AI Adoption in the Federal Government

Client: Booz Allen Hamilton

May 2020

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Acknowledgements

The Columbia SIPA Booz Allen Hamilton Capstone Team would like to extend our deepest gratitude to our mentors, interviewees, and advisors who made our research project possible.

This report was produced for Booz Allen Hamilton (BAH) in conjunction with Columbia University's School of International and Public Affairs (SIPA) as a Capstone Consultancy project. The authors Cen Wei, Deergeer Mengke, Jessica Shaw, Maximillian Gahntz, Paula Cerda Crawford, Xinyu Zhong, and Xiwen Wang are graduate students of Columbia SIPA. Any views expressed here are the authors' own views and do not necessarily represent those of SIPA or BAH.

We would like to firstly thank our SIPA faculty advisors, Tim Meyer and Ulrike Zeilberger, both Adjunct Professors of International and Public Affairs, who oversaw this research project. We would also like to extend our gratitude to Booz Allen Hamilton, especially Geoff Buteau and Michael Fagundo, for their guidance and assistance. Additionally, we thank Suzanne Hollmann and Saleha Awal from the SIPA Capstone office for helping organize this project.

The report is informed by many interviews with experts in the field. We would like to thank them for their valuable contributions: Caryl Brzymialkiewicz, Chief Data & Analytics Officer (CDAO) of the Office of Inspector General (OIG), United States Department of Health and Human Services (HHS); Chris Chilbert, Chief Information Officer (CIO) of OIG HHS; Dorothy Aronson, CIO of Division of Information Systems, National Science Foundation (NSF); Ed Kearns, Chief Data Officer (CDO) at National Oceanic and Atmospheric Administration (NOAA); Joe Incorvia, Director of Command Operation for Naval Air Systems Command (NAVAIR); Captain John McGunnigle AI Director, Undersea Warfighting Development Center; Jose Arrieta, CIO at HHS; Tim Persons, Chief Scientist and Managing Director of the Science, Technology Assessment, and Analytics team at the United States Government Accountability Office (GAO); as well as a former senior government official who asked to remain anonymous.

At BAH, we would like to extend our gratitude to Catherine Ordun, Senior Data Scientist; Cutter Breton, Chief Technologist with BAH's Strategic Innovation Group; Graham Gilmer, Principal at BAH; Katherine Helfet, Senior Consultant at BAH Strategic Innovation Group; Stella Biderman,

Staff Scientist at BAH; and Christopher Anderson, Senior Associate with BAH's Strategic Innovation Group Analytics.

Abstract

As more organizations invest in and make use of artificial intelligence (AI), the United States public sector appears to be lagging behind in the adoption of AI. Based on desk research and interviews with experts from government and the private sector, this report seeks to shine a light on the obstacles federal departments and agencies face in the development and implementation of AI systems and on how these very obstacles can be overcome. In our analysis, we identify a range of different challenges public sector organizations face in AI adoption. The challenges can be organized along three distinct but interrelated dimensions, namely strategy, capabilities, and culture. Based on this analysis and drawing on examples of good practice from both the United States and abroad, the report provides recommendations for organizational guidelines and policies that better enable public sector organizations to successfully develop and implement AI.

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Section I: Introduction and Summary

While an increasing number of public sector organizations are making progress on adopting applications of AI in core and peripheral parts of their business, **adoption of AI in the public sector is still lagging**. The potential of using AI for government and the public good is tremendous, but the book on how the adoption of AI in government can be accelerated and improved remains open. Booz Allen Hamilton has asked our capstone team to address this issue.

Thus, this report seeks to **shine a light on the obstacles public sector organizations at the federal level face in the development and implementation of AI systems** and how these very obstacles can be overcome. The report focuses on organizational challenges that federal departments and agencies can tackle themselves, excluding exogenous obstacles such as regulatory hurdles. To find answers to our research questions, we have conducted extensive **desk research and interviews both with senior executives of federal departments and agencies as well as management consultants working with the federal government**. Through our review of the relevant written work and our interviews, we identified a wide range of obstacles that stand in the way of AI adoption in the public sector.

To organize our findings, we developed an analytical framework that structures the **identified obstacles along three distinct but interrelated dimensions: strategy, capabilities, and culture**. The first dimension addresses whether organizations pursue a strategic approach to advancing AI by outlining a unified vision as well as specific actions to be taken in pursuit of this goal. The capabilities dimension focuses on whether organizations have at their disposal the technical, human, and organizational resources necessary for successful AI adoption. Finally, the cultural dimension addresses shared values and behavior endemic to each organization that inhibit the adoption of AI.

Based on our findings and drawing from examples of good practices both in the United States public sector as well as abroad, we developed **eight recommendations in order to provide departments and agencies with a roadmap and concrete first steps** in their quest to implement and scale AI across their organization:

1. Put **strategy development first** to better coordinate and align the organization's efforts and to lay the foundation for successful AI adoption.
2. Provide **centralized data infrastructure, tools, and standards** to better harness data and to leverage economies of scale.
3. Build **centralized expertise and organic development capabilities** by setting up development labs or specialist units focusing on AI development and implementation.
4. Create acceptance for AI and overcome inertia and risk-aversion by adopting a lean startup **approach focused on fostering small, experimentation, and continuous feedback**.
5. Put end users at the center of the development process by adopting a **user-centered design approach** such as Design Thinking and setting up **cross-disciplinary teams**.
6. Enable top-level leadership to oversee and advance AI-centered projects through the creation of **executive training programs**.
7. Facilitate an **exchange of talent between government, the industry, and academia** by creating programs that attract external experts and allow staff to gain private sector experience.
8. Treat **culture as an integral part of making an organization ready for AI** by considering each organization's unique culture in AI strategy, development, and deployment.

The report is structured as follows: Section 2 provides a basic introduction to AI and its use in government, followed by the status quo of AI adoption in the United States public sector within Section 3. Section 4 and 5 elaborate on our methodological approach and analytical framework. Section 6 then discusses the various obstacles to AI adoption identified in our research. Section 7 provides an in-depth detail of recommendations. Finally, Section 8 concludes with an outlook on potential future research questions related to and emerging from this project.

Section II: What Is AI?

Technological Basics

Recent breakthroughs in AI have been enhanced by three concurrent developments: rapid advancement in computing power and capacity, an explosion in the creation and collection of data, and progress in the techniques and algorithms at the heart of AI.[1]

AI can be defined as "the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem solving."[2] More concretely, modern AI systems are developed to recognize and extrapolate patterns as well as, potentially, make recommendations and perform certain actions based on a pre-defined objective— essentially a mathematical function the algorithm seeks to maximize (or minimize, depending on the objective).

AI is a broad concept. What people mean when they talk about AI has shifted since the term was coined in the mid-1950s. For instance, in the 1980s, most research on AI focused on developing "expert" systems that encode, ideally, all human knowledge necessary to perform a given task in a set of hard rules. This approach, however, has been mostly abandoned. Instead, when people talk about AI today, they primarily mean Machine Learning, and more specifically, Deep Learning. These two terms can be viewed as subsets of AI, and Deep Learning can be viewed as a subset of Machine Learning.

The term Machine Learning categorizes methods built on the idea that models can learn from data and "experience." This means that Machine Learning algorithms are adaptive and designed to improve their own performance over time. The term subsumes a variety of different approaches, such as regression-based methods, decision trees and random forests, or neural networks.

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[1] Jacques Bughin et al., "Notes from the AI Frontier - Modeling the Impact of AI on the World Economy" (McKinsey Global Institute, 2018), 5–6, https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20frontier%20Modeling%20the%20impact%20of%20AI%20on%20the%20world%20economy/MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018.ashx; Dario Amodei and Danny Hernandez, "AI and Compute," *OpenAI* (blog), May 16, 2018, m/blog/ai-and-compute/.

[2] McKinsey & Co., "An Executive's Guide to AI," 2018, 1, https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Analytics/Our%20Insights/An%20executives%20guide%20to%20AI/An-executives-guide-to-AI.ashx.

Neural networks, named in reference to but functioning quite differently from the human brain, are at the heart of what is called Deep Learning. A 2018 McKinsey report provides a brief summary of how a neural network functions:

> [I]interconnected layers of software-based calculators known as 'neurons' form a neural network. The network can ingest vast amounts of input data and process them through multiple layers that learn increasingly complex features of the data at each layer. The network can then make a determination about the data, learn if its determination is correct, and use what it has learned to make determinations about new data.[3]

Deep Learning methods, although they come with a set of specific challenges, are the state of the art in terms of performance with regard to a wide range of tasks, such as computer vision or natural language processing (NLP).

Pertaining to learning-based AI methods, it is also important to distinguish between supervised and unsupervised learning. In supervised learning, models are "trained", meaning that a model is fed a labeled data set and, in turn, learns to identify the features associated with each label. When exposed to new data, the model then predicts which label is most likely to fit the new data based on the previously learned features. In unsupervised learning, on the other hand, models are fed unlabeled and unstructured data. The model's task is to identify structure in the data on its own by identifying features that allow, for example, clustering or dividing the data points contained in a dataset.

It is crucial to also keep in mind the importance of data when discussing AI systems. No matter how sophisticated an algorithm is, it will perform poorly if "fed" with insufficient data (both in terms of quantity and quality). Successfully developing and deploying AI systems is thus dependent on a number of conditions, such as using data sets that are both accurate and unbiased or the availability of labeled data (for supervised learning systems).

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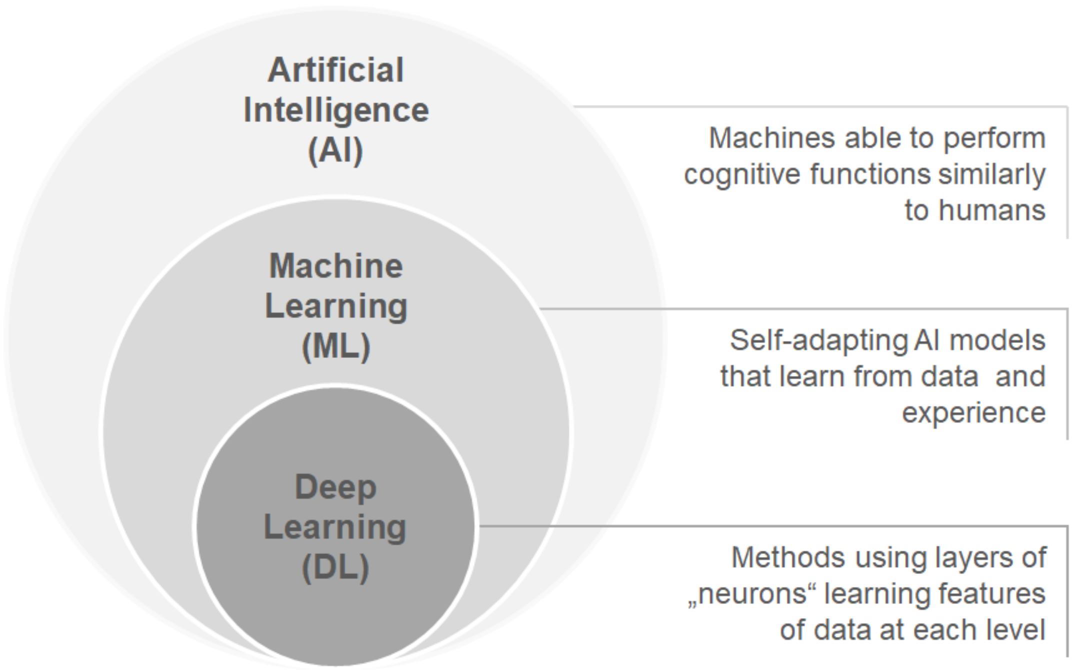
[3] McKinsey & Co., 6.

Figure 1: The Difference Between AI, Machine Learning, and Deep Learning



It is also important to note that AI systems are embedded in a social and organizational context. Their design must account for that and ensure that AI systems accommodate the specific needs and capabilities of the humans they interact with and the peculiarities of the processes they are integrated into.

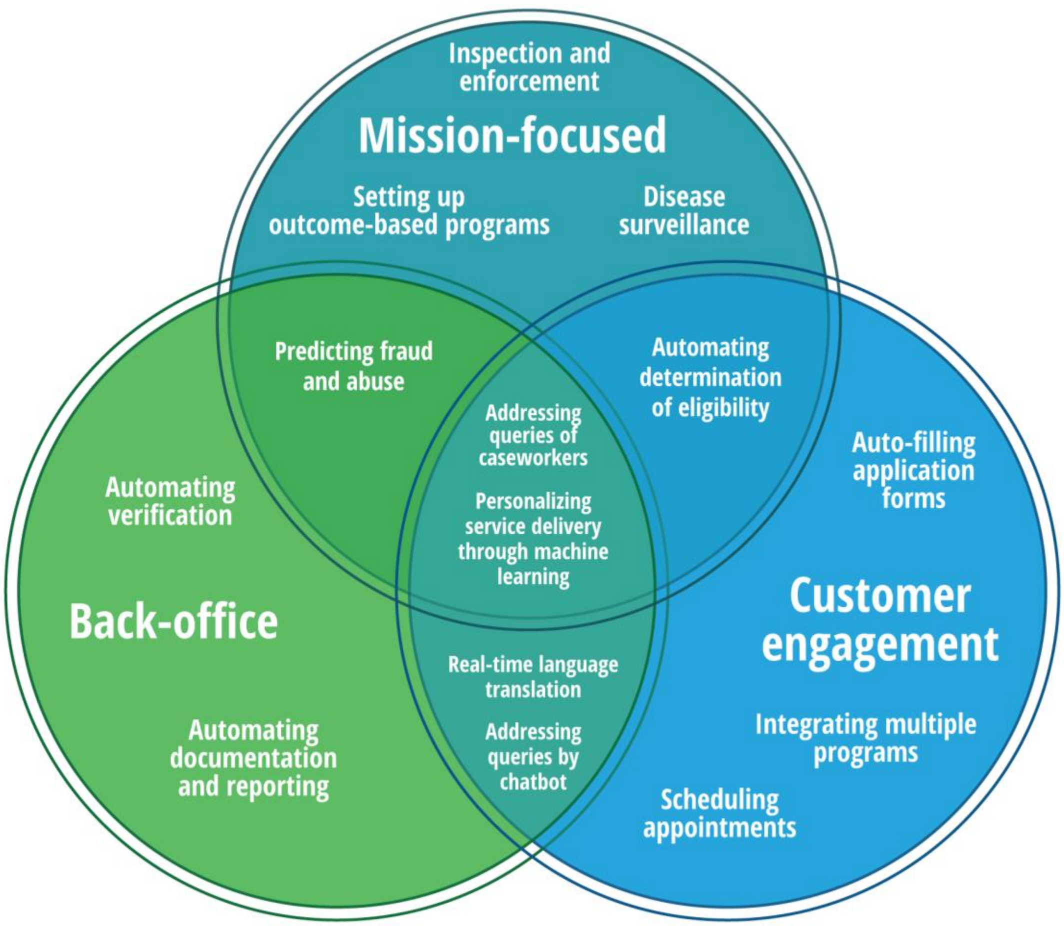
AI in the Public Sector

While the number of AI applications continues to grow daily, they generally are a form and or combination of object recognition (computer vision), pattern recognition, anomaly detection, and/or natural language processing/understanding (NLP/NLU).[4] The type and source of data depends on the specific application AI systems are used for. They can include, for example, image data from drone, satellite, or CCTV camera footage, encoded text or numerical data from case files or tax returns, or sensor data on infrastructure such as roads, bridges, or sewage systems.

[4] Karen Fullerton, "AI for the Public Sector," Text, Knowledge for policy - European Commission, December 3, 2018, https://ec.europa.eu/knowledge4policy/ai-watch/topic/ai-public-sector_en.

To distinguish between different use cases of AI in the public sector (and in this case specifically with regard to human services), Deloitte developed a practical framework differentiating between three main uses of AI: mission-focused uses, back-office uses, and use of AI for customer engagement. However, with some use cases, there is also substantial overlap between these three categories, with some use cases even relevant to all three of them. Figure 2 depicts the framework, highlights this overlap between the three different types of uses, and provides more detail on specific use cases.[5]

Figure 2: United States Government's Three Main Uses of AI for Delivery of Human Services



Source: Deloitte

[5] "Crafting an AI Strategy for Government Leaders | Deloitte Insights," accessed May 1, 2020, https://www2.deloitte.com/us/en/insights/industry/public-sector/ai-strategy-for-government-leaders.html#.

Beyond the specific technical specifications of use cases for AI systems, applications of AI further vary along a number of dimensions: First, they vary with regard to their technological complexity. Whereas some applications produce sufficient results with relatively simple models, others demand more advanced models and more computational power. Independent from technical complexity, AI systems also vary with regard to the nature of the task they seek to automate. An AI application can automate both mundane routine tasks or non-routine tasks which have previously been characterized by the use of human judgement. Whether an AI application performs a routine or a non-routine task can make a tremendous difference in regards to how staff and other stakeholders will respond to the adoption of a new AI system. The performance of routine versus non-routine has the potential to significantly shift the focus of individuals' jobs.

Finally, applications differ in terms of the risk they are associated with. Some applications of AI automate relatively inconsequential tasks, so that the negative effects caused by inaccuracies in an AI system are negligible. An example of such an application could be machine learning-based optical character recognition (OCR). OCR translates images of text into machine-readable text, for example the process of scanning a passport. Inaccuracies in such a system are essentially equivalent to typos if such a task were instead completed by humans. On the other hand, when influencing processes and decisions that directly affect the material well-being of humans, some automated systems and AI applications can produce substantial harmful effects due to poor accuracy or flawed input data. For instance, an algorithmic decision-making system intended to detect fraud in Michigan's unemployment insurance system wrongfully led to tens of thousands of people having to repay the benefits they received from October 2013 to September 2015.[6] Further, it has been well established in the academic literature that AI systems can produce outputs that are biased against certain vulnerable groups, for example against racial minorities or women.[7]

[6] Robert N. Charette, "Michigan's MiDAS Unemployment System: Algorithm Alchemy Created Lead, Not Gold," *IEEE Spectrum*, January 24, 2018, https://spectrum.ieee.org/riskfactor/computing/software/michigans-midas-unemployment-system-algorithm-alchemy-that-created-lead-not-gold; Human Rights Watch, "May 2019 Submission to the UN Special Rapporteur on Extreme Poverty & Human Rights Regarding His Thematic Report on Digital Technology, Social Protection & Human Rights," 2019, https://www.ohchr.org/Documents/Issues/Poverty/DigitalTechnology/HumanRightsWatch.pdf.

[7] For an overview of the issue see, for example, Ninareh Mehrabi et al., "A Survey on Bias and Fairness in Machine Learning," *ArXiv:1908.09635 [Cs]*, September 17, 2019, http://arxiv.org/abs/1908.09635.

Government organizations should thus also account for the risk associated with specific AI applications. Frameworks for risk assessment can help with this task. For example, a proposal put forward by the European Commission suggests that "a given AI application should generally be considered high-risk in light of what is at stake, considering whether both the sector and the intended use involve significant risks, in particular from the viewpoint of protection of safety, consumer rights and fundamental rights."[8] While AI as a technology and the organizations deploying it constantly evolve, it is impossible to come up with a comprehensive list of what applications may or may not be considered high-risk. Still, a risk-based framework distinguishing between high-risk and low-risk applications seems sensible in order to allow organizations to target their efforts in ensuring the safety and fairness of such systems.

Section III: The Status Quo of AI Adoption in the United States Public Sector

As one of the leading countries in AI research and adoption, the United States has already laid down the necessary groundwork for AI adoption in government. The White House underlines the United States' unique position, writing that:

> [O]ur approach strengthens and leverages the unique and vibrant American R&D ecosystem, combining the strengths of government, academia, and industry. [...] The result is a thriving R&D enterprise that maintains American leadership in AI technologies.[9]

In President Trump's 2019 Executive Order on "Maintaining American Leadership in Artificial Intelligence", the White House links this unique advantage of the United States to special ambition with regard to AI:

> The United States is the world leader in AI research and development (R&D) and deployment. Continued American leadership in AI is of paramount importance to maintaining the economic and national security of the United States and to shaping the

[8] European Commission, "White Paper on Artificial Intelligence - A European Approach to Excellence and Trust," February 19, 2020, 17, https://ec.europa.eu/info/sites/info/files/commission-white-paper-artificial-intelligence-feb2020_en.pdf.
[9] "Artificial Intelligence for the American People," The White House, accessed May 2, 2020, https://www.whitehouse.gov/ai/ai-american-innovation/.

global evolution of AI in a manner consistent with our Nation's values, policies, and priorities.[10]

To help achieve this goal, the Select Committee on Artificial Intelligence of the National Science & Technology Council published the "National Artificial Intelligence Research and Development Strategic Plan". The federal R&D on AI is guided by this strategic plan which outlines eight different strategies.[11] A 2019 progress report on the plan maps these strategies against the activities and investments of the federal R&D agencies and shows both the broad range of investments and research fields as well as the heterogeneity across agencies in their progress on the different strategies (see Table 1).[12]

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[10] The White House, "Executive Order on Maintaining American Leadership in Artificial Intelligence," The White House, February 11, 2019, https://www.whitehouse.gov/presidential-actions/executive-order-maintaining-american-leadership-artificial-intelligence/.

[11] Select Committee on Artificial Intelligence of the National Science & Technology Council, "The National Artificial Intelligence Research and Development Strategic Plan: 2019 Update," 2019.

[12] National Science and Technology Council, "2016–2019 Progress Report: Advancing Artificial Intelligence R&D" (White House, November 2019), https://www.whitehouse.gov/wp-content/uploads/2019/11/AI-Research-and-Development-Progress-Report-2016-2019.pdf#search='white+house+artificial+intelligence+best+practices'.

Table 1: Summary of Investments by Federal Entities in the Eight National AI R&D Strategies

AI R&D Strategies	AFOSR	Army	Census	DARPA	DHS	DoD*	DOE	DOT	FBI	FDA	GSA	HHS	IARPA	NASA	NIFA	NIH	NIJ	NIST	NOAA	NSF	NTIA	ONR	VA
1. Make long-term investments in AI research	X	X		X	X	X	X	X	X	X	X		X	X	X	X		X	X	X	X	X	
2. Develop effective methods for human-AI collaboration	X	X		X	X	X	X	X		X			X		X	X	X	X	X	X		X	
3. Understand and address the ethical, legal, and societal implications of AI		X		X	X	X	X	X							X	X				X	X		
4. Ensure safety and security of AI systems		X		X		X	X			X			X	X				X	X	X			
5. Develop shared public datasets and environments for AI training and testing						X	X	X		X	X	X	X	X		X		X	X	X	X	X	X
6. Measure and evaluate AI technologies through benchmarks and standards				X	X	X	X			X			X			X	X	X	X			X	
7. Better understand the national AI R&D workforce needs			X			X	X						X		X		X	X	X	X			
8. Expand public-private partnerships in AI to accelerate advances in AI		X		X	X	X	X		X	X		X			X	X	X	X	X	X			

* DoD performs R&D in the AI R&D Strategies through coordinated activities by its service agencies.

Source: National Science and Technology Council

Against this backdrop, it does not come as a surprise that the "AI Government Readiness Index 2019", produced by the consultancy Oxford Insights, ranks the United States fourth out of 194 countries.[13] The assessment is based on eleven metrics grouped in four clusters: Governance, Infrastructure and Data, Skills and Education, and Government and Public services.

Still, in regards to the actual adoption of AI, the United States public sector appears to be lagging behind the private sector. A 2019 Deloitte survey of decision makers in the public and private sector shows that far more governmental organizations find themselves in the earlier stages of AI adoption, compared to other sectors. Specifically, 45 percent of public sector respondents

[13] Hannah Miller and Richard Sterling, "Government AI Readiness Index 2019" (Oxford Insights, 2019), https://www.oxfordinsights.com/ai-readiness2019.

characterize their organizations as “starters” while only 14 percent are considered “seasoned” users of AI (see Figure 3).[14] A survey of decision makers from the federal government conducted by the Government Business Council (GBC) further reports that 40 percent of respondents said their organization had “no plans to implement AI” while only 16 percent of organizations were already deploying AI in “mission-central operations”.[15] The rest of the respondents were either planning on or in the process of implementing AI.[16] The 2019 Deloitte survey also finds that significantly fewer public sector respondents felt that AI is critical to their organization’s current and future success compared to their private sector counterparts. However, 74 percent of public officials still say that, two years from being surveyed, AI will be “very” or “critically” important to their organization’s mission.[17] Public sector organizations also invest the least of all sectors included in the survey (although investment is increasing) and are reported to be significantly less sophisticated in identifying AI use cases and implementing the technology compared to the private sector. Finally, only 8 percent of respondents to the GBC survey replied that progress on AI adoption is faster compared to other elements of IT modernization and transformation.[18] Different than the more than half of respondents which replied that AI Adoption is slower.

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[14] William D. Eggers, Sushumna Agarwal, and Mahesh Kelkar, “Government Executives on AI - Surveying How the Public Sector Is Approaching an AI-Enabled Future” (Deloitte, 2019), https://www2.deloitte.com/us/en/insights/industry/public-sector/ai-early-adopters-public-sector.html?id=us:2em:3na:4di5096:5awa:6di:MMDDYY::author&pkid=1006403.

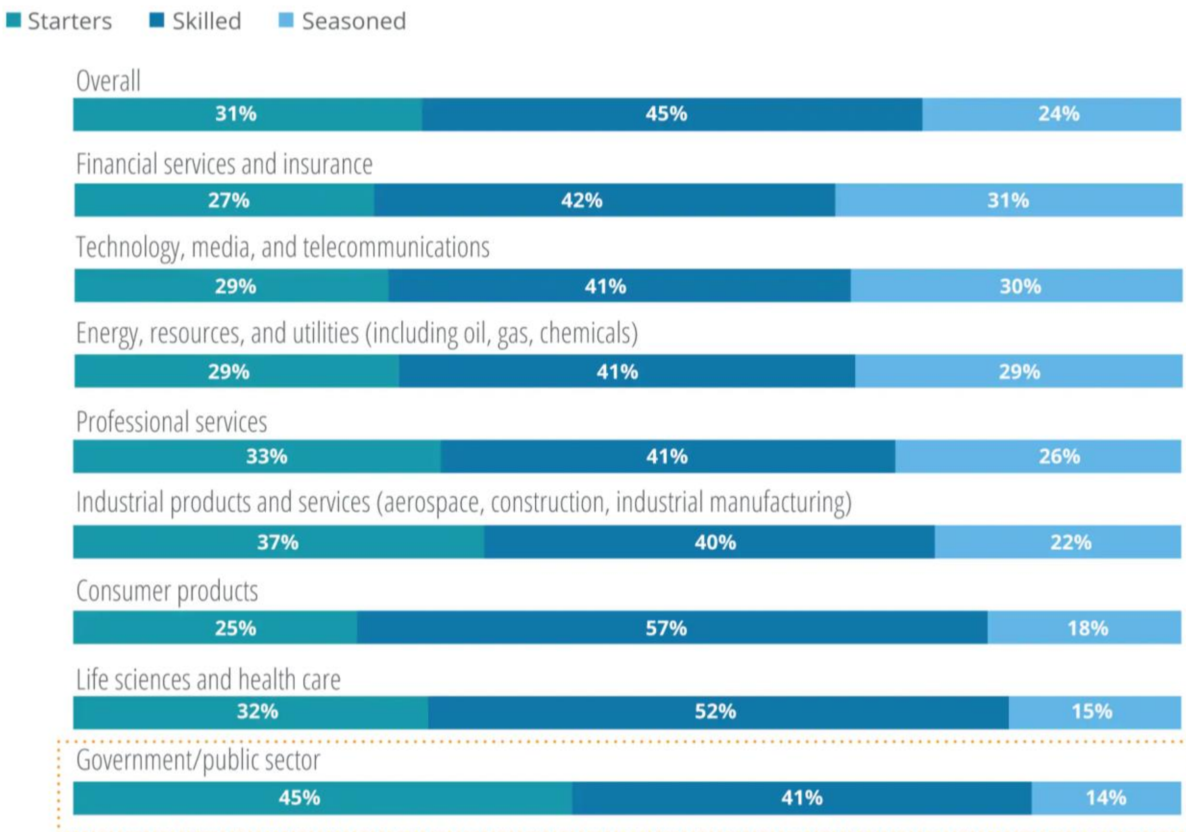
[15] Igor Geyn, “Is the Federal Government Ready for AI?” (Nextgov, April 2, 2019), https://www.govexec.com/insights/reports/federal-government-ready-ai-survey-supplement/155991/.

[16] Ibid.

[17] Eggers, Agarwal, and Kelkar, “Government Executives on AI - Surveying How the Public Sector Is Approaching an AI-Enabled Future.”

[18] Geyn, “Is the Federal Government Ready for AI?”

Figure 3: Self-reported AI Maturity Across Sectors



Source: Deloitte

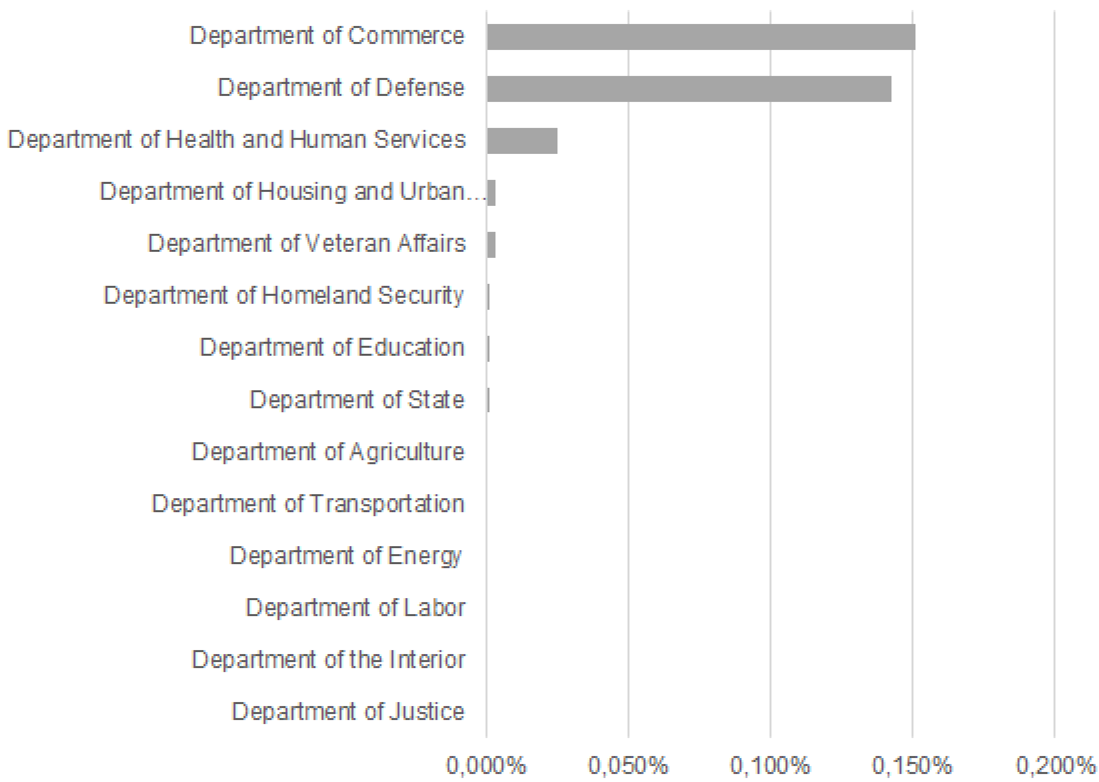
This evidence clearly points to shortcomings with regard to AI adoption in the United States' public sector at large. At the federal level, too, AI does not appear to be a strategic priority. Only the Department of Defense (DoD) has published a department-wide AI strategy. Further, only the DoD and the Department of Energy (DoE) have created organizational units specifically for the purpose of driving forward AI adoption within the respective departments.

Our own research appears to support this finding. Using NLP, we analyzed the federal departments' mandatory FY 2021 Annual Performance Plans and FY 2019 Annual Performance Report, to examine how frequently (weighted against the overall number of words in each report) the departments used key terms related to AI.[19] Our results in Figure 4 suggest that some departments

[19] The key terms used are "Artificial Intelligence", "AI", "Machine Learning", "Deep Learning", and "Neural Network". "Deep Learning" and "Neural Network" are not mentioned in any of the documents, hence not being included in Figure 4.

place significantly higher focus on AI as a strategic issue going forward. This applies especially to the Department of Commerce (DoC) and the DoD, with the Department of Health and Human Services (HHS) following in third. Other departments had no mention of AI within their performance plans and reports, namely the Department of Justice, Department of the Interior, Department of Labor, Department of Energy, Department of Transportation, and Department of Agriculture. Obviously, these reports do not mirror all of these organizations' efforts with regard to AI. Nevertheless, for some departments our findings indicate that AI continues to struggle to make the list of strategic priorities.

Figure 4: Frequency of AI Key Terms in Performance Plans & Reports (as % of whole document)



Section IV: Methodological Approach

To identify the organizational challenges government departments face in terms of development and implementation of AI systems (including ways these challenges can be overcome), we conducted both semi-structured expert interviews in addition to a review of existing relevant research. First, we conducted 16 interviews with senior leadership from several federal departments and agencies, both in the civil and military sectors. This included an interview with one expert who holds several decades of experience in the federal government. Second, we conducted interviews with Booz Allen Hamilton consultants working directly with clients in the federal government. This allowed us to gain both an internal and external perspective on AI adoption in a wide range of organizations. The list of interviewees can be found in the appendix to this report. Finally, we supplemented the findings from our interviews with findings from several government and third-party reports, public documents, and survey research. Although we did not conduct extensive case studies, we draw heavily on examples from the DoD and HHS. A substantial share (but not all) of our interviews with government officials were conducted with DoD and HHS executives. Further, substantially more public documents and research were available on AI within these two departments. We chose to do so to acquire a more extensive base of knowledge on both DoD and HHS, both of which belong to the more advanced organizations with regard to AI adoption according to our own research (see Section III). Therefore, allowing us to better contextualize our observations and extrapolate from our findings.

It is important to note that the evidence we collected from our interviews is merely anecdotal. A comprehensive overview of the state of AI adoption at the federal level at large *or* within specific organizations specifically would have required a far larger number of interviews. This would have gone beyond the scope of this project. However, we still were able to identify common themes and concerns that are broadly applicable across individual organizations. Thus, the findings from our interviews and desk research nonetheless provide important clues with respect to the challenges public sector organizations face in advancing their use of AI and how this can still be achieved. Our findings as well as our recommendations will be outlined in the following sections.

Section V: An Analytical Framework for AI Adoption in Government

The findings from our research span a wide range of different issues. Based on our interviews and desk research, we developed an analytical framework along which the identified *endogenous* obstacles to AI adoption in the federal government can be condensed and organized (see Figure 5). It is important to note that this does not include exogenous challenges, such as regulatory hurdles that cannot be addressed directly by the organizations individually. Our report aims at developing recommendations on what government organizations themselves can do to accelerate successful AI adoption. The framework uses three distinct (but interdependent) and exhaustive dimensions:

Strategy

This dimension encapsulates, most of all, whether an organization has a strategic approach to advancing AI adoption. This includes strategic and coordinated planning, strong leadership, and clear allocation of responsibility both with regard to personnel and organizational structure. Public sector organizations are continuously increasing their investment in AI, oftentimes substantially.[20] In order to ensure that organizations spend these financial resources efficiently, effectively, and prudently, it is critical that they approach such investments in a concerted, strategic manner.

Capabilities

Successful adoption of AI requires that an organization is equipped with the necessary resources. This includes both human resources, (i.e., a well-trained workforce with the knowledge required to successfully navigate the various stages of the lifecycle of AI systems) as well as the technical infrastructure, especially with regard to computing power and data management. Also included are organizational resources, such as adequate business processes.

Culture

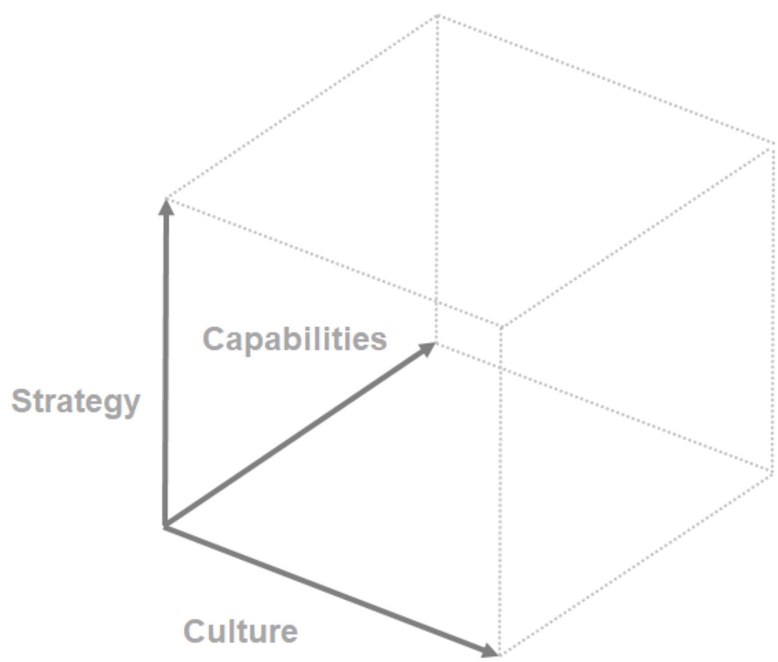
Finally, this dimension addresses the shared values and behaviors endemic to an organization. Organizational culture governs, for example, attitudes towards change as well as interactions between people within the organization. This conception is based on the view of organizations as social systems as opposed to a mere mechanistic entity. Thus, successful adoption of AI requires that organizational culture is aligned in a way that is conducive to the development and deployment of new technology as well as to the disruption of established processes and roles.

Adopting AI is, per se, possible regardless of how well an organization fares on each of these dimensions. However, we believe that truly successful adoption of AI in public sector organizations is contingent on sufficient performance on all three dimensions. Success, in this case,

[20] Eggers, Agarwal, and Kelkar, "Government Executives on AI - Surveying How the Public Sector Is Approaching an AI-Enabled Future."

meaning optimal use of AI and maximized value achieved through the use of AI. Why we believe this can easily be illustrated: Suppose an organization had a perfectly strategic approach to advancing AI and all resources necessary to do so, but at the same time had a culture diametrically opposed to the course set by leadership. In this scenario, AI adoption would stall, at the latest, during the roll-out of new AI systems and the diffusion of the technology within the organization. Similarly, a strategic approach and a culture aligned with the defined goals are necessary but not sufficient conditions for successful AI adoption. Without the necessary technical infrastructure and expertise, the development and deployment of AI systems would, at best, yield subpar applications and result in derailed projects at worst. Finally, where an organization can command all necessary resources and be culturally aligned, applications may meet high technical standards and be used effectively. However, a patchwork of applications across the organization would be likely to emerge, with the organization thus failing to appropriately leverage the otherwise conducive conditions for AI adoption.

Figure 5: A Three-Dimensional Analytical Framework for AI Adoption



Such a framework can not only be used to organize obstacles to AI adoption but also to assess how well organizations are prepared for successful adoption of AI. Based on this assessment, one could further define priorities and outline possible next steps specific to the organization in question.

Section VI: Obstacles to AI Adoption in the Public Sector

Public sector organizations face a variety of different challenges in moving forward with developing and deploying AI within their organization. Based on our interviews and desk research, we identified several challenges and obstacles which need to be overcome in order to achieve successful adoption of AI in government. Our findings are structured along the three dimensions discussed above.

Strategy

Even after the Executive Order on "Maintaining American Leadership in Artificial Intelligence" was signed in February 2019, only a handful of federal agencies have published strategies focusing particularly on AI. These agencies are the DoD, the National Oceanic and Atmospheric Administration (NOAA), the Department of Transportation (DoT, although only with regard to Automated Vehicles), the Food and Drug Administration (FDA, regulatory framework for AI medical devices), the National Institute of Standards and Technology (NIST).[21] Meanwhile, HHS has only published a data strategy and, according to one of our interviewees, has released internal guidance on AI, although it is not as comprehensive as the DoD's strategy.[22]

Further, our research found that even if an AI strategy is in place, organizations still can lack a sufficiently specific roadmap to implement these strategies as well as benchmarks for success. In the case of DoD, one of the most sophisticated public organizations with regard to AI, RAND Corporation points out both the lack of sufficient benchmarks and metrics of success in the DoD's strategy. It also emphasized the fact that the Joint Artificial Intelligence Center (JAIC), the

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[21] The White House Office of Science and Technology Policy, "American Artificial Intelligence Initiative: Year One Annual Report," February 2020, https://www.whitehouse.gov/wp-content/uploads/2020/02/American-AI-Initiative-One-Year-Annual-Report.pdf#search='American+Artificial+Intelligence+Initiative%3A+Year+One+Annual+Report'.
[22] The U.S. Department of Health and Human Services Data Council, "2018 HHS Data Strategy: Enhancing the HHS Evidence-Based Portfolio" (The U.S. Department of Health and Human Services Data Council, 2018).

centralized AI unit at the heart of the DoD's AI strategy, lacks a long-term road-map to lead AI advancement within the DoD.[23]

Several of our interviewees further lamented a lack of centralized authority and expertise within their organizations. While federal agencies could be particularly valuable in large organizations presiding over a large number of subordinate agencies, most lack such organizations or units that allow them to scale efforts and accelerate AI adoption through centralized coordination and implementation. Only the DoD, DoE, and the Department of Veteran Affairs (VA) have created organizations/units aiming to fulfil these functions.[24] In the case of the DoD, the Defense Innovation Board advocated to establish "a centralized, focused, well-resourced organization", as had happened with regard to nuclear weapons and precision guided weapons in 2016,[25] which subsequently happened with the establishment of JAIC in 2018.[26] Particularly in large organizations, centralization can help avoid duplicate research and development efforts and thus the misallocation of limited resources. For example, according to the interim report by the National Security Commission on Artificial Intelligence (NSCAI), chaired by former Google and Alphabet Executive Chairman Eric Schmidt, there were, at the time of publication, more than 600 projects underway in the DoD decentralized and fragmented across military services and agencies. The report further argues that the "DoD is struggling to shift bottom-up experiments into established programs of record. Individual programs are not creating a critical mass for organizational change."[27]

However, even if such organizations are established, equipping it with the necessary authority to fulfil its mandate is critical. For example, even though JAIC was established to accelerate and guide AI adoption across the DoD, it lacks the authorities required to live up to these very

[23] Danielle C. Tarraf et al., "The Department of Defense Posture for Artificial Intelligence: Assessment and Recommendations," Product Page (RAND Corporation, 2019), https://www.rand.org/pubs/research_reports/RR4229.html; "Joint Artificial Intelligence Center," accessed April 26, 2020, https://dodcio.defense.gov/About-DoD-CIO/Organization/JAIC/.
[24] The White House Office of Science and Technology Policy, "American Artificial Intelligence Initiative: Year One Annual Report." 3.
[25] Defense Innovation Board, "Recommendations," 2016, https://innovation.defense.gov/Recommendations/.
[26] Deputy Secretary of Defense, "Establishment of Joint Artificial Intelligence Center," June 27, 2018, https://admin.govexec.com/media/establishment_of_the_joint_artificial_intelligence_center_osd008412-18_r....pdf#search='jaic+established'.
[27] National Security Commission on Artificial Intelligence, "NSCAI Interim Report for Congress." 31-32.

expectations. As a RAND report argues, JAIC does not have the authority to directly invest in AI projects or to halt AI projects that are misaligned with the DoD's strategy.[28]

Finally, clear and decisive leadership is critical to advance organizations' AI aspirations. However, our interviews suggested that such leadership is not always present. Further, the GBC survey found that 42 percent of government officials think that a lack of direction from leadership is an obstacle to AI adoption.[29] In the case of the DoD, the NSCAI interim report points out that, as opposed to secretary-level understanding of the importance of AI adoption, "..it is not clear that these top-level beliefs and strategic priorities have been fully embraced by departments and agencies yet."[30]

Capabilities

Human Resources

A lack of adequate human resources shows to be a prominent obstacle faced by government agencies. The GBC survey shows that 36 percent of governmental officials think that a lack of technical expertise and staffing is one of the constraints hindering further AI adoption.[31] Our interviews corroborate this evidence, and the White House has publicly acknowledged the growing shortage of AI talent in the government as well as in industry and academia.[32] This broader trend is illustrated by an example from a report from RAND, which points to a dearth of technical talent in the Army. Although the Army is an organization with 481,750 soldiers, it has less than 500 data scientists on its payroll.[33]

Our research identifies several root causes for this issue. First, there is a global shortage of AI talent, with the global number of AI specialists alleged to be in the lower five-digit range.[34] In the United States, this is also due to the fact that colleges and universities cannot meet the undergraduate students' demand for AI and computer science programs in general, also because

[28] Tarraf et al., "The Department of Defense Posture for Artificial Intelligence." 47.
[29] Geyn, "Is the Federal Government Ready for AI?"
[30] National Security Commission on Artificial Intelligence, "NSCAI Interim Report for Congress." 31.
[31] Geyn, "Is the Federal Government Ready for AI?"
[32] The White House Office of Science and Technology Policy, "American Artificial Intelligence Initiative: Year One Annual Report." 17.
[33] Tarraf et al., "The Department of Defense Posture for Artificial Intelligence.", 106. *The Military Balance 2020*, Vol 1 (S.l.: Routledge, 2020), 46.
[34] Grace Kiser and Yoan Mantha, "Global AI Talent Report 2019" (jfgagne, 2019), https://jfgagne.ai/talent-2019/.

they lack a sufficiently large faculty.[35] Our research further found that federal agencies, including the DoD and HHS, are struggling to recruit talents in a tight labor market. The issue of a small talent pool is exacerbated by the fact that public sector organizations are not the most attractive option for such highly qualified professionals. These highly qualified professionals are given fewer opportunities for advancement and personal development as well as lower remuneration compared to the private sector.[36] Highlighted in the RAND report, the DoD has "outdated expectation that tech specialists - military or civilian - will need to be careerists" who remain in the DoD in the long run despite many engineers or data scientists potentially wanting or having to advance their careers by changing jobs.[37] Beyond recruiting problems, AI R&D is also inhibited by staffing caps imposed on federally funded research and development centers (FFRDCs), where much of the critical, mission-focused AI R&D is conducted. According to the GAO, this "significantly constrains" the capacities of FFRDCs.[38]

In addition to not being able to attract the required talent in the labor market, some agencies also fail to properly identify the kind of skills they need in the first place. For example, the interim report by the NSCAI points out that the DoD lacks effective measures to identify AI-relevant skills already existing in the workforce in DoD.[39] Interviews conducted by the Defense Innovation Board further suggest that rigid career paths and lack of leadership support in the military prevent existing technical talent from putting their AI skills to use.[40]

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[35] National Security Commission on Artificial Intelligence, "NSCAI Interim Report for Congress" (National Security Commission on Artificial Intelligence, November 2019), https://www.nscai.gov/reports, 39.

[36] For example, RAND points out the reason why DoD struggles is the "lack of clear mechanisms for growing, tracking and cultivating personnel who have AI skills, even as it faces a tight AI job market in DoD". Tarraf et al., "The Department of Defense Posture for Artificial Intelligence." Xiii, 60-64

[37] James Ryseff, "How to (Actually) Recruit Talent for the AI Challenge," *War on the Rocks*, February 5, 2020, https://warontherocks.com/2020/02/how-to-actually-recruit-talent-for-the-ai-challenge/.

[38] National Security Commission on Artificial Intelligence, "NSCAI Interim Report for Congress" 28; United States Government Accountability Office, "Defense Science and Technology: Actions Needed to Enhance Use of Laboratory Initiated Research Authority" (United States Government Accountability Office, December 2018), 28, https://www.gao.gov/assets/700/696192.pdf.

[39] National Security Commission on Artificial Intelligence, "NSCAI Interim Report for Congress.", 37.

[40] Defense Innovation Board, "Workforce Now: Responding to the Digital Readiness Crisis in Today's Military" (Defense Innovation Board, October 31, 2019), https://media.defense.gov/2019/Oct/31/2002204196/-1/-1/0/WORKFORCE_NOW.PDF.

Government is also struggling with upskilling its existing technical staff as many federal agencies lack effective training programs. For example, HHS attests itself a lack of data science training.[41] Further, educational programs are necessary to not only train engineers and data scientists, but also to make the entire workforce able to take full advantage of AI within their organizations. As one interviewee pointed out, AI will likely affect all fields and occupations, and stressed that government agencies have to adjust training and education with respect to this change.

A lack of expertise and training not only applies to technical staff but also to upper and middle management. Many officials in management functions lack a sufficient understanding of what AI is, what value it can create, and how development and implementation work. One interviewee suggested senior management lacking such basic knowledge of AI prevents them from effectively promoting AI projects. Such voices are echoed by the GBC survey, which shows that 44 percent of government officials think that a lacking conceptual understanding of AI is a large constraint for the implementation of AI.[42]

Additionally, there are common misconceptions about AI within the government. One public official interviewee suggested that many still have an apocalyptic view of what AI is. On the other end of the spectrum, however, some also tend to have unrealistic expectations of what AI can do. Interviewees indicated that another challenge for some public officials, especially for those using decision support systems, is the shift from deterministic to probabilistic thinking associated with AI and with predictive analytics.

Technical Resources

Another important issue for public sector organizations is insufficient data collection and storage. Mentioned specifically within the DoD, data is not collected and stored properly and thus the data is not always understandable or traceable. One interviewee cited the digitization of old data as a hurdle for organization. Such availability issues are illustrated by an account from Lt. Gen. Jack Shanahan, Director of JAIC at the DoD, who, discussing drone surveillance footage, describes that "it was on tapes somewhere that someone had stored, and a lot of the video gets stored for a certain

[41] The Center for Open Data Enterprise, "Sharing and Utilizing Health Data for AI Applications," Roundtable Report (The Centerfor Open Data Enterprise, 2019), https://www.hhs.gov/sites/default/files/sharing-and-utilizing-health-data-for-ai-applications.pdf, 13.
[42] Geyn, "Is the Federal Government Ready for AI?"

amount of time and then gets dumped. We had to physically go out and pick tapes up."[43] Furthermore, even if data is available, data quality oftentimes prohibits its use. As one interviewee said with regard to large departments like HHS, it is very hard to "tame" and clean the vast amounts of data they have access to and to make use of it on a technical level.

Our research also found outdated and inadequate computing resources to be an issue. An interviewee who had interacted with numerous federal agencies, including DoD, HHS, and the VA, pointed out that limited and old computing resources were a key problem. The NSCAI interim report also points out that the DoD is lagging in the modernization of "the cloud and computing platforms necessary for data storage, compute resources, network communications, and algorithm development."[44] In the case of HHS, a report published by The Center for Open Data Enterprise also points out that HHS lacks the infrastructure to manage and analyze large sets of data.[45] Additionally, lacking interoperability of different systems within organizations hinder optimal data sharing and usage.[46]

Organizational Resources

A lack of adequate financial resources is another primary obstacle for AI adoption in the United States public sector. The survey conducted by GBC reports that 50 percent of governmental officials think a lack of financial resources is the main obstacle for the implementation of AI.[47] This lack of financial resources appears to apply especially to AI R&D. In its 2020 first quarter recommendations, the NSCAI points out that "the U.S. government's support for AI R&D has not kept pace with the field's revolutionary potential."[48] RAND also criticizes the lack of a long-term budget commitment to JAIC within the DoD as it has no clear authority to request its own budget.[49]

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[43] Sydney Freedberg, "Pentagon's AI Problem Is 'Dirty' Data: Lt. Gen. Shanahan," *Breaking Defense*, November 13, 2019, https://breakingdefense.com/2019/11/exclusive-pentagons-ai-problem-is-dirty-data-lt-gen-shanahan/.

[44] National Security Commission on Artificial Intelligence, "NSCAI Interim Report for Congress." 33-34

[45] The Center for Open Data Enterprise, "Sharing and Utilizing Health Data for AI Applications." 13.

[46] Tarraf et al., "The Department of Defense Posture for Artificial Intelligence"; The Center for Open Data Enterprise, "Sharing and Utilizing Health Data for AI Applications." 59, 118.

[47] Geyn, "Is the Federal Government Ready for AI?"

[48] National Security Commission on Artificial Intelligence, *NSCAI First Quarter Recommendations*, vols. (National Security Commission on Artificial Intelligence, March 2020), 6, online, Internet, 19 Apr. 2020., Available: https://www.nscai.gov/reports; National Security Commission on Artificial Intelligence, *NSCAI Interim Report for Congress*. 25.

[49] Tarraf et al., "The Department of Defense Posture for Artificial Intelligence." 48.

Further, our interviews point to public sector organizations lacking capacities for developing and deploying AI at the process level. One such example is the lack of established processes for software development projects that are on par with practices in the private sector. Additionally, interviewees also lamented insufficient knowledge transfer across departments and agencies. Bureaucratic and lengthy procurement processes pose another challenge, especially in cases when the duration of procurement far exceeds the time needed for delivery of the procured service.[50]

Box 1: Public Sector AI adoption and COVID-19

"In the midst of every crisis lies great opportunity," Albert Einstein once said. This is, to some degree, also the case during the ongoing COVID-19 crisis. As some of our interviewees have suggested, the crisis has contributed to breaking down some barriers their respective organizations had previously faced with regard to adopting AI. For instance, the crisis seems to have positively affected people and organizations' willingness to share data, both internally and externally. Further, it has induced stronger collaboration across organizations in moving forward AI and analytics solutions. At HHS, a COVID-19-related additional inflow of funding has further accelerated AI adoption.

Culture

According to several interviews, AI development oftentimes tends to be a siloed process with little interaction between developers and end users and little (field) testing before deployment.[51] This can have substantial adverse effects on uptake, ease of use, and the success of AI projects in general. Clearly, the idea of user-centered development, which is widespread in the private sector, is not yet widely established in the public sector. Additionally, as one interviewee working within the DoD explained, fighters (i.e., end users) are also underrepresented in the bodies overseeing military R&D. One interviewee further discussed that many technical experts in engineering and

[50] National Security Commission on Artificial Intelligence, "NSCAI Interim Report for Congress." 32.
[51] Tarraf et al., "The Department of Defense Posture for Artificial Intelligence." 53-54.

statistical analysis roles face difficulties in adapting to working collaboratively in interdisciplinary teams. Increasingly this is the case in modern software development and data analytics.

Data sharing, even beyond purely technical reasons, is a major challenge faced by public sector organizations with one interviewee explicitly calling it a “culture issue”. This is due to the fact that data is oftentimes viewed as a liability rather than a strategic asset, a perspective sometimes culminating in conflicts between CIOs (prioritizing security) and CDOs (prioritizing leveraging the data). Others point out that regularly the default *modus operandi* within organizations seems to be to protect data instead of actively (or passively) making it available across the organization. As an HHS report notes, “it can take 12 to 18 months to get access to data from various agencies and offices within HHS”.[52]

Furthermore, some interviewees lamented risk aversion within their respective organizations. This is reflected both in reluctance towards experimentation in software development in general and in AI development specifically. This can be seen true also in a culture that assigns disproportionate weight to failure, stacking the odds against adoption of new technologies like AI and disruptive change within the organization.

Finally, when AI is viewed by employees as making decisions instead of providing decision support, this exacerbates employees’ fear of losing their jobs. Such fears of job replacement, as several interviewees suggested, can create resistance to further AI adoption within the organization. This hinders further AI adoption by resistance from employees.

[52] The Center for Open Data Enterprise, “Sharing and Utilizing Health Data for AI Applications.” 13.

Box 2: Obstacles to AI adoption in the Private Sector

The private sector, too, faces a wide range of challenges in adoption AI in business, many of them similar to those faced by government organizations. Evidence from six different surveys provides an overview of these obstacles.[53]

The most commonly cited obstacle for private enterprises is a lack of talent. In all surveys but one, between 40 and 57 percent of respondents expressed the view that lack of talent is holding back AI adoption in their organization. In this context, an O'Reilly survey finds that the biggest skills gaps exist in AI modeling and data science, maintaining business use cases, and data engineering. A lack of data as well as issues with the quality of data are other frequently cited factors in AI adoption. However, there is a lot of variation across the different surveys, with the share of respondents bemoaning these issues ranging from 18 to 57 percent. Further, three surveys find that 17, 26, and 46 percent of respondents respectively claim that there is insufficient awareness of the (potential) value provided by AI within their organizations. Similarly, between 25 and 43 percent of respondents lament a lack of an AI strategy, whereas 19 to 49 percent highlight a lack of executive sponsorship/ownership as a barrier to AI adoption. Finally, one survey points out that 24 percent of respondents think that a lack of collaboration across teams is holding back AI adoption.

[53] McKinsey, "Adoption of AI Advances, but Foundational Barriers Remain," accessed April 23, 2020, https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain, Gartner, "3 Barriers to AI Adoption," accessed April 23, 2020, //www.gartner.com/smarterwithgartner/3-barriers-to-ai-adoption/. MIT Technology Review Insights and EY, "Digital Challenges: Overcoming Barriers to AI Adoption," MIT Technology Review, accessed April 23, 2020, https://www.technologyreview.com/2019/05/28/135184/digital-challenges-overcoming-barriers-to-ai-adoption/. Ben Lorica and Nathan Paco, "AI Adoption in the Enterprise," accessed April 23, 2020, https://www.oreilly.com/data/free/ai-adoption-in-the-enterprise.csp. IDC, "Infographic: Staying Ahead of the Game with Artificial Intelligence," accessed April 23, 2020, https://blog.datarobot.com/infographic-staying-ahead-game-artificial-intelligence. Snaplogic, "The AI Skills Gap," SnapLogic, accessed April 23, 2020, https://www.snaplogic.com/resources/infographics/ai-skills-gap-research.

Section VII: Recommendations

Based on the findings discussed in the previous section, we developed eight recommendations to public sector organizations seeking to advance their internal use of AI. These recommendations span across all three dimensions of our analytical framework and cover actions that can and should be realized in short-term, medium-term, and long-term. They don't constitute an exhaustive list (as there are many more challenges that are specific to an organization or that may have not come up during the process of our research) but rather serve to provide a sense of direction and a roadmap with key steps to be taken for organizations seeking to expedite the process of AI adoption.

1. Put Strategy Development First

Public sector organizations seeking to truly leverage the potential of AI need a clear-cut strategy articulating how they want to achieve this. A strategy is not a vision statement, but a concrete plan. Thus, developing an AI strategy involves not only formulating a desired outcome and a set of specific goals but, crucially, also outlining the specific steps necessary to get there. Formulating a clear-cut strategy is a challenge. It involves making difficult choices, such as deciding what areas and challenges to focus on or on what technologies to invest in but also helps align subsequent actions with an overall goal. Developing a good strategy, which includes metrics and benchmarks that allow to measure its success, is only a first step with many more to follow. Yet it is the foundation for success because such a strategy can be instrumental in building a compelling case for acquiring additional funding.

2. Provide Centralized Data Infrastructure, Tools, and Standards

AI will likely permeate large parts of departments and agencies. Building infrastructure and capabilities locally throughout these organizations will result in inefficient use of resources, a patchwork of technological infrastructure, and uncoordinated efforts. Using economies of scale through centralization and the creation of a shared foundation of technology, tools, and standards would go a long way in advancing AI adoption.

A foundational aspect here is data management. Data has long become an important strategic asset for any organization, but its importance will continue to grow with more rapid adoption of AI. It is thus critical to lay the foundation necessary to properly harness and leverage the data that organizations have at their disposal. To do so, organizations should improve interoperability and/or create centralized data management platforms that integrate previously decentralized data repositories and break up data silos. An example of such an undertaking is the DoD's "Joint Enterprise Defense Infrastructure" (JEDI), an enterprise cloud solution which the DoD is currently in the process of procuring.

Providing a robust and powerful cloud environment would also enable the development of AI platforms at the departmental or agency level. These platforms would provide, for example, computing power, access to shared data, development tools, and libraries to ensure standardized development as well as a high standard of security. This is the approach pursued by the DoD's JAIC in building the "Joint Common Foundation" (JCF), an AI platform that will run on the JEDI cloud.

To harmonize data and increase accessibility across the organization, it is increasingly important to develop data standards, for example with regard to metadata and using the same identifiers as well as naming/labeling conventions within data sets. This is instrumental to facilitate better data sharing. Yet, it must be ensured that following data standards is not so time consuming and resource intensive as this ultimately leads to the discouragement of sharing across organizational units. In this context it will be worthwhile to look to the National Institute of Standards and Technology (NIST), which has been working on guidance on the development of technical standards for AI following the White House's Executive Order on "Maintaining American Leadership in Artificial Intelligence".[54] The success of such standardization initiatives has been demonstrated, for instance, by the Colorado Department of Healthcare Policy and Financing (HCPF). Data sharing across this department has been improved substantially following the development of a data sharing template which has been adopted by all agencies within the department.[55]

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[54] National Institute for Standards and Technology, "U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools," 2019, https://www.nist.gov/system/files/documents/2019/08/10/ai_standards_fedengagement_plan_9aug2019.pdf.

[55] Ryan Howells, Cristal Gary, and Lia Winfield, "Data Challenges and Opportunities: Leveraging Data Analytics, Interoperability, and Artificial Intelligence to Improve Outcomes for State Health and Human Services" (Leavitt Partners, IBM Watson Health, 2018), https://cdn2.hubspot.net/hubfs/4795448/White%20Papers/Data%20Challenges%20and%20Opportunities%20-%20May%202018.pdf?utm_campaign=White%20Papers&utm_source=hs_automation&utm_medium=email&utm_content=68280258&%20_hsenc=p2ANqtz-

3. Build Centralized Expertise and Organic Development Capabilities

Centralization should not only occur at the technical but also at the organizational level. Economies of scale can also be achieved by building centralized expertise and growing organic development capabilities at the department or agency level. This allows government organizations to better be able to be the provider of AI applications and not only the owner reliant on procuring software solutions. Of course, this does not mean that AI applications should *all* be developed in-house, but it enables organizations to weigh whether internal capabilities are sufficient to develop a specific solution or whether outside help is needed.

Despite some justified criticism, one example of this is the JAIC, the focal point of the DoD's AI strategy. In addition to providing the JCF, JAIC's mission is to serve as a DoD-wide repository of technical and processual expertise as well as a standard-setter and to both coordinate AI deployment efforts at large and implement specific large-scale AI projects. Additional inspiration can be drawn from the Air Force's project "Kessel Run": Started in 2017, Kessel Run is an in-house software lab, modeled after private sector software companies, and generally hailed as a success. Upon proof of concept, the "software factory" has grown to a size of more than 2,000 staff members within three years and is applying agile development methodology to projects across the Air Force.[56] Building an in-house provider of AI solutions outside of the conventional line organization of a department or agency, if done successfully, could decrease reliance on outside software providers and potentially result in cost savings for the organization. Further, since the development unit would work on projects across the organization, it would develop unique expertise on and familiarity with particular needs and idiosyncrasies within the organization.

4. Move Fast, But Don't Break Things

Government organizations are not known for moving fast or for being early adopters of innovations in process or technology. Bureaucracy is, in fact, inherently rule-bound, slow-moving, and risk-averse. Overcoming these idiosyncrasies must be a targeted, conscious effort. But doing

8INI0EbvkZUw90UgcuBP3q7YPv_2mxLr7ofZe3r5AbP_z47hxtf1_Q5IwBW_vf4XTvH0DMrdPpPJdzXTdK3f_niwoF7Q&_hsmi=68280258.

[56] Rachel S. Cohen, "The Air Force Software Revolution," *Air Force Magazine*, 2019, https://www.airforcemag.com/article/the-air-force-software-revolution/; Jim Perkins and James Long, "Software Wins Modern Wars: What the Air Force Learned from Doing the Kessel Run," *Modern War Institute* (blog), January 17, 2020, https://mwi.usma.edu/software-wins-modern-wars-air-force-learned-kessel-run/.

so is critical to demonstrate the value and potential of AI and to create acceptance among leadership, middle management, and ground-level staff.

A potential path is to borrow from a method that has proven successful in the private sector, namely the lean startup model. The method is built on the idea of rapid prototyping and continuous and iterative deployment. Adopting this approach brings several advantages: First, as has been shown repeatedly, failure of large, costly IT projects creates negative momentum for innovation. Introducing new technological solutions further is a disruption of existing processes and established software. Breaking with these routines can result in significant backlash. Starting small with so-called "minimum viable products" and continuing development only if feedback is positive will prevent such momentous setbacks. This could contribute to fostering a culture more accepting of failure and more open to experimentation. Secondly, starting small (instead of adopting a rigid, large-project approach) allows for more experimentation in product development, potentially opening up new courses of action and yielding new solutions.

5. Put End Users at the Center of the Development Process using Design Thinking

Similarly, it is important to keep in mind who will end up using a new application and to adopt their point of view in the development process. An AI system can use state-of-the-art algorithms, good data, and be highly accurate but implementation can still fail if the needs of the end users are not sufficiently taken into consideration. Usability, including interpretability and explainability of AI systems' outputs, is key here. Thus, it is important for organizations to follow a strictly user-centric design approach. End users must be involved in the development process from start to finish, with repeated feedback loops as an integral part of this process. This is so the end users and developers co-create solutions that optimally fulfill their purpose. This signifies a shift from old, top-down patterns of behavior to a more bottom-up approach.

Following such an approach requires working in cross-disciplinary teams. It is not sufficient to have developers only working on a new application. Instead, development teams should also draw on the experience of members with backgrounds in, for example, user experience design, product management, or facilitation. The toolbox of methodologies one can draw on to enable user-centric development is rich and diverse. For instance, organizations could use the Design Thinking approach, a systematic, iterative technique aiming to facilitate ideation and development that has been widely adopted across the private sector (and, in some instances, also in government).[57]

6. Enable Top-Level Leadership to Oversee and Advance AI-Centered Projects

A lack of buy-in and understanding with regard to the potential of AI for among public sector organizations' senior leadership is a major barrier to successful adoption of the technology. To overcome this barrier, it is important to enable leadership to see the value of AI and to oversee strategy development and implementation by building basic knowledge of both the technology itself as well as related aspects. This can be done through executive training programs at the departmental or even at a cross-departmental level.

Inspiration for such executive training programs can be drawn from the United Kingdom, where a "National Leadership Centre" (NLC) accepted its inaugural cohort in the fall of 2019. The NLC is a 12-month program providing a group of more than 100 senior government leaders with skills and expertise pertaining to new technologies, such as AI. It includes continuous coaching as well as residential modules and is implemented with support from the University of Oxford and the Massachusetts Institute of Technology.[58]

An added benefit of programs like this is that it creates and strengthens networks of senior government executives and thus allows for a better exchange of ideas and experiences across the public sector. Here, too, the NLC points to potential pathways by building a digital platform seeking to connect and provide with support and content about 1,500 government executives.[59]

7. Facilitate an Exchange of Talent between Government, Industry, and Academia

Recruiting AI talent is a tremendous challenge for government organizations in an already tight market for experts in engineering and data science. However, technical excellence in government

[57] For a brief and accessible introduction to Design Thinking, see, for example, Hasso Plattner Institute of Design at Stanford, "An Introduction to Design Thinking - Process Guide," accessed May 1, 2020, https://dschool-old.stanford.edu/sandbox/groups/designresources/wiki/36873/attachments/74b3d/ModeGuideBOOTCAMP2010L.pdf; SAP, "Introduction to Design Thinking," SAP User Experience Community, September 12, 2012, https://experience.sap.com/skillup/introduction-to-design-thinking/.

[58] "Government to Train Public Sector Leaders on AI and Robotics," PublicTechnology.net, September 13, 2019, https://www.publictechnology.net/articles/news/government-train-public-sector-leaders-ai-and-robotics.

[59] "Government to Build Digital Service to Connect Top Public Sector Leaders," PublicTechnology.net, August 13, 2019, https://www.publictechnology.net/articles/news/government-build-digital-service-connect-top-public-sector-leaders.

service is of paramount importance if the government is to not be entirely reliant on outside providers of technology solutions. Thus, public sector organizations must find creative alternative pathways to bringing in expertise and additionally must ensure that existing staff has opportunities to advance and further develop their skills.

A major challenge for the government is to bring in seasoned professionals or researchers in technology or related fields. This could be ameliorated by offering entry points that constitute a middle ground between remaining in industry or academia and entering public service indefinitely. A possible example could be fixed-term "public service sabbaticals" for professionals from the technology industry or for academics who could take a leave of absence from their positions in order to support government efforts at developing and implementing AI for a limited amount of time.

Government departments and agencies could temporarily bring in young professionals, recent graduates, or graduate students for project-based fellowships. A template for such programs could be, for example, "Tech4Germany", a fellowship initiated by the German Federal Chancellery. Through the three-month fellowship, young professionals with backgrounds in engineering, data science, product management, and user experience design, are brought together with federal ministries and agencies to work on software development projects.[60]

Government organizations must increase their ability to both retain and upskill existing talent. This may include offering public servants opportunities for "excursions" to the private sector. A potential approach would be to build partnerships with technology firms and to second personnel, for example middle management or technical staff, for a limited amount of time. Seconded staff would gain exposure to a different culture of experimentation, more agile processes, and new methods and tools, returning to their home organizations with new ideas and experiences. These partnerships could also be used for fast-track apprenticeships for junior staff which would allow them to shadow and learn from their private sector counterparts.

[60] "Tech4Germany," accessed May 1, 2020, https://tech.4germany.org/.

8. Treat Culture as an Integral Part of Making an Organization Ready for AI

Finally, as our findings show, culture is an integral but oftentimes neglected aspect in the digital transformation of government in general and in the successful adoption of AI in particular. Culture is an organizational layer that is deeply ingrained in all stages of AI adoption (from strategy to development to deployment). At the same time, culture is something that is unique in every organization. This means the cultural obstacles government organizations are confronted with in advancing their AI readiness vary from case to case. To overcome these obstacles, it is important that departments and agencies first take stock of cultural artifacts that are impeding innovation. Based on this assessment, they must incorporate these in strategy development and consider how each subsequent activity and measure interact with an organization's culture. Because of the unique cultural context, it is important to be aware of the fact that there is no panacea or standard blueprint to speed up AI adoption that works equally well across all government organizations. Instead, what is needed are roadmaps that are carefully designed and tailored to the unique needs of each department or agency.

Box 3: Developing Ethical AI

Over the course of the past few years, ethical concerns associated with the use of AI have become a key part of the debate around the technology. This is also reflected in widespread concerns held by the general public.[61] This is, for example, due to some algorithmic decision making and other AI systems being shown to produce severe harm in case of inaccuracies as well as bias against certain sub-populations.[62] Adverse effects on individual privacy are another concern frequently cited with regard to AI. To address these valid concerns, organizations must ensure that they respect human and civil rights in the development and deployment of AI systems.

To promote the use of such "ethical AI", more than 160 organizations from industry, academia, civil society, and the public sector have put forward AI ethics guidelines or principles.[63] In the United States., the DoD was the first department to publish a set of such principles in 2020.[64] Researchers from Harvard University and ETH Zurich have analyzed samples of these documents and analyzed a combined total of thirteen principles on which these documents converge respectively: These include safety and security, accountability, transparency and explainability, fairness and justice, human control of the technology, clear responsibilities, privacy, and the promotion of human values.[65] However, developing these principles can only be a first step. So far, they don't represent more than a broad mission statement. In order to ensure that organizations develop and deploy AI systems that are aligned with these principles, clear *operational* guidelines must be devised and staff working on AI projects must be sensitized about the ethical concerns relevant to their work.

Section VIII: Conclusion and Areas for Future Research

This report set out to identify the various endogenous challenges that federal departments and agencies in the United States face on their road to harnessing the potential of AI and to provide recommendations on how these challenges can be overcome.

Although our findings may not provide definitive and universally applicable answers to the question of how to accelerate and improve public sector AI adoption, our research provides public sector organizations with an analytical framework that can help take stock of current AI readiness and guide their efforts to achieve their goal. Furthermore, our recommendations can serve as a roadmap for organizations and inspire first steps to take in order for them to become experienced in developing, procuring, and using AI systems. Our recommendations focus on: strategy development; centralized data infrastructure as well as technical tools and standards; centralized, organic capabilities for AI development; approaches to AI development that are rooted in the lean startup model and user-centered design; creative pathways to bringing in outside experts and retaining as well as upskilling existing talent; and culture as a critical factor in fostering AI readiness.

This is a fast-moving field characterized by rapid technological advances and high complexity, which is a terrain that is difficult to navigate for government. But in order to fully harness the value that AI-based solutions can provide, public sector organizations need to develop a strategy, acquire the capabilities, and foster a culture that enables them to do so nonetheless. This report comes at an early stage in this journey. As the circumstances within organizations change and as technology

[61] Aaron Smith, "Public Attitudes Toward Computer Algorithms," *Pew Research Center: Internet, Science & Tech* (blog), November 16, 2018, https://www.pewresearch.org/internet/2018/11/16/public-attitudes-toward-computer-algorithms/; World Economic Forum, "Ipsos Global Poll for the World Economic Forum Shows Widespread Concern about Artificial Intelligence," 2019, https://www.ipsos.com/sites/default/files/ct/news/documents/2019-07/wef-ai-ipsos-press-release-jul-1-2019_0.pdf; Baobao Zhang and Allan Dafoe, "Artificial Intelligence: American Attitudes and Trends" (Oxford: Future of Humanity Institute, 2019), https://governanceai.github.io/US-Public-Opinion-Report-Jan-2019/.

[62] See, for example, Joy Buolamwini and Timnit Gebru, "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification," in *Conference on Fairness, Accountability and Transparency*, 2018, 77–91, http://proceedings.mlr.press/v81/buolamwini18a.html; Charette, "Michigan's MiDAS Unemployment System: Algorithm Alchemy Created Lead, Not Gold"; Human Rights Watch, "May 2019 Submission to the UN Special Rapporteur on Extreme Poverty & Human Rights Regarding His Thematic Report on Digital Technology, Social Protection & Human Rights"; Jeff Larson et al., "How We Analyzed the COMPAS Recidivism Algorithm," *ProPublica* (blog), 2016, https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm; Mehrabi et al., "A Survey on Bias and Fairness in Machine Learning."

[63] AlgorithmWatch, "AI Ethics Guidelines Global Inventory," AI Ethics Guidelines Global Inventory, 2020, https://inventory.algorithmwatch.org.

[64] U.S. Department of Defense, "DOD Adopts Ethical Principles for Artificial Intelligence," 2020, https://www.defense.gov/Newsroom/Releases/Release/Article/2091996/dod-adopts-ethical-principles-for-artificial-intelligence/.

[65] Jessica Fjeld et al., "Principled Artificial Intelligence: Mapping Consensus in Ethical and Rights-Based Approaches to Principles for AI," Berkman Klein Center Research Publication (Cambridge, MA, January 15, 2020), https://doi.org/10.2139/ssrn.3518482; Anna Jobin, Marcello Ienca, and Effy Vayena, "The Global Landscape of AI Ethics Guidelines," *Nature Machine Intelligence* 1, no. 9 (September 2019): 389–99, https://doi.org/10.1038/s42256-019-0088-2.

improves, our findings and recommendations must be continuously revisited and adapted. It should be noted that endogenous obstacles are not all that holds government back with regard to AI adoption. They also face regulatory hurdles, for example data protection and procurement regulations, that need to be considered.

In light of all this, there is plenty of research yet to be conducted. First, our own research only provides a first, non-exhaustive snapshot of obstacles to AI adoption. This research could be enhanced either by a) conducting in-depth case studies of a small number of organizations using our three-dimensional analytical framework or b) by conducting a quantitative survey of public servants tasked with advancing the use of AI within their organizations. Future research could also provide additional insights in causal relationships between the different obstacles identified in our report. Additionally, more depth could be added to our recommendations by identifying more examples of best practices both in the United States and abroad.

Finally, the success and failure of public sector AI adoption is not only decided at the organizational level. As briefly discussed above, public policy plays an important role in this matter. Future research could seek to identify needs and potential courses of action at the policy level. But harnessing the potential of AI is not a challenge unique to the United States. As almost every developed country has made the technology a strategic priority and published an AI strategy by now, it would be worthwhile looking into which approaches these countries pursue and what the United States can learn from them.

Appendix

Appendix A: List of interviewees

Name	Organization	Role
Anderson, Chris	Booz Allen Hamilton	Senior Associate
Aronson, Dorothy	National Science Foundation, Division of Information Systems	Chief Information Officer
Arrieta, José	Department of Health and Human Services	Chief Information Officer
Biderman, Stella	Booz Allen Hamilton	AI Researcher
Brenton, Cutter	Booz Allen Hamilton	Chief Technologist for AI & Analytics with DoD
Brzymialkiewicz, Caryl	Department of Health and Human Services, Office of the Inspector General	Chief Data and Analytics Officer
Chilbert, Chris	Department of Health and Human Services, Office of the Inspector General	Chief Information Officer
Gilmer, Graham	Booz Allen Hamilton	Principal
Helfat, Katherine	Booz Allen Hamilton	Senior Consultant
Incorvia, Joe	Command Operation for NAVAIR	Director
Kearns, Ed	National Oceanic & Atmospheric Administration; Department of Commerce	Chief Data Officer; Interim Chief Data Officer
McGunnigle, John	Undersea Warfighting Development	AI Director

	Center	
Ordun, Catherine	Booz Allen Hamilton	Senior Data Scientist
Persons, Tim	U.S Government Accountability Office	Chief Scientist, Managing Director Science, Technology, Analytics
Sivagnanam, Elanchezhian	National Science Foundation, Division of Information Systems	Chief Enterprise Architect
Anonymous expert	Defense sector	

Appendix B: Frequency of AI Key Terms in Departments Performance Plans and Reports

Department	Artificial Intelligence	AI	Machine Learning	Keyword ratio to whole document
Department of Commerce	13	29	2	0.151%
Department of Defense	32	101	11	0.143%
Department of Health and Human Services	2	4	1	0.025%
Department of Housing and Urban Development	1	0	1	0.003%
Department of Veteran Affairs	1	0	0	0.003%
Department of Homeland Security	1	0	0	0.002%
Department of Education	1	0	0	0.001%
Department of State	1	0	0	0.001%
Department of Justice	0	0	0	0.000%
Department of the Interior	0	0	0	0.000%
Department of Labor	0	0	0	0.000%
Department of Energy	0	0	0	0.000%
Department of Transportation	0	0	0	0.000%
Department of Agriculture	0	0	0	0.000%

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