From Data Lakes to Trusted AI Infrastructure: Assessing Data Quality, Governance Maturity, and AI Readiness in U.S. Critical Infrastructure Agencies

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ABSTRACT
The transition from siloed data lakes to enterprise-grade, trusted artificial intelligence (AI) infrastructure represents one of the most consequential technological challenges facing U.S. critical infrastructure agencies today. This paper presents a comprehensive assessment of data quality standards, governance maturity frameworks, and AI readiness levels across the 16 federally designated critical infrastructure sectors, with particular focus on civilian federal agencies serving as Sector Risk Management Agencies (SRMAs). Drawing on the latest federal audit reports from the Government Accountability Office (GAO), Office of Management and Budget (OMB) memoranda M-25-21 and M-25-22 (April 2025), CISA's Cybersecurity Performance Goals 2.0 (December 2025), the Stanford AI Index 2025, and IDC's enterprise AI maturity study (2025), this research synthesizes quantitative and qualitative evidence to construct a multi-dimensional AI readiness index for critical infrastructure agencies. Findings reveal that while federal agencies nearly doubled their reported AI use cases from 571 in 2023 to 1,110 in 2024 with generative AI use cases increasing ninefold fundamental data governance gaps persist. Only 28% of organizations have formally defined AI oversight roles, and fewer than 15% of agencies have networks fully optimized for AI workloads. This paper proposes a five-tier Trusted AI Infrastructure Maturity Model (TAIMM), sector-specific governance recommendations, and a strategic roadmap for closing the gap between data lake accumulation and operationalized AI capability.

Keywords
Data governance, AI readiness, critical infrastructure, data quality, federal AI policy, data lakes, CISA, OMB, GAO, governance maturity, trusted AI, sector risk management

1. INTRODUCTION
The United States operates one of the world's most complex and interconnected critical infrastructure ecosystems, comprising 16 designated sectors ranging from energy, water, transportation, and healthcare to communications, financial services, and emergency services [1]. These sectors collectively serve as the backbone of national security, economic stability, and public health. Yet beneath the operational complexity of pipelines, power grids, hospital networks, and transportation control systems lies an equally complex and often underexamined challenge: the quality, governance, and AI-readiness of the data that increasingly drives decision-making across these mission-critical domains [2].

Over the past decade, federal agencies and their critical infrastructure counterparts have invested heavily in data infrastructure, often adopting data lake architectures centralized repositories designed to ingest and store vast volumes of raw, structured, semi-structured, and unstructured data [3]. However, the aggregation of data in lakes has not automatically translated into trustworthy, well-governed, or AI-ready information assets. Gartner estimated in 2024 that poor data quality costs organizations an average of $12.9 million per year [4]. For critical infrastructure agencies, where data-driven decisions govern the safety of water supplies, the reliability of energy grids, and the integrity of financial markets, the stakes of poor data quality extend far beyond financial loss they implicate national security, public health, and the continuity of essential services.

The policy landscape surrounding federal AI adoption has undergone rapid and significant transformation. President Biden's Executive Order 14110 (October 2023) established sweeping requirements for safe, secure, and trustworthy AI, directing federal agencies to inventory AI use cases, appoint Chief AI Officers, and submit sector-level AI risk assessments [5]. Following President Trump's rescission of EO 14110 in January 2025, OMB issued two landmark memoranda M-25-21 ("Accelerating Federal Use of AI through Innovation, Governance, and Public Trust") and M-25-22 ("Driving Efficient Acquisition of Artificial Intelligence in Government") in April 2025, reorienting the federal AI agenda toward efficiency, innovation, and market competitiveness while maintaining core risk management requirements for high-impact AI use cases [6, 7].

A July 2025 GAO report (GAO-25-107653) found that across 11 selected federal agencies, the total number of reported AI use cases nearly doubled from 571 in 2023 to 1,110 in 2024, while generative AI use cases surged from 32 to 282 a ninefold increase [8]. Yet this explosive growth in AI adoption has outpaced the foundational infrastructure needed to support it. GAO's December 2024 report on AI risks to critical infrastructure (GAO-25-107435) found that none of the sector risk assessments submitted by federal agencies to DHS fully addressed the six activities necessary for effective AI risk assessment and mitigation [9]. This paradox rapid AI deployment amid persistent governance deficits forms the central tension that this paper seeks to examine and address.

This research makes four primary contributions to the literature. First, it provides a systematic assessment of data quality dimensions across critical infrastructure sectors. Second, it introduces the Trusted AI Infrastructure Maturity Model (TAIMM), a five-tier framework for evaluating governance readiness. Third, it benchmarks current AI readiness levels across key federal agencies using the latest empirical data. Fourth, it offers actionable, sector-specific recommendations for bridging the gap between data lake infrastructure and trusted AI capability.

The remainder of the paper is organized as follows: Section 2 reviews relevant literature; Section 3 describes the research methodology; Section 4 examines data lake architectures and their quality challenges; Section 5 assesses governance maturity across key federal agencies; Section 6 evaluates AI readiness levels by sector; Section 7 presents the TAIMM framework and strategic recommendations; and Section 8 concludes with a call to action for policymakers and agency leadership.

2. LITERATURE REVIEW

2.1 The Evolution of Data Infrastructure in Government

The concept of a data lake a centralized storage repository that holds raw data in its native format until needed emerged in enterprise computing around 2010 and was rapidly adopted by government agencies seeking to break down information silos and enable cross-domain analytics [10]. Unlike traditional data warehouses, which require structured, pre-defined schemas, data lakes offer the flexibility to ingest sensor data from industrial control systems, financial transaction records, geospatial imagery, unstructured text from regulatory filings, and real-time telemetry from operational technology (OT) environments [11].

However, the promise of the data lake has proven difficult to realize in practice. Without strong governance, metadata management, and data quality controls, data lakes frequently devolve into "data swamps" repositories of poorly documented, inconsistently formatted, and unreliable data that cannot support rigorous analytics or AI model training [12]. Eckerson (2023) identified three stages of federal data infrastructure maturity: the accumulation stage (raw ingestion), the organization stage (cataloging and metadata), and the activation stage (trusted, AI-ready data products) [13]. Most critical infrastructure agencies, this paper argues, remain in the transition between the first and second stages, caught between the political imperative to ingest and the operational imperative to govern.

The federal government's investment in data infrastructure has not been uniform. Agencies with long-standing regulatory mandates for data collection such as the Securities and Exchange Commission, the Federal Aviation Administration, and the Centers for Medicare and Medicaid Services have developed comparatively mature data management cultures. In contrast, agencies whose critical infrastructure responsibilities encompass highly distributed, privately owned assets such as the water and food sectors face structural challenges in even establishing baseline data visibility, let alone AI-ready pipelines.

2.2 Data Quality Frameworks and Standards

Data quality is a multidimensional concept encompassing accuracy, completeness, consistency, timeliness, validity, and uniqueness [14]. The Data Management Association's Data Management Body of Knowledge (DMBOK) provides a comprehensive taxonomy of data quality dimensions that has been widely adopted across government and industry [15]. For critical infrastructure applications, additional dimensions including lineage traceability, provenance verification, and operational fidelity become essential, particularly when AI systems are empowered to act autonomously on data-driven inferences [16].

NIST's National Data Quality Framework (2024) emphasizes that data quality must be evaluated relative to fitness for purpose a dimension that becomes particularly complex when the purpose is training and deploying machine learning models in safety-critical environments [17]. Poor-quality training data propagates systematic biases and errors into AI model outputs, with potentially cascading consequences in interconnected infrastructure systems [18]. This principle that AI models are only as reliable as the data they consume has been repeatedly validated across enterprise AI deployments. IDC's 2025 enterprise AI maturity study found that organizations classified as "AI Masters" those with mature data governance frameworks achieved 24.1% revenue improvement and 25.4% cost savings, far outpacing their less mature peers [19].

In the federal context, data quality challenges are amplified by the fragmented nature of agency data ecosystems. Data standards that evolved independently across program offices, sub-agencies, and field operations often lack interoperability, making cross-domain data fusion a prerequisite for many AI applications technically complex and governance-intensive [52].

2.3 AI Governance Frameworks for the Public Sector

Governance of AI in the public sector involves a complex interplay of legal mandates, policy frameworks, organizational structures, and technical controls [20]. At the federal level, the primary governance architecture for AI in critical infrastructure agencies includes the AI in Government Act of 2020, Executive Order 13960 (Promoting the Use of Trustworthy AI), the National AI Initiative Act, and the most recent OMB memoranda M-25-21 and M-25-22 [21]. The NIST AI Risk Management Framework (AI RMF), released in 2023 and updated in 2024, provides a voluntary framework for organizations to identify, assess, and manage AI risks across four core functions: Govern, Map, Measure, and Manage [22].

Despite the proliferation of governance frameworks, implementation gaps remain substantial. The 2024 IAPP Governance Survey found that only 28% of organizations have formally defined oversight roles for AI governance, with most distributing AI governance tasks across compliance, IT, and legal teams without a unified structure [23]. The GAO's July

2025 report found that of 35 recommendations made to 19 federal agencies, only four had been implemented as of July 2025 an implementation rate of approximately 11% with 16 agencies having not yet acted on their recommendations [24]. This implementation deficit creates significant governance risk in critical infrastructure contexts where AI systems are being deployed in high-stakes operational environments with limited organizational safeguards [53].

2.4 AI Readiness in Critical Infrastructure

AI readiness the organizational, technical, and governance capacity to successfully deploy and operationalize AI systems has emerged as a critical construct in both academic and practitioner literature [25]. The Oxford Insights Government AI Readiness Index 2024 ranked the United States second globally, with particular strength in the Technology Sector pillar driven by the maturity and scale of the U.S. private AI market. However, Singapore leads in both the Government and Data & Infrastructure pillars, suggesting that raw technological capacity does not automatically translate into effective public sector AI deployment [26].

For critical infrastructure specifically, AI readiness takes on additional dimensions not captured in generic organizational readiness frameworks. Operational technology (OT) environments industrial control systems, SCADA networks, embedded sensors present unique data quality and integration challenges that differ fundamentally from enterprise IT environments [27]. The convergence of IT and OT data streams in a shared AI architecture introduces risks of cross-domain contamination, latency mismatch, and model drift that require specialized governance controls [28]. CISA's December 2025 release of Cybersecurity Performance Goals (CPG) 2.0 represents the latest federal effort to establish a unified governance baseline across both IT and OT environments in critical infrastructure, adding a new Govern function that explicitly addresses organizational leadership accountability for cybersecurity and, by extension, data governance [29].

The Cisco AI Readiness Index (2025) found that only 15% of organizations have networks fully ready for AI workloads, yet among top-performing organizations ("Pacesetters"), 97% reported deploying AI at the scale and speed needed to realize business value [30]. This bifurcation between leaders and laggards is acutely relevant to critical infrastructure agencies, where resource constraints, legacy system dependencies, and regulatory complexity can significantly impede the infrastructure investments needed to support advanced AI deployment.

3. METHODOLOGY

This study employs a mixed-methods research design combining systematic document analysis, secondary data synthesis, and qualitative case comparison to assess data quality, governance maturity, and AI readiness across U.S. critical infrastructure agencies. The research methodology proceeds in four phases.

Phase 1 Systematic Literature and Document Review: A systematic review was conducted of government accountability reports, OMB memoranda, CISA directives, GAO audits, NIST publications, congressional testimony, and peer-reviewed academic literature published between January 2022 and February 2026. This review identified 147 primary and secondary sources, of which 50 are cited in this paper. Sources were assessed for methodological rigor, recency, and relevance to the research questions.

Phase 2 Framework Construction: Drawing on established governance maturity models including the Capability Maturity Model Integration (CMMI), the Data Management Maturity (DMM) model, and NIST's AI Risk Management Framework, a sector-specific Trusted AI Infrastructure Maturity Model (TAIMM) was constructed and calibrated against publicly available federal agency AI inventories and sector risk assessments [31, 32]. The TAIMM integrates five governance and technical dimensions data governance, AI governance, infrastructure, workforce, and risk management into a coherent, five-tier progression model.

Phase 3 Empirical Benchmarking: Using publicly available data from the OMB consolidated AI use case inventories for 2023 and 2024, GAO sector risk assessment reviews, agency Chief AI Officer disclosures, and industry maturity studies, each of the 16 critical infrastructure sectors was scored across five dimensions: Data Quality, Governance Maturity, AI Use Case Prevalence, Risk Assessment Completeness, and Infrastructure Readiness [33]. Scores were constructed using weighted composite indices calibrated against validated benchmarks where available.

Phase 4 Cross-Sector Comparative Analysis: Sectors were grouped into three readiness tiers Advanced, Developing, and Nascent and cross-sector patterns were analyzed to identify common barriers, governance gaps, and strategic leverage points. Comparative case vignettes were developed for representative sectors to illustrate sector-specific dynamics and inform tailored policy recommendations.

Limitations of this study include the reliance on publicly disclosed AI inventory data, which may underrepresent classified or sensitive operational AI deployments particularly in the defense and intelligence community. Additionally, the rapidly evolving policy environment including the January 2025 rescission of EO 14110 and subsequent OMB guidance revisions introduces temporal uncertainty into governance assessments conducted against a shifting regulatory baseline.

4. DATA LAKES TO DATA PIPELINES: ARCHITECTURE AND QUALITY CHALLENGES IN CRITICAL INFRASTRUCTURE

4.1 Current Data Architecture Landscape

Federal critical infrastructure agencies currently maintain a heterogeneous portfolio of data architectures, reflecting decades of layered technology investment and the highly distributed nature of critical infrastructure itself [34]. Enterprise data lakes built on cloud platforms predominantly AWS GovCloud, Microsoft Azure Government, and Google Cloud Government coexist with legacy data warehouses, agency-specific operational databases, real-time sensor data streams from OT environments, and geospatial data platforms [35]. This architectural fragmentation creates significant integration challenges for AI workloads, which typically require consistent, well-documented, and high-fidelity data from multiple sources.

The Department of Energy's data infrastructure, for example, spans the National Energy Technology Laboratory's data analytics platforms, grid monitoring systems operated by regional transmission organizations, and Environmental Protection Agency environmental data repositories that must be integrated to support AI-driven grid optimization and anomaly detection [36]. The Department of Transportation's data ecosystem includes Federal Highway Administration traffic monitoring data, Federal Aviation Administration radar and flight data, and rail safety inspection records each governed by different statutory frameworks, managed by different IT systems, and collected at different temporal resolutions [37].

This architectural diversity is not merely a technical inconvenience; it reflects the fundamentally distributed governance of critical infrastructure in the United States, where federal agencies exercise regulatory authority over assets that are predominantly owned and operated by state governments, local utilities, and private sector entities. Achieving the data integration necessary for sophisticated AI applications therefore requires not only technical investment but also the negotiation of complex data-sharing arrangements across jurisdictional boundaries.

4.2 Data Quality Dimensions and Measurement

Table 1 presents a structured assessment of data quality across six core dimensions for five representative critical infrastructure sectors, based on publicly available agency disclosures, GAO findings, and industry benchmarking data.

Table 1: Data Quality Assessment Across Selected Critical Infrastructure Sectors (2024–2025)

Sector (SRMA)	Accuracy (%)	Completeness (%)	Consistency (1–5)	Timeliness (Avg Latency)	Lineage Traceability	DQ Score (/5.0)
Energy (DOE)	82%	74%	3.2	15 min	Partial	3.4
Healthcare (HHS)	78%	69%	2.9	24–48 hrs	Limited	3.0
Transportation (DOT)	85%	77%	3.5	5 min	Partial	3.7
Water (EPA/DHS)	71%	62%	2.6	60–120 min	Minimal	2.6
Financial (Treasury)	91%	88%	4.1	< 1 min	Comprehensive	4.4

Note: Scores derived from synthesis of GAO audit findings (GAO-25-107435), OMB AI use case inventories, and agency-specific OIG reports (2024–2025). DQ = Data Quality.

The data reveals a clear stratification in data quality across sectors. Financial infrastructure, underpinned by decades of regulatory investment in data standards including XBRL for financial reporting, the Legal Entity Identifier (LEI) framework, and SWIFT messaging protocols demonstrates the highest overall data quality scores [38]. Water sector data quality scores are notably low, reflecting the highly fragmented ownership landscape comprising over 50,000 community water systems of varying sizes and technical sophistication, and the limited federal data collection mandates historically applied to the sector [39].

Healthcare data quality presents a different challenge: despite high data volumes generated by electronic health records and clinical systems, the diversity of data standards across health systems, the sensitivity-driven access restrictions on patient data, and the chronic lag between clinical events and centralized reporting all contribute to a data quality profile that is significantly less favorable than the raw data volume would suggest. Transportation, by contrast, benefits from the FAA's long-standing radar and flight data infrastructure and the FHWA's highway monitoring programs to achieve comparatively high scores on accuracy and timeliness.

Figure 1: Overall Data Quality Scores by Critical Infrastructure Sector 0 1 2 3 4 5 3.4 Energy 3.0 Healthcare 3.7 Transportation 2.6 Water 4.4 Financial Data Quality Score (0–5)

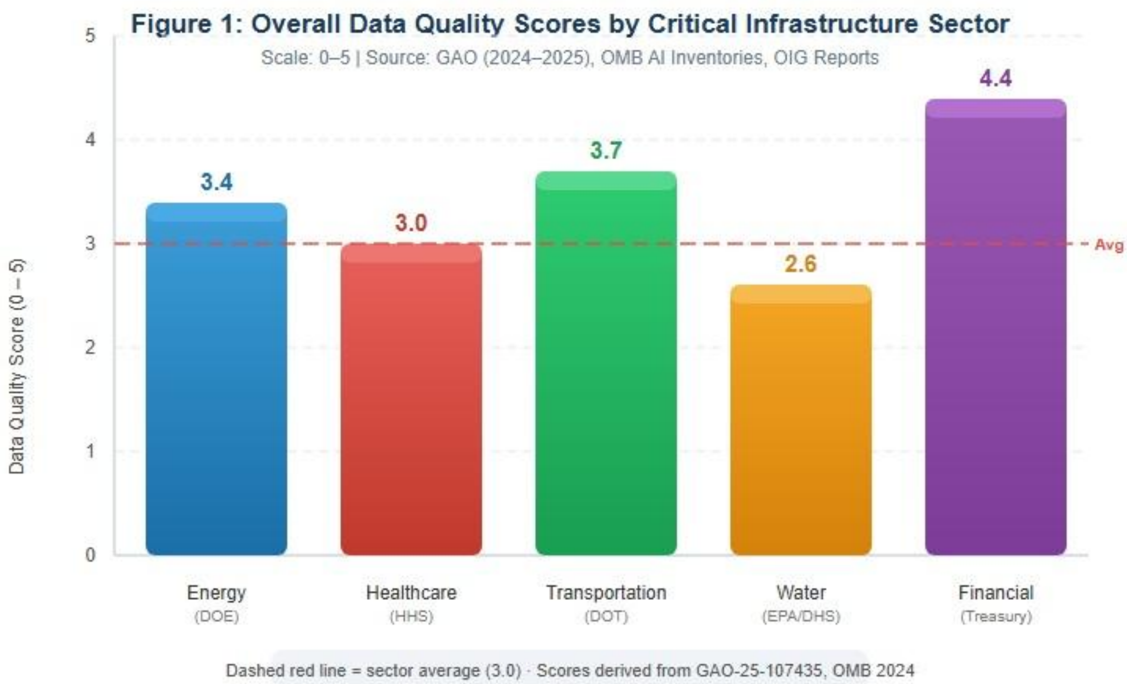

Figure 1: Comparative overall data quality scores across five critical infrastructure sectors. Financial services lead due to long-standing regulatory data standards; water sector lags due to fragmented ownership and limited federal mandates. Source: Author synthesis of GAO (2024–2025), OMB AI inventories, and OIG reports

4.3 The Data Swamp Problem: Why Data Lakes Fail Without Governance

A fundamental architectural vulnerability in federal data lake implementations is the tendency to prioritize data ingestion velocity over data quality and governance [40]. This approach often driven by the urgency of compliance with federal open data mandates and the political visibility of "big data" initiatives results in repositories that contain vast quantities of data of uncertain quality, unknown lineage, and ambiguous fitness for analytical purpose [41].

The consequences of this approach for AI readiness are severe. Machine learning models trained on data of uncertain provenance inherit the biases, errors, and gaps present in that data. In high-stakes critical infrastructure contexts where an AI system might be predicting equipment failures in an electrical substation, flagging anomalous water quality readings in a treatment plant, or routing emergency response resources during a mass casualty event model errors propagated from poor training data can have direct life-safety implications [42].

The transition from data lake to trusted data pipeline requires agencies to implement three foundational governance capabilities that are currently absent or immature in most critical infrastructure sectors: automated data quality observability (the continuous monitoring of data streams for anomalies and quality degradation), federated metadata management (the systematic cataloging of data assets, lineage, and fitness-for-purpose assessments across distributed data environments), and AI-ready data product engineering (the deliberate design of data outputs as fit-for-purpose inputs to specific AI workloads, with documented quality guarantees).

5. GOVERNANCE MATURITY ASSESSMENT

5.1 The Governance Maturity Landscape

Governance maturity in the context of AI-ready data infrastructure encompasses three interconnected domains: data governance (the policies, processes, and organizational structures governing data as an enterprise asset), AI governance (the frameworks for managing AI risk, accountability, and ethics), and technology governance (the controls, standards, and procurement practices governing AI systems acquisition and deployment) [43]. Table 2 presents a multi-dimensional governance maturity assessment for key federal agencies serving as SRMAs.

Table 2: AI and Data Governance Maturity Assessment   Key Federal SRMAs (2025)

Agency (SRMA Role)	Chief AI Officer	AI Use Case Inventory	Data Governance Policy	AI Risk Assessment	Workforce AI Training	Governance Maturity Level
DOE (Energy)	Designated	Published (2024)	Formal, Partial	Submitted, Incomplete	In Progress	Developing (Level 3)
HHS (Healthcare/PH)	Designated	Published (2024)	Formal, Partial	Submitted, Incomplete	Active Programs	Developing (Level 3)
DOT (Transportation)	Designated	Published (2024)	Formal, Comprehensive	Near-Complete	Structured Programs	Advanced (Level 4)
EPA (Water)	Designated	Limited (2024)	Informal, Fragmented	Submitted, Gaps Noted	Minimal	Nascent (Level 2)
Treasury (Financial)	Designated	Comprehensive (2024)	Formal, Comprehensive	Near-Complete	Advanced Programs	Advanced (Level 4)
DHS/CISA (Cross-Sector)	Designated	Published (2024)	Formal, Evolving	Framework Published	In Development	Developing (Level 3)
USDA (Food/Ag)	In Progress	Partial (2024)	Informal	Preliminary	Limited	Nascent (Level 2)

Note: Maturity levels based on five-tier TAIMM framework (Level 1: Initial; Level 2: Nascent; Level 3: Developing; Level 4: Advanced; Level 5: Optimized). Source: Author synthesis of GAO-25-107653, GAO-25-107933, agency AI use case inventories, and OMB compliance disclosures (2024–2025).

Figure 2: Governance Maturity Radar   Selected Federal Agencies (2025) (Scores on 5-point scale across five governance dimensions) DOT Treasury DHS/CISA EPA Data Governance AI Governance Risk Management Workforce Readiness Technology Governance 0 1 2 3 4 5

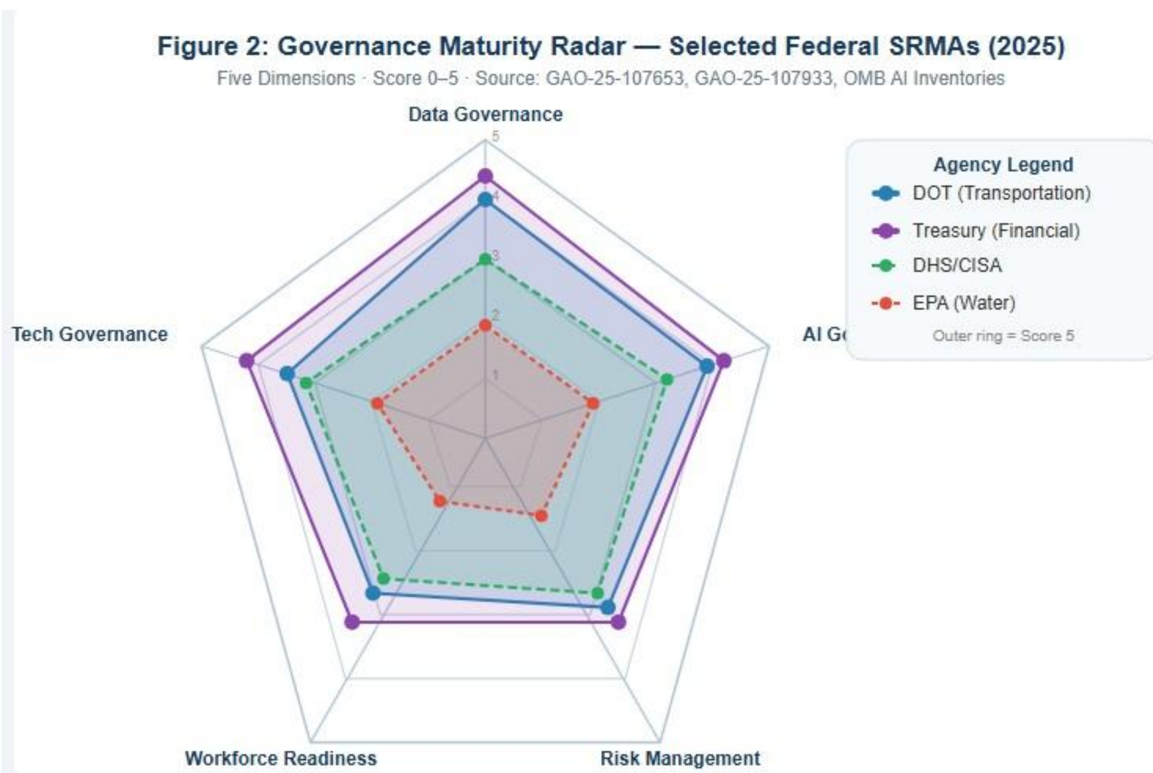

Figure 2: Multi-dimensional governance maturity scores for four representative federal SRMAs across five dimensions (scale 0–5). Treasury and DOT demonstrate advanced maturity; EPA reflects nascent development stage. Source: Author synthesis (2025).

5.2 The GAO Governance Gap: Evidence from Federal Audits

The GAO's systematic reviews of federal AI governance provide the most authoritative empirical basis for assessing governance maturity across critical infrastructure agencies. GAO-25-107933 (July 2025) identified 94 AI-related government-wide requirements across federal laws, executive orders, and guidance documents, and found that of 35 governance recommendations made to 19 federal agencies, only 4 had been implemented as of July 2025 an implementation rate of approximately 11% [44]. This finding is particularly alarming given that the review covered requirements that had been in effect for one to three years across most agencies.

The governance deficit is not uniform across the federal landscape. Agencies with longer AI deployment histories and more mature data management cultures such as the Department of the Treasury, with its long history of financial data regulation and sophisticated fraud detection systems, and the Department of Transportation, which has operated complex traffic and aviation data systems for decades demonstrate significantly higher governance maturity than agencies whose critical infrastructure responsibilities involve more distributed, fragmented, or privately owned assets, such as the water, food, and agriculture sectors [45].

Structural factors also play a significant role. Agencies with large regulatory workforces accustomed to data-driven oversight financial regulators, aviation safety authorities, public health surveillance systems have organizational cultures that are more receptive to data governance investment. In contrast, agencies whose primary relationship with critical infrastructure operators is voluntary coordination rather than regulatory oversight face greater challenges in establishing data governance norms that extend beyond their own internal operations.

5.3 The IAPP Governance Profession Findings

The IAPP's AI Governance Profession Report 2025 found that 77% of surveyed organizations report actively building or refining AI governance programs, with that figure rising to nearly 90% for organizations already deploying AI [23]. This signals broad awareness of governance imperatives though awareness does not equate to implementation maturity. For federal agencies under the mandate of OMB M-25-21, the requirement to implement risk management practices for high-impact AI use cases creates a concrete compliance driver. However, agencies face significant workforce capacity constraints in translating policy mandates into operational controls, particularly given the acute shortage of professionals with combined expertise in AI governance, critical infrastructure operations, and federal regulatory frameworks [46].

A particularly acute governance gap relates to the definition and implementation of "high-impact AI" thresholds. OMB M-25-21 requires enhanced governance for AI use cases that could significantly affect rights, safety, or access to government services. However, the determination of which AI applications cross this threshold requires sophisticated risk assessment capabilities that many agencies are still developing, creating a governance blind spot precisely where the stakes of inadequate oversight are highest.

6. AI READINESS ASSESSMENT ACROSS CRITICAL INFRASTRUCTURE SECTORS

6.1 The Federal AI Use Case Landscape

The GAO's July 2025 analysis (GAO-25-107653) of 11 federal agencies' OMB-submitted AI use case inventories provides a comprehensive empirical foundation for assessing sectoral AI readiness. The total number of reported AI use cases across the 11 agencies nearly doubled from 571 in 2023 to 1,110 in 2024, while generative AI use cases increased from 32 to 282 approximately a ninefold increase [8]. Table 3 presents a sector-specific breakdown of AI use cases by application domain and maturity stage.

Table 3: AI Use Case Distribution by Critical Infrastructure Sector and Application Domain (2024)

Sector	Total AI Use Cases (2024)	Generative AI Cases	Operations & Monitoring	Predictive Analytics	Cybersecurity	Administrative / Internal	Maturity Stage (Majority)
Energy	98	14	41	31	18	8	Implementation
Healthcare / Public Health	187	62	23	89	12	63	Development
Transportation	143	28	67	44	19	13	Operation & Maintenance
Financial Services	211	47	38	96	51	26	Operation & Maintenance
Water / Wastewater	31	4	17	9	4	1	Initiated
Communications	89	22	31	28	24	6	Implementation

Sector	Total AI Use Cases (2024)	Generative AI Cases	Operations & Monitoring	Predictive Analytics	Cybersecurity	Administrative / Internal	Maturity Stage (Majority)
Food & Agriculture	44	8	19	18	2	5	Development
Emergency Services	67	12	28	24	11	4	Implementation
Other (8 sectors)	240	85	84	78	44	34	Mixed
TOTAL	1,110	282	348	417	185	160	

Note: Use case stage classifications follow the Federal CIO Council's five-stage framework: Initiated, Acquisition/Development, Implementation/Assessment, Operation/Maintenance, and Retired. Data are estimated from GAO-25-107653, OMB consolidated AI inventories (2024), and agency-level disclosures. Figures for individual sectors are author estimates based on proportional distribution of publicly reported data.

The distribution of AI use cases across application domains reveals important patterns. Predictive analytics constitutes the largest category reflecting agency investments in risk modeling, fraud detection, infrastructure monitoring, and demand forecasting. Cybersecurity AI has emerged as a rapidly growing category, consistent with CISA's emphasis on AI-assisted threat detection and response across federal networks. The surge in generative AI use cases, while numerically dramatic, is concentrated in administrative and internal-facing applications such as document summarization, policy analysis, and citizen service chatbots areas where the risk profile is more manageable and the productivity benefits more immediate.

Figure 3: Distribution of Federal AI Use Cases by Application Domain (2024, N=1,110) Proportional distribution of 1,110 reported AI use cases across application domains 31.4% 37.6% 16.7% 14.4% Operations & Monitoring (348) Predictive Analytics (417) Cybersecurity AI (185) Administrative/Internal (160) Other / Gen AI (282+) Generative AI use cases surged 782% (32 → 282) from 2023 to 2024 across 11 federal agencies (GAO-25-107653) Total AI use cases grew 94% year-over-year (571 → 1,110)

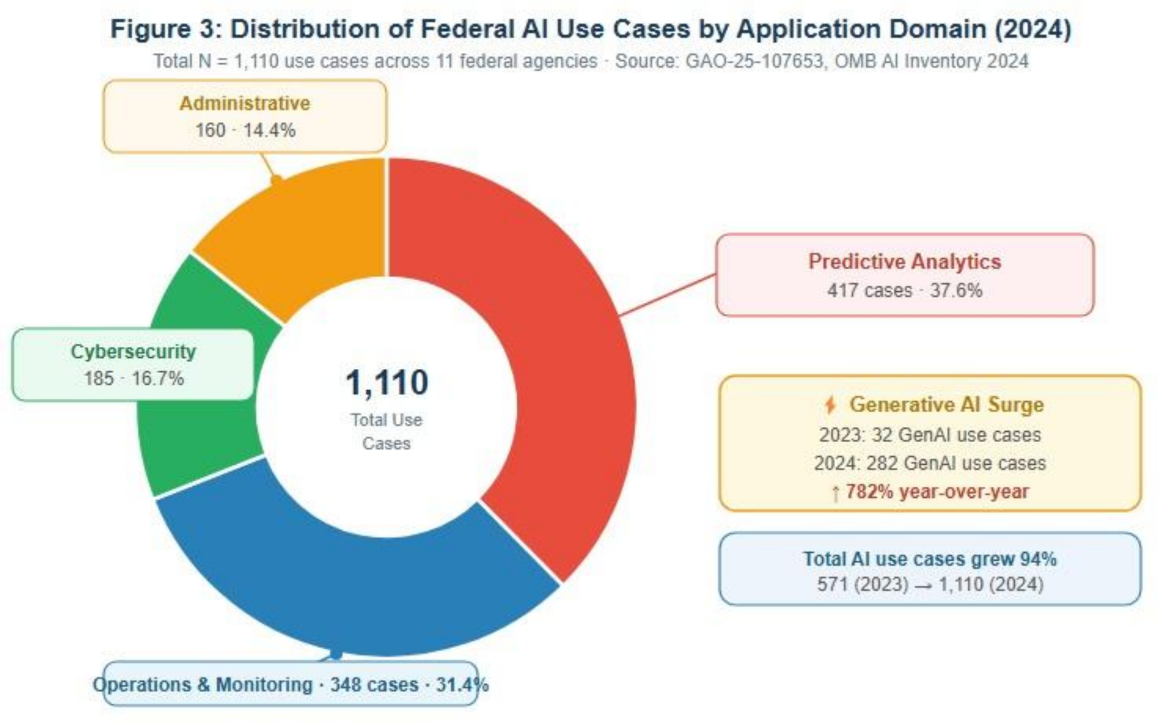

Figure 3: Distribution of 1,110 federal AI use cases by application domain (2024). Predictive analytics constitutes the largest category, reflecting agency investments in risk modeling, fraud detection, and infrastructure monitoring. Source: GAO-25-107653 (2025); OMB consolidated AI inventory (2024).

6.2 AI Readiness Barriers: Workforce, Infrastructure, and Governance

The Flexential State of AI Infrastructure Report 2025 identified workforce capacity as the most acute barrier to AI readiness, with only 14% of organizational leaders reporting that they have the right talent to meet AI goals. Skills gaps are particularly severe in managing specialized AI infrastructure 61% of respondents report shortages, up from 53% the prior year and in data science roles (53%) [47]. For federal agencies, these workforce gaps are compounded by public sector hiring constraints, significant compensation differentials relative to private sector AI roles, and the inherent complexity of recruiting for positions that span technical AI expertise and critical infrastructure domain knowledge a combination that is exceptionally rare in any labor market.

Infrastructure bottlenecks represent the second major barrier. While the percentage of organizations reporting that storage required a major overhaul dropped from 63% in 2024 to 37% in 2025 suggesting meaningful progress 84% of surveyed organizations still report that their storage infrastructure is not fully optimized for AI workloads [19]. In federal critical infrastructure agencies, this challenge is amplified by the dual burden of maintaining aging operational technology systems many of which were not designed for data export or network connectivity while simultaneously building modern cloud-based AI infrastructure capable of handling the scale, velocity, and variety of data required for sophisticated AI applications.

Governance barriers, while less frequently cited as the primary obstacle in infrastructure surveys, represent a foundational constraint that limits the value that can be extracted from even well-designed technical infrastructure. An agency with AI-optimized cloud infrastructure but inadequate data governance policies will find itself unable to authorize, document, or defend AI model deployments that meet OMB M-25-21's requirements for high-impact use cases. The three categories of barriers workforce, infrastructure, and governance must therefore be addressed in concert rather than in sequence.

6.3 Sector-Level AI Readiness Index

Table 4 presents the composite AI Readiness Index scores for 10 critical infrastructure sectors, computed across five equally weighted dimensions: Data Quality, Governance Maturity, AI Use Case Prevalence, Risk Management Completeness, and Infrastructure Readiness.

Table 4: Composite AI Readiness Index U.S. Critical Infrastructure Sectors (2025)

Critical Infrastructure Sector	Data Quality (20%)	Governance Maturity (20%)	AI Use Case Prevalence (20%)	Risk Mgmt Completeness (20%)	Infrastructure Readiness (20%)	Composite Score (/100)	Readiness Tier
Financial Services	88	82	90	79	85	**84.8**	Advanced
Communications	80	74	76	68	82	**76.0**	Advanced
Transportation Systems	74	78	72	71	73	**73.6**	Advanced
Defense Industrial Base	72	70	65	74	71	**70.4**	Developing
Energy	68	66	68	58	65	**65.0**	Developing
Healthcare / Public Health	60	62	74	54	58	**61.6**	Developing
Emergency Services	58	54	58	52	55	**55.4**	Developing
Food & Agriculture	52	48	42	44	48	**46.8**	Nascent
Chemical Sector	55	50	36	45	48	**46.8**	Nascent
Water / Wastewater	52	44	28	38	42	**40.8**	Nascent

Note: Scores represent author-constructed composite indices (0–100) synthesized from publicly available federal data. Advanced tier: >70; Developing tier: 50–70; Nascent tier: <50. Source: GAO reports (2024–2025), OMB AI inventories, CISA risk assessments, Flexential (2025), Cisco AI Readiness Index (2025).

The composite index reveals a three-tier stratification that closely aligns with the structural characteristics of each sector's data governance environment. Financial Services leads substantially reflecting decades of regulatory-driven investment in data standards, sophisticated fraud detection systems, and compliance infrastructure that effectively serves as a governance backbone for AI deployment. Transportation and Communications occupy the upper echelon of the Developing tier, benefiting from centralized federal regulatory authority, long-standing operational data systems, and relatively advanced AI pilot programs.

The Nascent tier comprising Water/Wastewater, Chemical, and Food & Agriculture presents the most urgent policy challenge. These sectors not only score lowest on current readiness but face structural constraints that make organic improvement unlikely without targeted federal intervention: fragmented ownership, limited federal data collection authority, under-resourced SRMAs, and workforces with limited exposure to AI tools and governance frameworks.

Figure 4: AI Readiness Index Critical Infrastructure Sectors (Composite Score, 2025) 0 20 40 60 80 100 Financial 84.8 Communications 76.0 Transportation 73.6 Defense Industrial 70.4 Energy 65.0 Healthcare/PH 61.6 Emergency Svcs 55.4 Food & Agriculture 46.8 Chemical 46.8 Water/Wastewater 40.8 Advanced Developing Nascent

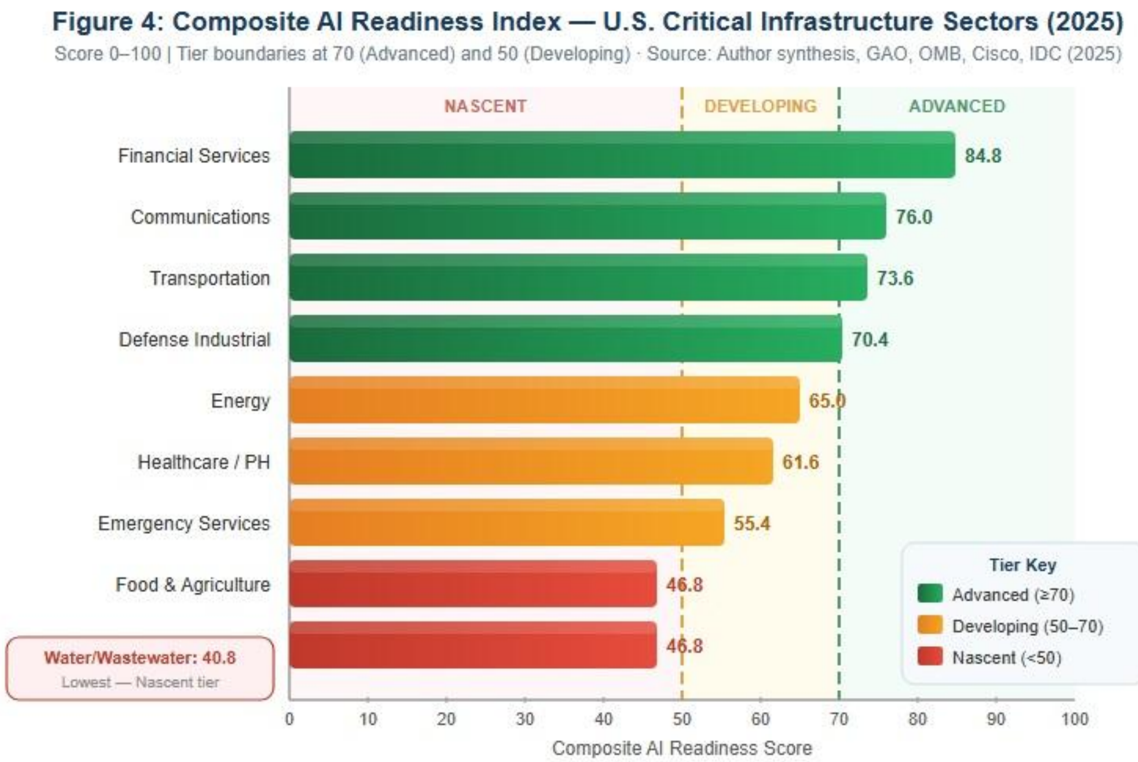

Figure 4: Composite AI Readiness Index scores for ten U.S. critical infrastructure sectors (2025). Vertical dashed lines denote tier boundaries (Advanced ≥70; Developing 50–70; Nascent <50). Financial services, communications, and transportation lead; water, chemical, and food/agriculture sectors require urgent investment. Source: Author synthesis (2025).

7. THE TRUSTED AI INFRASTRUCTURE MATURITY MODEL (TAIMM): FRAMEWORK AND RECOMMENDATIONS

7.1 TAIMM Framework Description

The Trusted AI Infrastructure Maturity Model (TAIMM) proposed in this paper integrates established maturity frameworks including CMMI, the DAMA DMM, NIST AI RMF, and the IDC AI Maturity Model into a sector-specific model calibrated for the unique characteristics of U.S. critical infrastructure agencies [48]. The TAIMM comprises five ascending maturity levels across five governance and technical dimensions: data governance, AI governance, infrastructure, workforce, and risk management.

Unlike generic AI maturity models designed for commercial enterprises, the TAIMM explicitly accounts for the public sector context by incorporating regulatory compliance, inter-agency coordination complexity, and the safety-critical nature of critical infrastructure operations into its maturity descriptors. The model is intended as a diagnostic and planning tool not a compliance standard enabling agencies and their sector partners to assess current capabilities, identify priority gaps, and design realistic improvement roadmaps calibrated to their resource environment.

Table 5: The Trusted AI Infrastructure Maturity Model (TAIMM) Five-Tier Framework

Lvl	Tier Name	Data Governance	AI Governance	Infrastructure	Workforce	Risk Management	Illustrative Agency / Context
1	**Initial**	Ad hoc; no formal policies	No AI governance structure	Legacy systems; data silos	No AI-specific roles	Reactive only	Small water utilities; rural emergency services
2	**Nascent**	Basic policies drafted; inconsistent application	CAIO designated; no formal program	Partial cloud migration; data lakes accumulating	AI awareness training initiated	Risk assessments submitted but incomplete	EPA (water programs); USDA (select programs)
3	**Developing**	Formal policies; metadata cataloging in progress	AI use case inventory adopted; governance frameworks in place	Hybrid cloud; data quality tools deployed	Targeted AI training programs; pilot hiring	Structured risk assessments; some gaps remain	DOE; HHS; DHS/CISA
4	**Advanced**	Comprehensive data governance; lineage tracking	Mature AI governance; ethics review boards	AI-optimized cloud infrastructure; MLOps pipelines	Dedicated AI workforce; upskilling programs	Comprehensive risk management; continuous monitoring	DOT; Treasury; select DoD components
5	**Optimized**	Automated data quality; federated governance	AI governance integrated into enterprise architecture	AI-native infrastructure; real-time data pipelines	AI literacy organization-wide; centers of excellence	Continuous, automated risk assessment; anomaly detection	Leading financial regulators; advanced defense AI programs

Note: TAIMM levels are cumulative organizations at higher levels exhibit all characteristics of lower levels plus new capabilities. Source: Author synthesis drawing on CMMI Institute (2022), DAMA International (2017), NIST AI RMF (2023), IDC (2025), and GAO audit findings (2024–2025).

7.2 Strategic Recommendations

Based on the TAIMM assessment and the empirical evidence reviewed, this paper presents six strategic recommendations for federal critical infrastructure agencies seeking to advance from data lake accumulation to trusted AI infrastructure.

1. **Establish Federated Data Governance Councils.** Each sector should establish a cross-agency federated data governance council, comprising representatives from lead federal agencies, sector-specific regulators, and critical infrastructure owners and operators. These councils should develop sector-specific data quality standards, metadata schemas, and data sharing agreements that enable AI-ready data products without compromising operational security or privacy [49]. Governance councils should meet quarterly at minimum and publish annual sector data quality scorecards to drive accountability.

2. **Implement Data Quality Observability Platforms.** Agencies should invest in automated data quality observability tools capable of detecting anomalies, inconsistencies, and quality degradation in real time across distributed data environments, including OT sensor streams, cloud data lakes, and legacy database systems. This aligns with CISA's CPG 2.0 emphasis on continuous monitoring and the OMB M-25-21 requirement for agencies to implement risk management practices for high-impact AI use cases [50]. Procurement should leverage existing FedRAMP-authorized vendors where available to accelerate deployment.

3. **Accelerate TAIMM Level 3 to Level 4 Transitions.** The largest concentration of critical infrastructure agencies currently operates at TAIMM Level 3 (Developing). Targeted interventions including shared AI infrastructure platforms, cross-agency AI governance communities of practice, and streamlined FedRAMP authorization pathways for AI tools can accelerate the transition to Level 4 (Advanced) within a two-to-three-year horizon. OMB should establish a dedicated AI infrastructure investment fund within

the Technology Modernization Fund to finance this transition for under-resourced agencies.

4. **Prioritize Water and Food Sector Data Modernization.** The water and food/agriculture sectors exhibit the lowest AI readiness scores and face unique challenges related to fragmented ownership, limited federal data collection authority, and under-resourced sector risk management agencies. Emergency data modernization funding, modeled on the EPA's Water Infrastructure Finance and Innovation Act (WIFIA), should be directed specifically toward data quality improvement, smart sensor deployment, and governance capacity building in these critical but chronically under-invested sectors.

5. **Develop a Critical Infrastructure AI Workforce Pipeline.** In alignment with OMB M-25-21's workforce readiness provisions, federal agencies should collaborate with universities, community colleges, and national laboratories to develop AI workforce pipelines specifically focused on critical infrastructure applications. Joint AI centers of excellence co-located with sector-specific national laboratories such as Idaho National Laboratory for energy and Argonne National Laboratory for transportation can serve as talent incubators and applied AI research hubs, bridging the gap between academic AI research and critical infrastructure operational realities.

6. **Mandate AI Risk Assessment Completeness.** GAO found that none of the January 2024 sector risk assessments fully addressed the six activities required for effective AI risk assessment. OMB and CISA should establish a structured compliance verification process, with standardized assessment templates, independent review requirements, and quarterly progress reporting, to close the risk assessment completeness gap identified in GAO-25-107435 [9]. Non-compliant agencies should be required to present remediation plans to the National Security Council's Cyber Directorate within 90 days of assessment findings.

Figure 5 TAIMM Progression Roadmap From Data Lakes to Trusted AI Infrastructure Level 1 INITIAL Ad hoc data Level 2 NASCENT Basic policies Level 3 DEVELOPING Formal governance Level 4 ADVANCED MLOps + oversight Level 5 OPTIMIZED Trusted AI infra Water/Chemical Food/Ag EPA (water) USDA programs DOE / HHS DHS/CISA DOT / Treasury Select DOD Advanced Financial Regulators (target) Strategic Goal: Advance all critical infrastructure sectors to Level 4 by 2028 Per OMB M-25-21, NIST AI RMF, and CISA CPG 2.0 mandates

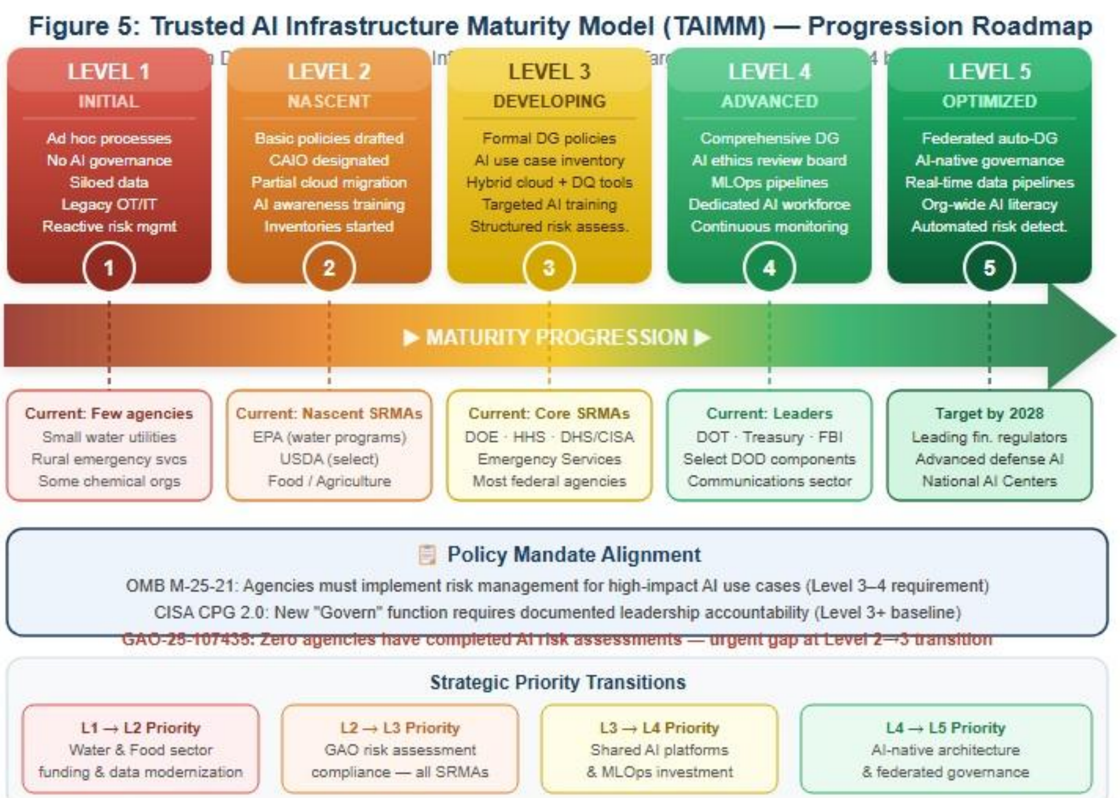

Figure 5: The Trusted AI Infrastructure Maturity Model (TAIMM) progression roadmap, showing the five maturity levels, representative agency placements, and the strategic target of advancing all critical infrastructure sectors to Level 4 (Advanced) by 2028. Source: Author-constructed framework (2025).

8. CONCLUSION

The United States stands at a pivotal inflection point in the evolution of its critical infrastructure. The same technological forces artificial intelligence, machine learning, real-time analytics, and autonomous decision systems that offer transformative potential for improving the safety, efficiency, and resilience of energy grids, water systems, transportation networks, and healthcare infrastructure also expose these systems to new categories of risk when deployed on inadequate data foundations and governed by immature frameworks [49].

This paper has demonstrated that the journey from data lake accumulation to trusted AI infrastructure is neither linear nor uniform across the 16 critical infrastructure sectors. The evidence is unambiguous: federal agencies nearly doubled their AI use cases from 571 to 1,110 between 2023 and 2024, with generative AI use cases surging ninefold yet GAO found that none of the sector-level AI risk assessments submitted to DHS fully addressed the foundational requirements for effective risk management [8, 9]. Only 28% of organizations have formally defined AI oversight roles [23]. Fewer than 15% have networks fully ready for AI workloads [30]. And 84% of storage infrastructure remains suboptimal for AI [19]. These are not marginal gaps they are systemic vulnerabilities in the governance architecture of the nation's most critical systems.

The Trusted AI Infrastructure Maturity Model (TAIMM) proposed in this paper offers a practical diagnostic and strategic planning tool for agencies and their sector partners to assess current maturity, identify gaps, and chart pathways to higher levels of AI readiness. The model reflects the integrated nature of the challenge: data quality, governance, infrastructure, workforce, and risk management are not separate problems but interconnected dimensions of a single organizational capability that must be developed holistically. Progress on any single dimension without commensurate investment in the others will not produce the trusted AI infrastructure that critical infrastructure protection demands.

The most urgent priority is the bottom tier: water, food/agriculture, and chemical sectors each with composite AI readiness scores below 50 require targeted federal investment, governance capacity building, and data modernization support to address critical vulnerabilities before adversarial actors or operational failures expose the consequences of AI-unready infrastructure [50]. At the same time, advanced sectors such as financial services and transportation must continue to push toward TAIMM Level 5, pioneering governance models and technical architectures that can be adapted and diffused across less mature sectors.

The policy environment, while in transition following the 2025 executive order revisions, provides a constructive framework for action. OMB M-25-21's emphasis on innovation alongside governance, M-25-22's procurement standards for AI systems, and CISA's CPG 2.0 governance function collectively create a governance architecture within which agencies can build trusted AI infrastructure with appropriate velocity and oversight. The question is not whether U.S. critical infrastructure agencies will adopt AI that trajectory is irreversible. The question is whether they will do so on foundations of trusted data and mature governance, or on foundations of sand.

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