Research Report

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Benchmarking Data Use and Analytics in Large, Complex Private-Sector Organizations

Implications for Department of Defense Acquisition

KEY FINDINGS

- There is a broad consensus on data governance and analytics guiding principles (e.g., lessons in creating a data-focused organization).
- Data governance and strategy are critical enablers of analytics capability. Emphasis should be on how analytics contributes to an organization's strategic goals.
- Organizational design should be federated: a strong central chief data officer with core governance and analytics function and distributed analytics capabilities within business units.
- Resource requirements for analytics vary widely and are driven by strategic objectives and tailored to where an organization starts (i.e., existing data analytics capabilities).
- Approach implementation using change management strategies. Becoming a data-driven organization was viewed as a transformative change in business processes.
- Data and analytics maturity models reflect commercial benchmarks and provide a road map for improving analytics capabilities. An organization's journey using this road map will vary, as, for example, not every capability needs to achieve the highest level.

Public and private organizations are increasingly aware of the potential value of data and analytics to improving organizational performance and outcomes. The U.S. Department of Defense (DoD) is one of those organizations. Its size, complexity, security needs, and culture have created a challenging environment for successful use of data in decisionmaking. Over the past five years, the RAND Corporation has studied how DoD governs, manages, secures, and uses data within its acquisition institutions.[1] These data lay an important part of the foundation for decisions on DoD's weapon system acquisition portfolio. The private sector faces similar data challenges, so the Office of the Under Secretary of Defense for Acquisition and Sustainment [OUSD(A&S)] asked us to expand this research to the private sector, focusing on how the private sector addresses data governance and analytics. The research is driven by OUSD(A&S)'s interest in developing and applying advanced analytics to acquisition challenges. One key insight from the research is that the functions associated with the office of a chief data officer (CDO) and associated data governance and data management are foundational requirements to pursue an analytics strategy in any organization.

The key findings presented in the box are applicable to data governance and analytics practices in the DoD acquisition community. We elaborate on these findings below.

Study Objectives and Approach

Our prior research examined the acquisition data governance and management framework currently used by the Office of the Secretary of Defense (OSD) and the services, the current state of analytics within DoD's acquisition community, and how private-sector data practices might apply to DoD.[2]

The objectives of this study were to

- benchmark data collection and use in large, complex commercial enterprises—in particular, the use of advanced data science techniques and analytics
- draw lessons applicable to the DoD acquisition data and analytics environment, with the aim to improve DoD acquisition analytics capabilities.

DoD has been improving its use of acquisition data for program management, portfolio review, and oversight purposes, and DoD has the opportunity to leverage the methods and tools increasingly used by the commercial data community. These more advanced analytics methods might enable DoD to look more broadly across the portfolio. However, the potential for advanced data science techniques to help disentangle the complicated issues surrounding acquisition is largely speculative.[3]

In an effort to address that potential, we examined commercial data practices that might translate to the DoD acquisition community in the areas of data governance and analytics. Benchmarking select private-sector data governance and analytics practices helps establish a baseline against which DoD practices can be compared. That comparison helps identify areas in which DoD could improve and suggests actions or approaches to make those improvements.[4]

We designed a three-pronged approach to address these objectives:

- semistructured interviews with CDOs of large, complex commercial firms and other experts in data governance and analytics[5]
- a focused review of trade literature, academic articles on data governance and analytics, case studies published in business journals, and publications from major consulting firms specializing in helping commercial firms establish or improve data analytics capabilities[6]
- a review and comparison of several commercial- and government-sector data and analytics maturity models.[7]

The interview protocol ensured that a standard set of topics was covered but also allowed flexibility for wider discussion. Interviews focused on establishing, expanding, or improving an organization's data analytics capability, although the discussions often covered additional topics associated with data governance and use in commercial firms. Topics covered included the following:

- investment in or spending level on data and analytics (from data ingestion to use)
- key organizational characteristics, such as the kinds of strategic objectives
- the placement and interrelationship of functions within the organization structure
- the basic structural model (centralized, federated, or decentralized) that was employed
- staff size and skill set
- the role of culture and norms
- processes for planning and budgeting for analytics, including identifying and prioritizing use cases for analytics and making investment trade-offs associated with data analytics
- types of analytics performed, tools used, and the characteristics of the data collected (e.g., structured versus unstructured, authoritative sources, format)
- potential implementation challenges when standing up or improving the data analytics

capabilities of an organization and solutions to those challenges.

We interviewed a total of 14 individuals—a mix of private-sector, government, and academic CDOs and subject-matter experts in consulting firms and academia. The choice of interviewees was intended to capture a wide range of perspectives and professional experience. The interview sample was limited but diverse:

- CDO at a larger internet retailer
- CDOs at two major financial firms
- CDO at a large pharmaceutical firm
- CDO at a large multimarket firm
- subject-matter experts at three management consulting firms
- CDOs of two large government organizations
- former federal chief data scientist
- CDO at a top engineering school
- academic specializing in data analytics
- academic specializing in organizational theory and change management.

The three management consultants have both a deep and a broad perspective on commercial data governance and analytics practices based on helping firms establish and realize value from data analytics. The two academics also have a broad perspective, based on working with multiple commercial firms. The CDOs themselves had all worked at more than one firm or government agency; the views they expressed and the lessons they shared were based on deep experience as practitioners in multiple firms and environments.

The literature review supplemented the interviews with CDOs and other subject-matter experts. We used trade literature, academic articles on data governance and analytics, case studies published in business journals, and publications from major consulting firms specializing in helping commercial firms establish or improve data analytics capabilities. In addition, we focused on multiple data and analytics maturity models that suggest ways to measure an organization's capability for analytics.[8] The core concepts appear to be relatively consistent across models, even between private-sector and government data and analytics maturity models.[9] There is some variation in emphasis (e.g., data governance versus analytics) or terminology across maturity models; however, the existence and conceptual convergence of so many maturity models suggest that the basic principles of data governance, management, and analytics are conceptually mature.

Caveats and Assumptions

The data life cycle can be described as having the following stages: generation, collection, processing, storage, management, analysis, visualization, and interpretation.[10] Issues and challenges associated with data management and governance occur throughout this life cycle, including the development and enforcement of standards, quality assurance, access, and security. We designed the interview protocol to emphasize specific aspects of data governance and analytics of immediate interest to our DoD sponsor rather than exploring each stage of the data life cycle.[11]

This research design has some limitations, particularly in developing the generalizability of the results given the small number of interviewees. Nevertheless, we believe that the findings presented here are credible, because of the remarkable consistency among independent interviewees, the literature, and the aggregated experience reflected in the multiple maturity models we reviewed. The transferability of lessons from the private sector to the public sector is also an issue, since the operating environment and incentive structure in government are very different from those of the private sector. The most obvious difference is the lack of a profit motive in government, which has implications for how the value of analytics is viewed and measured. Finally, little publicly available empirical evidence ties implementation of specific data governance and analytics practices to improved public-sector organizational performance. Nevertheless, the continued commercial investment in analytics capabilities, as well as the growing line of business in management consulting firms, suggests that these processes do add value.

Key Findings

Key finding 1: Consensus exists on data governance and analytics guiding principles.

A key finding of our research is the broad consensus on the guiding principles associated with data governance and analytics. These principles, which largely relate to implementation, are consistent in the literature, among subject-matter experts, and across data analytics maturity models. This consensus suggests that data governance and analytics are relatively mature concepts in the commercial sector. The guiding principles consist of the following:

- Data are viewed as an enterprise-wide strategic asset.
- Data governance and strategy are critical enablers of analytics capability.
- Analytics should be targeted at creating value for the organization, measured against the organization's strategic goals.
- Becoming a data-driven organization involves changes in culture and business processes, which in turn require sustained investment and senior-leader engagement across the organization.
- Tailoring the general principles of data governance and analytics to the characteristics and needs of a specific organization is required through the implementation process.

This review revealed a high degree of scholarly and professional convergence in terms of core concepts, data frameworks, and maturity models. Although there is some variation in terminology, we found that the guiding principles associated with the data life cycle (generation, collection, processing, storage, management, analysis, visualization, and interpretation[12]) are consistent within the reviewed literature and maturity models. The literature also emphasized that commercial firms make business-relevant trade-offs regarding data governance, management, and analytics. This is not a complete list of data analytics guiding principles; it reflects the main themes that emerged from multiple sources in all three lines of research.

As noted in our past research, the DoD acquisition community has implemented elements of these principles.[13] This includes a data governance and management framework for acquisition program data, as well as ongoing efforts to improve the use of analytics to inform decisionmaking.

Key finding 2: Data governance and strategy are critical enablers of analytics capability. Emphasis should be on how value-add analytics contributes to an organization's strategic goals.

The interviewees reported that a data governance and analytics strategy is a critical enabler of an organization's analytics capability. The strategy ties the purpose of analysis activities—and the data required to support those analyses—to an organization's strategic goals. The data strategy describes how analytics is to be used in the organization's decisionmaking processes. In the context of this strategy, data governance and analytics are considered as a means to an end, not an end in themselves. Data are treated as a strategic asset, and the analytics is the mechanism through which that asset contributes toward an organization's goals.[14] *All* interviewees stated these basic principles and noted that the alignment of analytics with goals means that the analytics directly supports business decisions. In other words, analytics is specifically targeted and focused to add value to an organization, measured against its strategic goals.

Broadly speaking, a data governance and analytics strategy guides organizational decisionmaking pertaining to data acquisition, storage, access, use (analytics), and security. This decisionmaking includes specifying policies for governance, access, security, standards and quality assurance, and the roles, responsibilities, and authorities of the various stakeholders (e.g., users, analysts, and the IT department). Specifically, each step of the data life cycle involves costs and potential benefits,[15] and the data governance and analytics strategy specifies how decisionmakers should approach such trade-offs.[16] A point of emphasis from the interviews is that the strategy referred to here is enterprise-wide and includes both governance *and* analytics (not one or the other).[17] The data governance and analytics strategy should explicitly align with enterprise strategic goals. In practice, that means the purpose of data collection and analysis is to support those goals. Contributing toward achieving an organization's strategic goals is the basis for the value data and analytics bring. In the context of DoD acquisition, data governance and analytics should be mission-oriented; several interviewees noted that it is not about the data or analytics per se; rather, it is about how analytics contributes to mission success.

One key challenge in creating a value-driven data strategy is to tie data governance and analytics policies to business outcomes. Specifically, one of our interviewees noted that because the return to investment on analytics may take a long time to materialize, some firms may abandon data analytics too early.[18] However, this problem can be mitigated in several ways. One—as our interviewees noted—is to develop analytics capabilities in tandem with a use case and a particular outcome in mind when first developing analytics capability.[19] Additionally, some of our interviewees highlighted the importance of expanding the concept of *benefit*. Although tracing a direct path from an analytics capability to a financial outcome is desirable, other benefits that accrue—such as increased stakeholder awareness or increased talent retention—should not be overlooked as a viable justification for investing in an analytics capability.[20] The data strategy should align strategic goals to outcomes and highlight the role of analytics in achieving those goals. In practice, this means identifying data use cases that add value (i.e., improve outcomes) to the organization.

Although the data governance and analytics strategy should be aligned with the organization's strategic goals and missions, the strategy is not static. Most interviewees noted that the strategy is dynamic and should be flexible enough to adapt to changes in goals, missions, or operating environment and responsive enough to take advantage of opportunities (such as new data or new tools for analysis or presentation) that may emerge over time. It was also noted that it is not possible (or necessarily desirable) to specify every possible use case. The strategy should contain enough detail to specify known high-value use cases but also allow for new use cases to emerge.

Although the data governance and analytics strategy should be aligned with the organization's strategic goals and missions, the strategy is not static.

Key finding 3: Organizational design should be federated: a strong central CDO with core governance and analytics function and distributed analytics capabilities within business units.

The organizational design of the data analysis and governance functions within the overall organization has an important effect on these supporting functions. In this context, design includes both organizational structure and the role, responsibilities, and authorities of the structure's component parts. At the highest (and somewhat overly simplified) level, data analysis and governance organizational structures may be characterized as centralized, decentralized, or federated in terms of how those data and analytics responsibilities and authorities are distributed and the relative autonomy of these components.[21] In a centralized structure, authority and responsibility for execution of business functions are concentrated in a single organization (i.e., department or unit). In contrast, a decentralized structure distributes those data and analytics authorities and responsibilities to organizations across the enterprise, with more autonomy and less mandated coordination. A federated structure organizes data analytics in a way that lies between those extremes, with a central hub or core group responsible for many governance functions but still with some autonomy in business units to tailor analytics to their specific needs. The current organizational structure of DoD acquisition—and data governance and analytics within the acquisition community—can be considered federated. OSD retains acquisition policy governance responsibilities, while execution occurs in the military services.

A recurrent theme throughout our interviews was a strong tendency toward a federated or "hub-and-spoke" organizational structure.[22] This was the recommended structure for large, complex organizations with multiple business units. Our interviewees were clear that data affect almost every employee and business unit, and therefore there cannot be a separate business unit that is exclusively dedicated to data governance or analytics.[23] Rather, the CDO is the central hub—a center of excellence (CoE) for data governance and analytics—with analytics cells distributed in the business units. Although the bulk of analytics is executed in the analytics cells of the business units, the CoE has responsibility for data governance and analytics policy, establishing standards and rules, establishing and maintaining the data architecture, developing and diffusing tools and best practices, and building enterprise-wide support. The CoE also has some analytics capability to address enterprise-wide challenges and problems. Analytics cells in the business units help ensure that data analytics supports the strategic goals of the business unit (which should be aligned with overall corporate goals) and bring the analytics function closer to the responsible activity. The leadership and subject-matter experts in the business units are better able to identify value-added analytics tasks and ensure that the results of the analytics cells are directly applied to business decisions and processes.

From a top-down perspective, several of our interviewees expressed the need for an analytics executive (e.g., a CDO or chief analytics officer or combined chief data and analytics officer) and for that office to have direct access to the C-suite and other key decisionmakers.[24] This ensures organization-wide support for the implementation of data governance and analytics policies and that large-scale organizational decisions are informed by analytics. A CEO has an enterprise view of the organization and should have an enterprise view of analytics across functional areas.[25] The CDO reporting to the CEO can provide this enterprise-wide view.

It was apparent from our interviews that the federated or hub-and-spoke model was preferred for large, complex commercial organizations with multiple business units (or lines of business). Interviewees also recognized that many organizations do not fit the simple model of a central headquarters hub and direct authority over business units. DoD is a case in point. Although OSD is analogous to a headquarters central hub, the military services also have secretariats. From OSD's perspective, the military services might be considered as "business units"; the military services have independent statutory authority to train and equip the operational force. There are also functional communities—acquisition, logistics, intelligence, test, and so on—that can be considered as a different kind of business unit. Several interviewees noted that, in these more complex organizations, the business units should be performing some data governance and management roles within their particular specialty, consistent with guidance from the headquarters CDO.

To further enhance the analytics capability within an organization, many interviewees noted that a crucial position (or function) is the "data translator."[26] These data translators must bridge several gaps. First, they must be able to translate key data governance concepts and analytics tools from the CoE to the analysts in the business units. This translation involves making sophisticated data management and analysis techniques available and understandable to a data-minded employee within a business unit. Second, a data translator must help transform analytics results into business value.[27] This key role ensures that the analytics decisions are tied to specific business and strategic goals and that key strategic decisionmakers have input into the kinds of analyses performed and can use the results of those analyses to inform decisions. One interviewee recommended that the data translator be located organizationally within a business unit rather than the analytics hub or CoE, arguing that such proximity increases the likelihood that the translator is able to identify high-value analytics use cases.

In addition to organizational design, our interviewees noted that building a successful analytics capability requires accommodating a new culture throughout the organizational hierarchy.[28] This does not mean that the organization needs a completely new culture. Instead, the existing culture must understand the potential value of data and the responsibilities associated with realizing this value that may redound to each individual.

Our interviewees and the organizational design literature also underscored the importance of organizational ambidexterity to developing a novel capability. *Organizational ambidexterity* refers to an organization's ability to adapt or respond to a changing environment by simultaneously performing two functions: Exploit present conditions using existing capabilities and develop and explore novel capabilities to situate the organization favorably in a future environment. In the case of developing and exploring a novel organizational capability, such as analytics within a government agency, the organizational ambidexterity literature underscores the importance of trade-offs with respect to resource allocation over time. The overallocation of resources to current processes and challenges will likely result in an organization that is unprepared for the future. At the same time, overinvestment in exploratory tools and analytics may jeopardize an organization's near-term performance. One interviewee recommended that a novel suborganization charged with an exploratory mandate, such as advanced analytics, might benefit from having longer-term reporting requirements.[29] For example, an organization applying advanced analytics might need to be sheltered by senior leadership from the more near-term, exploitive, and results-focused orientation of the larger organization and business units.

O'Reilly and Tushman recommend five practical actions for ensuring organizational ambidexterity.[30] Here we adapt these recommendations for the topic of concern: establishing or developing a novel, exploratory analytics capability within a government agency:

- First, an organization must articulate a "strategic intent" that defends the case for a near-term exploitation focus and longer-term exploration.[31] Such an articulation provides the rationale by which a unit charged with the development of future capabilities can forego resource use for the sake of exploration activities with uncertain payoffs.
- Second, an organization must formulate and adopt a set of values promoting interunit trust and cooperation.
- Third, senior leadership must own the data and analytics process and be responsible for the outcomes associated with a data and analytics strategy.[32]
- Fourth, exploitative units and exploratory units should have separate organizational architectures. However, these organizational architectures should be carefully integrated to ensure strategic alignment and allow for the sharing of common resources.

The overallocation of resources to current processes and challenges will likely result in an organization that is unprepared for the future. At the same time, overinvestment in exploratory tools and analytics may jeopardize an organization's near-term performance.

- Finally, senior leadership must pay attention to and resolve the conflict that results from the tension inherit in near-term exploitation and longer-term novel exploratory activities.[33]

Key finding 4: Resource requirements for analytics vary widely and are driven by strategic objectives and tailored to where an organization starts.

A crucial question for an organization seeking to advance its analytics capabilities is how to determine the level of resources dedicated to or invested in analytics. Through the discussions and the literature, we found that no single correct answer applies to all organizations; in fact, the answer is highly variable and relatively unique to each organization and the nature of the data analytics problem being addressed. However, most interviewees discussed resources in a similar way, underscoring several principles. For instance, similar to the overall analytics strategy, resourcing decisions should be value-driven. In other words, resource allocation to data governance and analytics should be aligned with its expected impact on the organization's strategic goals and desired outcomes. This impact includes making the inevitable trade-off decisions required of any investment. Multiple interviewees suggested identifying low-investment, high-value opportunities as a starting point. This suggestion raises the question of how *value* is defined. As noted earlier, commercial firms usually monetize the meaning of value (i.e., profit, revenue, sales increases, savings). In a government context, *value* takes on a much broader and less precise set of meanings, including process speed, transparency, compliance, stakeholder engagement, budget or cost, efficiency, and effectiveness. The overarching consideration for government organizations is to define *value* in terms of a product's contribution to an agency's mission.

Publicly available sources suggest that many firms are making large investments into big data and analytics. For example, UPS spends more than $1 billion annually on big data.[34] Similarly, Apple revealed that it plans to spend $2 billion per year for five years on data centers.[35] Finally, from a macroperspective, some forecasts suggest that big data alone (which are only a portion of analytics) will be worth over $100 billion by 2027. Our interviewees also gave a broad range of investment sizes for optimal analytics resourcing. One interviewee suggested that between 1 and 4 percent of total enterprise labor costs is an appropriate amount of investment in analytics.[36] Other interviewees suggested between $10 million and $300 million in annual investment in data analytics; the large variation is explained by differences in the size and nature of the firm, the nature of the analytical problem, the business environment in which the firm operates, the role of analytics in achieving business objectives, and the relative maturity of a firm's existing analytics capability. However, none of these estimates should be used as a benchmark. Instead, they illustrate that the appropriate investment in data and analytics is highly dependent on the anticipated role of analytics to the organization. Since DoD operates across several environments, these estimates imply that DoD may appropriately have significant heterogeneity in its analytics resourcing across the organization.

Another key resource-related question is how to staff an analytics capability, including staff size, skill mix, and how to recruit and retain talent. Although the focus is often placed on "data scientists" (e.g., in 2012, *Harvard Business Review* called data scientist the "sexiest job of the 21st century"[37]), core disciplines within the CDO team and the business units are broader, including business process analysis, data governance or architecture, data management, and data visualization.[38] Qualified data scientists will often have several competing offers and thus be relatively expensive to obtain. As a result, the 2015 median data scientist base salary was estimated to be $104,000.[39] However, hiring seasoned data scientists is not the only way to recruit and retain talent. As some of our interviewees noted, some organizations invest in upskilling efforts that focus on increasing the analytics proficiency of those already employed by the company.[40] Another interview subject recommended the cultivation of communities of practice for organizations that desire to develop an analytics capability.[41] In particular, the interviewee recommended identifying individuals with an interest or aptitude in data analytics and building an

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institutionalized means by which the these individuals can meet regularly. By establishing a community of data analytics practice, DoD would build momentum and buy-in for the nascent analytics capability and ensure that data-savvy personnel are not left out of the process.

However, another option is to obtain talent externally. This can be done through strategic partnerships, or, as one of our interviewees noted, outright acquisition of a data-focused startup.[42] In the government context, strategic partnerships can be accomplished through contractual arrangements (e.g., utilizing contractors such as Systems Engineering and Technical Assistance [SETA] support, federally funded research and development centers [FFRDCs], or university affiliated research centers [UARCs]). The option of directly acquiring a data analytics firm is not available to the U.S. government. Staffing models should be tailored to an organization's strategic objectives; the decision to develop a capability organically (upskill) versus leveraging external capabilities depends on several factors, including the role of analytics in the organization, current level of capability, and constraints on outsourcing.

Interestingly, many interviewees noted that, when hiring staff within the private sector, they were much more interested in the capabilities of prospective staff than in educational background. As a result, most candidate evaluation processes apparently include some form of analytics skills testing, requiring prospective staff to demonstrate relevant skill sets.

In the federated model described above, the central hub (the CDO's organization) was described by many interviewees as relatively small—between 15 and 150 staff, depending on the nature of the analytics problem, size of the overall organization (including number and complexity of business units), and how responsibilities are distributed between the central hub and the spokes (business units). Position descriptors of staff in the central hub commonly consist of some combination of data scientists, data architects, data engineers, subject-matter analysts, and IT professionals. Similarly, the analytics cells in the business units would also be composed of a mix of these skill sets, though with fewer data architects and more subject-matter analysts, with staffing levels sized to meet the needs of that business unit. Some interviewees noted that, in some business units, the analytics cell performed many of the same tasks as the central hub but tailored to that unit's goals, missions, or functions. Paralleling the view of how analytics capabilities should evolve within an organization, many interviewees suggested starting small and then scaling up as the value of analytics is demonstrated as a good implementation strategy.

Another resource related concern is the IT infrastructure supporting analytics. Obviously, some IT infrastructure is a prerequisite for analytics. But most interviewees suggested that trying to fully design or invest in such infrastructure up-front is not possible. Rather, IT infrastructure should be developed incrementally and in parallel with the evolving analytics capability of the organization. The amount and form of IT infrastructure investment should align with the nature of the analytics problem, the data architecture, and the role of analytics in the organization. Consideration should also be given to the cost and efficiency of specific trade-offs, including cloud versus local server architecture and enterprise versus business-unit-specific software. As noted earlier, the organization will likely need to adapt to changes in technology, market, and other environmental factors. This preferences incremental investment within the context of a longer-term enterprise strategic data analytics plan.

Interviewees tended to agree regarding who should be making resource investment decisions related to data analytics and IT infrastructure—an executive-level strategic planning board—but showed less agreement on where responsibility for the IT infrastructure should be located within the organization. Some interviewees indicated that IT infrastructure was part of the CDO's organization, while others placed it in an enterprise IT department external to the CDO.

Key finding 5: Approach implementation using change management strategies: Becoming a data-driven organization was viewed as a transformative change in business processes.

Establishing or expanding a data analytics capability is a significant organizational change that may involve changes or impacts in decisionmaking processes, business processes, organizational structure, and organizational culture. Some interviewees suggested that establishing or expanding a data analytics capability is transformative and should be treated the same as other major organizational change initiatives are treated. Several other interviewees suggested the explicit application of a change management strategy to facilitate implementation.[43] Change management strategies are designed to address the challenges associated with significant organizational change. Such challenges include identifying the problem correctly, establishing and communicating the need for change, training and resourcing, and overcoming the existing barriers to change present in any large, complex organization. Change management strategies emphasize specific principles or activities, including sustained leadership support and engagement that clearly communicates the need for and value of data analytics, incrementally building support through small, high-value demonstrations of analytics, providing incentives to change behavior in the appropriate direction, appropriate training and resourcing of data governance and analytics activities, and transparently showing how data-driven decisions add value toward achieving strategic goals. All of these principles and activities were also emphasized by our interviewees.

Another key to successful implementation is to retain leadership support and engagement through continuous value demonstration, even if not at full scale. As one of our interviewees succinctly summarized, this can be obtained by "prototyping your way into change."[44] Of course, prototypes can go only so far. As another one of our interviewees noted, this means there is a delicate balance between "easy wins" and large, generalizable advances.[45]

Key finding 6: Data and analytics maturity models reflect commercial best practices and provide a road map for improving analytics capabilities.

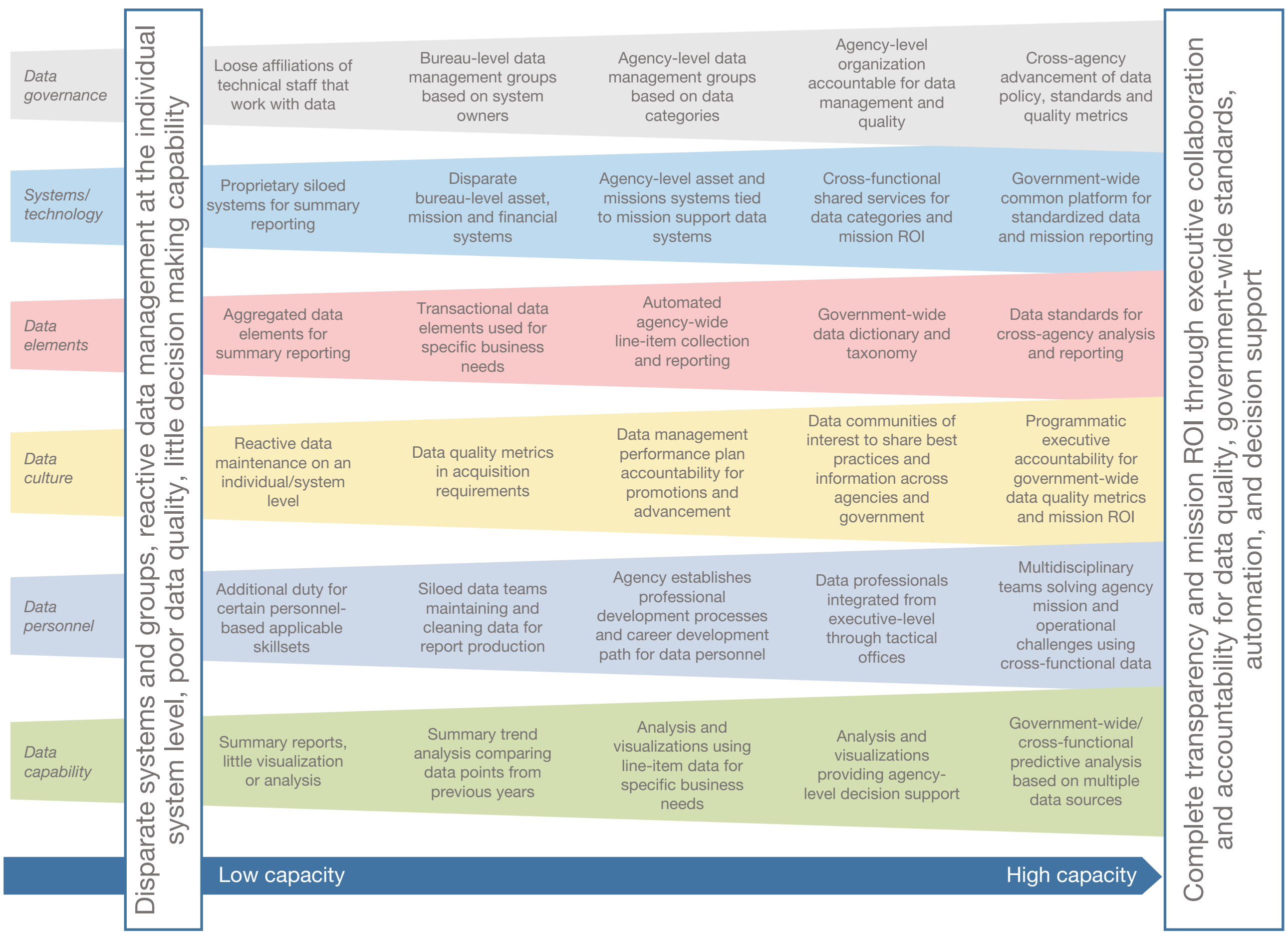
Maturity models have at least two purposes.[46] First, a maturity model can be used to identify an organization's status with regard to the maturity of a given process of interest. That is, maturity models can serve an evaluative function. Maturity models can also be used as a planning tool to articulate the next step and the end state in an organization's journey to greater maturity for the process in question. The Software Engineering Institute articulates these functions, succinctly stating that maturity models "provide a way for organizations to approach problems and challenges in a structured way by providing both a benchmark against which to assess capabilities and a roadmap for improving them."[47] The data and analytics maturity models that we reviewed for this analysis provide progressive levels of capabilities and sophistication in the analytics process by which organizations can benchmark. Maturity models locate the status of a process undertaken by an organization in terms of the level of maturity of the process in question. *Maturity* here refers to the sophistication with which a process or subprocess is undertaken. Holding other factors constant, greater maturity is preferred to less maturity. Given the complexity of the processes they attempt to describe, maturity models break the focal process into subprocesses or dimensions.

The Data Cabinet, an interagency initiative run out of the Office of Science and Technology Policy, produced a maturity model tailored to the government but representative of data and analytics maturity models generally (Figure 1).[48] This model identifies six dimensions: data governance, systems/technology, data elements, data culture, data personnel, and data capability. As the maturity model represents overall organizational performance with regards to data maturity, the offices responsible for advancing organizational maturity will include several outside the CDO's (e.g., chief information officer [CIO], human resources, chief technology officer).

Besides subdividing the process under scrutiny, maturity models define stages of maturity. In the Federal Data Maturity Model, an organization's maturity on each of these dimensions is split into five milestones. For example, the data capability dimension comprises the ability to complete five analytical tasks of increasing maturity: summary reports, trend analysis, business unit specific analytics, agency level decision support, and government-wide cross-functional analytics. In Figure 1, the rows describe the key elements or dimensions of analytical capability, with the stages of maturity progressing from left to right. The overall level of an organization's data capability is then assessed by reading down through the columns. It is not intended that every organization aspire to or resource the highest level of maturity for each dimension of analytics capability; rather, the desired future states will reflect

FIGURE 1

Federal Data Maturity Model



SOURCE: Data Cabinet, undated.

NOTE: ROI = return on investment.

Data personnel tend to be in siloed teams, but there is movement toward a broader analytics community and explicit recognition of data and analytics-related skill sets.

organizational values and the level of contribution of data maturity to organizational objectives.

Our review of data and analytics maturity models advises building analytics capability incrementally, and, as mentioned above, the majority of interviewees concurred. Many interviewees also noted the considerable value inherent in relatively basic analytics tools, such as descriptive statistics and root cause analysis, which provide insight into the relationships among factors of interest and their effect on outcomes. In general, mastery of lower levels of analytics capability is required to move to the next level. The models identify the attributes (or elements) required to attain a given level of capability; in practice, an organization may improve unevenly, maturing more rapidly in some elements of capability than in others. The maturity models all suggest that at least some levels of data governance and management are prerequisites to analytical capability. At higher levels of analytical capability, processing and storage of data move from stove-piped to integrated. All models recognize the need to tailor implementation to account for the specific organizational environment, strategic goals, and the nature of the data problems facing the organization. Although each model we reviewed uses slightly different language or tends to emphasize some elements over others (e.g., data governance versus analytics), maturity models reflect mature concepts and are consistent across both private-sector and government-oriented models.

We applied the federal data maturity model to DoD acquisition (OSD, military services, and other DoD agencies and components), based largely on the portfolio of prior research cited earlier.[49] This prior research included direct observation and interaction with the OSD and service organizations responsible for data governance and analytics, as well as participation in and attendance at Acquisition Visibility Steering Group and Working Group meetings. Acquisition program data governance between OSD and the services is fairly mature (e.g., the Acquisition Visibility Data Framework [AVDF] in the Defense Acquisition Visibility Environment), but not all acquisition-relevant information is governed within that framework. Similarly, the AVDF captures and defines a large set of program acquisition data, but not all relevant acquisition information is defined and captured yet. Data systems are agency-unique, but some automated collection, reporting, and sharing have been accomplished, particularly for those data elements defined in the AVDF. Although some pockets of the DoD acquisition enterprise have or understand the culture required to make the best use of data, data culture is relatively less mature than other elements of the model. Data personnel tend to be in siloed teams, but there is movement toward a broader analytics community and explicit recognition of data and analytics-related skill sets. The AVWG and AVSG provide both working-level and executive-level mechanisms for collaboration on data governance and analytics across the DoD enterprise. Similarly, data analysis and visualization currently tend to be oriented toward specific independent business unit (agency) needs and decisions, rather than a more integrated enterprise view. Finally, a single office within the Under Secretary of Defense for Acquisition and Sustainment now has responsibility for several critical elements of data governance and analytics: The Principal Deputy Assistant Secretary of Defense, Acquisition Enablers (PDASD[AE]), has responsibility for acquisition policy (including data-related elements of those policies), acquisition data management and governance, and acquisition analytics. This reorganization allows improved integration of policy, data management and governance, and analytics.

The point of our analysis is not to critique the data analytics capability of the DoD acquisition community but rather to illustrate how a data analytics maturity model can be useful to characterize current status and identify what can be done next to improve analytics capability and the value of that capability to the overall DoD enterprise, within the context of specific objectives that lead to mission value.

Possible Courses of Action

Even with proper resourcing and appropriate data science skills, the path to successful implementation of an analytics capability is complex and multifaceted. As our interviewees suggested, there is no single "one-size-fits-all" implementation strategy. However, consensus exists on guiding principles of data governance and analytics, which can be used by the DoD acquisition community as appropriate. Our key findings can assist PDASD(AE), the sponsor of this research, in multiple ways as this DoD office matures its analytics capabilities. The findings suggest several potential courses of action for PDASD(AE):

- Data governance and strategy are critical enablers of analytics capability, so we recommend that PDASD(AE) create and maintain a data governance and analytics strategy for acquisition. This strategy includes establishing mission- and outcome-oriented strategic goals for acquisition analytics. Data and analytics needs are defined by the range of use cases tied to acquisition strategic goals and desired outcomes. The strategy should be updated periodically in response to changes in strategic goals, maturing analytics capabilities, and changes in the acquisition environment. The strategy should also identify a set of metrics that can measure whether analytics is having a value-added impact on DoD acquisition goals. This step is in addition to identifying a set of metrics that address progress toward DoD acquisition goals themselves, specifying the data needed to populate those metrics, and establishing the protocols and processes required to collect those data.
- Acquisition within OSD is currently using a federated organizational design. To further improve the organizational design, given its current role and responsibilities, PDASD(AE) is positioned to expand its role in data governance, management, and analytics specific to acquisition—a role previously described as the CoE. The functional foundation largely exists: PDASD(AE) already includes acquisition policy, data governance, and analytics. PDASD(AE) would constitute the relatively small central acquisition data governance and analytics capability, with additional acquisition analytics organizations elsewhere in OSD and DoD components. This positions PDASD(AE), in continued collaboration with the acquisition information managers in the services, to build on the acquisition data governance structure achieved to date. PDASD(AE) would continue to collaborate with the OSD and service CDOs as part of a larger DoD-wide analytics capability. However, it is unclear that PDASD(AE) is

A data analytics maturity model can be useful to characterize current status and identify what can be done next to improve analytics capability and the value of that capability to the overall DoD enterprise.

Further maturing the data analytics capability within the DoD acquisition community would be transformative.

resourced appropriately to fulfill the role as the CoE.

- Expand the existing Acquisition Visibility Steering Group and Working Group to include analytics. Acting as the data council for the acquisition function, this expanded group can provide guidance on both acquisition data governance and analytics and continue to provide a forum for OSD and service collaboration and information sharing.
- DoD leadership needs to see that resources are being spent efficiently. Demonstrating value quickly through the use of analytics activities to help solve or bring clarity to a pressing issue for the organization is one way to justify use of resources for analytics. Specifically, this assessment can be done by using a prototype or pilot for these specific analytics activities. Resources (e.g., staff, funding) can be allocated according to the prototype requirements and the foundational activities needed for longer-term acquisition data analytics. This process would be in line with the incremental value-add demonstrations of analytics recommended by many of the interviewees.
- Further maturing the data analytics capability within the DoD acquisition community would be transformative and may require changes or impacts in decisionmaking processes, business processes, organizational structure, and organizational culture. Change management strategies are designed to address the challenges associated with significant organizational change. Specific principles or activities in change management that could be applied include sustained leadership support and engagement that clearly communicates the need for and value of data analytics; incrementally building support through small, high-value demonstrations of analytics; providing incentives to change behavior in the appropriate direction; appropriate training and resourcing of data governance and analytics activities; and transparently showing how data-driven decisions add value toward achieving strategic goals.
- Over the past several years, substantial progress has been made in the data governance area of acquisition program information by OUSD(A&S) in collaboration with the services. For instance, the AVDF has been adopted because it contains the authoritative definitions of data required for acquisition category (ACAT) I programs, and the framework is being voluntarily adopted by the services for ACAT II–IV programs in their own reporting systems. The Federal Data Maturity Model provides a high-level road map for incremental enhancement of acquisition data governance and analytics. A more comprehensive application of that model to DoD acquisition would identify specific actions to take to improve analytics across the DoD enterprise. The acquisition community within OUSD(A&S) should continue to build on and leverage existing infrastructure, the common data framework for program information, and existing analytics capability.

Glossary of Terms

"**Advanced analytics** is a part of data science that uses high-level methods and tools to focus on projecting future trends, events, and behaviors. This gives organizations the ability to perform advanced statistical models such as 'what-if' calculations, as well as future-proof various aspects of their operations."

—Sisense, "What Is Advanced Analytics?" webpage, undated. As of March 26, 2020:
https://www.sisense.com/glossary/advanced-analytics/

"**Data architecture** describes how data is collected, stored, transformed, distributed, and consumed."

—Leandro DalleMule and Thomas H. Davenport, "What's Your Data Strategy?" *Harvard Business Review*, May–June 2017. As of March 26, 2020:
https://hbr.org/2017/05/whats-your-data-strategy

"When a company employs a '**data-driven**' approach, it means it makes strategic decisions based on data analysis and interpretation. A data-driven approach enables companies to examine and organise their data with the goal of better serving their customers and consumers. By using data to drive its actions, an organisation can contextualise and/or personalise its messaging to its prospects and customers for a more customer-centric approach."

—AT Internet, "Glossary: Data-Driven," webpage, undated. As of March 26, 2020:
https://www.atinternet.com/en/glossary/data-driven/

"**Data governance** is a system for defining who within an organization has authority and control over data assets and how those data assets may be used. It encompasses the people, processes, and technologies required to manage and protect data assets."

—Thor Olavsrud, "What Is Data Governance? A Best Practices Framework for Managing Data Assets," CIO, February 11, 2020. As of March 26, 2020:
https://www.cio.com/article/3521011/what-is-data-governance-a-best-practices-framework-for-managing-data-assets.html

"**Data management** is an administrative process that includes acquiring, validating, storing, protecting, and processing required data to ensure the accessibility, reliability, and timeliness of the data for its users."

—Molly Galetto, "What Is Data Management?" webpage, NGDATA, March 31, 2016. As of March 26, 2020:
https://www.ngdata.com/what-is-data-management/

"**Data science** is a method for gleaning insights from structured and unstructured data using approaches ranging from statistical analysis to machine learning. For most organizations, data science is employed to transform data into value in the form improved revenue, reduced costs, business agility, improved customer experience, the development of new products, and the like."

—Thor Olavsrud, "What Is Data Science? Transforming Data into Value," CIO, July 3, 2019. As of March 26, 2020:
https://www.cio.com/article/3285108/what-is-data-science-a-method-for-turning-data-into-value.html

"A **data strategy** is a plan designed to improve all of the ways you acquire, store, manage, share and use data."

—SAS Institute, *The 5 Essential Components of a Data Strategy*, 2018, p. 4. As of March 26, 2020:
https://www.sas.com/content/dam/SAS/en_us/doc/whitepaper1/5-essential-components-of-data-strategy-108109.pdf

"**Data visualization** is the graphical representation of information and data. By using visual elements like charts, graphs, and maps, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data."

—Tableau, "Data Visualization Beginner's Guide: A Definition, Examples, and Learning Resources," webpage, undated. As of March 26, 2020:
https://www.tableau.com/learn/articles/data-visualization

Notes

[1] Jessie Riposo, Megan McKernan, Jeffrey A. Drezner, Geoffrey McGovern, Daniel Tremblay, Jason Kumar, and Jerry M. Sollinger, *Issues with Access to Acquisition Data and Information in the Department of Defense: Policy and Practice*, Santa Monica, Calif.: RAND Corporation, RR-880-OSD, 2015; Megan McKernan, Jessie Riposo, Jeffrey A. Drezner, Geoffrey McGovern, Douglas Shontz, and Clifford A. Grammich, *Issues with Access to Acquisition Data and Information in the Department of Defense: A Closer Look at the Origins and Implementation of Controlled Unclassified Information Labels and Security Policy*, Santa Monica, Calif.: RAND Corporation, RR-1476-OSD, 2016; Megan McKernan, Nancy Young Moore, Kathryn Connor, Mary E. Chenoweth, Jeffrey A. Drezner, James Dryden, Clifford A. Grammich, Judith D. Mele, Walter T. Nelson, Rebeca Orrie, Douglas Shontz, and Anita Szafran, *Issues with Access to Acquisition Data and Information in the Department of Defense: Doing Data Right in Weapon System Acquisition,* Santa Monica, Calif.: RAND Corporation, RR-1534-OSD, 2017; Megan McKernan, Jessie Riposo, Geoffrey McGovern, Douglas Shontz, and Badreddine Ahtchi, *Issues with Access to Acquisition Data and Information in the Department of Defense: Considerations for Implementing the Controlled Unclassified Information Reform Program*, Santa Monica, Calif.: RAND Corporation, RR-2221-OSD, 2018; Jeffrey A. Drezner, Megan McKernan, Badreddine Ahtchi, Austin Lewis, and Douglas Shontz*, Issues with Access to Acquisition Data and Information in the Department of Defense: Streamlining and Improving the Defense Acquisition Executive Summary (DAES) Process and Data*, Santa Monica, Calif.: RAND Corporation, 2018, Not available to the general public; Jeffrey A. Drezner, Megan McKernan, Austin Lewis, Ken Munson, Devon Hill, Jaime Hastings, Geoffrey McGovern, Marek Posard, and Jerry M. Sollinger, *Issues with Access to Acquisition Data and Information in the Department of Defense: Identification and Characterization of Data for Acquisition Category (ACAT) II–IV, Pre-MDAPs, and Defense Business Systems*, Santa Monica, Calif.: RAND Corporation, 2019, Not available to the general public; Philip S. Anton, Megan McKernan, Ken Munson, James G. Kallimani, Alexis Levedahl, Irv Blickstein, Jeffrey A. Drezner, and Sydne Newberry, *Assessing Department of Defense Use of Data Analytics and Enabling Data Management to Improve Acquisition Outcomes*, Santa Monica, Calif.: RAND Corporation, RR-3136-OSD, 2019a.

[2] McKernan et al., 2017; Drezner et al., 2019; Anton et al., 2019a.

[3] Philip S. Anton, Megan McKernan, Ken Munson, James G. Kallimani, Alexis Levedahl, Irv Blickstein, Jeffrey A. Drezner, and Sydne Newberry, *Assessing the Use of Data Analytics in Department of Defense Acquisition*, Santa Monica, Calif.: RAND Corporation, RB-10085-OSD, 2019b, p. 1.

[4] The results of this research are consistent with both the Foundations for Evidence-Based Policymaking Act (Pub. L. 115-435, 2019) and the Federal Data Strategy (Office of Management and Budget, Office of Science and Technology Policy, Department of Commerce, and Small Business Administration, "Federal Data Strategy: Leveraging Data as a Strategic Asset; What Are the Practices?" webpage, undated) and may help DoD implement elements of both.

[5] The RAND Human Subjects Protection Committee determined that this research was not human subjects research.

[6] See, for example, McKinsey Analytics, *Analytics Comes of Age*, New York: McKinsey & Company, January 2018.

[7] See, for example, Gartner's Maturity Model for Data and Analytics (Rob vander Meulen and Thomas McCall, "Gartner Survey Shows Organizations Are Slow to Advance in Data and Analytics," press release, Gartner, Inc., February 5, 2018), IBM's Maturity Model for Big Data and Analytics (Chris Nott, "A Maturity Model for Big Data and Analytics," IBM Big Data and Analytics Hub, May 26, 2015), and the Data Cabinet's Government-Wide Data Maturity Model (Data Cabinet, *The Federal Government Data Maturity Model*, Washington, D.C.: National Technical Information Service, undated).

[8] For example, see vander Meulen and McCall, 2018; Nott, 2015.

[9] An additional example of a government-tailored maturity model is Data Cabinet, undated.

[10] Jeannette M. Wing, "The Data Life Cycle," *Harvard Data Science Review*, July 1, 2019.

[11] A more comprehensive benchmarking study might delve into each of these data life-cycle stages more deeply.

[12] Wing, 2019.

[13] Drezner et al., 2019; Anton et al., 2019b.

[14] Authors' interviews, November 1, 2019; November 4, 2019; November 6, 2019; and November 7, 2019.

[15] Paul P. Tallon, "Corporate Governance of Big Data: Perspectives on Value, Risk, and Cost," *Computer*, Vol. 46, No. 6, 2013.

[16] We discuss some of these trade-offs under "Resources."

[17] Almost every interviewee (12 of 14) discussed the data governance and analytics strategy in this way.

[18] Authors' interview, October 30, 2019.

[19] Authors' interview, November 1, 2019.

[20] Authors' interview, November 1, 2019.

[21] One definition of a *federated analytics organizational model* is the following: "A centralized group of advanced analysts is strategically deployed to enterprise-wide initiatives" (Julio Hernandez, Bob Berkey, and Rahul Bhattacharya, *Building an Analytics-Driven Organization: Organizing, Governing, Sourcing and Growing Analytics Capabilities in CPG*, Dublin: Accenture, 2013, p. 8).

[22] Authors' interviews, October 23, 2019; November 4, 2019; and November 7, 2019.

[23] Authors' interview, November 22, 2019.

[24] The C-suite consists of CEO, chief financial officer (CFO), chief operating officer (COO), and CIO. *C-suite* denotes the enterprise-level senior leadership. Within DoD, potential equivalents might be the Secretary of Defense, Deputy Secretary of Defense, chief management officer, chief information officer, Office of the Secretary of Defense chief data officer, and others. Authors' interview, November 7, 2019.

[25] Gloria Macías-Lizaso Miranda, "Building an Effective Analytics Organization," McKinsey & Company, October 2018.

[26] "A data translator is a conduit between data scientists and executive decision-makers. They are specifically skilled at understanding the business needs of an organization and are data savvy enough to be able to talk tech and distil it to others in the organization in an easy-to-understand manner" (Bernard Marr, "Forget Data Scientists and Hire a Data Translator Instead?" *Forbes*, March 12, 2018).

[27] Authors' interview, November 7, 2019.

[28] Authors' interview, November 1, 2019.

[29] Authors' interview, November 1, 2019. This interviewee used the analogy of Skunk Works, originally known for innovative and streamlined business and engineering processes, within the large Lockheed organization.

[30] Charles A. O'Reilly III and Michael L. Tushman, "Organizational Ambidexterity in Action: How Managers Explore and Exploit," *California Management Review*, Vol. 53, No. 4, 2011.

[31] O'Reilly and Tushman, 2011, p. 9.

[32] O'Reilly and Tushman, 2011, p. 9.

[33] We note that these five actions are similar to and consistent with the actions required under most change management frameworks.

[34] Mark van Rijmenam, "Why UPS Spends over $ 1 Billion on Big Data Annually," *Datafloq*, May 22, 2014.

[35] Jordan Novet, "Apple Will Boost Its Spending on Data Centers by $10 Billion over the Next 5 Years," CNBC, January 17, 2018.

[36] Authors' interview, November 1, 2019.

[37] Thomas H. Davenport and D. J. Patil, "Data Scientist: The Sexiest Job of the 21st Century," *Harvard Business Review*, Vol. 90, October 2012.

[38] Authors' interviews, November–December 2019. See also Jane M. Wiseman, *Data-Driven Government: The Role of Chief Data Officers*, Washington, D.C.: IBM Center for the Business of Government, September 19, 2018.

[39] John King and Roger Magoulas, "2015 Data Science Salary Survey," O'Reilly Media, Inc., September 22, 2015.

[40] Authors' interview, November 22, 2019.

[41] Authors' interview, November 1, 2019. One definition of *communities of practice* is "groups of people who share a concern or a passion for something they do and learn how to do it better as they interact regularly." Etienne Wenger-Trayner and Beverly Wenger-Trayner, "Communities of Practice: A Brief Introduction," Wenger-Trayner.com, 2015. The DoD acquisition community has established a number of communities of practice based on functional areas. See Defense Acquisition University, "Communities of Practice," webpage, undated.

[42] Authors' interview, November 1, 2019.

[43] A change management strategy lays out a set of principles and activities that should be followed to best implement and institutionalize change in an organization. Change management has also been referred to as *business process reengineering*. For examples, see Chapter 7 in Frank Camm, Laura Werber, Julie Kim, Elizabeth Wilke, and Rena Rudavsky, *Charting the Course for a New Air Force Inspection System*, Santa Monica, Calif.: RAND Corporation, TR-1291-AF, 2013. Our primary citations on organizational change are John P. Kotter, *Leading Change*, Boston: Harvard Business School Press, 1996; A. S. Judson, *Changing Behavior in Organizations: Minimizing Resistance to Change*, Cambridge, Mass.: Basil Blackwell, 1991; Timothy J. Galpin, *The Human Side of Change: A Practical Guide to Organization Redesign*, 1st ed., San Francisco: Jossey-Bass Publishers, 1996; Sergio Fernandez and Hal G. Rainey, "Managing Successful Organizational Change in the Public Sector," *Public Administration Review*, Vol. 66, No. 2, 2006; David Osbourne and Ted Gaebler, *Reinventing Government: How the Entrepreneurial Spirit Is Transforming the Public Sector*, New York: Penguin Books, 1993; Michael Hammer and James Champy, *Reengineering the Corporation: A Manifesto for Business Revolution*, New York: HarperCollins, 1993.

[44] Authors' interview, November 22, 2019.

[45] Authors' interview, November 7, 2019.

[46] This key finding aligns with the Federal Data Strategy, practice 15: "Assess Maturity: Evaluate the maturity of all aspects of agency data capabilities to inform priorities for strategic resource investment." Office of Management and Budget et al., undated.

[47] Richard Caralli, Mark Knight, and Austin Montgomery, *Maturity Models 101: A Primer for Applying Maturity Models to Smart Grid Security, Resilience, and Interoperability*, Pittsburgh, Pa.: Software Engineering Institute, Carnegie Mellon University, November 2012, p. 2.

[48] Data Cabinet, undated.

[49] See, especially, Drezner et al., 2019; Anton et al., 2019a.

References

Anton, Philip S., Megan McKernan, Ken Munson, James G. Kallimani, Alexis Levedahl, Irv Blickstein, Jeffrey A. Drezner, and Sydne Newberry, *Assessing Department of Defense Use of Data Analytics and Enabling Data Management to Improve Acquisition Outcomes*, Santa Monica, Calif.: RAND Corporation, RR-3136-OSD, 2019a. As of April 15, 2020: https://www.rand.org/pubs/research_reports/RR3136.html

———, "Assessing the Use of Data Analytics in Department of Defense Acquisition," Santa Monica, Calif.: RAND Corporation, RB-10085-OSD, 2019b. As of March 4, 2020: https://www.rand.org/pubs/research_briefs/RB10085.html

Camm, Frank, Laura Werber, Julie Kim, Elizabeth Wilke, and Rena Rudavsky, *Charting the Course for a New Air Force Inspection System*, Santa Monica, Calif.: RAND Corporation, TR-1291-AF, 2013. As of March 4, 2020: https://www.rand.org/pubs/technical_reports/TR1291.html

Caralli, Richard, Mark Knight, and Austin Montgomery, *Maturity Models 101: A Primer for Applying Maturity Models to Smart Grid Security, Resilience, and Interoperability*, Pittsburgh, Pa.: Software Engineering Institute, Carnegie Mellon University, November 2012. As of January 8, 2020: https://resources.sei.cmu.edu/asset_files/WhitePaper/2012_019_001_58920.pdf

Data Cabinet, *The Federal Government Data Maturity Model*, Washington, D.C.: National Technical Information Service, undated. As of March 1, 2020: https://my.usgs.gov/confluence/download/attachments/624464994/Federal%20Government%20Data%20Maturity%20Model.pdf

Davenport, Thomas H., and D. J. Patil, "Data Scientist: The Sexiest Job of the 21st Century," *Harvard Business Review*, Vol. 90, October 2012, pp. 70–76.

Defense Acquisition University, "Communities of Practice," webpage, undated. As of January 9, 2020: https://www.dau.edu/training/career-development/logistics/p/Communities-of-Practice

Drezner, Jeffrey A., Megan McKernan, Badreddine Ahtchi, Austin Lewis, and Douglas Shontz, *Issues with Access to Acquisition Data and Information in the Department of Defense: Streamlining and Improving the Defense Acquisition Executive Summary (DAES) Process and Data*, Santa Monica, Calif.: RAND Corporation, 2018, Not available to the general public.

Drezner, Jeffrey A., Megan McKernan, Austin Lewis, Ken Munson, Devon Hill, Jaime Hastings, Geoffrey McGovern, Marek Posard, and Jerry M. Sollinger, *Issues with Access to Acquisition Data and Information in the Department of Defense: Identification and Characterization of Data for Acquisition Category (ACAT) II–IV, Pre-MDAPs, and Defense Business Systems*, Santa Monica, Calif.: RAND Corporation, 2019, Not available to the general public.

Fernandez, Sergio, and Hal G. Rainey, "Managing Successful Organizational Change in the Public Sector," *Public Administration Review*, Vol. 66, No. 2, 2006, pp. 168–176.

Galpin, Timothy J., *The Human Side of Change: A Practical Guide to Organization Redesign*, 1st ed., San Francisco: Jossey-Bass Publishers, 1996.

Hammer, Michael, and James Champy, *Reengineering the Corporation: A Manifesto for Business Revolution*, New York: HarperCollins, 1993.

Hernandez, Julio, Bob Berkey, and Rahul Bhattacharya, *Building an Analytics-Driven Organization: Organizing, Governing, Sourcing and Growing Analytics Capabilities in CPG*, Dublin: Accenture, 2013. As of March 4, 2020: https://www.accenture.com/us-en/~/media/accenture/conversion-assets/dotcom/documents/global/pdf/industries_2/accenture-building-analytics-driven-organization.pdf

Judson, A. S., *Changing Behavior in Organizations: Minimizing Resistance to Change*, Cambridge, Mass.: Basil Blackwell, 1991.

King, John, and Roger Magoulas, "2015 Data Science Salary Survey," O'Reilly Media, Inc., September 22, 2015. As of January 8, 2020: https://www.oreilly.com/ideas/2015-data-science-salary-survey/

Kotter, John P., *Leading Change*, Boston: Harvard Business School Press, 1996.

Macías-Lizaso Miranda, Gloria, "Building an Effective Analytics Organization," McKinsey & Company, October 2018. As of January 8, 2020: https://www.mckinsey.com/industries/financial-services/our-insights/building-an-effective-analytics-organization

Marr, Bernard, "Forget Data Scientists and Hire a Data Translator Instead?" *Forbes*, March 12, 2018. As of March 4, 2020: https://www.forbes.com/sites/bernardmarr/2018/03/12/forget-data-scientists-and-hire-a-data-translator-instead/#51ef9690848a

McKernan, Megan, Nancy Young Moore, Kathryn Connor, Mary E. Chenoweth, Jeffrey A. Drezner, James Dryden, Clifford A. Grammich, Judith D. Mele, Walter T. Nelson, Rebeca Orrie, Douglas Shontz, and Anita Szafran, *Issues with Access to Acquisition Data and Information in the Department of Defense: Doing Data Right in Weapon System Acquisition*, Santa Monica, Calif.: RAND Corporation, RR-1534-OSD, 2017. As of April 15, 2020: https://www.rand.org/pubs/research_reports/RR1534.html

McKernan, Megan, Jessie Riposo, Jeffrey A. Drezner, Geoffrey McGovern, Douglas Shontz, and Clifford A. Grammich, *Issues with Access to Acquisition Data and Information in the Department of Defense: A Closer Look at the Origins and Implementation of Controlled Unclassified Information Labels and Security Policy*, Santa Monica, Calif.: RAND Corporation, RR-1476-OSD, 2016. As of April 15, 2020: https://www.rand.org/pubs/research_reports/RR1476.html

McKernan, Megan, Jessie Riposo, Geoffrey McGovern, Douglas Shontz, and Badreddine Ahtchi, *Issues with Access to Acquisition Data and Information in the Department of Defense: Considerations for Implementing the Controlled Unclassified Information Reform Program*, Santa Monica, Calif.: RAND Corporation, RR-2221-OSD, 2018. As of April 15, 2020: https://www.rand.org/pubs/research_reports/RR2221.html

McKinsey Analytics, *Analytics Comes of Age*, New York: McKinsey & Company, January 2018. As of January 8, 2020: https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Analytics/Our%20Insights/Analytics%20comes%20of%20age/Analytics-comes-of-age.ashx

Nott, Chris, "A Maturity Model for Big Data and Analytics," IBM Big Data and Analytics Hub, May 26, 2015. As of March 1, 2020: https://www.ibmbigdatahub.com/blog/maturity-model-big-data-and-analytics

Novet, Jordan, "Apple Will Boost Its Spending on Data Centers by $10 Billion over the Next 5 Years," CNBC, January 17, 2018. As of January 8, 2020: https://www.cnbc.com/2018/01/17/apple-to-boost-data-center-capex-by-10-billion.html

Office of Management and Budget, Office of Science and Technology Policy, Department of Commerce, and Small Business Administration, "Federal Data Strategy: Leveraging Data as a Strategic Asset; What Are the Practices?" webpage, undated. As of March 19, 2020: https://strategy.data.gov/practices/

O'Reilly, Charles A., III, and Michael L. Tushman, "Organizational Ambidexterity in Action: How Managers Explore and Exploit," *California Management Review*, Vol. 53, No. 4, 2011, pp. 5–22

Osbourne, David, and Ted Gaebler, *Reinventing Government: How the Entrepreneurial Spirit Is Transforming the Public Sector*, New York: Penguin Books, 1993.

Riposo, Jessie, Megan McKernan, Jeffrey A. Drezner, Geoffrey McGovern, Daniel Tremblay, Jason Kumar, and Jerry M. Sollinger, *Issues with Access to Acquisition Data and Information in the Department of Defense: Policy and Practice*, Santa Monica, Calif.: RAND Corporation, RR-880-OSD, 2015. As of April 15, 2020: https://www.rand.org/pubs/research_reports/RR880.html

Tallon, Paul P., "Corporate Governance of Big Data: Perspectives on Value, Risk, and Cost," *Computer*, Vol. 46, No. 6, 2013, pp. 32–38.

vander Meulen, Rob, and Thomas McCall, "Gartner Survey Shows Organizations Are Slow to Advance in Data and Analytics," press release, Gartner, Inc., February 5, 2018. As of March 1, 2020: https://www.gartner.com/en/newsroom/press-releases/2018-02-05-gartner-survey-shows-organizations-are-slow-to-advance-in-data-and-analytics

van Rijmenam, Mark, "Why UPS Spends over $ 1 Billion on Big Data Annually," *Datafloq*, May 22, 2014. As of January 8, 2020: https://datafloq.com/read/ups-spends-1-billion-big-data-annually/273

Wenger-Trayner, Etienne, and Beverly Wenger-Trayner, "Communities of Practice: A Brief Introduction," Wenger-Trayner.com, 2015. As of January 8, 2020: https://wenger-trayner.com/introduction-to-communities-of-practice

Wing, Jeannette M., "The Data Life Cycle," *Harvard Data Science Review*, July 1, 2019. As of March 4, 2020: https://hdsr.mitpress.mit.edu/pub/577rq08d

Wiseman, Jane M., *Data-Driven Government: The Role of Chief Data Officers*, Washington, D.C.: IBM Center for the Business of Government, September 19, 2018. As of January 15, 2019: https://www.innovations.harvard.edu/sites/default/files/Data-Driven-Government.pdf

About This Report

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