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Does AI Capacity Require Human Capacity?

Federal AI Adoption and Workforce Climate Across U.S. Agencies

An exploratory, source-validated cross-agency study linking the 2024 Federal Employee Viewpoint Survey to the 2025 Federal AI Use Case Inventory

Author
Joseph Atalla, PhD

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Los Angeles Metro Area
California, USA

RESEARCH AT A GLANCE

This exploratory study links 2024 federal workforce climate measures to the 2025 public AI use case inventory. Across 11 agencies and 1,810 individually reported AI use cases, employee engagement showed no statistically reliable association with the share of systems deployed or piloted. Performance Confidence also showed a small, uncertain association in the eight-agency secondary sample. These results do not establish that people are unimportant to AI implementation. They indicate that broad workforce climate is an insufficient proxy for AI-specific readiness. Technical talent, training, governance, data, infrastructure, acquisition capability, and mission fit require direct measurement.

11	1,810	–0.091	0.788
agencies in the primary analytic sample	individually reported AI use cases	Spearman rho for engagement versus deployment/pilot share	permutation p-value for the primary association

PRIMARY FINDING

Broad workforce climate alone does not explain cross-agency AI implementation differences in this sample. The findings are exploratory, ecological, and non-causal.

About TDTI. The Trusted Data and Technology Institute is a California nonprofit public benefit corporation that advances data and technology quality, integrity, security, and responsible use through research, education, and practical collaboration, with a focus on trusted data, responsible AI evaluation, cybersecurity assurance, and public-sector technology. **Contact:** info@trusteddti.com · trusteddti.com · California

Abstract

Federal agencies are accelerating artificial intelligence (AI) adoption while simultaneously reporting challenges in attracting, developing, and retaining AI expertise. This study asks whether broad workforce climate is empirically associated with public AI implementation across agencies. We linked validated 2024 Federal Employee Viewpoint Survey (FEVS) Employee Engagement Index (EEI) results to agency-level counts in the Office of Management and Budget's 2025 Federal Agency AI Use Case Inventory. The primary analytic sample contains 11 agencies and 1,810 individually reported AI use cases. The primary AI outcome is the deployment/pilot share: deployed plus piloted use cases divided by all individually reported use cases. Because the agency sample is small and portfolio measures are skewed, Spearman rank correlations are paired with 10,000-permutation p-values, bootstrap intervals, Kendall tau, Pearson sensitivity statistics, leave-one-agency-out checks, and a simple HC3-robust regression. EEI was not associated with deployment/pilot share (rho = -0.091, permutation p = 0.788). EEI was also not associated with AI portfolio breadth (rho = -0.173) or high-impact share (rho = -0.057). In the eight-agency secondary sample, Performance Confidence showed a small positive but highly uncertain association with deployment/pilot share (rho = 0.156, permutation p = 0.718). These results do not imply that human capacity is unimportant. Rather, they show that broad organizational climate measures are insufficient proxies for AI-specific readiness. Future federal AI-readiness research should directly measure technical talent, AI training, governance capacity, mission fit, infrastructure, acquisition capability, and budget authority.

Keywords: *artificial intelligence; federal agencies; workforce readiness; employee engagement; public administration; AI governance; FEVS*

PRIMARY EMPIRICAL RESULT

Across 11 agencies, the 2024 Employee Engagement Index was not associated with the 2025 share of reported AI use cases that were deployed or piloted (Spearman rho = -0.09; permutation p = 0.79). Broad workforce climate, by itself, does not explain cross-agency AI implementation differences in this sample.

RESEARCH STATUS

Independent Research Study - Website Edition. This paper analyzes publicly available government data. It is not an evaluation commissioned by, or on behalf of, any federal agency. Findings are ecological and non-causal.

WHAT THIS STUDY DOES - AND DOES NOT DO

It tests cross-agency association using public, source-validated data. It does not rank agencies, infer causality, claim that more AI is inherently better, or treat FEVS engagement as a direct measure of AI skill.

Executive summary

- Federal AI use is expanding quickly. OMB reports 3,611 individually reported 2025 AI use cases, including 1,818 deployed/piloted and 445 high-impact use cases.
- GAO has documented AI talent and training challenges across multiple agencies, motivating a test of whether workforce conditions co-vary with implementation.
- The 11-agency sample spans EEI scores from 69% to 86% and AI deployment/pilot shares from 37.2% to 100.0%.
- No statistically reliable relationship emerged between EEI and AI implementation share, AI portfolio breadth, or high-impact share.
- The practical implication is measurement-related: agencies and researchers need AI-specific human-capital indicators rather than assuming that a generally engaged workforce is automatically an AI-ready workforce.

1. Introduction

Artificial intelligence has moved from an experimental government technology to a growing operational portfolio. The Office of Management and Budget (OMB) reported 3,611 individually reported federal AI use cases in the 2025 inventory, of which 1,818 were deployed or piloted, and 445 were classified as high-impact. The same reporting cycle introduced streamlined consolidated reporting for certain commercial off-the-shelf uses, further reflecting AI's diffusion into routine government software (OMB, 2026).

This expansion raises a human-capital question. AI systems do not deploy themselves. Public agencies need technical expertise, acquisition knowledge, governance processes, subject-matter integration, leadership sponsorship, and employees capable of adapting workflows around new tools. GAO's review of generative AI found that selected agencies faced difficulty attracting and developing AI expertise and maintaining workforce training as capabilities evolved (GAO, 2025). A later procurement review similarly found that agencies sometimes struggled to access data scientists and other technical experts needed to evaluate AI contractor proposals (GAO, 2026).

Yet empirical evidence connecting workforce conditions to agency-level AI adoption remains thin. Public-sector AI scholarship has emphasized organizational design, managerial competence, technology acceptance, legitimacy, and governance. It has not generally linked federal workforce climate data to a government-wide AI-use inventory. This paper provides an exploratory test using two public data systems: the 2024 Federal Employee Viewpoint Survey (FEVS) and the 2025 OMB Federal Agency AI Use Case Inventory.

The central question is deliberately narrow: do agencies with more favorable workforce climate scores also show broader or more mature public AI portfolios? The study does not assume that the answer must be yes. A positive association would suggest that general organizational conditions may help support technology implementation. A null association would imply that broad engagement measures are too distal and that AI-specific capability, mission, resources, and governance need to be measured directly.

2. Policy and research context

2.1 Federal AI policy

Federal AI policy has shifted toward accelerated adoption coupled with risk governance. OMB Memorandum M-25-21 directs agencies to take a forward-leaning approach to AI while maintaining safeguards for civil rights, civil liberties, and privacy (OMB, 2025). GAO has separately documented extensive government-wide AI management and personnel requirements and the need for agencies to build AI talent and management capacity (GAO, 2024).

The 2025 OMB inventory is therefore more than a technology list. It is an administrative record of agencies' reported AI activity under a common reporting regime. The public summary distinguishes all individually reported use cases from those reported as deployed/piloted and identifies high-impact uses. These fields support a first-pass comparison of portfolio scale, implementation status, and high-impact concentration across agencies, while still requiring caution because reporting practices, missions, and exclusions differ.

2.2 Why workforce conditions may matter

Public-sector AI adoption requires organizations to balance experimentation with bureaucratic routines. Selten and Klievink (2024) found that public organizations use different structural approaches to organize data and AI work, and that technical expertise and integration with core processes create distinct adoption benefits and barriers. Sandoval-Almazan et al. (2024) found limited AI implementation competencies among public managers and linked openness to digitalization with stronger competencies. Haesevoets et al. (2025) likewise found differences in AI adoption attitudes between public managers and non-managerial employees.

These studies motivate a capacity perspective, but they do not imply that a generic employee-engagement score is equivalent to AI readiness. FEVS EEI measures conditions conducive to engagement, including leadership, supervisory relationships, and intrinsic work experience. Performance Confidence (PCI) captures employee perceptions that their work unit can meet customer needs, contribute to agency performance, produce high-quality work, and adapt to changing priorities (OPM, 2024a, 2024b). Both are plausible organizational-climate indicators, but neither directly measures AI literacy, software engineering, data science, model-risk expertise, or AI acquisition skills.

3. Research questions

- RQ1. Is 2024 Employee Engagement associated with the 2025 share of an agency's publicly reported AI use cases that are deployed or piloted?
- RQ2. Is Employee Engagement associated with the breadth of an agency's publicly reported AI portfolio?
- RQ3. Is Employee Engagement associated with the share of reported use cases classified as high-impact?
- RQ4. In agencies with validated Performance Confidence data, is Performance Confidence associated with deployment/pilot share?

Because the study is exploratory and ecological, these questions are framed as associations rather than causal hypotheses. The temporal ordering - 2024 workforce climate preceding 2025 AI reporting - is useful descriptively but does not establish that workforce climate causes later AI adoption.

4. Data and methods

4.1 Data sources and sample

AI portfolio data come from OMB's official 2025 Federal Agency AI Use Case Inventory repository. Workforce data come from official 2024 FEVS agency reports and agency performance publications, with OPM's 2024 technical and government wide reports used to validate index definitions. Eleven agencies were included when an official agency EEI score could be validated, and a matching OMB AI summary record was available. The analytic sample is therefore purposive rather than a probability sample of the federal government.

4.2 Measures

Employee Engagement Index (EEI). EEI is the primary workforce-climate measure. OPM describes it as assessing critical conditions conducive to employee engagement. Agency scores are percent-positive values or the equivalent agency-reported engagement score.

Performance Confidence Index (PCI). PCI is a secondary measure of employees' confidence that their work unit can achieve goals and produce high-quality work. Official index values were used when available. DOE and DHS values were reconstructed transparently as the mean of their published Q20-Q23 percent-positive values, consistent with the 2024 OPM technical-report definition; sensitivity analysis excludes these two reconstructed values.

AI deployment/pilot share. The primary AI outcome equals OMB's count of deployed and piloted individually reported use cases divided by total individually reported use cases. The term "share" is intentional: it is not a quality score, capability score, or claim that pilot status equals full production deployment.

AI portfolio breadth. Because total AI counts are highly skewed, the study uses log(1 + total use cases) for association tests. High-impact share equals high-impact use cases divided by total use cases. A high-impact classification is a governance category, not a direct measure of system quality or organizational maturity.

4.3 Analysis

Spearman rank correlation is the primary association statistic because the agency sample is small and AI portfolio measures are skewed. Two-sided empirical p-values are estimated with 10,000 random permutations. Bootstrap resampling (5,000 samples) provides descriptive 95% intervals for Spearman rho. Kendall tau, Pearson correlation, leave-one-agency-out Spearman ranges, and an HC3-robust simple regression are reported as sensitivity analyses. Multivariable models are intentionally avoided because the sample is too small for stable adjustment.

5. Results

5.1 Analytic sample

Agency	AI total	Deployed/ pilot	Impl. share	High-impact	EEI	PCI
Commerce	223	223	100.0%	0	77	89
DHS	238	118	49.6%	55	69	79
EPA	29	14	48.3%	2	81	91
Education	56	56	100.0%	0	75	90
Energy	340	176	51.8%	29	80	91.8
GSA	49	20	40.8%	0	86	-
HHS	447	255	57.0%	2	78.7	-
HUD	11	6	54.5%	0	76	88
Interior	247	129	52.2%	0	73	85
Labor	41	23	56.1%	1	76	-
Treasury	129	48	37.2%	4	74	86.3

The 11 agencies account for 1,810 individually reported AI use cases in the OMB 2025 inventory. The median agency reported 129 use cases (range 11-447). Median deployment/pilot share was 52.2% (range 37.2%-100.0%). EEI ranged from 69% to 86%, with a mean of 76.9%.

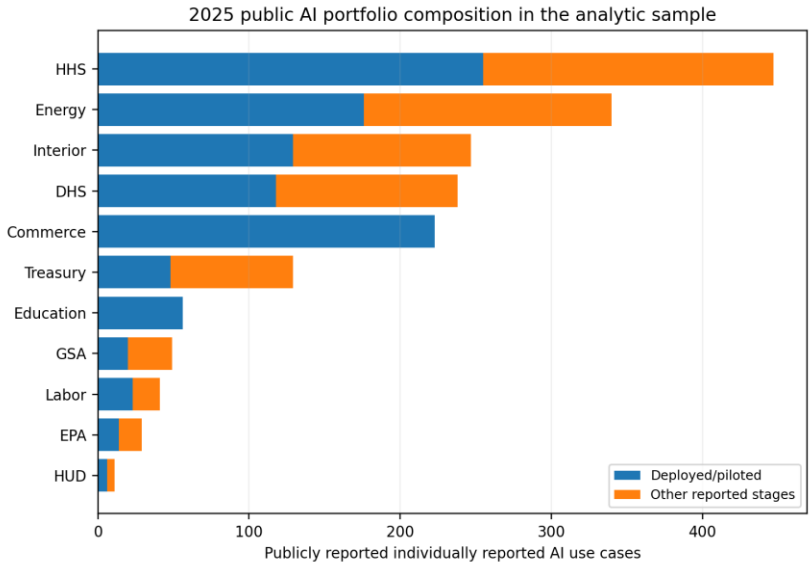


Figure 1. Composition of the 2025 individually reported AI portfolios for the 11-agency analytic sample. "Other reported stages" includes use cases not counted by OMB as deployed or piloted.

5.2 Primary association: engagement and implementation share

Employee Engagement was not associated with deployment/pilot share. Spearman rho was -0.091 (asymptotic p = 0.789; 10,000-permutation p = 0.788). The bootstrap 95% interval was wide [-0.829, 0.608], reflecting the small sample. Kendall tau was -0.093 (p = 0.695). A simple HC3-robust regression likewise produced a near-zero relationship (slope = -0.0068, p = 0.661, R^2 = 0.021).

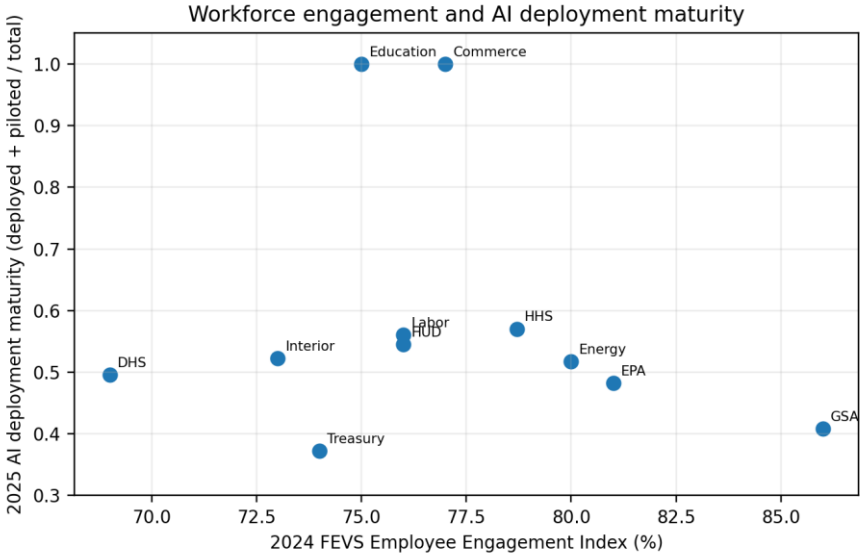


Figure 2. 2024 FEVS Employee Engagement Index versus 2025 deployment/pilot share. The scatter does not show a monotonic cross-agency relationship.

5.3 Secondary associations and robustness

Association	n	rho	Perm. p	Bootstrap 95% CI	LOO rho range
EEI vs implementation share	11	-0.091	0.788	[-0.83, 0.61]	[-0.36, 0.12]
EEI vs log AI portfolio size	11	-0.173	0.624	[-0.77, 0.55]	[-0.36, 0.01]
EEI vs high-impact share	11	-0.057	0.866	[-0.74, 0.74]	[-0.20, 0.28]
PCI vs implementation share	8	0.156	0.718	[-0.62, 0.95]	[-0.05, 0.49]
Official-index-only PCI vs implementation share	6	0.290	0.579	[-0.80, 1.00]	[-0.05, 0.87]

EEI also showed little association with AI portfolio breadth (rho = -0.173) or high-impact share (rho = -0.057). In the eight-agency PCI subset, the correlation with deployment/pilot share was positive but small and uncertain (rho = 0.156, permutation p = 0.718). Restricting PCI to the six agencies with directly reported official index values increased rho to 0.290, but the uncertainty remained substantial (permutation p = 0.579).

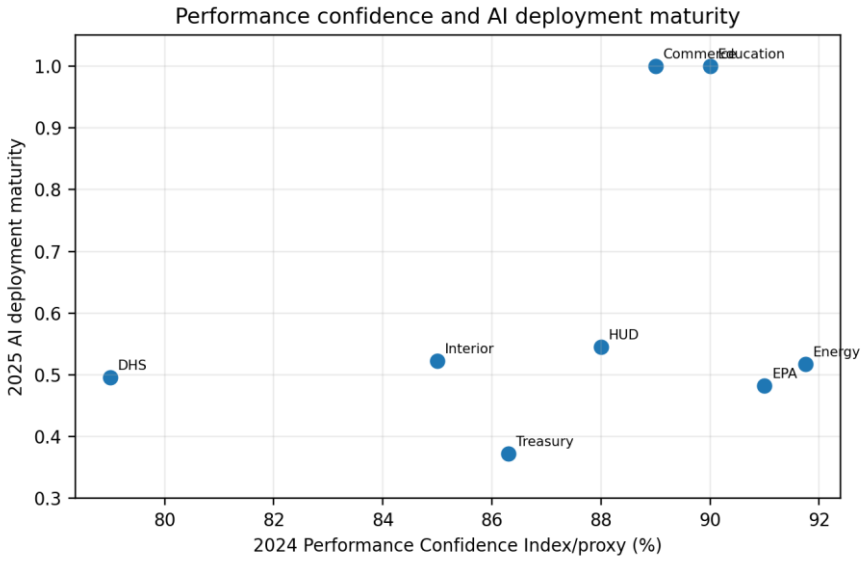


Figure 3. Performance Confidence versus deployment/pilot share in the eight-agency secondary sample. DOE and DHS PCI values are transparent four-item reconstructions from official Q20-Q23 results; the manuscript separately reports an official-index-only sensitivity test.

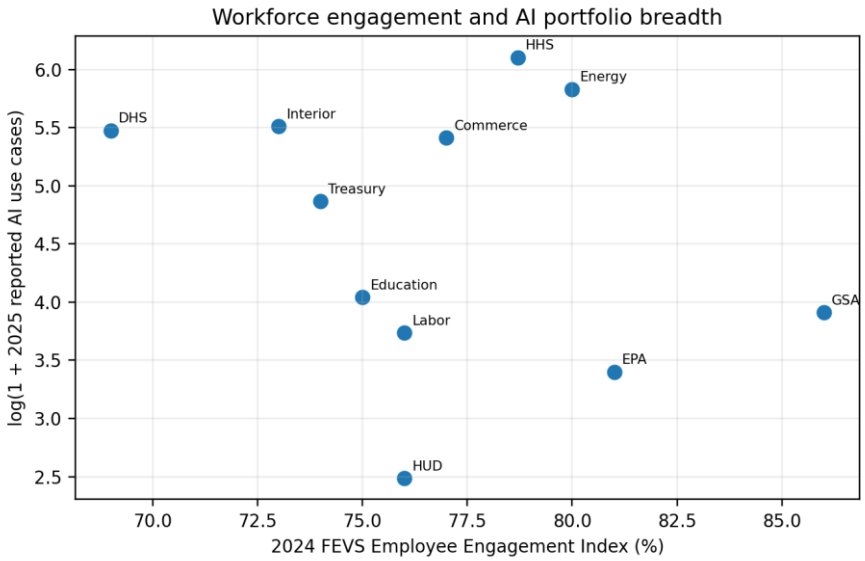


Figure 4. Employee Engagement versus log-transformed AI portfolio breadth. The relationship is weak and negative in this sample.

RESULT IN PLAIN LANGUAGE

The agencies with the most favorable general workforce climate were not consistently the agencies with the largest or most implementation-heavy public AI portfolios. The data therefore do not support using EEI or PCI alone as a proxy for federal AI readiness.

6. Discussion

6.1 The null result is informative

The study began with a plausible organizational-capacity proposition: agencies with stronger workforce conditions might be better positioned to move AI from exploration toward operational use. The observed data do not support that proposition when workforce conditions are represented by broad FEVS engagement. The primary rank correlation is essentially zero, and sensitivity analyses do not change the conclusion.

This should not be read as evidence that people do not matter to AI implementation. It instead exposes a measurement problem. Employee engagement is a general organizational-climate construct. An agency can have highly engaged employees while lacking scarce AI engineering talent, model-risk expertise, procurement skill, secure computing infrastructure, appropriate data, or mission opportunities suited to AI. Conversely, an agency may have a modest EEI score while maintaining specialized technical units and a mission that generates many AI use cases.

6.2 Mission and reporting architecture matter

The portfolio differences are substantial. Commerce and Education report 100% of their individually reported 2025 use cases as deployed or piloted, whereas Treasury, GSA, EPA, DHS, and several others report lower shares. These differences may reflect actual implementation patterns, but they may also reflect portfolio composition, mission, lifecycle timing, and agency reporting practices. OMB’s 2025 changes to reporting scope and COTS consolidation further complicate simple maturity comparisons.

High-impact concentration illustrates the same point. DHS reports 55 high-impact use cases out of 238, while several agencies in the sample report none. This does not mean DHS is less “ready.” It reflects mission exposure to rights- or safety-relevant uses and the classification rules applied to those use cases. High-impact share therefore belongs in a governance analysis, not a readiness ranking.

6.3 What human capacity should mean in AI research

A stronger operationalization of AI-specific human capacity would measure the stock and flow of relevant skills: data scientists, AI/ML engineers, software engineers, cybersecurity specialists, acquisition professionals, legal and privacy expertise, model evaluators, and mission specialists trained to supervise AI outputs. Training intensity, vacancy duration, retention, contractor dependence, and access to computing/data infrastructure would also matter. GAO's findings on hiring, expertise, training, and procurement challenges reinforce the need for these direct indicators (GAO, 2025, 2026).

The research implication is that "AI readiness" is multidimensional. Broad climate may be enabling, but it is neither necessary nor sufficient as a standalone empirical proxy. Future work should model technological capacity, organizational capability, governance, mission fit, procurement, and workforce skill together rather than expecting any single climate index to explain adoption.

7. Agency-level interpretive cases

The data are not designed for agency rankings, but several contrasts illustrate why simple workforce-to-AI narratives are risky.

- Commerce: EEI 77%, PCI 89%, 223 reported AI use cases, and all 223 counted as deployed/piloted. This combination is consistent with substantial implementation activity, but the study cannot attribute it to workforce climate.
- GSA: EEI 86%, the highest in the analytic sample, but 20 of 49 reported use cases are deployed/piloted (40.8%). Strong engagement clearly does not guarantee a high deployment/pilot share.
- DHS: EEI 69%, the lowest in the sample, with 118 of 238 use cases deployed/piloted and 55 high-impact. Mission and governance exposure appear more relevant to portfolio structure than a generic engagement score.
- Education: EEI 75% and all 56 reported use cases deployed/piloted. Its smaller portfolio and 100% implementation share underscore why both portfolio size and lifecycle mix should be considered.

These cases are descriptive illustrations, not causal process tracing. A rigorous case-study extension would require interviews, internal workforce data, budget information, AI strategy documents, and project-level implementation histories.

8. Implications for federal management

For agency leaders, the central implication is not to ignore engagement; it is to avoid confusing engagement with AI readiness. A workforce can be motivated yet still lack specialized AI capability. Agencies should therefore supplement existing employee-climate measures with direct AI workforce and operating metrics.

- Track AI-specific occupations, vacancies, time-to-hire, retention, contractor dependence, and internal mobility.
- Measure completion and demonstrated proficiency in AI, data, model-risk, cybersecurity, privacy, and acquisition training.
- Connect AI inventories to project lifecycle information: owner, mission objective, data readiness, governance review, evaluation status, and operational adoption.
- Measure implementation outcomes rather than counts alone: task performance, service quality, error rates, workforce time saved, user adoption, and incidents.
- Use portfolio comparisons as diagnostic signals, not league tables. Mission differences and reporting scope must remain visible.

9. Limitations

First, the analytic sample contains only 11 agencies. It is purposive and reflects the agencies for which compatible official workforce metrics were validated for this run. Statistical power is limited, intervals are wide, and one or two agencies can materially affect estimates.

Second, the analysis is ecological. EEI and PCI are agency-level aggregates; the AI inventory is also agency-level. The study cannot infer that individual employees with higher engagement cause AI projects to advance.

Third, EEI and PCI are not direct AI-readiness measures. They capture broad engagement conditions and performance confidence. The study lacks a standardized cross-agency measure of AI-specific skill, technical workforce share, training, budget, infrastructure, procurement capacity, or governance maturity.

Fourth, OMB's 2025 inventory is a public reporting system with defined exclusions and changed reporting rules. National-security and intelligence uses, certain research uses, and other excluded material are not represented. COTS consolidated reporting is separate from individually reported use cases. Agency counts therefore should not be treated as exhaustive measures of all AI activity.

Fifth, the primary AI outcome combines deployed and piloted systems. A pilot is not the same as full operational deployment. The ratio is best interpreted as an implementation-stage share in the public inventory, not a technology-maturity score.

Sixth, PCI was available for only eight agencies. Two PCI values were reconstructed from official Q20-Q23 percent-positive results according to the 2024 OPM definition. The official-index-only sensitivity sample contains only six agencies, making inference particularly uncertain.

Finally, the design is observational. The 2024-to-2025 ordering does not establish causality, and unmeasured mission, resources, leadership, contracting, technology infrastructure, and reporting practices are plausible confounders.

10. Conclusion

Federal AI adoption is expanding at a pace that makes workforce capability a legitimate management concern. However, this exploratory study finds no evidence that broad employee engagement, by itself, explains which agencies report a greater share of AI use cases in deployed or piloted status. Performance Confidence likewise shows no reliable relationship in the smaller secondary sample.

The result sharpens rather than weakens the human-capacity argument. If government wants to understand whether agencies are ready for AI, it must measure the capabilities AI actually requires. Engagement and confidence remain important organizational conditions, but federal AI readiness should be evaluated with direct measures of technical talent, training, governance, data, infrastructure, acquisition, mission fit, and implementation outcomes. That is the next empirical frontier for public-sector AI research.

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Primary data sources by agency

Agency	EEI	PCI	PCI method	Official 2024 source
Commerce	77.0	89.0	official_index	https://www.commerce.gov/sites/default/files/2024-10/2024%20FEVS%20At-a-Glance.pdf
Education	75.0	90.0	official_index	https://www.ed.gov/sites/ed/files/2024-11/fevs-results-2024.pdf
Energy	80.0	91.75	derived_four_item_mean	https://www.energy.gov/sites/default/files/2024-10/2024-FEVS-AES-DOE.pdf
Health and Human Services	78.7	-	-	https://www.hhs.gov/about/agencies/asa/ohr/employee-survey/index.html
Homeland Security	69.0	79.0	derived_four_item_mean	https://www.dhs.gov/sites/default/files/2024-10/24_1031_ochco_2024-summary-of-results-508.pdf
Housing and Urban Development	76.0	88.0	official_index	https://www.hud.gov/sites/dfiles/OCHCO/documents/2024-FEVS-HEART-Report.pdf
Labor	76.0	-	-	https://www.dol.gov/sites/dolgov/files/general/budget/2024/FY2024APR.pdf
the Interior	73.0	85.0	official_index	https://www.doi.gov/pmb/hr/doifevs
the Treasury	74.0	86.3	official_index	https://home.treasury.gov/about/careers-at-treasury/2024-federal-employee-viewpoint-survey-results
EPA	81.0	91.0	official_index	https://www.epa.gov/careers/2024-epa-employee-viewpoint-survey-summary
GSA	86.0	-	-	https://www.gsa.gov/system/files/GSA-FY2024-Annual-Performance-Report-Final-508-Jan-2025.pdf

OMB AI counts for all agencies were taken from the official 2025 Federal Agency AI Use Case Inventory repository listed in References. The complete machine-readable extracts used in this paper, including source URLs and validation notes, are included in the accompanying reproducibility package.

Data availability and reproducibility

The accompanying TDTI research package contains the two structured raw-data extracts, merged analytic dataset, statistical output, publication figures, full analysis script, paper-generation script, source-validation ledger, data dictionary, methods protocol, execution log, software requirements, and SHA-256 checksums. The primary analysis can be reproduced with `python scripts/analyze_study.py` using random seed 20261013.

CITATION RECOMMENDATION

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