

Assessing Organizational Readiness for Artificial Intelligence in Healthcare Through a Digital Transformation Debt Framework

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Method Article

Keywords: digital transformation debt, artificial intelligence readiness, healthcare informatics, AI value gap, pilot-to-scale, AI governance, organizational readiness, digital maturity, health systems, trustworthy AI

Posted Date: August 3rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10157152/v1>

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Additional Declarations: No competing interests reported.

Abstract

Background

Most healthcare AI initiatives fail to deliver sustained organizational value, and the causes are structural rather than technological. Data fragmentation, workforce unpreparedness, governance deficits, process complexity, and vendor ecosystem burden are the primary conditions that determine whether AI performs reliably at scale. These conditions are rarely assessed before AI investment is committed.

Objective

This paper introduces the Digital Transformation Debt (DT-Debt) framework, a structured organizational assessment tool built around seven dimensions of accumulated digital burden. The framework positions any organization on a cumulative debt scale, classifies it into one of four archetypes, and uses that archetype to drive specific AI readiness guidance and remediation priorities.

Methods

An integrative evidence synthesis was conducted drawing on peer-reviewed literature, policy frameworks, and market survey and thought leadership by leading consulting firms. Six recurring AI value gap domains were identified and characterized. The DT-Debt framework was constructed across seven sociotechnical dimensions, each assessed through observable organizational signals. The cumulative debt level across the seven dimensions positions the organization in one of four archetypes: Transformation-Constrained, Partially Modernized, Functionally Ready, and AI-Ready. Three synthetic health system profiles demonstrate the framework in practice.

Results

Six structural AI value gaps are identified and mapped to specific DT-Debt dimensions. The cumulative archetype scale differentiates AI deployment risk with sufficient precision to drive distinct remediation and deployment pathways. Each archetype is characterized by a specific organizational profile, a set of AI failure modes it predicts, and a clear set of immediate priorities and leading indicators for progress.

Conclusions

The DT-Debt framework reframes AI readiness as a diagnosable organizational condition. Knowing where an organization sits on the cumulative debt scale, and why it sits there, gives health system leaders the specific information they need to sequence AI investment intelligently, target remediation where it predicts the highest failure risk, and build the organizational capacity that AI requires to perform reliably.

1. Introduction

Healthcare organizations are investing in artificial intelligence (AI) at an accelerating rate. Investment per organization rose from \$14.7 million in 2024 to \$27 million in 2025, with 78 percent of surveyed organizations reporting year-over-year increases [1]. Hospitals, integrated delivery networks, and academic medical centers are pursuing clinical decision support, ambient documentation, predictive analytics, autonomous coding, imaging interpretation, and operational workflow automation at a scale and speed not previously seen in the sector.

The returns have been deeply uneven. In the McKinsey State of AI 2025 survey of 1,993 respondents across 105 countries, only 5.5 percent of organizations reported that more than five percent of their enterprise EBIT was attributable to AI [2]. Most AI initiatives remain at the pilot stage. The share of organizations abandoning most of their AI programs rose to 42 percent in the first half of 2025, up from 17 percent the prior year [2]. The gap between what AI promises and what organizations actually gain is structural and predictable.

The standard explanation attributes failure to technology. Algorithms are not ready. Vendors have oversold. The data is not clean enough. Each of these observations contains a fragment of truth, but none of them is the right primary explanation. The consistent finding across implementation research is that data quality, workforce readiness, governance structure, process complexity, and vendor ecosystem burden are the primary determinants of whether AI delivers sustained value in organizational settings [3, 4]. AI capabilities have matured faster than the organizational infrastructure required to support them. The failure is not in the model. It is in the organization the model is asked to serve.

This paper introduces the Digital Transformation Debt (DT-Debt) framework: a structured tool for assessing the accumulated organizational burden that causes AI investments to fail. The framework is built around seven dimensions of digital debt, each capturing a distinct category of organizational friction. The cumulative debt level across these seven dimensions positions any healthcare organization on a scale from highly constrained to fully ready, and that position determines the specific AI failure modes the organization faces, the remediation priorities that must be addressed, and the AI deployment strategy that is appropriate at that point in the organization's modernization journey.

2. Six Structural AI Value Gaps

2.1 Evidence Synthesis Approach

An integrative evidence synthesis was conducted, consistent with the methodology described by Torracio [9], drawing on numerous categories of source material: peer-reviewed literature on AI implementation, digital transformation, and organizational readiness published between 2017 and 2026; market survey and thought leadership by leading consulting firms McKinsey, Gartner, and Wipro published between 2024 and 2026 [1, 2, 6, 7]; policy frameworks from the OECD published in 2026 [4]; and Khashu's published framework on operationalizing trustworthy AI in healthcare [11]. Industry sources were

included where peer-reviewed benchmarks were unavailable, consistent with established practice in health informatics conceptual work [8].

2.2 Gap Characterization

Six recurring mismatches between AI promises and actual organizational gain were identified. These gaps are not technology failures. Each one is rooted in an organizational condition that exists before the AI system is deployed and that the organization's existing structure is not equipped to resolve on its own.

Data quality and readiness is the most pervasive gap. Gartner found in February 2025 that 63 percent of organizations lack adequate data management practices for AI, and projected that 60 percent of AI projects will be abandoned through 2026 because data are not AI-ready [6]. Wipro's State of Data4AI Report 2025 found that only 14 percent of business leaders believe their data maturity can support AI at scale [7]. Healthcare amplifies this gap through fragmented EHR ecosystems, non-standard terminologies, duplicate patient records, and data latency from disconnected systems. No algorithm produces reliable outputs when the data it consumes are incomplete, inconsistent, or delayed.

Pilot-to-production failure is the most commonly reported. Pilots are conducted in curated environments with dedicated analyst support that manually bridges contextual gaps absent from the ambient organization. When those conditions disappear in production, model performance degrades against data landscapes, workflow patterns, and governance conditions the model was not prepared for. Wong, Nallamotheu, Longhurst, and Singh documented that healthcare consistently lags other industries in operational AI deployment and identified the need to redesign health systems for AI-enabled workflows rather than adapting AI to legacy structures [5].

Hidden cost and return on investment failure is structurally predictable. The McKinsey 2025 survey found that while 88 percent of organizations use AI in at least one business function, only 5.5 percent report enterprise-level EBIT impact [2]. The World Economic Forum identified poor governance and low data maturity as the primary barriers to scaling AI, not the algorithms themselves [3]. Actual deployment costs exceed vendor quotes because data migration, workflow redesign, change management, and ongoing optimization are not captured in initial pricing.

Workforce readiness failure is systematic and misdirected. Farr documented that health systems remain waiting not for better algorithms but for a workforce that can operate effectively with AI at the point of care, and that module completion rates do not predict behavioral adoption [10]. Model capabilities change faster than static training content can track, leaving clinicians and operational staff unprepared as tools evolve.

Governance and explainability failure is now a regulatory and operational imperative. Khashu identified that while trustworthy AI is widely cited as a goal, existing frameworks address ethical principles and model properties without providing operational guidance for implementation in clinical and administrative workflows [11]. The OECD documents that AI systems must be explainable, traceable, and

ethically defensible to sustain institutional trust, and identifies governance gaps as primary adoption barriers [4].

Contextual and workflow integration failure is operationally decisive. Greenhalgh and colleagues established in the NASSS framework that technology programs fail not because of clinical limitations but because of misalignment and fragmentation at the organizational level [8]. In AI deployment, the contextual scaffolding that makes pilots appear successful disappears in production, and the resulting friction generates alert fatigue, workarounds, and disengagement that compound over time.

3. The Digital Transformation Debt Framework

The DT-Debt framework provides a structured way to assess the organizational conditions producing the six AI value gaps described in Section 2. It is built around seven dimensions of digital debt, each representing a distinct category of organizational friction that accumulated past digital decisions have created. The seven dimensions are assessed through observable organizational signals, and their cumulative level across the organization positions it on a scale from highly constrained to fully ready. That position determines the organization's transformation archetype and drives the specific AI readiness guidance that follows.

The framework rests on four established theoretical traditions. Technical debt theory, developed by Kruchten and colleagues [12] and extended to enterprise contexts by Lim and colleagues [13], establishes that short-sighted digital decisions accumulate as long-term structural costs that compound until addressed. Sociotechnical systems theory, operationalized for health IT by Sittig and Singh [14], frames digital performance as a function of interdependent technical and human factors. Digital transformation science, synthesized by Vial [15], characterizes transformation outcomes as shaped by governance, workforce, process, and data alignment. The NASSS framework developed by Greenhalgh and colleagues establishes that technology program success depends on organizational readiness across multiple non-technical dimensions at the system, organizational, and individual levels [8]. The DT-Debt framework operationalizes these traditions into a practical assessment instrument.

3.1 The Seven Debt Dimensions

Each dimension captures a distinct and well-documented category of organizational friction that impedes AI and digital performance. The seven dimensions are not independent: high debt in one dimension typically amplifies the consequences of debt in others. Technology Debt and Data Debt interact because fragmented integration architectures produce the interface gaps that create data quality problems. Governance Debt and Workforce Debt interact because unclear accountability structures allow shadow IT and competency gaps to persist without organizational response. Understanding each dimension individually and then reading them cumulatively is the core analytical discipline the framework requires.

Table 1 defines each of the seven dimensions, describes what it measures, and characterizes the observable signals associated with high debt in that dimension. These signals are designed to be assessable through structured conversation, document review, system analysis, and operational observation, without requiring dedicated measurement infrastructure.

Table 1
The seven DT-Debt dimensions: definitions and signals of high debt.

Debt dimension	What it measures	Signals of high debt
Technology Debt	The structural burden of legacy platforms, excessive EHR or system customization, and integration complexity. Reflects how much past technology investment now constrains the organization rather than enabling it.	Most core systems are more than a decade old with no active retirement plan; extensive non-standard customization that requires specialist maintenance; integration architecture dominated by point-to-point connections; substantial end-of-life infrastructure; recurring unresolved security vulnerabilities.
Data Debt	The quality, completeness, standardization, and timeliness of clinical and operational data. Reflects whether the data the organization produces can be trusted and used reliably by analytical and AI systems.	Pervasive missingness in critical clinical and operational fields; inconsistent or non-standard coding across systems; most interfaces not FHIR- or API-enabled; persistent duplicate patient records without active resolution; significant data latency that prevents near-real-time use.
Process Debt	The manual burden, variability, and inefficiency embedded in clinical and operational workflows. Reflects how much organizational friction is baked into the way work actually gets done, as distinct from how it is supposed to get done.	Most workflow steps performed manually with no automation roadmap; high number of handoffs creating delay and error; wide variation in how the same process is performed across units; frequent rework; cycle times substantially above comparable benchmarks.
Workforce Debt	The gap between the digital competency that AI-enabled workflows require and the competency the existing workforce currently holds. Includes readiness to adopt, ability to operate, and capacity to adapt as tools evolve.	A substantial proportion of staff do not meet defined digital competency expectations; large backlog of overdue required training; widespread use of unauthorized tools as workarounds; high rates of technology-related burnout; significant non-adoption of required tools within defined windows.
Governance Debt	The structural absence of the policies, data stewardship roles, and decision rights that accountable digital and AI operations require. Reflects whether the organization has the authority structures to make digital decisions consistently and defend them.	Large proportion of required digital and data governance policies outdated or absent; most data domains lack assigned stewards with defined accountability; overlapping or unclear governance authority; frequent unresolved audit findings; digital investments made without alignment to organizational strategy.
Vendor Debt	The contractual, architectural, and operational constraints imposed by the existing vendor ecosystem. Reflects how much the organization is locked into past procurement decisions that now limit flexibility, increase cost, and impede modernization.	Deep dependency on one or more vendors with contractual or technical barriers to switching; long-term, rigid contracts not accommodating change; numerous redundant systems performing overlapping functions; large backlog of unimplemented change requests; frequent SLA non-compliance with limited consequence.

Debt dimension	What it measures	Signals of high debt
Experience Debt	The usability and accessibility deficits in patient-facing and clinician-facing digital tools. Reflects the degree to which the digital environment produces burden, fragmentation, and disengagement rather than supporting the people using it.	Consistently low usability ratings from patients and clinicians; multiple safety or quality incidents with a digital interface contributing factor; highly fragmented digital experience requiring navigation of many separate portals; most tools not meeting accessibility standards; tools procured without user input.

3.2 From Seven Dimensions to a Cumulative Debt Scale

No single dimension determines an organization's overall readiness for AI. The cumulative level of debt across all seven dimensions, viewed together, determines the structural conditions the organization is operating within and the AI failure modes it faces. An organization with low debt in five dimensions but high debt in Data Debt and Governance Debt still faces two of the most consequential AI failure risks simultaneously, because data quality undermines every model's training and inference supply, and governance absence prevents any model from being defended under regulatory scrutiny.

The cumulative assessment proceeds in two steps. First, each of the seven dimensions is assessed as high, moderate, or low debt based on the observable signals described in Table 1. The assessment relies on practitioner judgment informed by the signal descriptions, applied through structured conversation with operational leaders, informaticists, clinical staff, and governance bodies. Second, the pattern of assessments across the seven dimensions is used to position the organization on the cumulative debt scale and assign it to one of four transformation archetypes. The archetypes are not rigid categories. They are anchors on a continuum, designed to give health system leaders a practical language for describing their organization's current state and the specific investment priorities that follow from it.

The four archetypes are: Transformation-Constrained, for organizations where high debt predominates across four or more dimensions; Partially Modernized, for organizations with moderate or high debt in three to five dimensions but at least one or two at low debt; Functionally Ready, for organizations with low or moderate debt in most dimensions and high debt in no more than one or two; and AI-Ready, for organizations with low debt across all or nearly all seven dimensions. These archetypes are described in detail in Section 3.3.

Two dimensions carry greater weight in the cumulative assessment because their debt has consequences that cut across multiple AI failure modes simultaneously. Data Debt, when high, undermines model performance regardless of what the model is doing or which workflow it is serving. Governance Debt, when high, prevents any AI output from being defended, documented, or made accountable, regardless of the technical quality of the model. When either of these two dimensions is assessed as high, the organization's overall readiness classification should not be higher than Partially Modernized, even if other dimensions are at low debt.

3.3 The Four Transformation Archetypes

Table 2 describes the four transformation archetypes, including the debt profile across the seven dimensions that characterizes each archetype, the organizational conditions that profile produces, and the AI readiness implication that follows. The table is the central instrument of the framework: it connects the debt assessment to organizational reality and organizational reality to AI strategy.

Table 2

The four DT-Debt transformation archetypes: debt profiles, organizational characteristics, and AI readiness implications.

Archetype and debt pattern	Debt profile across seven dimensions	Organizational characteristics	AI readiness implication
Transformation-Constrained High debt predominates across four or more of the seven dimensions	Technology, Data, and Governance debt are typically the most severe. Process and Workforce debt compound the structural fragility. Vendor and Experience debt add cost and adoption risk. The organization is held back on multiple fronts simultaneously.	Operations rely heavily on legacy systems and manual processes. Data is fragmented, incomplete, and not consistently governed. Digital governance is either absent or ineffective. Staff experience significant technology-related burden. The organization is in a reactive mode with digital decisions made in silos and limited strategic coherence.	Deploying AI in this environment predicts failure across all six AI value gap categories. Data quality will undermine model performance. Governance absence will prevent explainability and regulatory defense. Workforce burden will generate workarounds. Foundational remediation must precede any AI investment beyond low-risk administrative applications.
Partially Modernized Moderate or high debt in three to five dimensions, with at least one or two at low debt	Debt is uneven across the seven dimensions. The organization has made progress in some areas while others remain significantly burdened. Technology or Data debt is often high while Workforce or Experience debt may be more manageable. The profile is heterogeneous rather than uniformly impaired.	The organization has completed some modernization cycles and holds identifiable capabilities alongside visible gaps. Digital governance exists but has coverage holes. Workforce competency is adequate in some roles with defined gap populations in others. Process automation is partial. The overall digital posture is unstable because high-debt dimensions constrain performance even where low-debt dimensions are capable.	AI is viable in dimensions assessed as low debt, with structured shadow-mode validation protocols. Deploying AI in high-debt dimensions without prior remediation predicts the same failure modes as in the Transformation-Constrained archetype, localized to those domains. Sequencing AI deployment by dimension-level debt, starting in the lowest-debt areas, is the critical discipline at this stage.
Functionally Ready Low or moderate debt in most dimensions; high debt in no more than one or two	The majority of dimensions are at low or moderate debt. One or two elevated areas remain, typically Vendor Debt or Experience Debt, which create identifiable risk but do not undermine the broader organizational foundation.	The organization operates with predominantly modern, well-integrated platforms and consistent data governance. Workforce competency is broadly current. Process standardization is achieved in most areas. Leadership has a	AI deployment across the enterprise is viable with active performance monitoring. The remaining elevated dimensions should be excluded from or carefully managed within AI deployment scopes. Real-time model performance monitoring, clinician co-

Archetype and debt pattern	Debt profile across seven dimensions	Organizational characteristics	AI readiness implication
	Technology, Data, and Governance dimensions are generally sound.	coherent digital strategy that guides investment decisions. The elevated dimension or dimensions represent known challenges under active management rather than systemic dysfunction.	design cycles, and cross-departmental AI governance should be in place. The organization is ready to advance from pilots to scaled enterprise deployment.
AI-Ready Low debt across all or nearly all seven dimensions	All seven dimensions are at low debt. Technology is modern and well-integrated. Data is complete, governed, and FHIR-enabled. Processes are standardized and largely automated. Workforce competency is high and continuously updated. Governance is active and accountable. Vendor relationships are flexible. The digital experience is coherent and usable.	The organization has resolved the foundational organizational conditions that cause AI to fail. Digital decisions are made strategically and documented. Data can be trusted as a training and inference substrate. The workforce can adopt and adapt to AI-enabled workflows. Governance structures can provide the auditability and explainability that regulatory and clinical trust requires.	Full enterprise AI deployment, including generative and agentic applications, is organizationally viable. The six AI value gap risks that derail most healthcare AI initiatives are structurally mitigated. The organization can pursue advanced AI use cases and participate in cross-system benchmarking. Sustaining continuous model governance and workforce upskilling is the priority at this stage, not foundational remediation.

4. Mapping AI Value Gaps to DT-Debt Dimensions

The six AI value gaps characterized in Section 2 are not random or unpredictable organizational events. Each one is a direct consequence of specific, observable conditions in one or more of the seven DT-Debt dimensions. Table 3 presents the mapping, identifying for each AI value gap the root cause, the DT-Debt dimension or dimensions that predict it, and a description of how high debt in those dimensions produces the gap in practice.

Table 3
Six AI value gaps mapped to predicting DT-Debt dimensions.

AI value gap	Root cause	Predicting DT-Debt dimension(s)	How high debt in those dimensions produces the gap
Data quality and readiness	AI models are trained and inferred against data that is incomplete, inconsistently coded, and not structured for analytical use.	Data Debt (primary)	Pervasive field missingness and non-standard coding cause models to produce unreliable outputs from the first inference. Non-FHIR interfaces prevent data from flowing between systems. High Data Debt is the single strongest predictor of AI project abandonment because it operates at the foundation of every model's training and inference data supply [6, 7].
Pilot-to-production failure	Pilots succeed in curated environments with manual contextual scaffolding that disappears in production, causing accuracy and reliability to degrade.	Technology Debt; Process Debt	High Technology Debt creates integration barriers invisible in pilots: legacy systems and point-to-point interfaces that worked around during controlled testing become blockers in full deployment. High Process Debt means the workflow variability and manual steps present in production were not represented in pilot training conditions, causing model performance to degrade against real inputs [5].
Hidden cost and return on investment	Vendor quotes and business cases underestimate the organizational work required to deploy AI because they do not account for the debt the AI must integrate into.	Vendor Debt; Process Debt	High Vendor Debt means AI platform integration requires bespoke development not captured in quoted costs. Rigid contracts limit renegotiation when requirements change. High Process Debt means workflow redesign, a major cost driver, is more extensive than anticipated when processes are highly variable and manual. Both conditions combine to produce the systematic cost overruns documented in the McKinsey 2025 survey [2].
Workforce readiness	Clinicians and operational staff cannot effectively use AI tools because they lack the competency, the trust, or the freedom from existing digital burden to engage with new tools.	Workforce Debt	High Workforce Debt organizations have staff who are already fatigued by inadequate digital tools, have developed shadow IT workarounds that signal disengagement from sanctioned systems, and lack the competency foundations to engage with AI-enabled workflows. These conditions predict AI workaround behavior regardless of how well the model performs [10].

AI value gap	Root cause	Predicting DT-Debt dimension(s)	How high debt in those dimensions produces the gap
Governance and explainability	AI decisions cannot be documented, traced, or defended because the governance structures required for accountability do not exist.	Governance Debt	High Governance Debt means policies, stewardship roles, and decision rights are absent or unclear. Each AI model deployed without traceability infrastructure adds to regulatory liability. The OECD documents governance gaps as primary barriers to AI adoption equal in severity to data quality deficits [4]. Khashu establishes that operational implementation of trustworthy AI requires structural governance conditions that most organizations have not built [11].
Contextual and workflow integration	AI produces outputs that are technically correct but cannot be acted upon reliably because the clinical and operational workflow context is too fragmented or variable for the model to serve consistently.	Process Debt; Experience Debt	High Process Debt organizations have workflows that are highly variable across units, making it difficult for a model trained under one set of assumptions to serve multiple teams consistently. High Experience Debt means the digital environment is already generating alert fatigue and disengagement, and AI adds to rather than reduces that burden. Greenhalgh and colleagues document these as the organizational-level conditions that cause technology programs to fail even when the technology itself is sound [8].

The mapping reveals three important structural relationships. First, Data Debt and Governance Debt appear as predictors across the broadest range of AI value gaps. High Data Debt undermines both the data quality gap and contributes to pilot-to-production failure. High Governance Debt drives the explainability gap and impedes the contextual integration that AI requires to perform consistently across workflows. This is why these two dimensions carry elevated weight in the cumulative assessment described in Section 3.2.

Second, Process Debt appears as a predictor in three of the six gaps: pilot-to-production failure, hidden cost, and contextual integration. This reflects the fact that workflow complexity and variability are not just operational problems. They are AI deployment problems, because AI models are trained under assumptions of workflow consistency that highly variable organizations cannot sustain in production.

Third, Workforce Debt operates through a distinctive mechanism. It does not directly affect whether the AI model performs well. It determines whether the people whose behavior the AI is meant to support or change can actually engage with it. An organization can have excellent data, sound governance, and a technically well-performing model, and still fail to achieve behavioral adoption if Workforce Debt is high.

5. Application to Synthetic Health System Profiles

To demonstrate the framework's practical application, three synthetic health system profiles are described and assessed using the seven dimensions and archetype scale. The profiles are built from patterns of organizational conditions documented in the implementation literature, not from data collected from any specific institution. Debt levels were assigned by applying the criteria from Table 1 to the described conditions.

Organization L presents conditions associated with low debt across all seven dimensions. Its technology infrastructure is predominantly modern, vendor-supported, and API-integrated. Clinical and operational data are complete, consistently coded, and available through FHIR-enabled interfaces. Workflows are largely standardized and automated. Workforce competency is current and maintained through active upskilling programs. Governance is defined and accountable across all material data domains. Vendor relationships are structured for flexibility. Patient and clinician usability is consistently rated favorably. The cumulative assessment places Organization L in the AI-Ready archetype. The primary organizational objective is scaling AI value, not resolving debt. This organization can pursue generative AI and agentic applications with confidence in its organizational foundation.

Organization M presents mixed conditions. Technology infrastructure includes both modern platforms and legacy systems with a visible modernization backlog. Data completeness is adequate in major clinical domains but inconsistent in operational and ancillary systems. FHIR adoption is underway but incomplete. Process standardization has been achieved in some areas with persistent variation in others. Workforce competency is adequate in most roles with a defined gap population in clinical informatics. Governance is established but has coverage holes in less visible data domains. Vendor relationships are moderately flexible with some restrictive terms under negotiation. Clinician usability ratings are mixed with known pain points. Technology Debt and Data Debt are assessed as moderate to high; the remaining dimensions are at moderate or low debt. The cumulative assessment places Organization M in the Partially Modernized archetype. AI is viable in lower-debt domains such as administrative automation and ambient documentation, with shadow-mode validation required before any system assumes operational authority. Clinical decision support over non-FHIR data sources should be deferred until Data Debt is reduced.

Organization H presents conditions associated with high debt across the majority of dimensions. Core systems are predominantly legacy with extensive customization and point-to-point integration. Critical data fields have pervasive missingness and inconsistent coding. Most interfaces are not FHIR-enabled. Process variability is extensive, with wide variation in how core workflows are executed across clinical and operational units. Workforce debt is elevated across all five signals: major skill gaps, widespread shadow IT, and high technology-related burnout. Governance gaps are pervasive, with most data domains lacking assigned stewards. Vendor relationships are rigid with a large backlog of unimplemented change requests. Clinician usability is poor with a fragmented patient-facing experience. The cumulative assessment places Organization H in the Transformation-Constrained archetype.

Deploying AI in this environment, in any clinical or operational workflow beyond low-risk administrative applications, predicts failure across all six gap categories documented in Section 2. The investment priority is debt reduction, and the AI business case should be made for data governance, pipeline modernization, and governance establishment rather than model acquisition.

6. Archetype-Specific AI Readiness Guidance

Each archetype on the DT-Debt scale requires a distinct set of organizational priorities, AI deployment decisions, and progress measures. Table 4 presents the archetype-specific guidance in full. The sections below describe the reasoning behind each archetype's recommendations.

Table 4

Archetype-specific AI readiness guidance: priorities, deployment decisions, and leading indicators.

Archetype	Immediate organizational priorities	AI deployment guidance	Leading indicators of progress
Transformation-Constrained	Conduct a dimension-by-dimension DT-Debt assessment to establish a baseline and identify where debt is most severe. Establish an AI governance council before any AI models are deployed. Begin data pipeline remediation, legacy retirement planning, and master data management. Set explicit debt reduction milestones as prerequisites for clinical AI deployment approval.	Defer clinical and operational AI deployment until at least Data Debt and Governance Debt are reduced to moderate levels. Permit AI only in low-risk, reversible administrative applications with no direct clinical decision consequence, such as scheduling assistance or documentation support, where model errors carry minimal harm potential. Do not approve AI platform procurement without a parallel debt reduction plan.	Proportion of critical data fields reaching completeness targets. Number of data domains with assigned and active stewards. Progress against legacy retirement milestones. Governance policy coverage rate across required digital domains.
Partially Modernized	Map dimension-level debt profiles to specific AI use cases under consideration. Prioritize process standardization, FHIR interface enablement, and governance gap closure in the dimensions that predict failure for the AI use cases the organization is pursuing. Invest in role-specific workforce upskilling with behavioral validation rather than module completion tracking.	Run shadow-mode AI validation in parallel with existing workflows before any system assumes operational authority. Restrict AI pilots to the dimensions assessed as low debt. Require a parallel-run period of sufficient duration to detect performance instability before clinical deployment. Expand to moderate-debt dimensions only after targeted remediation in those areas is confirmed.	Number of AI use cases successfully exiting shadow-mode validation. FHIR interface adoption rate across clinical data domains. Reduction in shadow IT incidence. Workforce competency attainment rates in roles targeted for AI-enabled workflows.

Archetype	Immediate organizational priorities	AI deployment guidance	Leading indicators of progress
Functionally Ready	Address the one or two remaining elevated dimensions through targeted remediation. Establish real-time AI model performance monitoring infrastructure. Build cross-departmental AI governance with defined escalation paths and model review cycles. Implement clinician co-design processes to align model outputs with workflow requirements as both evolve.	Proceed with phased enterprise AI rollout sequenced by dimension-level debt. Include advanced use cases such as clinical decision support and predictive analytics in lower-debt domains. Active model performance monitoring with defined response protocols for degradation should be in place before any AI system assumes operational authority at scale.	Model performance stability across production environments over time. Clinician adoption rates for AI-enabled workflows. Reduction in AI-related workaround behavior reported through incident or safety systems. Progress toward resolution of the remaining elevated debt dimensions.
AI-Ready	Sustain continuous model governance and performance review cycles. Maintain workforce upskilling programs that keep competency current as model capabilities evolve. Participate in cross-system benchmarking to contextualize performance. Publish outcomes data to contribute to the evidence base for the field.	Deploy full enterprise AI including generative and agentic applications where clinical and operational evidence supports it. The six AI value gap risks that derail most healthcare AI initiatives are organizationally mitigated at this stage. Innovation and value creation, not debt remediation, are the appropriate investment priorities.	AI-attributable impact on clinical and operational outcomes. Enterprise AI coverage as a proportion of targeted use cases. Workforce AI competency maintenance rates. Contribution to published benchmarking or outcomes research.

6.1 Transformation-Constrained

For organizations in this archetype, the investment case for AI should be redirected before it is submitted. The business case at this stage is not for AI models. It is for the organizational conditions that AI requires: data governance, pipeline modernization, legacy retirement, and governance council establishment. Approving AI platform procurement without a parallel debt reduction plan is not a calculated risk. It is an organizationally predictable path to the pilot purgatory, cost overruns, and clinical disengagement documented in Section 2.

The immediate step is a dimension-by-dimension DT-Debt assessment to establish a baseline. This baseline serves two purposes. It identifies which dimensions require the most urgent remediation and which can be sequenced later. And it creates the explicit, documented readiness milestones against which future AI deployment approvals can be gated. Explicit milestones are essential in this archetype

because without them, organizational and vendor pressure will restart the cycle of premature AI deployment before the foundational conditions are in place.

6.2 Partially Modernized

Organizations in this archetype face a discipline problem more than a capability problem. The capability to support AI exists in some dimensions. The discipline required to sequence AI deployment by dimension-level debt, rather than deploying uniformly across the organization, is what separates successful AI programs from expensive failures at this stage.

Shadow-mode validation is the most important risk mitigation available. Running AI in parallel with existing workflows, before it assumes operational authority, exposes the performance gaps that do not appear in pilots. It also creates the organizational learning that builds clinician trust in AI outputs before those outputs carry clinical consequence. The parallel-run period should be long enough to detect performance instability across a representative range of operational conditions, not just under favorable input distributions.

6.3 Functionally Ready

The shift from Functionally Ready to AI-Ready requires resolving the one or two remaining elevated dimensions and building the monitoring infrastructure that sustains AI performance over time. Organizations at this stage frequently underinvest in model performance monitoring because they have successfully deployed AI and the urgency that drove earlier remediation has diminished. The operational discipline required to sustain AI performance is different from the discipline required to deploy it initially, and organizations that do not build that discipline will experience gradual performance degradation that generates the same disengagement outcomes as failure at earlier stages.

6.4 AI-Ready

AI-Ready organizations have resolved the foundational organizational conditions that cause AI to fail in the other three archetypes. The priority at this stage is not remediation. It is sustaining the conditions that make AI performance reliable as both organizational and model conditions change over time. Workforce competency must be continuously updated as model capabilities evolve. Model performance must be continuously monitored as patient populations, workflow patterns, and data inputs shift. Governance structures must be sustained and kept current with regulatory developments. The organizations achieving the strongest AI returns in the McKinsey 2025 survey are in this archetype, and their returns reflect the compounding advantage of having built the organizational foundation before scaling deployment [2].

7. Discussion

7.1 Contributions

This paper makes four contributions. First, it characterizes six structural AI value gaps in healthcare using multi-source evidence with verified authorship and confirmed DOIs. Second, it introduces the DT-Debt framework, which provides a structured seven-dimension assessment that positions any organization on a cumulative debt scale and classifies it into one of four archetypes. Third, it maps the six AI value gaps to the specific DT-Debt dimensions that predict them, showing that AI failure is not random but a direct consequence of identifiable organizational conditions. Fourth, it provides archetype-specific AI readiness guidance with distinct priorities, deployment decisions, and progress indicators for each position on the debt scale.

The framework's design reflects a specific methodological choice. A qualitative, signal-based rubric was selected over a quantitative scoring instrument because the organizations that most need readiness assessment, those at the Transformation-Constrained end of the scale, are the least likely to have the data collection infrastructure that a 35-indicator quantitative instrument requires. The rubric is accessible through structured conversation, document review, and operational observation. It produces the dimension-level differentiation required to sequence AI deployment decisions without requiring measurement systems that do not yet exist.

7.2 Relationship to Existing Frameworks

The DT-Debt framework complements existing digital maturity models such as HIMSS EMRAM and the NHS Digital Maturity Assessment. Those frameworks measure capability presence and adoption milestones, answering what the organization has achieved. The DT-Debt framework measures accumulated friction, answering what is preventing the organization from extracting value from what it already has. A health system can achieve high maturity scores while carrying high DT-Debt in dimensions that will predict AI failure. The two perspectives are complementary and most informative when used together.

The relationship to Khashu's published framework for operationalizing trustworthy AI [11] is additive rather than overlapping. That framework establishes the structural conditions AI systems require to be explainable, traceable, and clinically reliable. The DT-Debt framework establishes whether those conditions currently exist within the organization. Together, they address the design requirements for trustworthy AI and the organizational readiness to implement them.

7.3 Implications for Practice

The central practical implication is that the AI investment decision and the DT-Debt assessment should occupy the same planning cycle. An organization approving AI platform procurement without first conducting a dimension-level DT-Debt assessment and assigning itself to an archetype is committing investment without a readiness baseline. The archetype determines what that investment should be used for: debt remediation in Transformation-Constrained organizations, targeted domain remediation and shadow-mode deployment in Partially Modernized organizations, phased enterprise rollout in Functionally Ready organizations, and scaled innovation in AI-Ready organizations.

The staged guidance in Section 6 is also a board-level narrative. It gives health system leaders a principled explanation for why foundational investment in data governance, workforce readiness, and governance structures is a prerequisite for AI return on investment, not a competitor to it. The organizations achieving the strongest AI returns in the McKinsey 2025 survey built those foundations before scaling deployment [2]. The DT-Debt framework provides the instrument to determine where an organization stands relative to those foundations and what must change.

7.4 Limitations and Future Research

The DT-Debt framework is introduced as a conceptual instrument supported by synthetic application rather than empirical validation. The four archetypes and the signal-based rubric represent structured interpretations of organizational conditions drawn from the implementation literature, not from a calibrated measurement instrument with tested inter-rater reliability. Future research should validate the rubric through structured expert review, inter-rater agreement studies, and multi-site application against actual AI implementation outcomes. Longitudinal application could reveal whether debt reduction in specific dimensions predicts corresponding improvements in AI deployment success. A quantitative extension of the framework, translating the qualitative rubric levels into measurable indicator thresholds, could provide greater precision for organizations with the infrastructure to support it.

8. Conclusions

Healthcare organizations are investing in AI at accelerating rates while the organizational conditions for AI success remain unbuilt in the majority of institutions. The six AI value gaps documented in this paper are not surprises that emerge after deployment. They are the predictable consequences of specific, diagnosable organizational conditions that the DT-Debt framework can assess before a single dollar of AI capital is committed.

The DT-Debt framework gives health system leaders three things they currently lack in most AI investment discussions. It gives them a structured language for describing the organizational conditions that determine AI readiness, built around seven dimensions that each represent a well-documented category of friction. It gives them a cumulative scale that translates those seven assessments into an organizational archetype with specific characteristics and specific failure modes. And it gives them archetype-specific guidance that converts the readiness assessment into concrete investment priorities, deployment decisions, and progress indicators.

Starting the AI journey on the right footing does not mean delaying AI. It means being precise about what the organizational foundation for AI looks like, honest about where the organization currently stands, and disciplined about sequencing investment to build that foundation before deployment in contexts where it does not yet exist. Organizations that do this will avoid the structural failure modes that have stalled the majority of healthcare AI initiatives. Organizations that do not will continue to invest in technology that their organizational conditions are not built to support.

Declarations

Author Contributions

K.K.: Conceptualization; methodology; formal analysis; writing (original draft); writing (review and editing).

Funding

The author received no external funding for this work.

Competing Interests

The author declares no competing interests.

Ethics Approval

Not applicable.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

Clinical Trial Number

Not applicable.

Data Availability

No datasets were generated or analyzed during the current study. Synthetic profiles were constructed by the author using the qualitative rubric described in Section 3.

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