

Artificial Intelligence in the Public Sector: A Maturity Model

AI



Artificial Intelligence in the Public Sector: A Maturity Model

Kevin C. Desouza

Queensland University of Technology

TABLE OF CONTENTS

Foreword	4
Executive Summary	6
Introduction	7
A Maturity Model For Designing, Developing, And Deploying Ai In The Public Sector . . .	10
Dimensions	11
Big Data	11
Computational Systems	13
Analytical Capacity	14
Innovation Climate	16
Governance and Ethical Frameworks.	17
Strategic Visioning	19
Levels of Maturity	20
Ad Hoc	20
Experimentation	21
Planning and Deployment	23
Scaling and Learning	25
Enterprise-Wide Transformation	26
Recommendations	27
Beyond Ad Hoc	29
Beyond Experimentation	30
Beyond Planning and Deployment	30
Beyond Scaling and Learning.	31
Conclusion.	32
Appendix	33
Acknowledgments	36
About the Author	37
Key Contact Information	38
Reports from the IBM Center for The Business of Government.	39

FOREWORD

On behalf of the IBM Center for The Business of Government, we are pleased to publish this new report, *Artificial Intelligence in the Public Sector: A Maturity Model*, by Kevin Desouza Professor of Business, Technology and Strategy at Queensland University of Technology.

Artificial intelligence (AI) has emerged as a force for public good in recent years. The technology is revolutionizing the way we derive value and insights from data in order to improve our daily lives. In addition, governments gather a treasure trove of pertinent data that can be used to execute important missions and improve services to the citizen. An effective AI program can greatly enhance the ability of the public sector to deliver on that promise.

The challenge has always been to design and implement an AI program that has all the critical elements in place to successfully achieve the goal of improved mission delivery and citizen services. An initial report commissioned by the IBM Center for The Business of Government, *Delivering Artificial Intelligence in Government: Challenges and Opportunities*, proposed an initial maturity model that gave public agencies a starting point for developing an AI capability. Subsequently, we have had the opportunity to fine tune the model, based on extensive research on how the public sector was deploying AI, documenting successful use cases and highlighting pitfalls and lessons learned.

The revised maturity model was shared with experienced public sector practitioners and feedback from these discussions led to a further revision. The revised model was then shared with a final group of reviewers that included public sector executives (both within and beyond the information systems domain), academics, and consultants.

We hope that this report provides public sector leaders a view into the “art of the possible” by emphasizing how AI programs can accelerate the transformation of government programs to better serve the public and by providing them a framework for establishing a successful AI program. We will continue to explore this topic and will provide further updates as the use of AI in the public sector continues to evolve.



DANIEL J. CHENOK



LEANNE HASELDEN

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

Leanne Haselden
Partner and Practice Area Leader
Advanced Analytics,
IBM Global Business Services
leanne.haselden@us.ibm.com

EXECUTIVE SUMMARY

Government agencies in the U.S. and around the world increasingly invest financial and human resources into artificial intelligence (AI) initiatives.

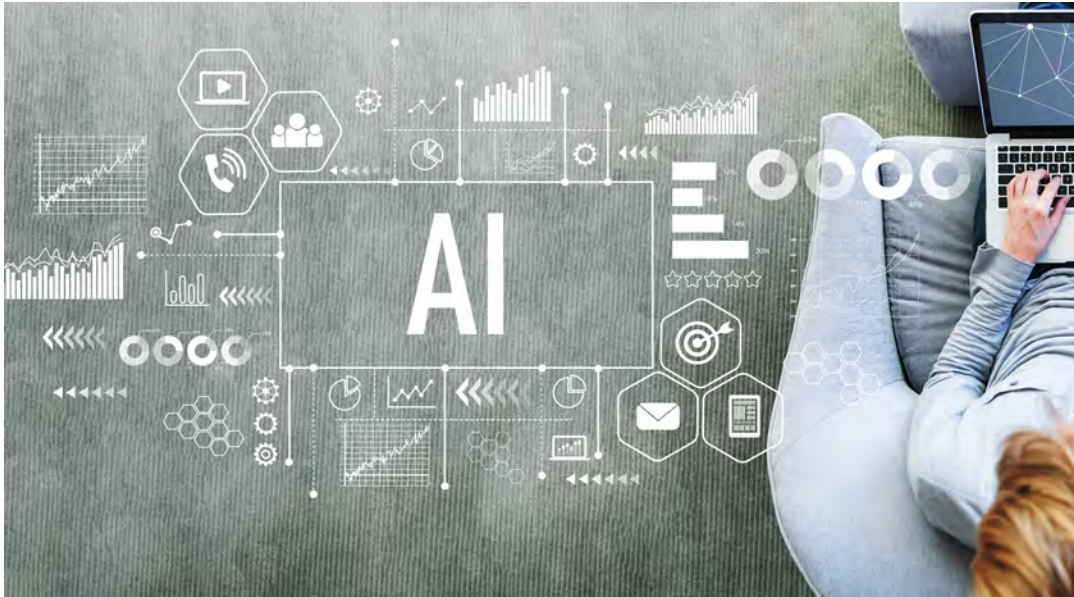
Advances in AI enable agencies to 1) increase efficiency of operations via automation, 2) innovate by empowering the public workforce with augmented intelligence for decision making, and 3) improve access to and quality of service delivery. Despite many success stories with AI, these initiatives present unique challenges during design, development, and deployment.

As such, agencies will benefit from a framework to enable them to get the highest value from their efforts and investments in AI. This report outlines a maturity model based on practical experience and research insights to provide such guidance, supporting evaluation and facilitating the success of AI projects in the public sector. To achieve success with AI, the model indicates that agencies must show proficiency on six core elements:

- Big data
- AI systems
- Analytical capacity
- Innovation climate
- Governance and ethical frameworks
- Strategic visioning

An agency's overall maturity with AI reflects their lowest level of proficiency on one or more of the six elements. Recognizing that proficiency on each element relates in part to performance across the other elements. The maturity model charts the progressive development of AI competencies from ad hoc to experimentation, planning and deployment, scaling and learning, and finally, enterprise-wide transformation.

INTRODUCTION



To raise the IQ of the public sector with artificial intelligence, we need to share lessons learned across agencies, benchmark ourselves, and collaborate to drive collective improvement and reduce waste.

—Senior Public Executive

Public agencies continue to invest in and deploy artificial intelligence (AI) across a multitude of domains.^{1,2,3,4} A recent IBM survey shows that 87 percent of government executives agreed that “cognitive computing plays a disruptive role in their organizations, and that they intend to invest in cognitive capabilities.”⁵ AI leverage advances across several information and computer science domains, including machine learning, natural language processing, sentiment analysis, deep learning, image and speech recognition, and robotics, among others.

1. Desouza, K. C. (2018). *Delivering Artificial Intelligence in Government: Challenges and Opportunities*. IBM Center for The Business of Government, 48.

2. Desouza, K. C., Dawson, G. S., & Chenok, D. (2020). Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. *Business Horizons*, 63(2), 205–213. <https://doi.org/10.1016/j.bushor.2019.11.004>.

3. Boyd, M., & Wilson, N. (2017). Rapid developments in Artificial Intelligence: How might the New Zealand government respond? *Policy Quarterly*, 13(4). <https://ojs.victoria.ac.nz/pq/article/view/4619>.

4. Chatfield, A. T., & Reddick, C. G. (2019). A framework for Internet of Things-enabled smart government: A case of IoT cybersecurity policies and use cases in U.S. federal government. *Government Information Quarterly*, 36(2), 346–357. <https://doi.org/10.1016/j.giq.2018.09.007>.

5. *IBM Institute for Business Value—Research, reports, and insights*. (2021, January 8). IBM. <https://www.ibm.com/thought-leadership/institute-business-value/>.

AI can operate in an autonomous mode (e.g., robotic process automation) and can also be deployed to augment human decision making. AI can contribute to augmenting the nature of work at public organizations and how they provide service for citizens. The efficiency, quality, and speed of a citizen engagement can be enhanced, particularly because AI can be used to process large amounts of data and facilitate decision making, modernize service delivery processes, reduce administrative burdens by automating repetitive tasks related to processing service applications, and facilitate resource allocation.

AI can also help the effectiveness of service delivery, for example, through supporting service personalization by using data in customer profiles and previous service interactions. In the context of citizen services, these systems can be categorized into at least five areas, including: answering service inquiries, assistance with finding and filling out forms, translation, routing requests, and drafting documents.⁶

AI applications are common across various domains in the public sector. Consider these cases:

- In New York and Los Angeles, the Coast Guard uses AI to randomize its boat patrol routes, making their day-to-day security-related activities less predictable for criminals.^{7,8} The same class of AI can help wildlife rangers to protect native African animals and plants more effectively by helping to decide which wildlife territories to patrol and to combat illegal animal poaching by predicting where poachers will set up traps.^{9,10}
- The Mexican government piloted an AI initiative in which algorithms were designed and used to classify and understand citizen petitions and then route them to the relevant department.^{11,12}
- AI-based chatbots deployed in a North Carolina government office free up operators' lines and customer help desks. Most service questions from the government office are simple and repetitive (for example, almost 90 percent of requests are about resetting passwords). Using the chatbots to answer the simpler questions has allowed customer agents to focus on more complex and time-sensitive service inquiries.^{13,14}

6. Mehr, H. (2017). Artificial Intelligence for Citizen Services and Government. Harvard Ash Center for Democratic Governance and Innovation, 19. <https://ash.harvard.edu/publications/artificial-intelligence-citizen-services-and-government>.

7. Teamcore Research Group, "AI and game theory for public safety and security." Retrieved from <https://teamcore.seas.harvard.edu/ai-and-game-theory-public-safety-and-security>.

8. Savitz, S., Davenport, A., & Ziegler, M. (2020). The Marine Transportation System, Autonomous Technology, and Implications for the U.S. Coast Guard. RAND Corporation. <https://doi.org/10.7249/PE359>.

9. Good, A. (2016, June 6). Artificial intelligence could turn poachers into prey. University of Southern California. <https://news.usc.edu/101501/artificial-intelligence-could-turn-poachers-into-prey/>.

10. National Science Foundation, "Outwitting poachers with artificial intelligence." Retrieved from <http://bit.ly/2oBRTLy>.

11. Mehr, H. (2017). Artificial Intelligence for Citizen Services and Government. Harvard Ash Center for Democratic Governance and Innovation, 19. <https://ash.harvard.edu/publications/artificial-intelligence-citizen-services-and-government>.

12. Gaut, G., Navarrete, A., Wahedi, L., van der Boer, P., De Unánue, A., Díaz, J., Clark, E., & Ghani, R. (2018). Improving Government Response to Citizen Requests Online. Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, 1–10. <https://doi.org/10.1145/3209811.3209872>.

13. Goldsmith, S. (2017). Artificial Intelligence Will Help Create a More Responsive Government. Government Technology. <https://www.govtech.com/opinion/Artificial-Intelligence-Will-Help-Create-a-More-Responsive-Government.html>.

14. Stamatidis, A., Gerontas, A., Dasyras, A., & Tambouris, E. (2020). Using chatbots and life events to provide public service information. Proceedings of the 13th International Conference on Theory and Practice of Electronic Governance, 54–61. <https://doi.org/10.1145/3428502.3428509>.

- The MySurrey app—an app deployed in Surrey, British Columbia, that deployed IBM Watson—efficiently responds to service inquiries. The app can handle 65 percent of inquiries, for which there is already self-help information on city websites. Watson, which uses machine learning to learn over time, reviewed over 3,000 documents related to sixteen city services and responds to 10,000 service inquiries.^{15, 16}
- Using AI-based Natural Language Generation (NLG), agencies can draft documents such as self-help information and service application files. The technique has already been deployed in newsrooms for data mining, creating text for datasets, and writing at a pace of 2,000 articles per second. The technique can also support non-data science staff in more easily understanding and using the data.¹⁷ Japan's Ministry for Economy, Trade, and Industry deployed an innovative solution to help parliament member offices respond to service inquiries from citizens by drafting responses using AI.¹⁸
- An AI-based chatbot has been deployed for providing targeted assistance with unemployment benefits in Australia. When used, the form that includes about 150 questions can be auto-filled based on the applicant's profiles, reducing the number of questions that need applicant's input to 10-15.¹⁹
- Given the initial successes with deploying AI and the massive investments being made in AI by national governments, many countries have developed national-level AI strategic plans.²⁰ In our analysis of thirty-three national-level AI strategic plans, modernizing the public sector through the deployment of AI is a key national priority for these nations. Public sector functions discussed in these plans cover the gamut from national security to immigration, smart cities, energy, and the environment, and transportation, among others.

While the interest and activity on AI are promising, for every success story with AI, there are several failed efforts. Failed efforts are not simply AI projects that do not get completed within time and budget constraints but are also ones that generate output that is biased, discriminatory, or even simply incorrect, resulting in harm to individuals. Successful design, development, and deployment of AI require an appreciation of the nuances of six elements: big data, AI systems, analytical capacity, innovation climate, governance and ethical frameworks, and strategic visioning.

15. Pereira, D. (2017, March 27). Watson helps cities help citizens. Medium. <https://medium.com/@daryl/watson-assists-cities-with-311-3d7d6898d132>.

16. Hurley, B. (2015). TIM Lecture Series - Improving the Self-Service Customer Experience: The Case of IBM Watson and Purple Forge. *Technology Innovation Management Review*, Ottawa, 5(9), 36-40.

17. Leppänen, L., Munezero, M., Granroth-Wilding, M., & Toivonen, H. (2017). Data-Driven News Generation for Automated Journalism. Proceedings of the 10th International Conference on Natural Language Generation, 188-197. <https://doi.org/10.18653/v1/W17-3528>.

18. Mehr, H. (2017). Artificial Intelligence for Citizen Services and Government. Harvard Ash Center for Democratic Governance and Innovation, 19. <https://ash.harvard.edu/publications/artificial-intelligence-citizen-services-and-government>.

19. Nili, A., Barros, A., & Tate, M. (2019). The public sector can teach us a lot about digitizing customer service. *MIT Sloan Management Review*, 60(2), 84-87.

20. Fatima, S., Desouza, K. C., & Dawson, G. S. (2020). National strategic artificial intelligence plans: A multi-dimensional analysis. *Economic Analysis and Policy*, 67, 178-194. <https://doi.org/10.1016/j.eap.2020.07.008>.

Public agencies often emphasize one or more components at the expense of others either deliberately or simply through lack of knowledge. One public agency that we studied invested significant time and resources in a data science unit to build two AI solutions. However, this investment was not matched with efforts to create an overall ethical framework to guide the use of data. As a result, the solutions were never deployed, resulting in a significant waste of taxpayer resources. In another instance, a city manager recounted how they had planned to experiment with robotic process automation but ran into issues because they had not taken the right care to prepare the workforce to engage in the development of the AI solution. As such, not only was the project abandoned but it also led to lower employee morale due to fears of being replaced due to automation. Even agencies that have significant technological expertise are encountering problems with AI implementations, which further shows that the public sector needs to develop appropriate models that support the success of these projects.

Immature efforts of design and deployment of AI are costly to the public, particularly to the taxpayer, as well as to both internal and external stakeholders. Thus, there is a need to develop models that provide guidance to public managers in terms of their current and future AI initiatives and how to mature them in a disciplined and effective way. Public agencies that understand where they stand in terms of their maturity on the six core elements are more likely to invest resources in AI at the appropriate level given their context and to achieve expected outcomes. On the other hand, if an agency invests in AI without addressing fundamental issues in one or more elements to get them to the desired level of required maturity, that agency is almost certain to see poor and/or negative outcomes.

This report outlines a maturity model to serve as an instrument that provides this guidance, support evaluation, and success of AI projects in the public sector.

A Maturity Model For Designing, Developing, And Deploying Ai In The Public Sector



Maturity models are popular in a wide assortment of fields from quality management to software engineering, education and learning, organizational design, and even information systems. While each maturity model has its own peculiarities, they all provide an evolutionary framework to guide improvements and/or advancements on one or more domains.

Consider, for example, one of the first maturity models developed by Phillip Crosby. His quality management maturity model was made up of six elements (management understanding and attitude, quality organization status, problem handling, cost of quality as a percentage of total sales, quality improvement actions, and summary of company quality posture) and five levels (uncertainty, awakening, enlightenment, wisdom, and certainty).²¹

Our domain of interest is AI design, development, and deployment efforts in the public sector.

Our maturity model has two dimensions (see Table 1 in Appendix). The first dimension represents the critical elements that need to be managed as AI projects are designed, developed, and deployed in the public sector. These elements can be divided into two domains: technical and organizational. The technical domain comprises big data, AI systems, and analytical capacity. The organizational domain includes innovation climate, governance and ethical frameworks, and strategic visioning. The second dimension outlines the maturity levels that begin with ad hoc, followed by experimentation, planning, and deployment, scaling and learning, and finally, enterprise-wide transformation. Next, we detail the core elements and then go through the levels of maturity.

How the Maturity Model Was Built?

The maturity model was constructed over several research projects over the last three years. An initial maturity model was proposed in the IBM Business of Government report *Delivering Artificial Intelligence in Government: Challenges and Opportunities*. Since its publication in 2018, we have had the opportunity to refine the model as we conducted research on how public agencies were deploying AI from chatbots to robotic process automation (RPA), and machine learning systems. The revised maturity model was shared with public sector professionals who had deep knowledge and experience when it came to deploying information systems. Feedback from these discussions led to a further revision of the maturity model. The revised model was then shared with a final group of reviewers that included public sector executives (both within and beyond that information system domain), academics, and consultants.

Dimensions

Big Data

AI relies on big data for its design and development, but once deployed, enables organizations to make sense of large data reservoirs through the application of machine learning algorithms. In an ideal world, public agencies should be able to access, integrate, and leverage data of interest in an effective and efficient manner.

21. Crosby, P. B. (1979). *Quality is Free: The Art of Making Quality Certain*. McGraw-Hill.

For example, the COVID-19 pandemic has spurred development of contact tracing and health management systems, including the use of AI in this context. Owing to the large population size and initial outbreak numbers, the Yuhang district of Hangzhou City developed and rolled out a smartphone app called 'Health Barcode,' which sought to replace paper permits. This software was rolled out a fortnight after the China-wide lockdown of February 7th, 2020. The application expanded and was adopted by national authorities for the use of over 900 million residents by month's end. This software is similar in nature to South Korea's COVID-19 SMS software and was a product of a public-private partnership.

Dynamic epidemic risk management is offered through a combination of individual self-reporting of health status, big data made available through transport systems, social media, the national COVID-19 database, and GPS/payment records. The use of AI allows for full retracing of individuals movements and persons in contact with COVID-19 carriers, which allow for three different levels of risk assessment for public citizens, low, medium, and high.²² However, most agencies continue to struggle with 1) understanding what data they have in-house, what data they can access both within, and beyond, the public sector, 2) integrating disparate data across heterogeneous systems, and 3) designing data governance frameworks to address the critical issues of data risk, safety, and use considerations.

Public agencies need to invest in understanding the data they have and how it is collected (captured), stored, and used. Doing so requires agencies to map out the data flows in and out of the agency. During our research, it was disconcerting to find that most agencies had only a limited view of their data assets. Consider, for example, the fact that while we continue to see a rise of open data platforms and the active publishing of data by public agencies, seldom do agencies track the value generated from these efforts.

To build AI projects, data is the most vital resource. More specifically, ensuring that the data is of good quality and can be assessed and analyzed is important. To build AI projects, agencies need to invest in understanding the value of their datasets. Toward this end, agencies need to be able to discern which datasets are ideal candidates to be used for designing AI projects. In addition, agencies must identify datasets that may have quality concerns (e.g., not being representative of the population or having a large amount of missing and/or erroneous entries).

In addition to data that resides within an agency, datasets need to be leveraged from stakeholders across the entire ecosystem. To tackle vexing problems with the aid of AI requires agencies to be able to draw on data that resides externally, either within other public agencies or beyond. Datasets will need to be integrated that reside with nongovernmental organizations (NGOs), the private sector, and even academia. Agencies often struggle in this respect due to lack of data interoperability either due to technical (e.g., data formats and discrepancies) or policy limitations (e.g., absence of data sharing covenants, legal impediments).

As data is the key ingredient for AI, it is vital that there are data governance frameworks that promote responsible innovation. Too often we find that agencies over-focus on the risks associated with data rather than the opportunities they can provide. While one might expect that the focus on risk and harm that arise from data would lead to stringent data controls and processes to assess use cases, we find that it is more common for agencies to simply have no governance and policy frameworks in place. As a result, data governance frameworks are critical to the development and use of AI and several elements need to be accounted for in it.

22. Lin, L., & Hou, Z. (2020). Combat COVID-19 with artificial intelligence and big data. *Journal of travel medicine*, 27(5). <https://doi.org/10.1093/jtm/taaa080>.

First, most important is data quality. As the adage goes—garbage in, garbage out. Data quality analysis is critical as AI ingests data and learns from it. As such, the use of data that is biased and incorrect will lead to AI development that causes harm. The second is risks and opportunities. A balanced approach to analyzing risks and associated opportunities will enable agencies to extract maximum value while minimizing harm. The third is sharing. As noted above, agencies can gain from having protocols that cover how and when data is shared, with whom and for what purpose.

Computational Systems

Computational systems are the engines that transform data into actionable insights and outcomes. As discussed earlier, AI applications leverage a range of computational techniques to ingest, analyze, visualize, and even act on data. AI can fully or partially automate tasks through the power of predictive data analytics, fed by multiple sources of historical and real-time data; learn from previous interactions and self-decide through the power of machine learning; and in some cases, such as chatbots, interact with users through natural language processing.

AI can also employ approaches such as robotic process automation (RPA) to fully automate repetitive tasks and tasks with a low level of discretion, resulting in freeing up a significant amount of unnecessary human labor. Additionally, AI can be used to partially automate more complex tasks or as a decision support tool through approaches such as augmented data management, text analytics, graph analytics, scenario modelling, and forecasting.

Today, chatbots are a popular example of AI applications that are being increasingly designed to use the power of computational systems to engage citizens in public service delivery. Using historical (e.g., data stored in the user profile) and real-time service interaction data, advanced chatbots can automate delivery of simple public services and support delivery of complex public services through identifying and negotiating the best service option that addresses an individual's specific needs.

The Dubai Electricity and Water Authority (DEWA) currently uses 'Rammis chatbots' in the customer service space. DEWA's use of this system has been successful, as the system operates with an understanding of questions in both Arabic and English while also demonstrating the ability to adapt and learn based on customer questions. The efficiency of the system has resulted in an 80 percent reduction of physical customer visits to DEWA departments.

In a similar manner, Malaysia has recently adopted the application of AI for determining the water quality index (WQI). WQI provides an effective assessment of the quality of surface water and environmental protection while ensuring clean water for public consumption. This system, which uses artificial neural networks (ANNs), has aided in the prediction of problems affecting water quality.²³

Despite the palatable interest in the potential of AI systems, public agencies face several challenges when it comes to designing, developing, and deploying these systems. Public agencies continue to struggle with modernizing their IT infrastructure.²⁴ While efforts have been made to leverage technologies such as cloud computing, much work remains to be done. Agencies often find themselves unable to build or acquire AI systems due to budgets and resources that are still devoted to keeping legacy systems up and running.

23. Al Marri, A., Albloosh, F., Moussa, S., & Elmessiry, H. (2019, November). Study on The Impact of Artificial Intelligence on Government E-service in Dubai. In *2019 International Conference on Digitization (ICD)* (pp. 153-159). IEEE.

24. Dawson, G. S. (2018). *A Roadmap for IT Modernization in Government*. IBM, 50. <http://www.businessofgovernment.org/report/roadmap-it-modernization-government>.

The public sector tends to demonstrate a preference for building AI solutions internally and to own and control these systems. This results in systems being developed that are often suboptimal, given the time it takes to build these rather than use solutions that are readily available externally. This mentality is in stark contrast to what is found in the private sector, where the dominant approach is to rent AI resources rather than building them internally. Simply put, given the rate of advancements in computational mechanisms and technologies, building systems internally is not only ineffective from a cost perspective but is often infeasible if one wants to deploy leading edge technologies.

The cumbersome acquisition processes that govern how an agency sources, secures, and implements computational systems also limit the agility by which agencies can take advantage of current innovations. As one CIO noted, “Our procurement processes are suited for waterfall software development not for the agile development world we live in.” It should be noted that significant efforts have recently been undertaken to modernize acquisition processes from a policy perspective. These efforts, however, have yet to take a significant hold given the calcification of historic practices.²⁵

Being able to integrate and connect multiple AI systems remains a challenge, which limits one’s ability to get effective outcomes that meet stakeholders’ expectations and needs. This is particularly true when it comes to linking transaction processing systems with AI that are focused on extracting insights from datasets that exist in different departments of an agency or between different agencies that collaborate in a value chain.

The portfolio of AI systems needs to be balanced. Most portfolios are focused on operational processing of data and systems that can support post hoc analysis. AI systems that can identify latent patterns and insights are a minority, and systems that can engage in predictive analysis and support automation are the smallest part of the overall portfolio. Some exceptions exist in agencies that are data-intensive by default, such as agencies whose mission is law enforcement or energy.

Designing, developing, and deploying AI is still in its infancy within public agencies. This places a greater burden on those involved with these efforts to capture and share lessons learned. Sharing lessons learned not only enables the agency to reflect on their experiences, but also increases the effectiveness of future engagements. Resources and time must be dedicated to enable lessons learned to be captured and shared. Given the current state of budgets and pressures faced by agencies, this imperative is often ignored.

Analytical Capacity

AI systems are only as good as the human analytical capacity that support them and refers to the human element related to designing, developing, and deploying AI. Organizations need a well-trained workforce that is analytically aware and has the aptitude to leverage data to derive evidence-driven insights. Public agencies face numerous challenges when it comes to recruiting, developing, and retaining analytical talent, including the general lack of analytic-savvy people in both government and in the general recruiting pool. Moreover, regardless of existing analytical talent, the need for the presence of deliberate mechanisms to leverage that talent to create organizational value is pivotal.

In a review of public sector best practices for data-based collaborations, NYU GovLab recommends that agencies should utilize data legacy managers already employed in the government,

25. Figliola, P. M. (2020). The Current State of Federal Information Technology Acquisition Reform and Management. Congressional Research Service, 11. <https://crsreports.congress.gov>.

such as geographic information system (GIS) teams, to tackle any institutional unpreparedness. Moreover, there are a plethora of extant trilateral collaborations in the data science and AI space which provide strong foundations for knowledge. An example is the University of Essex's collaboration with the Essex County Council, in which a professorship in data science and public policy was appointed as a chief scientific adviser to the council. Hailing from the Institute for Analytics and Data Science (IADS) within the School of Computer Science and Electronic Engineering, the IADS aids in connecting scholars, governments, and institutions in AI work. This relationship aids in leveraging the extant data and resources of the public sector with the AI expertise of businesses and the University of Essex to deliver public services.²⁶

When it comes to designing, developing, and deploying AI projects, agencies often lack a good understanding of what talents they need to have in their teams. An ideal talent capacity includes people who have expertise in multiple relevant areas such as data science, statistics, service design, and legal aspects. Particularly, the technical team needs to have expertise in areas such as identifying and using representative training data, road-testing AI through exposing them to a wide range of application scenarios, periodic auditing, aligning the potential outcomes with performance indicators, and managing risks related to misuse of data and potential cybersecurity risks such as malicious inputs. This is the strategy that the U.S. Marine Corps is using in its significant efforts to modernize its workforce when it comes to the design, development, and deployment of AI systems. Critical to this is to use cross-functional teams in the testing of AI applications throughout their lifecycle from initial concepts, to initial designs, and all the way through to the disposal (decommissioning) of systems.²⁷

To develop analytical capacity, agencies need to invest in developing talent. This remains a challenge for agencies, given the competition they face from the private sector for analytical talent.²⁸ Even in cases where talent is available, agencies struggle to groom and develop this into organizational-wide capacity. Public agencies also have limited ability to invest in new talent due to factors such as budget cuts. They also work with external stakeholders in mostly one-off and episodic manner. For example, they run a crowdsourcing competition such as a hackathon. These efforts rarely fully get integrated into the analytical capacity of the agency.

Since public agencies cannot develop all the analytical capacity needed in-house, agencies still need to access and engage external talent. However, agencies struggle to access and leverage this external talent. They seldom know what collaboration mechanism to use to engage (e.g., outsourcing, partnership, academia/industry collaboration). Moreover, the operationalization of methods of collaboration is seldom agile.

While a great analytical capacity can contribute to well-designed and well-executed AI projects, analytical talents cannot be highly effective if they work in isolation. For a highly mature and effective AI initiative, collaborative intelligence is required among these talents and various stakeholders of the project. Methods such as agile sprints and participatory design, particularly at the initial stages of a project where the problem space and potential ideas are being developed, can greatly contribute to an effective AI initiative that meets all stakeholders' expectations.

26. Mikhaylov, S. J., Esteve, M., & Campion, A. (2018). Artificial intelligence for the public sector: Opportunities and challenges of cross-sector collaboration. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2128), 20170357. <https://doi.org/10.1098/rsta.2017.0357>.

27. <https://www.businessofgovernment.org/blog/successful-adoption-intelligent-automation-government-case-marine-corps>.

28. Cyranoski, D. (2018). China enters the battle for AI talent. *Nature*, 553(7688), 260–261. <https://doi.org/10.1038/d41586-018-00604-6>.

The Patient Admission and Prediction Tool (PAPT) is an AI-enabled system that was developed by Australia's Commonwealth Scientific Industry and Research Organisation (CSIRO). By using data from various datasets, the system "provides an accurate prediction of the expected daily patient load to hospital emergency departments as well as patients' medical urgency and specialty, and how many will be admitted and discharged." PAPT allows hospital staff to plan more efficiently for staffing needs, which subsequently reduces patient wait times and allows for better overall treatment. Furthermore, the CSIRO has also developed a system called 'Spark,' which uses various data (such as geospatial data) for predicting bushfires (forest fire) spread. Spark offers more effective allocation of firefighting resources and firefighting development strategies in combating fires.²⁹

Similar AI projects with predictive algorithms have also been used in the deployment of policing resources. The Suzhou Municipality in China deployed the Suzhou Public Security Crime Prediction System in 2014 to predict both time and location of theft, aiding in more effective and rapid police deployment response.

Innovation Climate

Public agencies need to innovate if they are to deliver on their objectives given the ever-evolving environmental pressures. While innovation in the public sector continues to garner interest, we still see agencies struggle when it comes to digital transformation efforts.^{30,31}

Experimentation is critical to the ability to innovate.³² Yet in public agencies, experimentation is often shunned upon due to the perception of being deemed a failure and wastage of public resources. Data challenges such as incomplete and siloed datasets and a lack of investment necessary to upgrade legacy computational systems can significantly impact the ability of public agencies to innovate.

Risk management efforts often are significant barriers to innovation due to the fact that eliminating risk is overly emphasized to the point where new ideas, technologies, and processes are often discarded before they are given due considerations for experimentations, planning, and deployment.³³ In cases where new ideas and solutions make it through the screening process and are candidates for experimentation, the risk-averse nature of the agencies often leads management to select options that are safe, "low hanging fruits" and are limited to controlled settings—rather than taking on more opportunity-rich and grander challenges within a broader business network.

The perception of lack of innovation within agencies often leads to significant challenges to recruit and retain talent. This is more acute in cases where there are significant opportunities for talent outside the public sector, particularly in data science and AI technologies where the job opportunities in the private sector exceed the number of job applicants who have relevant skills.

29. Henman, P. (2020). Improving public services using artificial intelligence: Possibilities, pitfalls, governance. *Asia Pacific Journal of Public Administration*, 42(4), 209–221. <https://doi.org/10.1080/23276665.2020.1816188>.

30. Berryhill, J., Kok Heang, K., Clogher, R., & McBride, K. (2019). Hello, World: Artificial intelligence and its use in the public sector (OECD Working Papers on Public Governance No. 36). Observatory of Public Service Innovation OECD. <https://doi.org/10.1787/726fd39d-en>.

31. Mergel, I. (2016). Agile innovation management in government: A research agenda. *Government Information Quarterly*, 33(3), 516–523. <https://doi.org/10.1016/j.giq.2016.07.004>.

32. Desouza, K. C. (2014). Turning Governments into Innovation Machines. *Governing*. <https://www.governing.com/gov-institute/voices/col-intrapreneurship-government-disruptive-innovation.html>.

33. Bray, D. (2016). Idea to retire: Leaders can't take risks or experiment. Brookings. <https://www.brookings.edu/blog/tech-tank/2016/01/29/idea-to-retire-leaders-cant-take-risks-or-experiment/>.

Driving innovation within a public agency is no easy feat. The challenge of driving innovation with emerging technologies is even more complicated. Emerging technologies tend to have a high degree of uncertainty both in terms of their development trajectories and their performance outcomes. To create an environment conducive to innovation with AI, agencywide efforts are needed to nurture and harness entrepreneurial talent.

Governance and Ethical Frameworks

Governance and ethical frameworks are vital as oversight mechanisms to ensure that AI is deployed in a responsible manner and advance public value. Governance frameworks establish accountability and assign responsibility when it comes to AI design, development, and deployment. They serve as critical coordinating mechanisms to ensure that agencywide economies of scale, learning, and value can be secured. Ethical frameworks ensure that AI mitigates issues such as bias, discrimination, and harm. When AI fails or causes harm, these frameworks can assist in providing recourse mechanisms to compensate victims.

Regarding accountability, the process of “keeping humans in-the-loop” is a generally prescribed series of checks for automated decision making. Examples include the GDPR, EU-wide legislation on data protection, which introduced a series of safeguards for algorithm-based decision making. The European regulation established a general ban on subjecting an individual to automated decision-making processes, including profiling. However, Article 22 of the GDPR clarified the scope of application of the relevant rules. The application is limited only to cases in which the automated decision-making process produces legal effects or significantly affects the user, and the decision is based solely on automated data processing.

The legal effects of the automated decision-making process could be, for example, the refusal to cross a border and the refusal to grant a loan. The GDPR provided for exceptions to this prohibition. Hence, a data subject can be subjected to an automated decision-making process when the processing is necessary for the contract's conclusion. The processing is authorized by law, and the data subject has given his explicit consent to the processing.³⁴

The GDPR also afforded the introduction of minimum safeguards in specific circumstances where automated decision making would be permitted. An example of such a safeguard is “the right to obtain human intervention.” Safeguards are generally necessary when algorithmic decision making is fully automated and devoid of human decision making and/or intervention. However, if human intervention is necessary for such systems, there is a lack of robust studies regarding what implicit and explicit impacts algorithms may have on human decision makers. This emergent space is an area of key focus for behavioral public administration scholars.³⁵

Public agencies, due to their very nature, are quite comfortable designing and operating with governance frameworks. However, a closer examination of digital transformation frameworks reveals that they can be significantly improved. More specifically, there is a need to ensure that the digital transformation strategy of the agency is aligned with strategic undertakings.

There also needs to be better coordination between IT departments and the various program and policy offices in the agencies. Even today, the IT departments are often either called upon to a) fix technical problems or b) to report on exiting digital transformation efforts underway. Public agencies need more co-creation and coordination among internal stakeholders (e.g., agency's AI experts, data scientists, and service designers) and external stakeholders (e.g.,

34. Article 22 GDPR. <https://gdpr-info.eu/art-22-gdpr/>.

35. Busuioc, M. (2020). Accountable Artificial Intelligence: Holding Algorithms to Account. *Public Administration Review*. DOI: 10.1111/puar.13293.

citizens, customer advocacy groups, academic researchers, and third parties) when it comes to designing and developing AI solutions.

The need to think through the ethical dilemmas and considerations when it comes to autonomous or semiautonomous AI solutions is important. These not only need to account for issues such as the ethics of using data and the learning systems, which are ingredients of AI, but also on the impacts of these systems and how do they advance public value. In addition to efficacy, factors including transparency, fairness, and effectiveness of automated decisions should be considered among strict criteria for evaluating the agency's success at AI implementation.

The Oxford Insights' Government AI Readiness Index (proposed by Stirling et al., 2018) provides estimations for different country's preparedness with regards to the implementation of AI in public service delivery. The index has nine input metrics, which range from the digital skills available domestically to government innovation and existing data capabilities. It highlights which countries need further development before being able to roll out public sector AI solutions and identifies areas of improvement for Organization for Economic Co-operation and Development (OECD) nations. The factors that have been considered are public service reform (including innovation, digital public services, government effectiveness, digitization, and technology skills), economy and skills (particularly focusing on AI startups and quality of data), and digital infrastructure (available data and data capability).³⁶

The Government of Canada developed a digital questionnaire, called Algorithmic Impact Assessment, that outlines requirements for agencies' use of algorithms and data to help with ensuring the accountability, transparency, and fairness of AI outcomes that can affect society and prevent potential harm to citizens. The instrument is accessible on the open government portal. It is also available as open-source software (FOSS). The impact of the approach has diffused internationally, to the extent that members of the D9180, a large network comprising the most advanced digital nations, are considering using the instrument and customizing it to their own unique contexts. Germany and Mexico have particularly shown strong interest in adopting the instrument.^{37,38,39,40}

The European Union is working on a legal framework to regulate artificial intelligence. Recently, the European Commission proposed its first legal framework on AI. This proposal is the result of long and complicated work carried out by the European authorities. Previously, the European Parliament had issued a resolution⁴¹ containing recommendations to the European Commission. Before that, the EU legislators enacted the 2017 Resolution⁴² and the "Report on the safety and liability implications of Artificial Intelligence, the Internet of Things, and Robotics,"⁴³ accompanying the European Commission "White Paper on Artificial

36. Stirling, R., Miller, H., & Martinho-Truswell, E. (2017). Government AI Readiness Index. <https://www.oxfordinsights.com/government-ai-readiness-index>.

37. Government of Canada. (2018). Responsible AI in the Government of Canada. Google Docs. https://docs.google.com/document/d/1Sn_qBZUXEUG4dVk909eSg5qvfbpNIRhzleWPTBwbxY/edit.

38. Secretariat, T. B. of C. (2019, February 5). Directive on Automated Decision-Making. Government of Canada. <https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592>.

39. Government of Canada (2019), "Ensuring responsible use of artificial intelligence to improve government services for Canadians," Press release, 4 March, www.canada.ca/en/treasury-board-secretariat/news/2019/03/ensuring-responsible-useof-artificial-intelligence-to-improve-government-services-for-canadians.html.

40. Greenwood, M. (2019), "Canada's new Federal Directive makes ethical AI a national issue," *Techvibes*, 8 March, <https://techvibes.com/2019/03/08/canadas-new-federaldirective-makes-ethical-ai-a-national-issue>.

41. https://www.europarl.europa.eu/doceo/document/TA-9-2020-0276_EN.html.

42. https://www.europarl.europa.eu/doceo/document/TA-8-2017-0051_EN.html.

43. https://ec.europa.eu/info/publications/commission-report-safety-and-liability-implications-ai-internet-things-and-robotics-0_en.

Intelligence”⁴⁴ in 2020. The European Commission’s proposal elaborates a set of rules for market entry of AI systems. It prohibits certain AI practices, establishes requirements and obligations for high-risk AI systems, and establishes transparency requirements and rules on market monitoring.⁴⁵ After the adoption of the Commission’s proposal by the EU Parliament and member states, the new legal framework will be directly applicable throughout the European Union.⁴⁶

The Understanding Artificial Intelligence Ethics and Safety guidelines—another example of these frameworks—is currently the most extensive set of guidelines on ethics and safety of AI systems available for the public sector. The guidelines were proposed by Turing researchers and were later launched by the UK’s Minister for Implementation in June 2019. The instrument can help public agencies with identifying and elaborating on the potential harm for citizens caused by these systems. It also proposes robust, actionable measures to counteract the harm.⁴⁷

However, at present, there is no guiding policy within the U.S. public sector and so, for the moment, agencies are left to either create their own or attempt to follow (and improve upon) those in other countries.

Strategic Visioning

Leadership at public agencies needs to play an active role in creating environments that are supportive of the development of AI. How they are designed, developed, deployed, and regularly enhanced need to be incorporated into the long-term strategic plans of agencies. A good strategic visioning also considers the important fact that deploying AI can change the function and design of agencies given the affordances of AI for changing work processes and engaging citizens in public service delivery.

Ongoing AI advancements have allowed for various new opportunities to manifest in a range of different endeavors. One such response to the speed of these ongoing developments has been in New Zealand, where the Ministry of Business, Innovation, and Employment authored a business plan to support the use of AI. Titled *Building a Digital Nation and the Strategic Science Investment Fund 2017–24 Business Plan*, the vision is to “accelerate the safe adoption of AI technologies” (Ministry of Business, Innovation and Employment, 2017, p.7).⁴⁸ The plan seeks to establish a collaboration between the New Zealand government, Callaghan Innovation, industry, and the nascent AI forum to undertake research in identifying opportunities and mitigating risks for the use of AI. The AI forum sets an agenda for further discussion of policy and supports expanding awareness of AI. This forum will also provide evidence-based arguments to address concerns of AI doomsayers.

Functional affordances of AI can result in more efficiency and effectiveness and support public value because they can optimize processes in innovative ways and enable organizations to identify opportunities that were previously unexplored or were managed at a limited scale. Senior leadership therefore must increase their knowledge of AI and the affordances they provide to ensure that they can contribute to creating environments that are supportive of an innovative climate.

44. https://ec.europa.eu/info/publications/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en.

45. <https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-laying-down-harmonised-rules-artificial-intelligence-artificial-intelligence>.

46. Marcia, V., Desouza, K. C., (2021). The EU Path Towards a Regulation on Artificial Intelligence. Brookings. <https://www.brookings.edu/blog/techtank/2021/04/26/the-eu-path-towards-regulation-on-artificial-intelligence/>

47. Government of UK. (2019). Understanding artificial intelligence ethics and safety. GOV.UK. <https://www.gov.uk/guidance/understanding-artificial-intelligence-ethics-and-safety>.

48. Ministry of Business, Innovation and Employment (2017) Building a Digital Nation, Wellington: Ministry of Business Innovation and Employment. <https://www.mbie.govt.nz/business-and-employment/economic-development/digital-economy/digital-economy-research/>.

The rigor of design and benefits that are obtained from the development of AI in the public sector remain far behind potential opportunities. Digital transformation, and especially considerations of how AI needs to shape the future of the agencies and the delivery of public services, need to be core elements of the strategic plans. Agencies need the capacity to think strategically regarding how AI will shape how they deliver their services, achieve mission objectives, and continuously innovate to stay relevant.

While there are a few similarities between AI and traditional information systems, they are substantially different. Effective design, development and deployment, and timely enhancement of capabilities of AI require acknowledging that AI projects are a major part of agency's digital transformation and that they need sustainable funding models and resources. Funding models for AI need to support sustained commitment for designing, developing, and deploying these systems. This requires that agencies commit to projects that transcend political cycles.

Designing metrics to track the performance and contribution of AI to agencywide goals and objectives is a critical undertaking. Metrics on traditional IT systems and their performance are commonplace today.⁴⁹ While AI can certainly adapt these metrics, our research points to the fact that traditional metrics need to be supplemented by a unique set of metrics relevant to AI. For instance, RPA metrics that capture the uptime, number of errors, etc., while all important, represent only a part of the picture. Metrics should also account for how RPA has freed up employee time from cumbersome tasks, and the added value is that this time has created opportunity for workers to focus on higher-value tasks, and even the customer experience and satisfaction of stakeholders. To truly capture reliable metrics with AI, efforts need to be in place to benchmark performance pre and post AI implementation.

Levels of Maturity

The six elements discussed need to be assessed both individually and collectively in terms of their maturity. The maturity levels are noted below and go in increasing order of sophistication.

Ad Hoc

The public agency does not have a plan in place to design, develop, and deploy AI. Datasets remain an underutilized asset, computational systems lack necessary capabilities, and analytical capacity is limited or unavailable. There is limited appetite to innovate with AI, and this inertia also plays out with the absence of governance and ethical frameworks for AI.

At this level, most public agencies have just started to think about deploying AI. However, these initiatives are not of any strategic priority for them. Interest in AI initiatives is often expressed by a few employees who have some personal interest in AI-related innovations. At this level, agencies often lack the required datasets, computational systems are lacking or are trial versions, and there is limited analytical capacity to develop and reliably run learning algorithms. Leadership does not have any serious plan for developing ethical and data governance frameworks and is often unaware of these efforts.

49. Desouza, K. C. (2015). *Creating a Balanced Portfolio of Information Technology Metrics*, IBM Center for The Business of Government. IBM. <http://www.businessofgovernment.org/report/creating-balanced-portfolio-information-technology-metrics>.

There is limited insight into potential risks, and there is no risk management strategy in place. There are limited systematic processes to promote and manage any AI experimentation. In most cases, IT employees are the only staff who are aware of capabilities that AI has, and efforts are often limited to some sporadic efforts for inspecting data quality. No organization-wide strategy has been developed to address these deficiencies. There is a good chance that errors will happen due to lack of governance framework, and people might use data and build systems or prototypes that raise ethical issues. Conducting benchmarks, supporting an innovative culture, and aiming for establishing a required level of analytical capacity and computational systems can all together contribute to creating the required level of competency to prepare for AI experimentations.

Experimentation

The public agency is actively experimenting with AI. Experimental projects leverage datasets, computational systems are being designed and/or upgraded, and analytical capacity is being mobilized around these projects. There is a growing interest in learning from early experimental efforts, and there is a recognition to invest in designing ethical and governance frameworks that support responsible experimentation and innovation.

Experimentation is often the first practical step towards AI initiatives from an organizational-centric approach rather than the person-centric approach in the prior stage. The most important evolution from the ad hoc level is that the agency begins to take actions through specific pilot AI projects in a controlled organizational setting. These controlled settings often focus on either “low hanging” opportunities or grand challenges. The first approach enables agencies to bring their expertise to bear (e.g., application of RPA to increase efficiency and effectiveness of business processes that were conducted manually). Grand challenges on the other hand can create opportunities for leveraging innovations across the organization’s ecosystem.

The Department of Health and Human Services (HHS) is the largest providers of federal grants. An effective and efficient grants management process is critical to ensure that funds are allocated in the best possible manner. In 2017, the grants management process was far from ideal. Given the large number of partners that the HHS has to coordinate with, information was often difficult to share, which led to fragmented and siloed analysis. Moreover, both grantees and grant administrators spent a significant amount of time preparing and analyzing large amount of paperwork. The HHS recognized that even minor improvements to the grants management process and the systems that supported it would result in significant cost savings.

Experimenting with a human-centered design process, HHS uncovered various key pain points in the grants management process that could be improved upon. For example, Blockchain was used to create a digital dossier on grant recipients. This dossier fuses together data from disparate government databases. AI was used to reduce the time needed to analyze the large amount of paperwork for each grant submission to conduct risk assessment. Analysts used to spend as much as eight hours per assessment. Using AI, this time was cut down to about fifteen minutes. Moreover, the AI solution was able to flag information in applications for grant administrators to review that signaled potential risk factors.⁵⁰ It was only through experimenting with a novel approach that the HHS was able to achieve these outcomes.

50. Improving Outcomes in Government through Data and Intelligent Automation, <https://ourpublicservice.org/wp-content/uploads/2021/02/Intelligent-Automation-and-Data.pdf>.

At this level, while agencies hope for some successful outcomes, they are also open to any unexpected results and potential failures, all of which contribute to their learnings during the experimentation process. While the technical infrastructure and analytical capacity are low at this level, the agency will assign key personnel to pilot projects, which is an important necessary first step. Within the pilot projects, there will be an appetite for innovation; however, this will be tempered by the need to deliver quick wins and minimize risk. Ethical frameworks to guide initial experimental accountability are put in place. The leadership of the agency will be kept abreast about pilot projects but often treat them with benign neglect. Funding is generally limited to experimental projects and often these are quick-hit projects.

When agencies take a deliberate approach to experimentation, developed prototypes can be scaled more easily. The Department of Homeland Security's Procurement Innovation Lab (PIL) is a good case in point.⁵¹ The PIL allows for those within the DHS contracting community to experiment with new methods and processes; one such experiment led to the creation of the Contractor Performance Assessment Reporting System (CPARS). The CPARS was developed to integrate information from various sources to assess contractor past performance.

Employing the DHS's Commercial Solutions Opening Pilot (CSOP) authority (which allows for more rapid procurement of solutions under \$10 million), the solution is being built in an agile manner. The first phase involved small grants (under \$50,000) to nine contractors who had AI expertise and resources to build initial prototypes. Next, seven of the nine received further awards and advanced to the next stage for solution development. A third phase is then expected to narrow down the solution set for full implementation. Experimentation in this manner not only enables public sector agencies to do rapid prototype development but also allows them to draw on industry solutions.

Case Study

Transport Canada is using AI for risk-based reviews of their day-to-day air cargo records and activities. As the first step of experimentation, the agency used historical air cargo records and risk assessment data to explore opportunities and the applicability of unsupervised and supervised AI projects. Next, the agency designed a proof of concept and used a different subset of data to evaluate the natural language processing capability of the system. The steps resulted in unexpected insights about current hidden patterns that can potentially lead to risk. The agency was therefore able to use their AI to partially automate accurate risk assessments. They then successfully designed a dashboard and an initial version of a targeting interface that help employees with figuring out which cargo is potentially high-risk. There are initial planning and deployments underway about improving the approach, start implementation and then adapting it to other modes of transportation and customs and the border related activities.^{52,53}

51. <https://www.businessofgovernment.org/blog/successful-adoption-intelligent-automation-government-case-dhs-procurement-innovation-lab>.

52. OECD. Artificial Intelligence and the "Bomb-in-a-Box" Scenario: Risk-Based Oversight by Disruptive Technology. Observatory of Public Sector Innovation. Retrieved January 8, 2021, from <https://oecd-opsi.org/innovations/artificial-intelligence-and-the-bomb-in-a-box-scenario-risk-based-oversight-by-disruptive-technology/>.

53. OECD. (2018). Embracing Innovation in Government: Global Trends 2018 - OECD. OECD.Org. <http://www.oecd.org/gov/innovative-government/innovation2018.htm>.

Planning and Deployment

The public agency has put in a place a plan to design, develop, and deploy its first set of AI projects. Datasets for the initial set of AI projects are of sufficient quality, investments into computational systems necessary for AI are in place, and an initiative to attract, mobilize, and retain analytical talent is underway. Senior leadership is supportive of AI efforts and initial visioning efforts are underway to incorporate AI into strategic plans of the agency. An initial set of metrics are created and agreed upon to track investments and performance of the AI.

Outcomes from the previous level will provide meaningful planning data for deployment of AI projects. At this stage, AI initiatives are a part of agencies' strategic planning, agencies are highly interested in deploying AI solutions, they have a good understanding of benefits, costs and associated risks, and they have sufficient experience to start deploying them. As such, leadership has a good understanding about how to create opportunities to engage internal stakeholders and are generally supportive of these initial efforts. The City of Bryan, Texas, collaborated with Texas A&M University to deploy self-driving trolleys on public rights-of-way.⁵⁴ This project is illustrative of the kind of effort we would see at the experimentation stage. Led by Srikanth Saripalli, a Texas A&M faculty member, this initiative involved controlled experiments where autonomous trolleys were staffed with two safety workers and could carry up to four passengers. Data from the experiments were made available to increase transparency of the project—with the goal to increase public acceptance and trust in autonomous systems.

Agencies are now commissioning one or more AI projects. This often requires several major activities including: significant investments in computational resources, significant effort to recruit analytical capacity through public-private partnerships, dedication from recruited experts to build detailed datasets, and dedication from leadership for obtaining authorization from relevant legal authorities and putting in place data governance frameworks to formally establish accountability of AI projects.

The Veterans Administration deployed a chatbot in April 2020 to address the significant increase in queries regarding COVID-19 coming to its call centers.⁵⁵ Given the need to provide consistent responses to standard queries that were coming in, a chatbot was an ideal solution. The chatbot assisted with triaging calls coming in where responses to standard queries could be handled efficiently. The early success with the chatbot led to new information being added due to policy changes (e.g., the passage of Coronavirus Aid, the Relief and Economic Security Act, and the disbursements of stimulus payments by the Department of Treasury). Thanks to good planning, the success of the chatbot project could be easily tracked and evaluated (e.g., the number of queries resolved).

Given the success witnessed from initial AI projects, this stage shows some early work on strategic visioning around AI. AI projects are considered as potential transformational assets that can help reposition the agency, open up new avenues for innovation and service delivery, and even reorganize the internal functioning of the agency. Senior leadership begins to engage with AI projects. We witness the emergence of various groups (e.g., taskforces, committees) that explore various trajectories for AI within the agency.

54. Bullock, J.B., and Young, M.M. *Risk Management in the AI Era: Navigating the Opportunities and Challenges of AI Tools in the Public Sector*, Report, IBM Center for the Business of Government, 2020.

55. Bit by Bit: How Governments Used Technology to Move the Mission Forward During COVID-19, Report, Partnership for Public Service, December 2020. Retrieved from <https://ourpublicservice.org/wp-content/uploads/2020/11/Bit-by-Bit.pdf>.

Initial evaluation and quality control metrics will also be put in place and mechanisms for seeking feedback from necessary stakeholders will be established. These metrics are regularly communicated to stakeholders to keep them abreast of the AI projects and their performance. Successful initial deployments of the technology are the most important indication of an agency's readiness to move up to the scaling and learning stage.

Case Study

Belgium's government deployed a platform that helps with classifying contributions from citizens, identifies emerging ideas, highlights major trends, and clusters ideas by theme, demographic, and geographic location. For example, the government may realize that a neighborhood in a geographic location is prioritizing fixing issues with roads or installing more traffic stops. During the deployment phase, the agency learned that an effective human-machine interaction is essential for success of the project. The agency's employees needed to learn how to interpret the output generated by the system, trust it, and use it in day-to-day workflow. Moreover, the agency realized that the quality of input data (citizens' ideas and feedback) is crucial to reliably understand citizens' needs, showing the importance of providing guidance on submitting their contributions. Ongoing evaluation of the system through auditing and refinement of the platform has been conducted by the agency.⁵⁶

The Bureau of Labor Statistics (BLS) within the U.S. Department of Labor wanted to reduce the amount of tedious and repetitive tasks conducted by staff as they processed information on workplace injuries and illnesses.⁵⁷ The BLS collects data on workplace injuries from about 200,000 businesses a year. In 2015, this dataset consisted of injuries and illnesses of 2.9 million and over 752,000 from the private and public sector, respectively. Analyzing this data requires one to code the nature of occupation, injury, and analyze incident narratives. The BLS began experimenting with using AI for coding in 2014 with a focus on the easiest codes (i.e., the nature of occupations). During that year, 5 percent of all codes were assigned by AI. Having experienced success with this effort, the BLS increased its aspirations for AI. By 2016, nearly 50 percent of all codes were assigned by AI. These codes were not only more complicated than the initial set, the machine-generated coding was also more accurate than human coders. The scaling of the AI application and learning generated enabled the BLS to carefully plan and then manage the deployment of AI. The BLS workforce was also brought along this journey. The workforce could now focus on the more complex cases that were more interesting.

56. OECD. Unlocking the potential of crowdsourcing for public decision-making with artificial intelligence. Observatory of Public Sector Innovation. Retrieved January 8, 2021, from <https://oecd-opsi.org/innovations/unlocking-the-potential-of-crowdsourcing-for-public-decision-making-with-artificial-intelligence/>.

57. The Future has Begun: Using Artificial Intelligence to Transform Government.

Scaling and Learning

The public agency is enacting thoughtful and repeatable processes to select and implement AI and these processes encompass all aspects of AI implementation including technical, governance, and staffing. AI projects are viewed as a critical part of the agency; a concerted effort is being made to measure efforts against the metric developed in prior maturity levels.

In this stage, the agency will focus on extending the scale and scope of all AI efforts in a detailed and careful manner. Prioritization of opportunities is often led through collaboration between program heads and IT staff. Specific programs for recruiting new experts and upskilling the existing workforce are being conducted to develop a desired level of analytical capacity. Program leads clarify current computational capabilities and prioritize options for technology investments. The IT and functional departments make significant efforts towards linking datasets across programs, departments, and service interaction channels such as the agency's website, mobile app, and social media site. Leadership is aware of and fully supportive of AI projects.

Data governance protocols are carefully designed and executed to ensure that AI initiatives adhere to relevant ethical, legal, and policy frameworks. Disciplined efforts are made to develop guidelines for data auditing and resolving biases in data, minimizing associated societal and ethical issues. The agency is expected to follow the formal governance and policy frameworks to formally establish accountability for the AI initiatives.

The agency has developed a robust set of external partnerships to leverage AI innovations and implement them within the organization. Partnerships also support new experimentation projects.

Metrics and measures are in place and regularly assessed to evaluate AI projects and their contribution to creating public value. Learning mechanisms are in place to support the transfer of lessons learned across AI efforts to increase project performance and lower wastage of resources.

AI projects are now seen as a critical asset to the agency. Funding mechanisms are in place to support their development and maintenance. AI projects are now incorporated into the strategic plans of the agency and senior leadership is well-versed in the affordances they provide and the rationale behind their investments. For example, in 2019, the U.S. Department of Energy (DoE) created the Artificial Intelligence & Technology Office with the mission to “accelerate the delivery of AI-enabled capabilities, scale the Department-wide development of AI, synchronize AI applications to advance the agency’s core missions, and expand public and private sector strategic partnerships, all in support of American AI leadership.”⁵⁸ A critical role played by the Artificial Intelligence & Technology Office is to coordinate efforts underway across the DoE on AI. Moreover, the office is also leading the charge on organizing AI partnerships and initiatives that tackle a grand challenge. An example of this is the First Five Consortium that will bring together the public sector, industry, and academia to create AI-driven solutions to mitigate the impact of natural disasters.⁵⁹

58. <https://www.energy.gov/ai/artificial-intelligence-technology-office>.

59. <https://www.energy.gov/articles/department-energy-announces-first-five-consortium>.

Enterprise-Wide Transformation

The public agency has successfully integrated AI into a routine part of the environment and agencies can move quickly to implement additional AI projects as necessary into the environment. Because the necessary technical, governance and staffing infrastructures are in-place, design and deployment can proceed rapidly across the agency and these efforts are managed using a portfolio approach.

AI transformation projects conducted at the enterprise-wide level are the most mature AI initiatives. At this level, the public agency has used the lessons learned from the previous level. The agency also has a clear understanding of how AI can support the business of government, engaging citizens in service delivery and creating public value. As the agency feels less need to be cautious, projects can be implemented more aggressively albeit in a responsible manner.

Data governance frameworks have already been established successfully. This enables the agency to effectively use multiple data repositories across existing AI programs, the agency's various departments, and third parties' organizations. Effectiveness of computational systems are regularly monitored, and rich datasets are used and regularly audited to ensure that they meet the highest quality standards (e.g., in terms of representativeness of data), are free from biases, and meet all relevant regulations and ethical frameworks. The agency regularly updates the AI evaluation criteria. The strong innovation climate supports enhancing agile protocols to receive relevant feedback from various stakeholders—for example, citizens, software vendors, and academic researchers. The emphasis is on managing AI as a portfolio, rather than one-off efforts. Both citizens and employees see the value in engaging in AI-enabled service delivery.

Recommendations



The proposed maturity model outlines elements and five maturity levels for guiding AI initiatives in the public sector. Public agencies need to start small and be aware of the required upfront financial and time investment for data governance, computational systems, and analytical capacity.⁶⁰

Moving up a level requires a) successfully overcoming the limitations of prior level, and b) evaluating an organization's readiness for the next level. The evaluation requires knowing what limitations public agencies need to overcome at the current level and at the next level. Therefore, the elements and levels of the proposed maturity model are intertwined and inextricably linked, rather than operating in isolation.

At the ad hoc level, some individuals who have some personal interest in AI initiatives often start talking about their ideas, which can quickly grow if a suitable innovation climate exists. Showing organizational interest in establishing analytical capacity and computational systems can greatly contribute to creating the required level of competency to prepare for moving to the next level. External pressures—for example, efforts at other countries or peer public agencies deploying AI and seeing promising results—can often act as additional stimulants for agencies to move from the ad hoc level to the experimentation level. Public agencies, however, need to start with strategic plans that consider the cost and benefit of initiating an AI initiative, particularly in terms of potential risks and harm to citizens.

Managers in charge of AI experimentations often express that the ability to share learnings from experiments with peers can effectively facilitate learning and refinements to AI initiatives. Some even believe that this enables them to do rough benchmarking across different classes of AI. Using knowledge sharing networks can support sharing of lessons learned and can therefore facilitate collaboration with both internal (e.g., middle-range managers and staff in relevant departments that contribute to AI initiatives) and external stakeholders (e.g., academia, third parties, and other relevant public agencies). These efforts are paramount for public agencies to make the leap from the experimentation level to the planning and deployment level.

At both the planning and deployment level and the scaling and learning level, ongoing collaborations between program leaders and the IT department are of paramount importance. Detailed business cases need to be developed to clearly articulate how AI initiatives advance public value and engage citizens. Thoughtful medium-range plans are required to outline how efforts on AI projects are aligned to near-term priorities. While technical infrastructure and analytical capacity are low at this level, an organization that is interested in initiating an AI initiative would benefit from developing governance and ethical frameworks and assigning key personnel to plan for recruiting or upskilling analytical capacity. This allows the agency to build a solid base for moving to the highest level of maturity—i.e., the enterprise-wide level.

At any level of the model, public agencies are advised to regularly reflect on and share lessons learned and the costs and benefits of moving up a level. Metrics on AI projects should be developed and used for each level. Lack of such mechanism can lead to scaling of prior ineffective practices and poor strategies.

Specific steps can enable government agencies to move from one level to the next.

60. Nili, A., Barros, A., & Tate, M. (2019). The public sector can teach us a lot about digitizing customer service. *MIT Sloan Management Review*, 60(2), 84-87.

Beyond Ad Hoc

To move from the ad hoc level to the experimentation level, organizations need to:

- **Discover and validate quality datasets.** Public agencies have a wide assortment of datasets. A critical initial step to build AI systems is to discover datasets that might be of interest. Initially, datasets of interest might be those that are already validated (e.g., from traditional transaction systems). Datasets must be put through a rigorous validation process to ensure they are fit for purpose.
- **Encourage the development of AI prototypes.** Building a culture where prototyping is valued is important to increase technical innovation. At this stage of maturity, the agency should sanction several prototype projects and encourage staff to suggest other areas where AI systems can add significant value.
- **Understand the analytic capabilities of the organization.** Building the analytical capacity for the agency will require significant investments. An important first step is to conduct an inventory analysis of what analytical capabilities exist in the agency. In addition, understanding the current aspirations of the workforce when it comes to increasing their analytical capacity is also vital.
- **Focus efforts on “low hanging” fruit projects.** Demonstrated wins go a long way in building support for future AI efforts. The initial set of projects need to be carefully considered. Ideally, these are projects 1) where the agency can demonstrate success with minimal AI system development risks, 2) where the value for AI projects is significant given current pain points with existing processes, and 3) where the metrics to evaluate the performance of AI solutions are clear.
- **Develop initial governance strategies.** Agencies need to undertake the necessary work to put in place governance mechanisms when it comes to AI solutions. Initial efforts here can include creating taskforces to oversee the initial project and solicit input from the wider workforce on AI opportunities, priorities, and even concerns. The taskforce should also begin considering ethical and social considerations that might arise when designing, developing, and deploying AI solutions.
- **Inform leadership of AI prototype project outcomes.** It is vital for senior-level agency leadership to get engaged with AI. While one might not expect much support and endorsement at this stage, it is vital to begin to develop a communication strategy on AI efforts. The communicate should educate not only senior leaders but also the overall workforce. Ideally, regular communications should seek to educate staff on the value of AI, provide updates on ongoing efforts, and seek input and participation from those who want to engage on AI efforts.
- **Identify people within the organization who have started on AI projects.** These are often hobbyists who are doing small side projects, often as an outgrowth of their own personal interest in AI. Identify and encourage these people. It can help them prepare for more formal activities as the organization rises up the maturity ladder. The most straightforward way to do this is by sponsoring hackathons; often these people will jump at the chance to demonstrate their skills.
- **Shift winners from any AI hackathons to more technology-focused roles.** These winners often have the skills to shift the organization to more AI-centric thinking. Additionally, they bring an oft-needed sense of excitement, which can be useful in overcoming organizational inertia.

Beyond Experimentation

To move from the experimentation level to the planning and deployment level, organizations need to:

- **Develop and deploy data governance frameworks.** Drawing on initial efforts and lessons learned from experimental efforts, it is vital that the agencies now design and launch data governance frameworks. These frameworks should account for how data is inspected to ensure that they are fit for purpose. In addition, the development of these frameworks should provide opportunity for participation from various sectors of the workforce who have an interest in and are going to be impacted by AI solutions.
- **Create alliance with external stakeholders and train existing staff.** No public agency can go at AI solutions on their own. Simply put, it is too expensive and there will be significant wasted effort if one does not leverage existing AI capabilities that exist in the private sector and academia. Building alliances to advance AI solutions is critical if one is to scale up the capabilities required to conduct more large-scale AI projects. In addition, it is vital that the workforce be brought along the AI-enabled transformation journey. Communication and engagement with the workforce are vital at this stage, as their participation is critical to the success of AI projects.
- **Shift focus from risk-based value-based decisions.** Given the experiences from experimentation efforts, it is now possible for the agency to move beyond an over-emphasis on risk and caution to one where AI solutions are evaluated based on the public value they generate. Doing this requires one to have mechanisms in place to promote responsible innovation. Risks need to be considered and mitigated for, but the opportunity that AI solutions provide need to be given fair consideration.
- **Develop more robust governance frameworks to establish accountability.** For the initial set of projects, clear governance and accountability mechanisms need to be established. On a regular basis during the execution of AI projects, communications should be provided to key stakeholders on progress being made. In addition, it is vital to continuously test and audit key assumptions, expectations, and performance of the AI system.
- **Devise metrics for AI performance and value.** The creation of metrics is important to gauge the value of investments in AI efforts. Moreover, metrics allow one to track the performance of AI solutions over their predecessor practices.
- **Expand hackathon concepts from the previous stage.** However, in this stage, the hackathon moves from general hacking to much more specific hacking using agency provided data and targets. Additionally, the hackathon can be opened up to people outside of the organization to start to build an ecosystem of those who can be helpful in the transition. While in the previous stage hackathons are more exploratory, hackathons in this phase are more mature. Hackathons and crowdsourcing efforts, in general, can involve multiple-stage competitions where one moves from soliciting prototypes, to proof-of-concept, to fully implementable solutions.

Beyond Planning and Deployment

To move from the planning and deployment level to the scaling and learning level, organizations need to:

- **Finalize governance and data control frameworks based on what has been learned in prior stages.** Because AI-based projects are new, the governance and data control frameworks should be viewed as evolving rather than final form. Much is still to be learned from these early efforts and the governance and data control frameworks should accommodate the learning that is inevitable.

- **Implement learning mechanisms for capturing agencywide insights.** Capturing and acting on new insights will likely touch every aspect of how AI is developed and deployed. Rather than a “word of mouth” strategy, a formal strategy for capturing and conveying these lessons is necessary. The easiest strategy may be to create a task force that is in charge of implementing AI within the organization. Using a hub and spoke model, the task force can act as the hub for capturing and sharing the knowledge while still allowing the spokes to communicate with each other.
- **Shift from risk-based to benefits-based projects.** Government is rightfully cautious in the early days of a new technology in order to protect its citizens from experiencing harm from a new technology—and AI is no different. But, at this stage, the focus should change from a hyper focus on risk to one that balances risks with benefits.
- **Balance internal development with external stakeholders.** That is, despite the temptation to simply outsource AI development to consultants, there needs to be a balance between internal and external development. One of the key lessons from the data center outsourcing movement in the mid/late 1990s was the critical need to continue to maintain some in-house development capability. Building this internal capacity ensures that the organization does not become wholly dependent on external vendors and allows the organization to continue to hire “homegrown” talent.
- **Develop internal capacity to ensure that the right projects are green lighted for development.** This may commonly require some sort of AI-based steering committee that can compare, using its metrics, which projects have the most potential.
- **Develop and source from a robust set of external stakeholders.** While traditional software development is typically only done by large consulting firms, the burgeoning field of AI development opens up other sources of external stakeholders, including universities, think tanks and start-ups. The nature of agile development and “bite sized” pieces of AI allow this.
- **Develop acquisition strategies for dealing with a diverse set of external stakeholders.** A one-size-fits-all model is unlikely to allow for sufficient flexibility and speed to move quickly on a hot idea. Keeping some of these projects under the delegation authority for the department/agency is one way to encourage the ecosystem of external stakeholders to flourish.
- **Devise and track organization-wide metrics.** The need for good metrics permeates every aspect of this stage. Metrics need to be developed and then tracked to understand which metrics are most associated with successful outcomes and which ones are less important. Initially, the metrics captured should be based off the metrics used in other places throughout the organization, but this should be viewed solely as a starting place.

Beyond Scaling and Learning

To move from the scaling and learning level to the enterprise-wide transformation level, agencies need to:

- **Share governance and data control frameworks throughout the organization.** At this point, the governance and data control frameworks should be largely solidified as a result of moving through the prior stages. At this stage, these frameworks need to be shared and adhered to by all levels of the organization. If done properly, these frameworks should still encourage experimentation and innovation but should also be quite clear in terms of expectations. This is not to suggest that the frameworks are now written in stone and unchangeable but rather that they are adhered to and, as necessary, revised and updated.

- **Develop and implement agencywide processes while following a formal process for acquisition, deployment, and maintenance.** The acquisition, deployment, and maintenance processes developed in earlier stages are increasingly matured and adhered to but now agency-centric processes can be developed that adhere to other formal processes. Naturally, we would expect some iteration as the policies mature.
- **Incorporate analytics capabilities into all decision-making processes.** Once this stage has been reached, the organization should shift from always incorporating analytics into all decision making. This is not to suggest that other capabilities, such as the experience of key individuals, should be removed, but rather that analytics becomes another valuable input to the decision-making process.
- **Adopt a balanced view of costs, benefits, and risks into AI decision making.** In the previous stages, the focus shifted from a cost-based to a risk-based to a benefits-based framework for AI decision making. In this stage, the organization should adopt a balanced view of the three factors and this should closely align with how those factors are balanced in other decision-making processes. This reflects the maturing of AI from scary technology to an “all things for all people” technology to a balanced view of the cost, benefits, and risks. The increased maturity of the organization with AI will rightfully shift the importance of each factor based on the specific project under consideration.
- **Develop and require widespread training on governance and ethical frameworks.** At this point, the governance and ethical frameworks should be mature and shared throughout the organization. Formal training should be provided to all applicable users and little tolerance should exist for those who try to circumvent the frameworks.
- **Measure and make changes based on achievement of organization-wide metrics.** In the prior stages, a host of metrics were gathered and the goal was to see which metrics were most valuable and which could be trimmed out. In this stage, the number of metrics kept is likely to be smaller but more powerful than the metrics kept in previous stages since all of the metrics will have a direct and unique linkage to success. Based on these insightful metrics, changes can and should be made throughout the entire development, deployment, and maintenance lifecycle in order to achieve better outcomes.

Conclusion

This report has outlined a maturity model to guide evaluation, benchmarking, and improvements in efforts to design, develop, and deploy AI projects in the public sector. The public sector can extract significant value from AI if they leverage them in an effective and efficient manner while advancing public value. Public agencies can also waste significant resources and contribute to value destruction and negative societal outcomes if their AI efforts are immature. It is therefore essential that public agencies take the time to evaluate the maturity of their existing AI capabilities. Evaluating maturity can lead to an evidence-driven approach to investments and judicious use of public funds to improve the maturity of core elements required to leverage AI.

APPENDIX

Table 1. Maturity model for AI in the public sector.

Technical Elements			
	Big Data	Computational Systems	Analytical Capacity
Ad-Hoc	<ul style="list-style-type: none"> • Datasets are extremely limited • Quality of datasets is unknown and uncertified • Risks of using datasets incorrectly are high • Data governance frameworks do not exist 	<ul style="list-style-type: none"> • Required AI systems are not present • Renegade AI systems are bootstrapped by individual entrepreneurs • AI systems have limited capacity to ingest and analyze large-scale data 	<ul style="list-style-type: none"> • Agency lacks an organization-wide view on its analytical capacity or aptitude • Analytical capacity is sparse • AI developers, data scientists, and other analytical resources learn by self-teaching or are hobbyist
Experimentation	<ul style="list-style-type: none"> • Datasets are still limited • Datasets used for experiments go through ad hoc quality control • Risks of using selected datasets are identified • Data governance frameworks are constructed around experimental projects 	<ul style="list-style-type: none"> • Initial prototypes of AI are developed and/or acquired but are still primarily under the radar and are one off systems • AI systems have capacity to analyze data in limited contexts • AI systems are focused on analyzing past data and building associations between elements of interest (i.e., descriptive analysis) 	<ul style="list-style-type: none"> • Initial efforts are conducted to assess analytical capacity within the agency • Analytical capacity is centered around pilot projects • Initial efforts are commissioned for staff to receiving training to bolster their analytical capacity
Planning and Deployment	<ul style="list-style-type: none"> • Larger and richer datasets are constructed through fusing data from heterogeneous systems within the agency. Heavily structured data. • All datasets are put through quality control processes but still ad hoc • Risk management protocols are designed for selected group of data assets • Data governance frameworks around AI projects are put in place 	<ul style="list-style-type: none"> • AI systems are purchased and or licensed by departments and/or teams within the agency • AI systems can ingest and process and large-scale data • AI are focused not only focused on descriptive analysis but also on explanatory and predictive insights 	<ul style="list-style-type: none"> • Agency has an appreciation for its analytical capacity and aptitude • The agency has the required analytical capacity to undertake an initial set of operational projects • Alliances are formed with external stakeholders to tap into analytical capacity as needed • The agency has identified training resources for staff to bolster their analytical capacity
Scaling and Learning	<ul style="list-style-type: none"> • Datasets grow in complexity and also draw from systems, platforms, and organizations outside the agency. Increasingly unstructured data. • Data quality control processes are defined and generally followed. Processes are in place to learn from their applications at larger scales. Risk management protocols are refined to operate at larger scales. • Data governance frameworks are finalized and we begin to see the emergence of standards that are put in place to ensure interoperability and seamless integration of data across systems and environments. 	<ul style="list-style-type: none"> • Emergence of organization-wide development and acquisition of AI systems. A rich ecosystem is developed with external stakeholders to enable more agile AI acquisition and deployment. • The capabilities of AI systems are scaled to take on more data and different data • Predictive analysis and the deployment of autonomous systems become core foci for AI • Learning mechanisms are put in place to generate agencywide insights form AI deployments 	<ul style="list-style-type: none"> • The agency has an organization-wide view of its analytical capacity and has a strategy to address the gaps • Analytical capacity continues to increase enabling for AI to be deployed in other domains and scaled • The agency understands how to continue to develop analytical capacity while balancing its internal investments with the value provided from alliances with external stakeholders • The agency has programs and initiatives to facilitate training and learning on analytical tools and methodologies

Table 1. Maturity model for AI in the public sector cont.

Technical Elements			
	Big Data	Computational Systems	Analytical Capacity
Enterprise-wide Transformation	<ul style="list-style-type: none"> Rich datasets are available that provide insights across ecosystems of interest. Fully links structured and unstructured data. Data quality standards are established and consistently followed. Quality control processes are in place and regularly updated. Risk management protocols are in place to oversee data assets Data governance frameworks and standards are enterprise-wide and engrained in the organizational fabric 	<ul style="list-style-type: none"> Agencywide policies are in place and followed on AI acquisition, partnerships, and maintenance strategies. A robust ecosystem of external partners is in place and scanned for opportunities. AI have capabilities to ingest emergent data in an agile manner The entire gamut of analytics and intelligence-driven operations can be conducted by AI systems The agency has and follows a formal process for learning and improving its practices on AI acquisition, deployment, and maintenance 	<ul style="list-style-type: none"> The agency constantly monitors its analytical capacity across the agency and proactively fills gaps as necessary Analytical capacity is adequate and distributed across the agency The agency has robust alliances with external stakeholders to tap into analytical capacity in an agile manner Analytical capacity is seen a key asset of the agency and evidence-driven decision making permeates the organization

Organizational Elements			
	Innovation Climate	Governance and Ethical Frameworks	Strategic Visioning
Ad-Hoc	<ul style="list-style-type: none"> No appetite for innovation with AI Individuals are left to their own to experiment with AI AI projects are viewed as unacceptably risky AI deployments are done in the shadows No policies in place to recruit, develop, and retain talent needed to develop and manage AI systems 	<ul style="list-style-type: none"> No formal governance and policy frameworks to guide AI No ethical framework to guide design, development, and deployment of AI No accountability for AI 	<ul style="list-style-type: none"> AI projects are not part of the strategic agenda of the agency No funding provided for AI efforts
Experimentation	<ul style="list-style-type: none"> Low innovation appetite but openness to learning about AI Agency supports innovation on AI within controlled settings Risk continues to be the most significant factor that dominates AI adoption and use decisions Within pilot projects, focus is on addressing low hanging fruit type efforts where risk is low and results can be easily demonstrated Initial awareness that plans need to be developed to recruit, develop, and retain talent needed to develop and manage AI 	<ul style="list-style-type: none"> The need for formal governance and policy frameworks for AI is appreciated and recognized High-level and preliminary ethical frameworks to guide initial experimental projects are put in place Formal accountability for AI is limited to the teams that are involved with pilot projects Little formal oversight of governance activities Ethical frameworks are most often derived from other projects without regard for differences in domains 	<ul style="list-style-type: none"> Senior leadership is aware of AI pilot projects but are generally hands-off Limited one-off funding is provided for pilot projects

Organizational Elements			
	Innovation Climate	Governance and Ethical Frameworks	Strategic Visioning
Planning and Deployment	<ul style="list-style-type: none"> The agency has an appreciation for the value of AI and their role in modernizing operations Support is provided for innovation in a few targeted areas on AI Focus shifts from primarily risk-based to cost-based decisions with AI adoption and use decisions Within initial projects and planning, there is a broader appetite for innovation when it comes to AI Initial and limited-scope plans are developed to recruit, develop, and retain talent needed to develop and manage AI systems 	<ul style="list-style-type: none"> Formal governance and policy frameworks to guide AI are put in place but their usage is often sporadic Ethical frameworks to guide design, development, and deployment of AI are designed and are starting to be specific to AI and not simply adopted from other domains Accountability for AI is formally established and resides within specific project teams. However, actual accountability is uneven. 	<ul style="list-style-type: none"> Senior leadership is aware of AI efforts and are generally supportive of the initial projects Funding is provided for planning and initial deployments for AI Initial set of metrics to measure AI performance and value are constructed Early mentions of AI in key strategy documents appear but lack sufficient detail
Scaling and Learning	<ul style="list-style-type: none"> The agency is developing process for surfacing and supporting innovations on AI Risk and costs become less of a factor while potential benefits start to gain prominence in decision-making on AI adoption The agency has developed collaborative ecosystem to design, develop, and deploy AI with external stakeholders AI projects are more ambitious in scope and scale due to the learnings gained from initial projects Initial plans are scaled to recruit, develop, and retain talent needed to develop and manage AI systems 	<ul style="list-style-type: none"> Formal governance and policy frameworks to guide AI are in place and usage is mandated Ethical frameworks to guide design, development, and deployment of AI are implemented and generally communicated Accountability for AI is formally established and resides within specific departments Accountability principles are in-sync with those in the rest of the organization Formal training on governance and accountability begins to emerge 	<ul style="list-style-type: none"> Senior leadership is aware of and consistently supportive of AI projects Significant funding is earmarked for long-term AI projects Organizational-wide metrics to measure AI performance and value are constricted AI projects are now regular elements of the agency's strategic planning processes, artifacts (e.g., strategic plans), and discourse
Enterprise-wide Transformation	<ul style="list-style-type: none"> Agency has a fully agreed upon process for surfacing and supporting innovations in AI Balanced view of risks, opportunities, costs and benefits in decision making regarding AI The agency continuously monitors its ecosystem for new opportunities for collaborative alliances to design, develop, and deploy AI systems with external stakeholders AI projects span the entire gamut and a balanced portfolio of AI exist across the entire lifecycle Plans are regularly updated to update initiatives and incentives to recruit, develop, and retain AI talent across the agency 	<ul style="list-style-type: none"> Formal governance and policy frameworks to guide AI are in place and usage is communicated throughout the organization and are mandated Ethical frameworks to guide design, development, and deployment of AI are implemented and regularly evaluated and updated Accountability for AI is formally established and resides within a specific department that has the responsibility for agencywide coordination and alignment of AI activities Widespread training on governance and ethical frameworks is baked into the organization's training calendar 	<ul style="list-style-type: none"> Senior leadership is vocal in their support of AI projects Significant funding is earmarked for long-term AI projects Organizational-wide metrics are in place and tracked to measure AI performance and value. Metrics on AI performance and value are regularly communicated to internal and external stakeholders. AI projects are core contributors to achieving an agency's strategic objectives

ACKNOWLEDGMENTS

The author is grateful for the thoughtful comments received from Alfred Ho, Gregory S. Dawson, Clay Pearson, Christoph Buck, Valeria Marcia, and Mohammad Jabbari on earlier drafts of the report. The author is also grateful for the research assistance provided by Franziska Götz, Alireza Nili, and Samar Fatima. Finally, thanks to all attendees of seminars where early prototypes of the AI maturity model were presented for their valuable feedback.

ABOUT THE AUTHOR

Kevin C. Desouza is a Professor of Business, Technology and Strategy at Queensland University of Technology (QUT). At QUT, he leads the Robust Enterprise theme within the Centre for Future Enterprise and is co-leader of the Government Systems Domain in the Centre for Data Science. He is a Nonresident Senior Fellow in the Governance Studies Program at the Brookings Institution. He formerly held tenured faculty posts at Arizona State University, Virginia Tech, and the University of Washington. He holds or and has held visiting appointments at the London School of Economics and Political Science, Università Bocconi, Shanghai Jiao Tong University, the University of the Witwatersrand, and the University of Ljubljana.



KEVIN C. DESOUZA

Desouza has authored, co-authored, and/or edited nine books. He has published more than 150 articles in journals across a range of disciplines including information systems, information science, public administration, political science, technology management, and urban affairs. Desouza is the author of four reports for the IBM Center for The Business of Government, *Delivering Artificial Intelligence in Government: Challenges and Opportunities*, *Creating a Balanced Portfolio of Information Technology Metrics*, *Challenge.gov: Using Competitions and Awards to Spur Innovation and Realizing the Promise of Big Data*.

Several outlets have featured his work including Sloan Management Review, Stanford Social Innovation Research, Harvard Business Review, Forbes, Businessweek, Wired, Governing, Slate.com, Wall Street Journal, USA Today, NPR, PBS, and Computerworld. Desouza has advised, briefed, and/or consulted for major international corporations, non-governmental organizations, and public agencies on strategic management issues ranging from management of information systems to knowledge management, innovation programs, crisis management, and leadership development. Desouza has received over \$2 USD million in research funding from both private and government organizations.

For more information, please visit: <http://www.kevindesouza.net>.

KEY CONTACT INFORMATION

To contact the author:

Kevin C. Desouza

Professor of Business, Technology, and Strategy
QUT Business School
Faculty of Business and Law
Queensland University of Technology
Brisbane, Australia

kevin.c.desouza@gmail.com

REPORTS FROM THE IBM CENTER FOR THE BUSINESS OF GOVERNMENT



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

Recent reports available on the website include:

Agility:

The Road to AGILE GOVERNMENT: Driving Change to Achieve Success by G. Edward DeSeve
Transforming How Government Operates: Four Methods of Change by Andrew B. Whitford
Agile Problem Solving in Government: A Case Study of The Opportunity Project by Joel Gurin, Katarina Rebello
Applying Design Thinking To Public Service Delivery by Jeanne Liedtka, Randall Salzman

Digital:

Aligning Open Data, Open Source, and Hybrid Cloud Adoption in Government by Matt Rumsey, Joel Gurin
Innovation and Emerging Technologies in Government: Keys to Success by Dr. Alan R. Shark
Risk Management in the AI Era: Navigating the Opportunities and Challenges of AI Tools in the Public Sector by Justin B. Bullock, Matthew M. Young
Financial Management for The Future: How Government Can Evolve to Meet the Demands of a Digital World by Angela Carrington, Ira Gebler
A Roadmap for IT Modernization in Government by Dr. Gregory S. Dawson

Effectiveness:

Other Transactions Authorities: After 60 Years, Hitting Their Stride or Hitting The Wall? by Stan Soloway, Jason Knudson, Vincent Wroble
Guidance on Regulatory Guidance: What the Government Needs to Know and Do to Engage the Public by Susan Webb Yackee
Federal Grants Management: Improving Outcomes by Shelley H. Metzenbaum
Government Reform: Lessons from the Past for Actions in the Future by Dan Chenok, John Kamensky
COVID-19 and its Impact: Seven Essays on Reframing Government Management and Operations by Richard C. Feiock, Gurdeep Gill, Laura Goddeeris, Zachary S. Huitink, Robert Handfield, Dr. Rodney Scott, Sherri Greenberg, Eleanor Merton, Maya McKenzie, Tad McGalliard
How Localities Continually Adapt Enterprise Strategies to Manage Natural Disasters by Katherine Willoughby, Komla D. Dzighbede, Sarah Beth Gehl

Insight:

Using Technology and Analytics to Enhance Stakeholder Engagement in Environmental Decision-Making by Jenna Yeager
Making Federal Agencies Evidence-Based: The Key Role of Learning Agendas by Dr. Kathryn E. Newcomer, Karol Olejniczak, Nick Hart
Improving Outcomes in Government through Data and Intelligent Automation by The IBM Center for The Business of Government, Partnership for Public Service
Silo Busting: The Challenges and Successes of Intergovernmental Data Sharing by Jane Wiseman
Integrating Big Data and Thick Data to Transform Public Services Delivery by Yuen Yuen Ang
A Practitioner's Framework for Measuring Results: Using "C-Stat" at the Colorado Department of Human Services by Melissa Wavelet
Data-Driven Government: The Role of Chief Data Officers by Jane Wiseman

People:

Distance Work Arrangements: The Workplace of the Future Is Now by John Kamensky, Emily G. Craig, Michaela Drust, Dr. Sheri I. Fields, Lawrence Tobin
Preparing the Next Generation of Federal Leaders: Agency-Based Leadership Development Programs by Gordon Abner, Jenny Knowles Morrison, James Perry, Bill Valdez

Risk:

The Rise of the Sustainable Enterprise by Wayne S. Balta, Jacob Dencik, Daniel C. Esty, Scott Fulton
Managing Cybersecurity Risk in Government by Anupam Kumar, James Haddow, Rajni Goel

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 Global Business Services

With consultants and professional staff in more than 160 countries globally, IBM Global Business Services is the world's largest consulting services organization. IBM Global Business Services 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, DC 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