (and the government agencies that fund them) is that earmarked funding to update hospital IT infrastructure yields a double dividend: immediate efficiency gains and future readiness for AI (Li et al., 2023; Woods et al., 2023).

The NHS has also focused on data consolidation and governance at scale. One innovative project is the NHS Federated Data Platform, designed to integrate data across hospitals and regions, supporting both operational analytics and AI development. Although not without controversy (concerns about Big Tech involvement have been raised), the concept aims to provide a national data infrastructure, enabling each hospital to avoid the need to solve interoperability issues independently. In parallel, the NHS is working on Secure Data Environments – essentially safe platforms where sensitive patient data can be analyzed for research/innovation under strict controls. This mirrors what Singapore's NUHS did internally. The global takeaway is that central or federated approaches can accelerate AI by pooling resources and expertise, which is particularly relevant to public systems. U.S. public hospitals may consider regional data collaboratives (for example, a statewide health data trust) as a way to enable AI development on a larger dataset while sharing the burden of privacy protection and governance (Peek et al., 2023; Morley & Rocher, 2024; Kavianpour et al., 2022).

Canada offers lessons in governance and strategy. Canada's single-payer provincial health systems are collaborating on a joint action plan for health data and digital health, recognizing that modernizing these is critical for AI adoption. The Pan-Canadian AI for Health principles we discussed guide this effort. Notably, Canada places strong emphasis on equity, Indigenous data sovereignty, and public engagement in AI strategy. For example, one recommendation is to co-design digital solutions with practicing clinicians and to address barriers that prevent providers from participating in interoperability and data initiatives. This inclusive, ground-up approach parallels what we've seen with Tampa General's collaboration model – reinforcing that people must be at the center of AI efforts. Canadian health systems are also exploring innovative procurement by committing to common standards and policies across provinces, aiming to create a larger, unified market that incentivizes vendors to develop interoperable, safe AI tools. U.S. public hospitals, though more fragmented, could band together through organizations like the American Hospital Association or the National Association of Public Hospitals to collectively demand standards compliance and ethical safeguards from AI vendors (El Sabawy, 2024; Attard-Frost & Krishnamurthy, 2024).

Singapore's healthcare system, though much smaller, is a particularly interesting case of a government-driven, integrated approach to AI. Singapore identified healthcare as one of five key domains in its National AI Strategy, with an initial focus on chronic disease management and operational efficiency. Within the public system (which comprises regional health clusters like NUHS), they achieved a high degree of EHR consolidation – Singapore implemented a Next-Generation EMR (NGEMR) unified across multiple clusters. With most patient data on a single Epic-based platform (and a National Electronic Health Record that aggregates data nationally), Singapore created fertile ground for AI solutions that draw longitudinal data. NUHS then built in-house AI capabilities (the Endeavour AI platform for operations and the Discovery AI for research), leveraging this unified data. They've deployed a range of AI tools, including Pathfinder (an ED dashboard that predicts wait times), a 30-day readmission prediction model, and CHAMP (a chatbot that utilizes WhatsApp to help patients with chronic diseases adhere to their care plans). Impressively, all NUHS's AI tools are fully integrated into the clinical system – their AI platform syncs with the national EHR, providing a seamless user experience and a single dashboard for clinicians. This demonstrates how integration at design yields operational AI at scale. The U.S. context is obviously different, but specific large public systems (like the Veterans Health Administration or big municipal health systems) could emulate pieces of this: for instance, developing an internal AI center of excellence that builds and governs AI tools tailored to their population, rather than relying purely on third-party products (Chen et al., 2025).

Across these examples, common threads emerge: invest in foundational infrastructure, unify data and break silos, involve end-users deeply, and craft national/regional standards and policies to guide ethical AI. The product management perspective ties it all together by focusing on user-centric design (clinician and patient needs), iterative development and testing (pilots, feedback loops), and cross-functional coordination (IT, clinical, leadership alignment). Global best practices show that AI in healthcare is as much about change management and system design as it is about algorithms. U.S. public hospitals can accelerate their AI readiness by learning from these models – for example, adopting the NHS's emphasis on device/network upgrades, Canada's federated governance and emphasis on trust, and Singapore's integration and homegrown innovation approach (Woods et al., 2023; Peek et al., 2023).

10. Conclusion: A Roadmap to AI Readiness

Building AI-ready infrastructure in U.S. public hospitals is a complex but achievable goal. It requires a holistic strategy that touches every aspect of the health system: technology, data, processes, people, and oversight. From the analysis above, several key components of this roadmap emerge:

- Modernize and Integrate Core Systems: Replace or retrofit legacy IT systems and insist on interoperability standards so data can flow freely. This includes upgrading hardware (so staff have reliable devices and connectivity) and software (EHRs and ancillary systems that support open APIs and data exchange). Interoperability is non-negotiable – initiatives like adopting FHIR and participating in health information networks will lay the groundwork (Vorisek et al., 2022; Lewis et al., 2023).
- Establish Robust Data Infrastructure and Governance: Treat data as a strategic asset. Create unified data platforms or warehouses that aggregate clinical data for analysis, and enforce data quality improvement processes. At the same time, implement strong governance for privacy and ethics – de-identify data when appropriate, obtain consents or legal clearance for secondary use, and ensure compliance with HIPAA and other regulations at every step (Lewis et al., 2023; Ueda et al., 2024).
- Invest in Scalable Computing and Networking: Ensure the hospital has access to the computing power needed for AI – whether through on-premises GPU clusters or secure cloud partnerships. Build resilient network infrastructure to support AI applications in real time, and plan for hybrid cloud models that balance performance, cost, and compliance. Don't overlook cybersecurity; make AI systems part of a defensible network to protect against threats (Sachdeva et al., 2024; Rancea et al., 2024).

- Cultivate an AI-Ready Workforce and Culture: This might be the most important element. Provide education and training to raise AI literacy among clinicians and staff. Involve end-users early through co-design and pilot testing, so they trust and feel ownership of the solutions. Clearly communicate that AI is there to augment their work, not replace them. Also, strengthen internal IT and data teams – they will be the champions and maintainers of AI tools on the ground (Scott et al., 2024).
- Adopt Rigorous Procurement and Evaluation Practices: Don't be seduced by hype. Use a needs-driven approach to identify AI solutions, and evaluate them on integration capability, clinical evidence, and safety. Test promising tools on retrospective data and small pilots before scaling up. Negotiate contracts that include transparency, support, and monitoring obligations from vendors (Brady et al., 2024; Vasey et al., 2022).
- Implement Strong Governance and Ethics Oversight: Set up an AI governance committee or embed AI into existing ethics and quality structures. Establish policies for algorithm approval, monitoring, and incident response. Embrace principles of fairness, accountability, and transparency by design. Regularly audit AI outcomes for bias or errors and adjust course as needed. Remember that maintaining trust – among clinicians, patients, and the public – is paramount for long-term success (Labkoff et al., 2024; Andersen et al., 2024).

These elements are interdependent. For example, better data interoperability (technology) facilitates multi-site collaborations (people/process), which in turn can feed governance structures (policies for data sharing). A product manager's role is to coordinate these moving parts, ensuring that improvements in one area support the others. Perhaps most critically, leadership must articulate a clear vision: how will AI help fulfill the hospital's mission of improving patient care and community health? With that vision, each investment, whether upgrading an EHR interface or running an AI training workshop for staff, can be tied to the broader goal, sustaining momentum even when challenges arise.

The path will not be without obstacles. Public hospitals often operate under tight budget constraints and serve patient populations with complex social needs. But precisely because of that, the payoff from AI – in efficiency gains, preventive care, and population health management – could be especially large in these settings. Early successes, even modest ones like AI-assisted documentation reducing clerical burden, or a sepsis early warning AI averting ICU transfers, will build the case and attract further support (Tierney et al., 2024). There is also a compelling equity argument: leaving public safety-net hospitals behind in the AI revolution would risk worsening disparities between well-resourced health systems and those caring for the underserved. Conversely, bringing AI to public hospitals could help reduce disparities – for instance, AI triage tools could expand access to specialist insights in remote or underfunded areas, and workflow automation could free up clinician time for patients who are underserved. Emerging consensus recommendations on dataset transparency and representativeness underscore how to operationalize equity by design (Alderman et al., 2025).

In conclusion, making U.S. healthcare "AI-ready" is as much a policy and management challenge as a technical one. It demands visionary leadership, cross-sector collaboration, and sustained investment. Policymakers should consider targeted funding (grants or incentives) to help public hospitals upgrade infrastructure and train their workforce for AI – similar to past federal programs that supported EHR adoption. Hospital administrators and product managers must prioritize interoperability and user-centered design, learning from global peers and avoiding siloed decision-making. And throughout, an unwavering focus on ethical principles and clinical excellence must guide the way. If done right, AI can be a powerful ally in rebuilding strained public health systems – streamlining workflows, predicting and preventing illness, personalizing treatments, and ultimately improving outcomes for patients. As one health IT perspective emphasizes, the goal is responsible AI that advances health outcomes while safeguarding rights and trust (Ning et al., 2024). By building the necessary infrastructure and culture today, U.S. public hospitals can be ready to harness AI's huge potential while managing its risks – ensuring that this technology truly serves the public good in healthcare.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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