

Government Procurement and Acquisition: Opportunities and Challenges Presented by Artificial Intelligence and Machine Learning



Mohammad Ahmadi
Pardee RAND Graduate School

Dr. Justin B. Bullock
University of Washington



IBM Center for
The Business
of Government

Government Procurement and Acquisition: Opportunities and Challenges Presented by Artificial Intelligence and Machine Learning

Mohammad Ahmadi

Pardee RAND Graduate School

Dr. Justin B. Bullock

University of Washington

JULY 2023

TABLE OF CONTENTS

Foreword	4
Executive Summary	6
Introduction	8
Methodology	10
AI Use Cases in U.S. Government	11
Procurement Challenges and AI Opportunities	12
Procurement Challenge 1: Requirements Definition	12
Procurement Challenge 2: Competition and Pricing	15
Procurement Challenge 3: Contractor Oversight	18
Procurement Challenge 4: Federal Procurement Data	19
Procurement Challenge 5: Acquisition Workforce	19
Managing the Use of AI for Overcoming Procurement and Acquisition Challenges	21
A Relevant Process Model	29
Conclusion	31
About the Authors	32
Key Contact Information	33
Recent Reports from the IBM Center for The Business of Government	34

FOREWORD

On behalf of the IBM Center for The Business of Government, we are pleased to release a new report, *Using AI to Improve Government Procurement: Challenges and Opportunities*, by Justin Bullock at the University of Washington and Mohammed Ahmadi at the Pardee Rand Graduate School.

The federal government spends more than \$500 billion in the acquisition of goods and services annually. However, agencies face enduring challenges in modernizing the procurement process to support mission achievement, including requirements definition, competition, pricing, contractor oversight, federal procurement data, acquisition workforce, and small business participation.

This new report addresses using AI to transform public procurement, analyzing challenges and recommending ways to capitalize on opportunities. The report makes recommendations about how to use AI to transform public procurement, which can increase speed, efficiency, and effectiveness in acquiring goods and services that serve public needs by fostering facilitating intelligent automation across the federal acquisition system.

This report builds on multiple Center reports focused on using AI and automation to improve procurement and other government systems, including *Artificial Intelligence in the Public Sector: A Maturity Model*, *Improving Outcomes in Government Through Data and Intelligent Automation*, *Risk Management in the AI Era*, and *The Future Has Begun: Using Artificial Intelligence to Transform Government*.

The report also continues our ongoing efforts to develop improvement ideas for acquisition more broadly, most recently including *Other Transactions Authorities: After 60 Years, Hitting Their Stride or Hitting the Wall* and *Buying As One: Category Management Lessons from the United Kingdom*.



DANIEL J. CHENOK



JASON PROW



We hope that government procurement leaders and stakeholders find the report helpful in leveraging AI to improve the critically important process of acquiring goods and service to carry out agency missions.

Daniel J. Chenok
Executive Director
IBM Center for
The Business of Government
chenokd@us.ibm.com

Jason Prow
Senior Partner
Automation and Data Platforms
US Federal Consulting, IBM
jprow@us.ibm.com

EXECUTIVE SUMMARY

This study highlights five challenges for modern government procurement.

These procurement challenges, as made clear by the U.S. Government Accountability Office, include: (1) requirements definition, (2) competition and pricing, (3) contractor oversight, (4) federal procurement data, and (5) acquisition workforce.

These challenges appear to be persistent and difficult to combat. In addition, each challenge also calls forth a potential opportunity for AI tools to assist. AI can potentially aid in each of these challenges by: (1) improving the specification of procurement requirements using recommendation algorithms, (2) improving competition and pricing of goods for procurement through natural language models, (3) using computer vision and machine learning (ML) to assist with contractor oversight, (4) automating capture of federal procurement data, and (5) improving task performance through automation of standard intake forms. These procurement challenges, and the potential of AI to assist in each case, highlights specific opportunities for agencies to use AI effectively.

However, decisions about when and how to deploy AI within public organizations need to be carefully managed as part of a holistic and strategic approach. For this, a process could include: (1) building out a maturity model of AI integration within the organization, as part of a strategic plan for the use of AI, (2) ensuring that the AI models are built upon a strong, quality data foundation, (3) working to build organizational capacity to integrate AI and automation tools to the procurement process, (4) getting support for adequate resources as key to the success or failure of integrating these tools into the procurement process, (5) careful management of which sorts of tasks are suited to the use of AI tools for procurement, and (6) systematically ensuring that automation bias and “administrative evil” are not increased as a part of the adoption of these tools for procurement.

This discussion and analysis corresponds with the recent literature on deploying AI tools into public organizations. Recent work distills these concerns into three primary challenges for managing the integration of AI tools and machine agents into the work of the public sector:

1. Deciding the scope of tasks machine agents should complete
2. Enabling the government employees to work with machine agents
3. Retaining the role of humans and human control of decisions and actions¹

1. Bullock, J. B., Huang, H., & Kim, K.-C. (Casey). (2022). Machine Intelligence, Bureaucracy, and Human Control. *Perspectives on Public Management and Governance*, 5(2), 187–196. <https://doi.org/10.1093/ppmgov/gvac006>.



When deciding which tasks machines complete versus which tasks humans should complete, it is important to consider the nature of the task itself. Generally speaking, tasks that require more discretion, nuanced context, and are less routine and less standardized are better suited for human completion. On the other hand, tasks that are more routine, more standardized, or require little discretion, may be better suited to completion by AI. In choosing to incorporate these tools and agents for procurement, agencies will need more people skilled in ML and AI to understand how to develop, iterate, assess, and work with these tools.

These tools will also require changes to the ways in which agencies gather and utilize data and act in both the physical and digital domains. While some specific procurement tasks may benefit from the deployment of AI, adapting the workforce to use these new tools requires effective management strategies.

Finally, if AI tools are fully integrated into decision making for government procurement, systems should be built in a way that allows for appropriate oversight, assessment and alteration by human decision makers, and systems should follow design principles that are human-centered, stakeholder-focused, and lifecycle-scoped.

INTRODUCTION

A basic function of government involves providing goods and services to the public. The direct provision of public goods often frames a core justification for various government agencies.

To serve the public, governments procure a wide variety of goods and services. The acquisition process lies at the heart of agencies' abilities to provide goods and services in an effective, efficient, and equitable manner. Given high agency investments—annual procurement spend exceeds \$500 billion—and the complexity of government processes, procurement is an extremely challenging task to perform well. This impacts governments worldwide, and particularly large, federal governments such as that of the United States. Indeed, congressional panels and executive reports often highlight the challenges of procurement and acquisition, including two prominent GAO reports addressed in this report in more detail.

In 2007, a congressional advisory panel identified inefficient practices in the federal acquisition of goods and services.² This panel, while providing useful information, only began to point in the right direction. Despite numerous actions by Congress, the Office of Management and Budget (OMB) and executive branch agencies, a 2018 report of the U.S. Government Accountability Office found that these actions have not eliminated enduring challenges of federal acquisition.³ This 2018 GAO report in particular highlights six important challenges for improving federal procurement practices. The challenges include:

1. Requirement definition
2. Competition and pricing
3. Contractor oversight
4. Federal procurement data
5. Acquisition workforce
6. Small business participation

While these six GAO challenges do not represent the only hurdles facing procurement reform, they are challenges that AI and machine learning tools can help to address. AI applications can help improve effectiveness and efficiency across the U.S. federal procurement process.

In the past, advances in technology—such as databases, e-forms, and digitization of financial records—have helped to improve the procurement process and brought on new challenges. Recent studies on public administration and public management reflect a growing consensus that AI and ML tools, if carefully constructed and deployed, can help agencies complete certain types of tasks for governments. Similar tools have aided in the partial automation of government tasks that include loan applications and health and social services, albeit with mixed success. Opportunities exist for AI and ML tools to improve the functioning of procurement, but these opportunities will come with their own challenges that need to be carefully managed.

2. GAO. (2007). Federal Acquisition: Oversight Plan Needed to Help Implement Acquisition Advisory Panel Recommendations. U. S. Government Accountability Office. <https://www.gao.gov/products/gao-08-160>.

3. GAO. (2018). Federal Acquisitions: Congress and the Executive Branch Have Taken Steps to Address Key Issues, but Challenges Endure. GAO-18-627. <https://www.gao.gov/products/GAO-18-627>.

The IBM Center for The Business of Government has a series of reports that examine specifically how procurement practices may be improved by the use of AI. The first of these reports, *Delivering Artificial Intelligence in Government: Challenges and Opportunities* highlights eleven challenges and twenty recommendations across the categories of technology and data, workforce, and risk management.⁴ The challenges are worth mentioning here, and include legacy IT infrastructure, limited IT interoperability, IT project management capabilities, lack of prioritization of data-driven solutions, public workforce management practices, culture of IT ownership, limited capacity for system-level redesign, securing systems, risk aversion, ethical and social considerations, and governance. In this report, author Kevin Desouza highlights a specific procurement approach that could be amplified with the use of AI systems: automated reverse auctions.

More recently, the IBM Center published an article in the University of Pennsylvania Law School' *Regulatory Review* on how government can use AI to improve procurement. This paper discussed ways that leveraging AI to develop procurement innovations can help agencies and companies work together to implement acquisition strategies that clarify requirements and identify best value bidders. The report also addressed how AI can help agencies cut through the seemingly endless provisions of existing policy and guidance and enable rapid action to agency needs.⁵

This new IBM Center for The Business of Government report examines how U.S. federal procurement and acquisition may benefit and carefully integrate AI and ML tools to overcome long-standing challenges, including those identified by GAO. The report provides some definitions for these challenges, and briefly discusses why they are important for effective and efficient procurement. For each challenge, a potential opportunity is highlighted to take steps in response, and each opportunity involves an existing AI and ML tool. After presenting each opportunity, a corresponding AI use case illustrates the potential applicability of the use of AI tools to overcome, or at least improve upon efforts to mitigate, each challenge identified by GAO.

Next, the report situates deployment of AI tools into a broader management strategy and process. To effectively manage these AI tools for improving procurement, agencies need to: (1) develop a strategic maturity model (or adapt an existing model such as the one offered by the Desouza report cited above), (2) leverage the power and utility of data, (3) build organizational capacity, (4) seek resources, (5) carefully consider task management, and (6) avoid automation bias.

This report reflects an optimism that, if properly deployed and managed, AI tools could significantly improve the effectiveness and efficiency of government procurement. However, significant risks are involved with these tools and their deployment, so management needs to deploy them carefully.

4. Desouza, K. C. (2018). *Delivering Artificial Intelligence in Government: Challenges and Opportunities*. IBM Center for The Business of Government. <https://www.businessofgovernment.org/report/delivering-artificial-intelligence-government-challenges-and-opportunities>.

5. Chenok, Daniel (2022). How can Governments Use AI to Improve Procurement? *The Regulatory Review*, University of Pennsylvania Law School. <https://www.theregreview.org/2022/06/30/chenok-how-can-governments-use-ai-to-improve-procurement>.

METHODOLOGY

This report integrates results from three different methodological approaches to identify state-of-the-art algorithms, bring real-world examples from the private sector, and examine the approach of private sector actors to suggest a possible avenue for decision makers to invest in using artificial intelligence for federal acquisition.

Additionally, the report identifies challenges associated with applications of recommendations. This report can help government leaders to better understand the potential applications of artificial intelligence in federal agencies' public procurement, and in mitigating associated risks.

This study uses government reports, think tank studies, and scholarly publications identifying the federal government's challenges and opportunities in the acquisition of goods and services. This includes analysis of multiple U.S. Government Accountability Office reports identifying acquisition and procurement challenges (GAO reports include "Federal Acquisition: Oversight Plan Needed to Help Implement Acquisition Advisory Panel Recommendations" and "Federal Acquisitions: Congress and the Executive Branch Have Taken Steps to Address Key Issues, but Challenges Endure"). The report also reviews reports by think tanks such as reports by IBM Center for Government and RAND, as well as several public administration and machine learning scholarly publications. However, most current academic literature addresses AI and machine learning, not the applications of them in solving real problems of public administration.

The report also employs an analytical framework to examine how machine learning tools may influence the federal government's goods and services acquisition practices and processes. This framework builds from task-based and system-based frameworks to examine at what specific points in the procurement decision-making process AI and ML tools can be effectively deployed to improve government procurement of goods and services. This analysis highlights the vast opportunities and many challenges the use of AI tools presents to the procurement process.

Last, the report provides a detailed discussion and lessons learned section that further integrates the use of AI and ML tools into careful management and good governance practices. Here the academic literature offers analysis on identified approaches for carefully integrating AI and ML tools to governance more generally, as these tools become more common and more powerful throughout government systems.

AI Use Cases in U.S. Government

DIGITAL
Transformation



The dominant literature on AI in public administration focuses on theoretical applications of artificial intelligence and machine learning. These include frameworks discussed later in this report. However, there are fewer examples of using AI to solve real-world problems in the government relevant to procurement. These applications are mainly divided into natural language processing, tabular data, and computer vision, with structured and unstructured data that can represent problems faced in the acquisition field. Some examples of current applications follow.

The Internal Revenue Service (IRS) annually receives a large number of W-2s and 1099s from a wide range of entities, including employers, government agencies, and financial institutions. These forms contain information about payments made to individuals, clients, or Social Security beneficiaries. The IRS also receives 1098s from third parties that report taxpayers' payments for items claimed as deductions or credits, such as home mortgage interest payments and tuition payments. In addition, the IRS collects data from other government agencies, such as the Social Security Administration (SSA), to verify taxpayers' claims of child-related tax credits. The IRS is exploring the use of machine learning to improve its ability to identify tax returns for compliance review. The agency has already implemented the "Return Review Program," which uses a combination of traditional methods and machine learning to identify potentially questionable refunds on individual income tax returns. If successful, machine learning could help the IRS to better use the large amount of existing data in order to target enforcement efforts more effectively and productively.⁶

The U.S. Army collects unstructured data from a wide range of sources such as intelligence reports, satellite imagery, or social media. This data is often the best available information about the local population, enemy forces, and partner forces, but the data is rarely used for assessment because it lacks structure to enable easy analysis. A RAND study shows how machine learning can be used to extract useful information from unstructured text quickly and systematically from intelligence reporting, operational reporting, and social media.⁷

The Aviation and Transportation Security Act of 2001 requires the Transportation Security Administration (TSA) to screen all checked baggage at airports. To comply with this law, the TSA purchases, installs, and maintains baggage screening systems at airports through its Electronic Baggage Screening Program (EBSP). However, an analysis by RAND shows that the problem is well-suited for machine learning to solve, because the process involves analyzing complex image data to produce a binary outcome of whether a baggage is safe or not. ML algorithms often excel at problems that have large amounts of labeled data.⁸

Procurement Challenges and AI Opportunities

Procurement Challenge 1: Requirements Definition

Requirements define the need of government agencies. When procurement agents decide to initiate the acquiring process of goods, work, or services, they start by defining what they exactly need. To describe this, requirements should be clearly defined, achievable, and verifiable;⁹ and have a clear definition, simple as possible requirements, and only a few words

6. Holtzblatt, J., & Engler, A. (2022). Machine Learning and Tax Enforcement. Urban Institute. <https://www.urban.org/sites/default/files/2022-06/Machine%20Learning%20and%20Tax%20Enforcement.pdf>.

7. McKay, S., Hartnett, G. S., & Held, B. (2022). *Airline Security Through Artificial Intelligence: How the Transportation Security Administration Can Use Machine Learning to Improve the Electronic Baggage Screening Program*. RAND Corporation. <https://www.rand.org/pubs/perspectives/PEA731-1.html>.

8. McKay, S., Hartnett, G. S., & Held, B. (2022). *Airline Security Through Artificial Intelligence: How the Transportation Security Administration Can Use Machine Learning to Improve the Electronic Baggage Screening Program*. RAND Corporation. <https://www.rand.org/pubs/perspectives/PEA731-1.html>.

9. Hooks, I. (1994). Writing Good Requirements. *INCOSE International Symposium*, 4(1), 1247–1253. <https://doi.org/10.1002/j.2334-5837.1994.tb01834.x>.

to describe the need. Achievability refers to technical feasibility and budget availability: if something technically is not possible to design, produce, or deliver, or requires more budget than allocated, it is not achievable. Verifiability refers to conditions in which the delivered work, good, or service is accepted by the agency's contracting authority.

Requirement definition plays a critical role in enabling the successful delivery of contracts, with verifiable specifications delivered within the estimated budget and based on the agreed schedule. However, defining clear, achievable, and verifiable acquisitions is a complex and challenging process that can require years of field experience and an experienced team. Given frequent turnover, experience required to define needs is often missing and acquisition specifications are thus often unclear, unrealistic, or not verifiable.

Congressional reports show that some major Department of Defense contracts suffer from "unrealistic definitions" that cause significant delays in delivering the contract and increases in the cost of the contract.¹⁰ Years of major reforms, since 2007, have not produced sufficient outcomes. Workforce shortages intensify this challenge and necessitate more innovative solutions.



AI Procurement Opportunity 1: Specification Definition

Generally, acquisitions are either similar to past contracts, or introduce something to be designed, manufactured, or acquired for the first time as research and development. Having specification data from past contracts, pictures, video footage, and descriptions of purchased goods and contracted services can help to customize machine learning algorithms. By training recommender engines, ranking algorithms, and developing knowledge graphs, federal acquisition staff can write more clear, achievable, and verifiable specifications. By customizing algorithms they can search for an item, see its specification, and read a description about products or services similar to their requirements. If the item is a repetitive acquisition, service, or good that an organization needs to procure periodically, then the task is much easier. Machine learning algorithms learn from historical data; by learning from the data, algorithms can predict what kind of services and goods are needed.

Machine learning algorithms can even be trained to understand if a specification is realistic. Deep learning algorithms may be trained with a large dataset over realistic and unrealistic labeled data. The deep learning algorithms can use past data to develop a function that differentiates between realistic and unrealistic specifications. After deploying the algorithm, agency acquisition staff can check the specifications against the results from deep learning algorithms to assess performance.

These algorithms should not replace human expertise and judgment on defining needs clearly, feasibly, and verifiably. Machine learning algorithms can assist procurement agents and not replace their judgements and experience. A combination of recommender systems and algorithms similar to Google Knowledge Graph can enable procurement agents to be more efficient and effective in requirements definition for products or services similar to those acquired in the past.

10. GAO. (2018). Federal Acquisitions: Congress and the Executive Branch Have Taken Steps to Address Key Issues, but Challenges Endure. GAO-18-627. <https://www.gao.gov/products/GAO-18-627>.



AI Use Case 1: Recommendation Algorithms

Consumer platforms such as Amazon, Netflix, and Google seek to know exactly what someone is looking for out of millions of items, movies, and an ocean of information on the internet, and also seek to rank these preferences. To do so, many internet providers have developed recommender and ranking algorithms. Recommender systems offer users what they are likely willing to pay for. Recommendation systems support many successful businesses, recommending products and services to consumers based on past preferences and the current context. Government acquisition teams can learn from the experience of commercial providers in helping programs find what they are looking for, as described below.

Lessons from Commercial Recommendation Engines

Amazon.com uses recommendation algorithms to personalize Amazon's website for each user. From an enormous catalog of items, each user is offered some specific and small number of products which are tailored to their past purchasing history and based on similar items that were purchased by other users. For example the "item-to-item collaborative filtering" algorithm matches each purchased and rated item to a similar product, and then combines them in a recommended list for each user.¹¹ Initial Amazon algorithms found people with similar interests, looked into their purchased items, subtracted ones already been purchased from ones not purchased, and then recommended items not purchased yet.

A collection of different recommender algorithms at Netflix help users to find movies and series. Research suggests that a typical Netflix user loses interest after 60 to 90 seconds of searching the platform.¹² The company wants to offer compelling videos for the users so that stay on the network to watch more. To do so, Netflix developed algorithms such as personalized video ranker, Top-N video ranker, trending ranker, continue watching ranker, video-video similarity algorithm, page generation algorithm, search algorithms, and several other ways to keep users interested.¹³ Now not only does Netflix recommend products to users, but it also produces products based on the user's preferences. *House of Cards* scripts were even informed by the past aggregate behavior of the consumers.

Another popular algorithm comes from Google's search engine. When someone searches for anything on Google, it searches through hundreds of thousands of web pages to find the most relevant information for that specific search in a fraction of a second. Then it ranks the findings from the most relevant to the least relevant. To do this, Google first downloads a copy of the entire web in a never-ending process called web crawling. Then it scans all pages and makes a list of all words, like an index of a book, and pages that contain those words. The Google Search index contains hundreds of billions of web pages. Since the web is constantly updating, the crawling process never stops to keep up with change.¹⁴

11. Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing*, 7(1), 76–80. <https://doi.org/10.1109/MIC.2003.1167344>.

12. Gomez-Uribe, C. A., & Hunt, N. (2016). The Netflix Recommender System: Algorithms, Business Value, and Innovation. *ACM Transactions on Management Information Systems*, 6(4), 13:1-13:19. <https://doi.org/10.1145/2843948>.

13. Gomez-Uribe, C. A., & Hunt, N. (2016). The Netflix Recommender System: Algorithms, Business Value, and Innovation. *ACM Transactions on Management Information Systems*, 6(4), 13:1-13:19. <https://doi.org/10.1145/2843948>.

14. Google. (n.d.-a). Features—How Google Search Works. Google Search—Discover How Google Search Works. Retrieved November 28, 2021, from <https://www.google.com/search/howsearchworks/features/>.

Search for Google does not just match or rank words. It involves a much more complex and extremely challenging task from understanding human language to knowing real objects. The Google Knowledge Graph enables users to search for things, places, and people in a database of more than 500 billion facts.¹⁵ For example, if someone searches for Plato, Google Knowledge Graph returns a Wikipedia page on Plato on the left side. Then a summary on the right side which includes his birthplace, parents, his books, movies about him as well as contemporary philosophers of his time such as Aristotle and Socrates.

IBM also has a new platform called Watsonx. An AI and data platform designed with the three critical elements of an AI strategy in mind that may impact future recommendation innovations. Watsonx empowers enterprises to scale and accelerate the impact of AI across the business, leveraging data wherever it resides. Watsonx capabilities will impact digital labor, IT automation, security, sustainability and application modernization to increase enterprise productivity, performance, and speed.

Procurement Challenge 2: Competition and Pricing

Federal regulations require agencies to obtain goods and services with fair and reasonable prices, achieved through rigorous bidding processes in which potential suppliers compete. However, in certain circumstances, agencies can award contracts without competition. These sole source contracts ask only one supplier to supply goods or services.

Agencies can face a challenge, however, to ensure prices are fair and reasonable—irrespective of the nature of the contract. Several proposed approaches were found not to have yielded sufficient fairness and price reasonableness.¹⁶ These approaches include allowing more potential suppliers to compete, rigorous market research, employing private sector practices in competition and marketing, and interagency contracts such as placing an order against another agency's contract or using another agency's contracting operations to obtain desired goods or services.

GAO findings indicate that the competition rate, meaning competitive contracts versus noncompetitive contracts, over the years remained relatively steady and unchanged.¹⁷ Various reasons exist for this, such as preference for a specific vendor, inadequate acquisition planning, and restrictive government policies.



AI Procurement Opportunity 2: Improving Market Knowledge

Market research, adequate acquisition planning, and checking for reasonable and fair prices are three areas where machine learning algorithms have the potential to assist the acquisition workforce in competition and pricing. Even though natural language processing and voice processing are still evolving, in the near future they can help the federal acquisition workforce in answering questions and generating text with related references. Virtual acquisition assistants could search the web, acquisition datasets, and archived documents to develop answers to

15. Google. (2012, May 16). Introducing the Knowledge Graph: Things, not strings. Google. <https://blog.google/products/search/introducing-knowledge-graph-things-not/>.

16. GAO. (2018). Federal Acquisitions: Congress and the Executive Branch Have Taken Steps to Address Key Issues, but Challenges Endure. GAO-18-627. <https://www.gao.gov/products/GAO-18-627>.

17. GAO. (2018). Federal Acquisitions: Congress and the Executive Branch Have Taken Steps to Address Key Issues, but Challenges Endure. GAO-18-627. <https://www.gao.gov/products/GAO-18-627>.

open-ended questions with references. Voice-enabled assistants might allow the acquisition workforce to have conversations with them about market research and product knowledge.

Additionally, deep learning has the potential to assist in acquisition planning. By analyzing data of services and work contracts that are not adequately planned—and related features such as department, time of the year, or type of the goods and services—machines can learn about tasks prone to inadequate planning. This in turn can help the acquisition workforce to plan for enough time and resources to deliver a service or good in a timely manner and at a fair and reasonable price.

Yet knowing whether a proposed price is fair and reasonable is a challenge. Machine learning algorithms can help the acquisition workforce here as well. Models can be trained on estimating costs with reasonable accuracy based on leveraging data from open bidding. In the case of sole source contracts, prices could be checked against the estimated cost by algorithms to help examine whether they are fair or reasonable.



AI Use Case 2: Natural Language Processing

Organizations rely on different tools to research a product, such as interviews, surveys, focused groups studies, and market reports. However, these tools are often expensive or time consuming. AI has disruptive potential to make market research both less expensive and more efficient by leveraging large datasets.

Disruptive technologies such as voice processing and text processing have the potential to provide unique solutions for market research. Siri, Google Home, and Alexa are examples of artificially intelligent voice processing technologies that can assist humans in answering questions. There is a possibility to train these technologies for specific tasks that assist the acquisition workforce in the market.

Natural language processing (NLP) is a topic of artificial intelligence that attempts to understand and replicate human language. OpenAI has developed a model called ChatGPT with 175 billion parameters to generate news articles.¹⁸ A recent study found that over 300 applications are using GPT-3 that on average generates 4.5 billion words per day,¹⁹ and these numbers have increased throughout 2022 and 2023 with the deployment of both ChatGPT, GPT 3.5, and GPT 4. The usage includes feedback summaries, simple reports, creating new genres, answering complex queries, and searches that provide information from documents and knowledge bases.

18. Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., ... Amodei, D. (2020). Language Models are Few-Shot Learners. *ArXiv:2005.14165 [Cs]*. <http://arxiv.org/abs/2005.14165>.

19. OpenAI. (2021, March 25). GPT-3 Powers the Next Generation of Apps. OpenAI. <https://openai.com/blog/gpt-3-apps/>.

As a brief experiment, we asked ChatGPT (GPT-4 version) the following question:



What specific parts of the U.S. Federal Procurement System could be improved from machine learning?



ChatGPT responded:



Machine learning can enhance various aspects of the U.S. Federal Procurement System. Below are a few potential areas for improvement:

1. **Vendor Evaluation:** Machine learning could be utilized to analyze vendors' performance, past project completions, and risk factors more accurately. This might include natural language processing (NLP) analysis of past project reports, customer feedback, and more.
2. **Price Prediction:** Machine learning could be used to predict the cost of services or goods. This could lead to a better understanding of market trends and enable more accurate budgeting.
3. **Fraud Detection:** Algorithms could be created to identify patterns indicative of fraudulent activity. This could drastically reduce the incidence and impact of fraud in federal procurement.
4. **Contract Management:** ML can analyze previous contracts to identify areas where negotiations could be improved or streamline the contract development process. This can include spotting nonstandard clauses or identifying contracts that are likely to have cost overruns based on past patterns.
5. **Procurement Optimization:** Machine learning could help identify inefficiencies in the procurement process. This might include everything from the initial request for proposal stage to final contract execution.
6. **Supply Chain Risk Management:** ML can help assess and predict risks in the supply chain, such as potential vendor failure, delays, or geopolitical issues that could disrupt supply.
7. **Spend Analytics:** Analyzing purchasing data across the federal government to find trends, identify opportunities for consolidated purchasing, and ensure compliance with purchasing policies can be greatly enhanced with machine learning.
8. **Sustainability:** Machine learning algorithms could assess and score products and services based on sustainability factors, helping the federal government make more environmentally friendly procurement decisions.



It's worth mentioning that while machine learning offers many potential benefits, it's crucial to remember the human element in the process. Machine learning should be used as a tool to enhance human decision-making, not to replace it. Further, the introduction of machine learning and AI also presents challenges related to ethics, privacy, and data security that must be thoughtfully addressed.

Procurement Challenge 3: Contractor Oversight

Oversight is a post-award phase in which a procurement agency enters into a contract with a vendor. Through oversight, procurement agents make sure that goods, services, or other work are delivered based on the contracted terms.

Contract oversight poses several challenges to public entities. Sometimes, uncertainty about government functions causes confusion over the necessary amount of contractor oversight.²⁰ Moreover, ensuring that deliveries meet agreed terms is a technical challenge requiring both experience and knowledge of delivered items—a challenge that was intensified by Covid, when understaffing while working from home also contributed to lack of sufficient oversight and inspection in some agencies.



AI Procurement Opportunity 3: Oversight

Image and video analysis provide a great opportunity for good contract oversight. Detecting defects, analyzing risks, and finding opportunities to improve the quality of products faster and cheaper can be addressed by machine learning algorithms. The technology has already demonstrated capability in image classification, image segmentation, and object recognition. In more sophisticated and specialized ways, image processing is being used by multiple companies, and even in inspection of historical buildings.

In the future, humans might be assisted in inspecting the quality of buildings, service of vehicles, and goods by a combination of computer vision, machine learning algorithms, and robots such as drones. Computer vision presents a wide range of capabilities for federal acquisition to supervise and monitor the implementation of contracts and quality of delivered goods and services. However, the challenge involves having enough data to train models and to build algorithms.



AI Use Case 3: Some Market Offerings for Computer Vision and Machine Learning

Amazon Lookout for Vision uses image processing and sophisticated machine learning algorithms to spot product and process defects and anomalies.²¹ The process begins by capturing images and loading them into the tool, then the system creates training data. After that, Lookout for Vision creates a dashboard to monitor defects and improve processes. In the final step, the tool automatically detects defects and reports them. Amazon Lookout for Vision finds anomalies highly accurately with a very low cost compared to traditional defect detection techniques.

CrowdAI, by employing computer vision and machine learning, has tools for a wide range of industries such as aerospace, insurance, oil and gas, utilities, and industry to identify defects in products by visual inspection.²² CrowdAI uses image and video analysis to visually inspect equipment, and to check and predict quality of materials produced. This system has enabled manual inspection time to be decreased by 50 percent, defect detection to improve by 90 percent, a 35 percent increase of machine life, and a 50 percent decrease in downtime.

Google recently introduced Visual Inspection AI²³, providing a simple solution for a complex challenge. The process starts with image acquisition. Images are uploaded into Google's Cloud. Then labels are created for defect types, like scratches discoloration. To learn a defect,

20. GAO. (2018). GAO-18-627. <https://www.gao.gov/products/GAO-18-627>.

21. AWS. (2021). Automated Quality Inspection—Amazon Lookout for Vision—Amazon Web Services. Amazon Web Services, Inc. <https://aws.amazon.com/lookout-for-vision/>.

22. CrowdAI. (2021). CrowdAI | Computer Vision Platform for Everyone. <https://www.crowdai.com/>.

23. Google. (2021). Visual Inspection AI Google Cloud | Solutions. Google Cloud. <https://cloud.google.com/solutions/visual-inspection-ai>.

the system needs ten images. After training, the model performance can be evaluated. The last step in the process is to deploy the model for operation. The model can be deployed for a wide range of uses such as detecting defects in semiconductors or car welding or painting.

In 2018, Intel partnered with the China Foundation for Cultural Heritage Conservation (CFCHC) to “protect and preserve” the Great Wall of China by using computer vision and machine learning algorithms.²⁴ A Falcon 8+ drone of Intel flies over the wall, surveys it, and captures thousands of highly detailed images. Images then are turned into a 3D model and used for analyzing the structure. By using artificial intelligence algorithms, the teams can count missing bricks and analyze types of repairs, estimate repairment time, labor and material cost. The inspection previously took over a month to complete—now by using a combination of computer vision, drones, and machine learning, it takes three days to inspect.

Procurement Challenge 4: Federal Procurement Data

The primary procurement data repository of the federal government is the Federal Procurement Data System-Next Generation (FPDS-NG). Despite agencies having taken actions to improve data quality and reliability, GAO findings suggest that FPDS-NG has unreliable data at a granular level, lacks appropriate data validation processes, and lacks appropriate administration. This is despite the fact that in 2007, the Office of Management and Budget asked in a memorandum for chief acquisition officers for rigorous data verification and validation procedures.²⁵



AI Procurement Opportunity 4: Data Acquisition, Capture, and Storage

Procurement platforms should be able to capture data with little human intervention. Social media platforms and e-businesses track activities on their platforms. Similar techniques could be used for automating the capture and storage of acquisition data.



AI Use Application 4: Automated Data Capturing

Data fuels machine learning algorithms. Without enough reliable data, it is impossible to build accurate and reliable machine learning based solutions. The federal government can benefit from an automated data capturing and storing system. Automation can reduce the time it takes to collect the data manually, is a cost-efficient solution for reducing paperwork, and can minimize errors in data collection and validation.

Market developed tools can capture and digitize paper-based data. Optical character recognition (OCR) is a machine learning technique that extracts and collects data from printed documents such as financial reports, invoices, government documents, pictures, and pdf documents.²⁶ Intelligent Document Recognition (IDR) employs artificially intelligent techniques to extract data from documents. Software such as IBM Datacap leverages natural language processing, text analytics, and machine learning to capture data from printed documents.²⁷

Procurement Challenge 5: Acquisition Workforce

The acquisition workforce consists of engineers, cost estimators, project and program managers, contracting officers, and many others in the procurement pipeline who help federal agencies buy what they need. Since they are in charge of planning and contracting billions of

24. Intel. (2018, July 16). Intel Technology Aids in Preserving the Great Wall of China. Intel Newsroom. <https://newsroom.intel.com/news/intel-technology-aids-preserving-great-wall-china/>.

25. White House. (2007). Memorandum for Chief Acquisition Officers, and Senior Procurement Executives. https://www.whitehouse.gov/sites/whitehouse.gov/files/omb/assets/OMB/procurement/pro_data/fpds_030907.pdf.

26. Microsoft, 2021. <https://learn.microsoft.com/en-us/azure/cognitive-services/computer-vision/overview-ocr>.

27. IBM, 2021. <https://www.ibm.com/products/data-capture-and-imaging>.

dollars of contracts, understaffing, overwork, and lack of adequate training are all enduring challenges.²⁸ Congress established the Defense Acquisition Workforce Development Fund (DAWDF) to recruit, train, and retain Department of Defense (DoD) acquisition workforce. However, findings suggest that new training opportunities as well as early planning can help to overcome existing gaps.



AI Procurement Opportunity 5: Improving Task Performance

Artificial intelligence and automation change the nature of work; part of the change involves how public servants use their time.²⁹ According to a survey of 34,000 workers in 18 countries, technology can potentially reduce stress in the workplace by taking over dull and repetitive tasks, leaving more engaging work for humans.³⁰ Intelligent automation can greatly improve the efficiency of tasks performed by federal employees, especially those involving handling paper forms and written information. Automation can allow agencies to quickly analyze data by processing and interpreting written documents at a faster rate than humans and can assist agencies in planning activities and initiatives.



AI Use Application 5: HHS and Grant Funding

The Department of Health and Human Services (HHS) is the main provider of federal grant funding, with approximately 70 percent of such funding across the government.³¹ In fiscal year 2017, HHS distributed nearly \$500 billion in grants. However, the complex process of distributing grants within HHS and other agencies presents numerous challenges, including difficulties coordinating and sharing information among the various operating divisions, offices, and projects within HHS, and reliance on interconnected legacy IT systems. This process also requires grantees and grant administrators to spend significant amounts of time handling large amounts of paperwork.

Before granting an award, HHS employees typically spend an average of four to eight hours completing a risk assessment based on various data sources such as financial audits and past grants awarded to the prospective grantee. HHS has implemented blockchain technology to create the Grant Recipient Digital Dossier, which consolidates information about prospective grantees from various government databases. Artificial intelligence is then used to locate and summarize information about prospective grantees from a large number of documents.

AI can significantly reduce the time needed for risk assessment by providing grant administrators with quick access to relevant information about the applicant, without the need to search manually through multiple data sources—reducing a task of eight hours to a fraction of this. Additionally, AI can analyze information in the database to identify potential risks that grant administrators should further investigate, such as whether the grantee's previous work with the government suggests a lack of technical ability to fulfill the requirements of a new grant. By streamlining the process and reducing the number of staff hours required, AI has the potential to save the agency approximately \$142 million annually.

28. GAO. (2018). Federal Acquisitions: Congress and the Executive Branch Have Taken Steps to Address Key Issues, but Challenges Endure. GAO-18-627. <https://www.gao.gov/products/GAO-18-627>.

29. IBM Center for The Business of Government. (2021). *Improving Outcomes in Government through Data and Intelligent Automation*. <https://www.businessofgovernment.org/report/intelligent-automation>.

30. McKendrick, J. (2019, July 29). Automation And AI Actually Relieve Workplace Stress, And Customers Will Notice. *Forbes*. <https://www.forbes.com/sites/joemckendrick/2019/07/29/automation-and-ai-actually-relieve-workplace-stress-and-customers-will-notice/>.

31. IBM Center for The Business of Government. (2021). *Improving Outcomes in Government through Data and Intelligent Automation*. <https://www.businessofgovernment.org/report/intelligent-automation>.

Managing the Use of AI for Overcoming Procurement and Acquisition Challenges



```
14.
15. # Move the robot to the re
16. robot.Move(target)
17.
18. # Draw a hexagon and
19. for i in range(7):
20.     ang = 1*2*pi/7
21.
22. # Calcul
23. x = x
24. y =
25. z
26. target_pos.setPos([x,y,z]
27.
28. # Move to the
29. robot.Move(target_pos)
```

reference point:
reference target:

This report focuses on a handful of reported challenges in the acquisition process. However, challenges may differ across localities. Additionally, applications of machine learning algorithms need iterative testing and deployment. Using AI in federal acquisitions requires long-term investment and constant improvement, best tackled through an artificial intelligence strategy.

Indeed, creating value by using AI for acquisition requires a well-managed and coordinated long-term strategy. The strategy may begin with executing small AI projects, for example by using recommendation engines or knowledge graphs for training on existing acquisition data, to help the acquisition workforce define specifications for new needs. Appropriate training will allow the acquisition workforce to know the latest AI breakthroughs and their potential applications in the acquisition process.

Without an AI strategy, it will be extremely difficult to develop a competitive advantage in the age of AI. AI can improve efficiency and effectiveness across the acquisition workforce, can optimize operations, and can optimize data to solve acquisition challenges. However, none of this is possible without reliable, up-to-date, and machine-readable data. Developing AI products requires data, machine learning engineers, computational power, and a conducive environment for finding inefficiencies in operations and willingness to use AI to solve those problems.

Building a Maturity Model

To capture technical requirements, long-term survivability, and continuous improvement, procurement agencies should have a maturity model to guide them in adopting AI technologies.³² A maturity model can enhance performance, meet objectives, and evaluate organizational capacity.³³

Disregarding a maturity model may cause disruptive challenges to the organization, such as fairness and bias harm, AI decay, and withdrawal from AI. Fairness requires that all users be treated without discrimination. However, biases are common in machine learning algorithms, and saturate every phase of data collection, processing, and deployment. Unlike traditional methods, AI deployment is a long-term process that requires testing, validation, learning, and continuous improvement; if treated otherwise, AI decay is a serious risk. Anytime an AI system is deployed but not maintained properly, there is a risk of unpredictable behavior, which can cause mistrust in AI systems and eventual withdrawal from the technology. Organizations should have an AI maturity model to mitigate such risks.

Maturity models vary. An AI Maturity Playbook suggests exploring, experimenting, formalizing, and integrating four levels of AI maturity.³⁴ Other studies suggest five maturity levels, specifically for public administration. For example, in one study, (1) entry-level, (2) elementary, (3) operational, (4) proficiency, and (5) mastery are suggested as the five levels of maturity.³⁵ The IBM Center for the Business of Government has offered a maturity model for public agencies.³⁶ The report identifies six dimensions to achieve success in AI: (1) big data, (2) computational systems, (3) analytical capacity, (4) innovation climate, (5) government and ethical framework, and (6) strategic vision.

32. Charran, E., & Sweetman, S. (2018). AI Maturity and organizations. Microsoft Corporation. <https://query.prod.cms.rt.microsoft.com/cms/api/am/binary/RE4Dlvg>.

33. Sadiq, R. B., Safie, N., Rahman, A. H. A., & Goudarzi, S. (2021). Artificial intelligence maturity model: A systematic literature review. *PeerJ Computer Science*, 7, e661. <https://doi.org/10.7717/peerj-cs.661>.

34. Etlinger, S. (2018). The AI Maturity Playbook: Five Pillars of Enterprise Success. Altimeter@ Prophet Research Report.

35. Noymanee, J., Iewwongcharoen, B., & Theeramunkong, T. (2022). Artificial Intelligence Maturity Model for Government Administration and Service. 2022 International Conference on Digital Government Technology and Innovation (DGTI-CON), 66–70. <https://doi.org/10.1109/DGTI-CON53875.2022.9849184>.

36. Desouza, K. C. (2021). *Artificial Intelligence in the Public Sector: A Maturity Model* | IBM Center for The Business of Government. IBM Center for The Business of Government. <https://www.businessofgovernment.org/report/artificial-intelligence-public-sector-maturity-model>.

Data is the fuel for building AI systems. Organizations should clearly understand their data and how it is captured, stored, and processed. Computational systems transform data into insights and can partially or completely automate tasks in public administration. Organizations need a skilled workforce on data and AI to achieve analytical capacity. Thus, organizations should clearly understand the talent and skill needs that require an investment of resources. Delivering AI in the public sector requires an innovative environment that accepts a level of risk. To advance the public good, AI should be deployed ethically and governed fairly and equitably.

An AI maturity model for public sector procurement follows.

Table 1: An AI maturity model for public sector procurement

	Ad Hoc	Experimentation	Planning and Deployment	Scaling and Learning	Enterprisewide Transformation
Ask your customer	Public agencies just started to think about using data for machine learning but they lack the data	Data is siloed, maybe not machine-readable, or may be difficult to share	Datasets for initial deploying machine learning algorithm are sufficient	Relevant datasets are prepared, explored, and deployed to solve identified problems	Up-to-date, relevant, unbiased, and fully integrated datasets are available and collected automatically
Human Resource	A few employees have personal interest in AI	Agency assign key personnel to pilot projects	Efforts are underway to train and recruit AI talent	Personnel have advanced AI/ML education and experience	The agency has cutting-edge in-house ML/AI expertise
Machine Learning Proficiency	Analytical capacity is very limited	Started experimenting with ML/DS models and algorithms	Actively working on one or more AI projects	ML/MS products are tested, validated, deployed, and improved continuously	Machine learning algorithms routinely tested, validated, and deployed through interactive dashboards
Strategic Visioning	Organization is able to tolerate risk of testing, deploying, and maintaining AI systems	Organization leadership support sustainable investment on AI	Organization is committed to projects that transcends political cycles	Metrics are developed to track the long-term progress of organization in integrating AI	The procurement agencies integrated AI into their day-to-day processes
Governance and Ethical Frameworks	No serious plan for ethical data governance	Actions taken for developing ethical frameworks and data governance	Data governance and ethical frameworks are in place	Data governance metrics are continuously executed and monitored	Fair, reliable and safe, inclusive, transparent, accountable, and secure principles govern the organization

Leveraging Power of Data

Any machine learning product needs data. Building artificially intelligent products requires reliable, up-to-date, and machine-readable data. The more accurate the data, the better for accurate and effective AI-based solutions. However, questions exist about what type of data should be collected, when to collect, and how to ensure validity and reliability.

Data mainly takes three different forms: structured, unstructured, and semi-structured. Structured data fall in two categories of discrete and continuous data, sometimes called quantitative data. Examples of structured data are dates, product types, address, temperature, stock price, or types of acquisitions. The structured query language (SQL), developed by IBM, is a common programming language for managing structured data. Unstructured data or qualitative data comes in various forms such as audio, texts, or videos, and managed in non-relational (noSQL) databases. Globally around 80 percent–90 percent of data is unstructured, of which only 0.5 percent analyzed and used.³⁷ A third type of data structure is called semi-structured, such as under the JSON, XML protocols. This type of data combines unstructured and structured data.

Data acquisition, both structured and unstructured, is essential for building machine learning algorithms and understanding day to day operations. Moreover, data help models to analyze and understand inefficient practices in acquisition processes and challenges. Finally, data can help people to use AI in making fact-based decisions.

Automating data collection has value for several reasons. Manual data entry is time-consuming and costly, as it requires a lot of work for individuals to enter the data into a database. Manual efforts are also prone to errors, and manual entry of unstructured data is impractical. Automated data capture, on the other hand, is fast, cost-effective, and accurate.

Federal agencies should gather data at every step of the acquisition process. This can begin from planning for an acquisition, determining the acquisition strategy, defining requirements, choosing a contract type, conducting a bidding process, negotiating, and delivering on the acquisition post-award. After delivery, capturing high quality videos or pictures from the product or work can help for training purposes of machine learning algorithms.

Various kinds of tools support the capture of different types of data, such as sensors and cameras. Sensors are inexpensive and widely used for data capture, while cameras are also a popular choice. Scanners can convert printed documents into raw data, and other tools support extracting data from webpages, PDF documents, and scanned documents.

Government data is often scattered within and across agencies; acquisition data are often captured and stored by different agencies and in different formats. AI experts have difficulty accessing this data, but without such access there is no way to build accurate machine learning algorithms. To leverage the power of AI, a unified data warehouse can be a crucial step. With a unified data warehouse, machine learning engineers can use a wide variety of techniques to test hypotheses and can develop accurate and usable products.

37. Dialani, P. (2020, October 29). The Future of Data Revolution will be Unstructured Data. <https://www.analyticsinsight.net/the-future-of-data-revolution-will-be-unstructured-data/>.

Capacity Building

In the age of AI, having an in-house AI capacity is a competitive advantage. An in-house AI team can facilitate the transformation of the organization for AI. For government, such capacity will allow the U.S. to have a competitive advantage. As the National Security Commission on Artificial Intelligence highlights: “The impact of artificial intelligence (AI) on the world will extend far beyond narrow national security applications. The development of AI constitutes a new pillar of strategic competition, and it heightens the competition in existing pillars.”³⁸

Having in-house AI capabilities allows acquisition agencies to collaborate with various units within the organization. For example, an AI team can work with planning departments, cost estimation teams, the requirement definition workforce, and oversight units to understand their challenges and develop AI-based solutions. By working with different teams, from those responsible for requirement definition to those in charge of contract oversight, the AI team can gain specialized knowledge about the cost-effective application of AI.³⁹

An in-house AI team can work with different acquisition departments to address technical and other questions, and to build datasets around them. Datasets allow the AI team to test and validate different hypotheses and algorithms and even enable them to define new needs, saving time and money for addressing simple tasks and helping humans to solve more complex tasks.

An in-house team can examine and see which algorithms work best and which do not. The team can pilot projects and examine impact before scaling up while algorithms are improved and validated. Google, for example, on average, modifies algorithms six times a day. To reach this level of modification, Google runs around 200,000–300,000 of experiments per year. The aim of this relentless effort is to improve the quality of search results over time.

Finally, an in-house team can build an infrastructure that connects algorithms to the end users and learns from their feedback. Deploying and improving any algorithm requires a constant feedback loop that allows for further improvements, and also makes it much easier and more efficient for an AI team to develop, test, validate products.

Getting Financial Support

Managers should seek resources to help acquisition agencies to adopt an AI strategy. Adequate resources can significantly aid acquisition agencies in investing in artificial intelligence. It can also support establishing key performance indicators for transitioning the acquisition workforce to an AI environment.

Without sufficient resources, it will be challenging to adopt AI in the acquisition workforce to support AI needs for machine learning engineers, data and supporting infrastructure, and computational power. Additionally, there is risk of failure in testing and developing models within existing resources, causing agencies to hesitate to initiate AI adoption given natural resistance to change. Allocating a budget for federal acquisition departments can mitigate financial constraints and hesitancy to adopt the technology.

38. Schmidt, E., Work, R., Catz, S., Horvitz, E., Chien, S., Jassy, A., Clyburn, M., Louie, G., Darby, C., Mark, W., Ford, K., Matheny, J., Griffiths, J.-M., McFarland, K., & Moore, A. (2021). Final Report: National Security Commission on Artificial Intelligence. National Security Commission on Artificial Intelligence. <https://www.nscai.gov/wp-content/uploads/2021/03/Full-Report-Digital-1.pdf>.

39. Marr, Bernard (2016). “Big Data In Practice: How 45 Successful Companies Used Big Data Analytics to Deliver Extraordinary Results.”

Key performance indicators are critical for transitioning to AI. These indicators can serve as a benchmark to measure the speed at which organizations adopt artificial intelligence and gauge the degree of AI adoption over time. Budget allocation can be tied to reporting against performance metrics, and can signal the importance and seriousness of funding enterprises for adopting the technology.

Task Management

Task management for the use of AI tools and systems is a key feature of managing both opportunities and challenges for improving government procurement. The first challenge presented by task management involves developing a deep understanding of which specific actions in the procurement process should be automated by AI, compared to when AI should augment a task for a human, and compared to when an AI is unlikely to be helpful for completing a task. A recent case study of the Social Security Administration's (SSA) integration of AI tools into decision making for disability benefits presents a helpful case in this direction.⁴⁰ In this case AI tools were used to help gather, organize, and structure data in a way that aided the decision making of a judge, rather than replacing the human as the final decision maker. The authors report benefits to the use of AI in leveraging the power of data to enhance the quality of decision. Some parts of the information flow process to the decision maker were automated and organized by the AI system, while the decision to award benefits—a decision that is complex, contains uncertainty, and requires nuanced judgement—was retained by the human decision maker.

Procurement departments can similarly consider how to implement AI systems. This echoes what the public administration academic literature argues for using AI within governmental decision making and task completion more generally. The literature finds that when deciding whether to use AI or a human to complete a government task, agencies should consider the complexity of the task and the uncertainty around the task.⁴¹ Generally speaking, tasks lower in complexity and uncertainty lend themselves to greater benefits from automation, especially when there is reliable data, a standard approach, and clearly defined inputs and outputs reducible to numerical terms.

The literature also has a term for using AI for tasks that have typically been completed by a human but may now be completed by AI: artificial discretion.⁴² One study points to five known government decision-making challenges for which artificial discretion may help:

1. Inaccurate predictions on consequential discretionary tasks, such as placing a child into foster care or granting a small business loan
2. Inconsistent quality of discretion through variance in accuracy across managers, or variance across time because of decision fatigue or emotional shocks
3. Bias in discretion, such as inconsistent citation rates in policing
4. Corruption that results when discretionary tasks are used to gain influence, such as granting government contracts to political allies

40. Glaze, K., Ho, D. E., Ray, G. K., & Tsang, C. (n.d.). Artificial Intelligence for Adjudication: The Social Security Administration and AI Governance. In J. B. Bullock, Y.-C. Chen, J. Himmelreich, V. M. Hudson, A. Korinek, M. M. Young, & B. Zhang (Eds.), *The Oxford Handbook of AI Governance* (p. 0). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780197579329.013.46>.

41. Bullock, J. B. (2019). Artificial Intelligence, Discretion, and Bureaucracy. *The American Review of Public Administration*, 49(7), 751–761. <https://doi.org/10.1177/0275074019856123>.

42. Young, M. M., Bullock, J. B., & Lecy, J. D. (2019). Artificial Discretion as a Tool of Governance: A Framework for Understanding the Impact of Artificial Intelligence on Public Administration. *Perspectives on Public Management and Governance*, 2(4), 301–313. <https://doi.org/10.1093/ppmgov/gvz014>.

5. The high labor costs of semi-routine bureaucratic tasks that require some discretion, such as processing applications to administer permits

Building on these criteria, AI may be applied to procurement tasks to improve procurement predictions, standardize the process to minimize variance across managers, decrease bias in favoritism towards vendors, decrease opportunities for corruption, and save on labor for processing of basic input data.

Given these potential benefits, three general types of uses emerge for public managers to consider applying artificial discretion towards:

1. Creating structured data from unstructured inputs, such as images, sensors, or text
2. Leveraging large and multidimensional data sets to identify patterns, generate new insights, or make accurate predictions
3. Eliminating human components of simple administrative tasks through automation⁴³

These types of tasks are represented in the SSA case and applicable to procurement challenges.

Building out this logic further, these three types of tasks can be generally mapped onto three different categories of users. For tasks that require low levels of discretion, automation may be most helpful. For tasks that require medium levels of discretion, decision support systems and tools can identify patterns and make accurate predictions to aid in the decision-making process. For tasks that require high levels of discretion, often both complex and uncertain, AI can be used more effectively for new data generation, basic relationship discovery, and to help structure the data.

Finally, these authors also provide criteria for when it is appropriate to apply artificial discretion. They argue that in making this determination, the above-mentioned considerations should be weighted to understand how they influence:

- Effectiveness
- Efficiency
- Equity
- Manageability
- Legitimacy and political feasibility

Each of these criteria represent important values, challenges, and trade-offs for public managers and government officials to consider.

Avoiding Automation Bias

While it is important to evaluate individual tasks for whether they are appropriate to the use of AI by government, there are other concerns that arise in considering the impact of using AI more systematically throughout government agencies and public organizations. Decisions about task completion present two additional risks for government agencies: automation bias and, as one study has termed, “administrative evil.”

43. Young, M. M., Bullock, J. B., & Lecy, J. D. (2019). Artificial Discretion as a Tool of Governance: A Framework for Understanding the Impact of Artificial Intelligence on Public Administration. *Perspectives on Public Management and Governance*, 2(4), 301–313. <https://doi.org/10.1093/ppmgov/gvz014>.

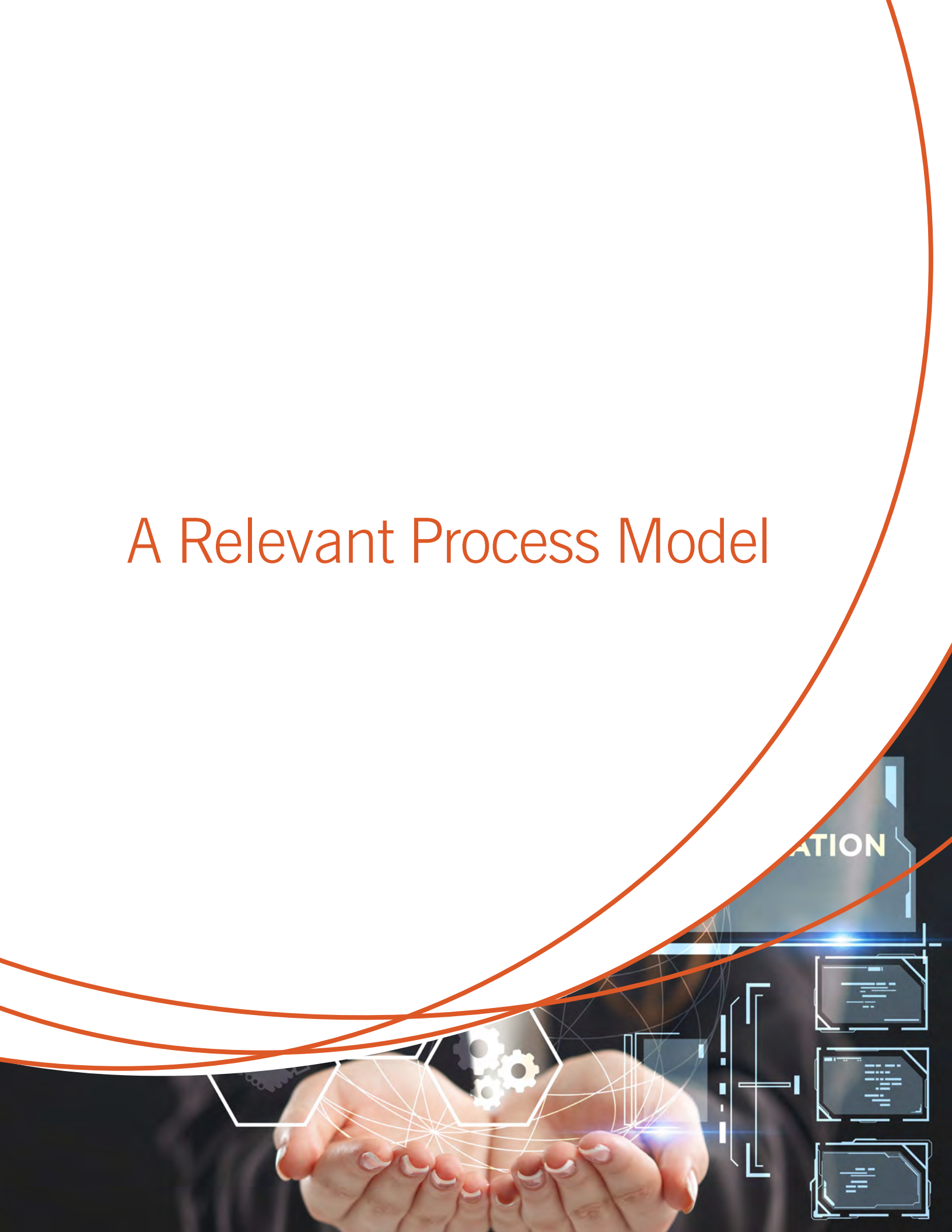
Automation bias has been closely studied in the context of aviation and other fields. Once tools of automation enter into the decision-making calculus of a workflow, there is a tendency to over-rely on the technology rather than being diligent in ensuring the quality of automation in a given decision context. Within the public sector, early experimental evidence suggests that automation bias does present serious concerns for effective, efficient, and equitable decision making.

In addition to this concern of spreading automation bias within agencies and organizations that adopt AI systems, there is also the concern for the spread of "administrative evil". As one study has noted, this can occur when organizations commit harmful acts upon individuals, leading to unnecessary suffering. If AI is applied without care it can pervert organizational decision making in the direction of "dehumanization, opacity (technical inscrutability), quantification bias, organizational value misalignment, and AI exuberance."⁴⁴ Absent careful and ethical applications of technology, these types of administrative risks can occur without harmful intentions by either the developers of AI systems or the government officials implementing them.

Taken together, these use cases and risks highlight both the potential opportunities for using AI to improve procurement challenges, and the risks AI presents for organizational decision making—since decisions about procurement are not made in a vacuum but rather as part of the organizational decision-making process. The good news is that prior academic research, including IBM Center reports, provide insights into how to use of AI tools for improving procurement while mitigating risk.

44. Young, M. M., Himmelreich, J., Bullock, J. B., & Kim, K.-C. (2021). Artificial Intelligence and Administrative Evil. *Perspectives on Public Management and Governance*, 4(3), 244–258. <https://doi.org/10.1093/ppmgov/gvab006>.

A Relevant Process Model



To use AI to overcome current procurement challenges, Yu-Che Chen and Michael Ahn offer a process model that government organizations can deploy to help them manage these decisions. In their study “Governing AI Systems for Public Values: Design Principles and a Process Framework,” Chen and Ahn argue that there are four phases to the development and deployment of AI systems that are used by public agencies.⁴⁵ These four phases include:

1. Goal setting
2. Iterative development decisions on data, models, and results
3. Decisions on public service
4. Assessment of the impacts made by the AI system

Furthermore, they argue that these phases should be guided by design principles that are:

1. Human-centered
2. Stakeholder-focused
3. Lifecycle-scoped

To tie this more directly and clearly to the five opportunities and cases in this report—specification requirements, pricing and competition, contract oversight, federal procurement data, and acquisition workforce—such strategies can help agencies to guard against misusing these technologies as well.

For example, this report has highlighted throughout the importance of more data, more automated collection of data, and better quality data. However, once collected, data is often used both for direct intended purposes and for other purposes that may serve the data collector or stakeholders. Thus, while more data is needed, systematically, to make better use of AI and ML tools, sound governance processes around this collection are very important such as those highlighted in this report. Sound governance includes a formal iterative assessment and goal setting process, ensuring that these processes remain focused on humans and improving their lives, and ensuring that they are appropriately scoped and managed given the myriad externalities associated with data once it had been collected, particularly digital data which is relatively easily stored, shared, and manipulated.

As digital tools of increasing intelligence are further integrated into public organizations and governance processes, agencies must be deliberate in how best to address challenges. Effective, efficient, and human-centered strategies can realize the positive opportunities for federal procurement and acquisition, while also protecting against the misuse of these tools.

45. Chen, Y.-C., & Ahn, M. (2022). Governing AI Systems for Public Values: Design Principles and a Process Framework. In J. B. Bullock, Y.-C. Chen, J. Himmelreich, V. M. Hudson, A. Korinek, M. M. Young, & B. Zhang (Eds.), *The Oxford Handbook of AI Governance*. Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780197579329.013.31>.

CONCLUSION

This report identifies numerous opportunities by which the U.S. federal government might improve the effectiveness, efficiency, and human-centered approach to its procurement and acquisition of goods in services. Challenges to procurement include: (1) unclear and unknown specification and requirement definitions, (2) ensuring competition among contractors and competitive pricing for contracts, (3) oversight of selected contractors, (4) quality, quantity, and well-maintained data, and (5) educating and adjusting the acquisition workforce to reflect the opportunities presented by AI and ML. To address these enduring challenges, AI and ML tools may be helpful, including recommendation algorithms, natural language processing, visual data and machine learning, and automation.

These tools were mapped onto specific tasks that might help in overcoming obstacles to good procurement practices. These good procurement practices by the use of algorithms and AI is also explored in recent work by Cary Coglianese and colleagues.⁴⁶ For specification and requirements definition, recommender algorithms could play a role for the procurement team to develop more clear and precise specifications and requirement definitions. Large language models may have the capacity to promote clear and precise specifications from a specific project and may also be useful to procurement pricing and competition. These models can quickly return large amounts of knowledge on expected prices, potentially leading firms, and suggestions of firms that could provide the needed goods and services.

Another potential positive use would be to support effective project management oversight of contractors. Computer vision and machine learning can be paired to provide “eyes on the ground” on contract performance, as an effective method for proactive monitoring. Additionally, an automation system that captures, analyzes, and categorizes data for information relevant to federal procurement decision making could assist with improving federal procurement databases. Finally, government coworking alongside both generative AI and large language models can improve their own performance on tasks, such as finding, developing, and submitting grants.

While these tools may be helpful in addressing procurement challenges and opportunities, agencies can also focus on the more complex task of managing the implementation of AI effectively into overall decision-making systems. Several areas of consideration emerge for public procurement managers as they address how best to realize the benefits of these tools while not sacrificing values and performance of the organization’s overall goals. These areas of consideration include:

- Build a maturity model
- Leverage power of data
- Build capacity
- Seek resources
- Careful task management
- Avoid automation bias

These areas of consideration point to the importance of keeping governance processes, particularly as related to the adoption of AI tools, human-centered, stakeholder-focused, and lifecycle scoped. If public procurement managers work diligently to maintain good governance practices, then advanced tools of AI, ML, natural language processing, machine vision, automated data collection and structuring, and recommendation algorithms could significantly improve federal procurement and acquisition.

46. Contracting for Algorithmic Accountability. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3853208 and Procurement as AI Governance. <https://ieeexplore.ieee.org/document/9540751>.

ABOUT THE AUTHORS

Mohammad Ahmadi is a doctoral fellow in the Technology Applications and Implications Stream at Pardee RAND Graduate School. He has an M.P.S.A. in policy analysis from Texas A&M University and a B.Eng. in civil engineering from the University of Herat. His research interests include artificial intelligence, machine learning, and large language models.



MOHAMMAD AHMADI

Dr. Justin B. Bullock is an Associate Professor Affiliate of Governance at the Evans School of Governance at the University of Washington and a Senior Researcher for Convergence Analysis. Dr. Bullock is a world-renowned scholar and expert in public policy, governance, public administration, technology, artificial intelligence (AI), management, and organizational theory.



DR. JUSTIN B. BULLOCK



KEY CONTACT INFORMATION

Mohammad Ahmadi

Doctoral Fellow
Pardee RAND Graduate School

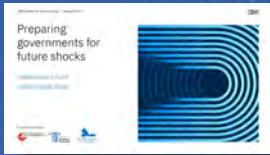
Email: mahmadi@pardeerand.edu

Dr. Justin B. Bullock

University of Washington

Email: jbull14@uw.edu

RECENT REPORTS FROM THE IBM CENTER FOR THE BUSINESS OF GOVERNMENT



Preparing governments for future shocks: Collaborating to build resilient supply chains

by Robert Handfield Ph.D.



Preparing governments for future shocks: An action plan to build cyber resilience in a world of uncertainty

by Tony Scott



Managing the New Era of Deterrence and Warfare: Visualizing the Information Domain

by Brian Babcock-Lumish



The Future of AGILE GOVERNMENT

by G. Edward DeSeve



A Guide to Adaptive Government: Preparing for Disruption

by Nicholas D. Evans



Leveraging Data for Racial Equity in Workforce Opportunity

by Temilola Afolabi



Off to a Running State Capital Start: A Guide for New Governors and Their Teams

by Katherine Barrett and Richard Greene



Mobilizing Cloud Computing for Public Service

by Amanda Starling Gould



For a full listing of our reports, visit www.businessofgovernment.org/reports

25 YEARS CONNECTING RESEARCH TO PRACTICE



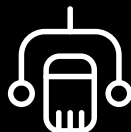
Five Easy Ways to Connect
businessofgovernment.org



Blog



Reports



Interviews



Magazine



Books

IBM Center Research Announcement

The IBM Center for The Business of Government connects research to practice, supporting work by scholars that benefits government through real-world experience and analysis. Our Center's reports are intended to spark the imagination—crafting new ways to think about government. We identify trends, new ideas, and best practices in public management and innovation.

We encourage applicants to review our research areas closely in selecting a topic, or a cross-cutting set of topics. We are looking for very practical findings and actionable recommendations—not just theory or concepts—in order to assist executives and managers to more effectively respond to mission and management challenges.

For more details on our latest proposal deadlines and application form, please visit: <https://www.businessofgovernment.org/content/research-stipends>.

We look forward to hearing from you!



IBM Center for
The Business
of Government

Insights

Conversations

Information

Action

About the IBM Center for The Business of Government

Through research stipends and events, the IBM Center for The Business of Government stimulates research and facilitates discussion of new approaches to improving the effectiveness of government at the federal, state, local, and international levels.

About IBM Consulting

With consultants and professional staff in more than 160 countries globally, IBM Consulting is the world's largest consulting services organization. IBM Consulting provides clients with business process and industry expertise, a deep understanding of technology solutions that address specific industry issues, and the ability to design, build, and run those solutions in a way that delivers bottom-line value. To learn more visit ibm.com.

For more information:

Daniel J. Chenok

Executive Director

IBM Center for The Business of Government

600 14th Street NW

Second Floor

Washington, D.C. 20005

(202) 551-9342

website: www.businessofgovernment.org

e-mail: businessofgovernment@us.ibm.com

Stay connected with the IBM Center on:



or, send us your name and e-mail to receive our newsletters.



IBM Center for
The Business of Government