EasyChair Preprint

№ XXX

The State of AI in Government: An Analysis of Adoption Patterns at the USDA

Hrishitva Patel

EasyChair preprints are intended for rapid dissemination of research results and are integrated with the rest of EasyChair.

September 9, 2025

The State of AI in Government: An Analysis of Adoption Patterns at the USDA

Abstract

The promise of generative AI (GenAI) has captured the global imagination, yet its journey into the heart of government remains a mystery. While the private sector sprints toward an AI-driven future, the public sector seems to be taking a different, more deliberate path. This study pulls back the curtain on this digital divide by examining 89 AI projects from the USDA's public inventory. We found that the fanfare surrounding GenAI masks a quiet reality: conventional technologies like Natural Language Processing (NLP), Computer Vision (CV), and Traditional Machine Learning (ML) overwhelmingly dominate the landscape, with GenAI representing a mere fraction of total cases. This study contributes to IS research by highlighting the cautious trajectory of AI adoption in government and discussing implications for the diffusion of emerging technologies, accountability, and digital innovation ecosystems.

1. Introduction

In recent years, AI has transcended its technical roots to become a central concern in IS research, drawing attention for its profound organizational, ethical, and policy implications (Abbasi et al., 2024; Sun & Medaglia, 2019). Globally, governments are increasingly leveraging AI for everything from service delivery to decision support and regulation (Mergel et al., 2019). Yet, while technologies like generative AI have recently captured global headlines, their practical integration into public sector workflows remains poorly understood.

To shed light on this emerging trend, we turn to the U.S. Department of Agriculture (USDA) as a compelling case study. The USDA is a federal executive department that provides leadership on a wide range of critical issues, including food, agriculture, natural resources, and rural development. Established in 1862, its mission is expansive and deeply embedded in the nation's infrastructure, from managing national forests to overseeing food assistance programs. Given its diverse and mission-critical responsibilities, the USDA offers an ideal environment to examine the diffusion of new technologies in a risk-averse, highly-regulated public sector context.

This paper addresses the central question: To what extent has generative AI been adopted compared to traditional AI methods in a U.S. federal agency? By analyzing the USDA AI Use Case Inventory (U.S. Department of Agriculture, Office of the Chief Information Officer, 2025), we provide an empirical assessment of AI adoption patterns.

2. Literature Review

2.1 AI Adoption in the Public Sector

Prior IS scholarship has examined how digital technologies diffuse across government organizations, highlighting issues of legitimacy, accountability, and risk aversion (Janssen & van den Hoven, 2015; Zuiderwijk et al., 2021). AI adoption in government is often shaped by

**The annotations reported in this study were produced directly by the ChatGPT API and were not content coded, validated by third parties, or independently verified by the authors.*

mission-critical reliability concerns, regulatory compliance, and ethical considerations (Wirtz et al., 2018).

2.2 Generative AI as Digital Innovation

Generative AI represents a shift from task-specific automation (e.g., NLP classifiers, CV detection) toward models capable of producing new text, code, and images. IS scholars frame GenAI as both an enabler of organizational creativity and a source of governance challenges (Berente et al., 2021; Brynjolfsson & McAfee, 2017). The public sector's cautious approach reflects a tension between innovation and responsible use (Mergel et al., 2019).

3. Methods

To conduct a systematic analysis, each AI use case was annotated using the ChatGPT API (latest model, GPT-4.1 at the time of analysis). The annotation task relied on three columns from the dataset: "Agency-owned Data Description," "Intended purpose and expected benefits of use case," and "Topic Area." These fields captured the underlying data modality, functional application, and domain context, thereby providing a holistic basis for classification. The model was instructed to categorize each case into one of four AI types: Traditional Machine Learning (ML), Natural Language Processing (NLP), Computer Vision (CV), or Generative AI (GenAI). This semi-automated procedure was carried out with the aim of identifying potentially interesting insights. Although some cases seemed ambiguous (to the human eye/authors) due to limited or generic descriptions, the hope was that these automated classifications might offer valuable insights into how OpenAI's GPT-4.1 could interpret heterogeneous AI deployments. The final annotations were subsequently visualized to facilitate comparative analysis*.

Prompt:

"You are an expert in Artificial Intelligence classification.
Given the following fields from a dataset of U.S. federal AI use cases:

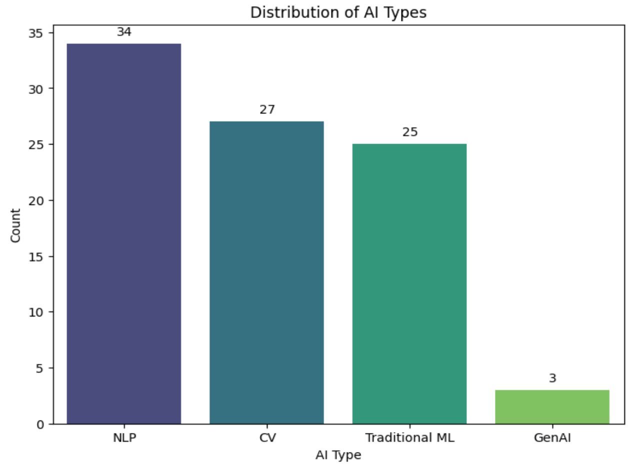
1. Agency-owned Data Description
2. Intended purpose and expected benefits of use case
3. Topic Area

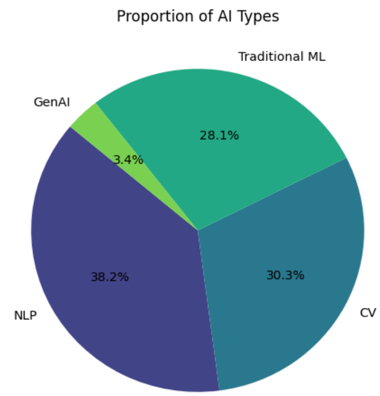
Classify the AI system as one of the following categories:
- Traditional Machine Learning (ML)
- Natural Language Processing (NLP)
- Computer Vision (CV)
- Generative AI (GenAI)

Base your classification on both the data modality and the functional application.
Output only the category name."

**The annotations reported in this study were produced directly by the ChatGPT API and were not content coded, validated by third parties, or independently verified by the authors.*

4. Results





As seen from the pictures above, the distribution of AI types across USDA projects is as follows:

- **NLP:** 34 projects (38.2%)
- **CV:** 27 projects (30.3%)
- **Traditional ML:** 25 projects (28.1%)
- **GenAI:** 3 projects (3.4%)

Visualizations (Figure 1 – bar chart, Figure 2 – pie chart) demonstrate that USDA AI adoption is dominated by conventional techniques, with minimal generative AI presence.

5. Discussion

5.1 Diffusion of Emerging Technologies

These findings support the argument that public agencies adopt novel technologies incrementally rather than disruptively (Mergel et al., 2019). Despite widespread discourse on GenAI, USDA's implementations remain grounded in NLP and CV—technologies with longer track records of reliability.

5.2 Responsible AI and Risk Aversion

The scarcity of GenAI projects may reflect concerns around accountability, fairness, and explainability, which have been central in IS discussions on digital governance (Janssen & van den Hoven, 2015; Wirtz et al., 2018). Agencies face heightened scrutiny when deploying AI in rights-impacting contexts, leading to preference for mature, less controversial techniques.

6. Conclusion

**The annotations reported in this study were produced directly by the ChatGPT API and were not content coded, validated by third parties, or independently verified by the authors.*

This study provides a novel empirical perspective on AI diffusion, directly challenging the assumption of widespread GenAI adoption in government. The USDA's overwhelming reliance on mature NLP, CV, and ML technologies serves as a powerful case study for IS research. Our findings underscore that in the public sector, the diffusion of innovation is a fundamentally political and social process, constrained by the imperatives of accountability and public trust (Rogers, 2003).

The limited presence of GenAI is not just a statistical finding but an institutional outcome that deserves further exploration. We acknowledge that the data may not capture the full picture. It's possible that agencies are intentionally not disclosing sensitive or experimental AI projects, or that our semi-automated classification methodology, while systematic, was limited by the generic descriptions provided in the public inventory. As celebrated IS scholar Geoffrey Moore noted in *Crossing the Chasm* (Moore, 2014), early-stage, "innovator" projects often exist in a separate space from mainstream adoption, and this may be particularly true in a risk-averse environment like the public sector.

Therefore, the slow and deliberate trajectory of GenAI in this context is a testament to the unique governance challenges that digital innovation presents for public organizations. The USDA's trajectory serves as a valuable case study, providing a baseline for future qualitative studies to explore the "why" behind these trends. What are the specific organizational debates, policy hurdles, and risk assessments that shape the path of new technologies in government? Are agencies deliberately not disclosing this information? Addressing these questions could reveal fascinating insights into the complex relationship between innovation and governance in the digital public sector.

References

Abbasi, A., Parsons, J., Pant, G., Sheng, O. R. L., & Sarker, S. (2024). Pathways for design research on artificial intelligence. *Information Systems Research, 35*(2), 441–459. https://doi.org/10.1287/isre.2024.editorial.v35.n2

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly, 45*(3), 1433–1450. https://doi.org/10.25300/MISQ/2021/16274

Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.

Janssen, M., & van den Hoven, J. (2015). Big and open linked data (BOLD) in government: A challenge to transparency and privacy? *Government Information Quarterly, 32*(4), 363–368. https://doi.org/10.1016/j.giq.2015.11.007

**The annotations reported in this study were produced directly by the ChatGPT API and were not content coded, validated by third parties, or independently verified by the authors.*

Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, *36*(4), 101385. https://doi.org/10.1016/j.giq.2019.06.002

Moore, G. A. (2014). *Crossing the Chasm: Marketing and Selling Disruptive Products to Mainstream Customers* (3rd ed.). Harper Business.

Rogers, E. (2003). Diffusion of Innovations 5th. Free Press.

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, *36*(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008

U.S. Department of Agriculture, Office of the Chief Information Officer. (2025, May 8). *Department of Agriculture inventory of artificial intelligence use cases* [Dataset]. Data.gov. Retrieved September 9, 2025, from https://catalog.data.gov/dataset/department-of-agriculture-inventory-of-artificial-intelligence-use-cases

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2018). Artificial Intelligence and the Public Sector—Applications and Challenges. *International Journal of Public Administration*, *42*(7), 596–615. https://doi.org/10.1080/01900692.2018.1498103

Zuiderwijk, A., Chen, Y. C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly*, *38*(3), 101577. https://doi.org/10.1016/j.giq.2021.101577

Notes: **The annotations reported in this study were produced directly by the ChatGPT API and were not content coded, validated by third parties, or independently verified by the authors.*