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Adaptive data governance for research data management

Madison Golden¹

Abstract

The field of research data management librarianship has grown significantly in past years but continues to face the challenges of knowledge gaps, frequent changes to policy and guidance, and the complexity and context that comes from data that varies both in type and format. As a research data librarian, I face these issues on a daily basis and have adopted an adaptive approach that combines multiple styles to balance the individual needs of researchers while complying with policies and best practices. This approach was adopted from my past experience in data governance at a corporation in which we faced the same core challenges. Incorporating the four styles of data governance as laid out by Gartner provides a framework for librarians and data governance specialists alike to prioritize competing needs and guide researchers through the data lifecycle. The benefits of this approach include increased flexibility in data management practices, continuous improvement of services and resources, efficiency, and empowerment of researchers and related stakeholders.

Keywords

Research data management, data governance, adaptive data governance, data librarianship

Introduction

While research data management support in academic libraries is becoming an essential service, work remains to be done to balance priorities and offer the most impactful services possible with the resources available. Policies and standards emerging from various organizations, training gaps, and the complexity and context of academic research datasets create a challenging landscape for researchers and librarians alike (Sheikh et al, 2023). These challenges are best met with a flexible and institution-specific approach that can balance individual researcher needs with policies and best practices.

Prior to becoming a research data librarian, I had three years of experience in data analytics and data governance at a large insurance corporation. During this time, analysts and data engineers encountered many of the same challenges as researchers; complying with policies, managing sensitive data, and documenting data workflows. The data governance team was created to address these issues and included ten people. We primarily collaborated with data engineering teams to apply security, classify data, and standardize metadata for datasets across the organization. Additionally, we worked with data analysts to understand the data they were subject matter experts in, as well as, assisting them in finding the appropriate data. We trained all groups working with data on the company's data policies and the data catalog we managed for the company. Members of the team

also coordinated a data stewardship program to expand our reach and receive continuous input from across the company. Throughout these efforts, my manager employed the adaptive data governance approach to balance the fast-paced and goal-oriented approach of the company's leadership with the longer term goal of achieving proper data management. This paper proposes how Gartner's adaptive data governance model can be mapped onto the field of research data management librarianship. Gartner is a research and consulting firm located in the United States that focuses on business and technology. According to their website, Gartner specializes in "actionable, objective insights", along with "expert guidance and tools" (Gartner, 2025). They have been in business for over 40 years and work with businesses in nearly 90 countries and territories (Gartner, 2025). This approach will assist data librarians and those in related positions to balance policy and best practices with the individual needs of researchers and departments, as well as develop services and resources as data management maturity grows on campus.

There are several existing guides and frameworks for developing research data management services. The Digital Curation Center developed the Research Infrastructure Self-Evaluation (RISE) Framework in 2017 to "facilitate RDM service planning and development at the institutional level" (Rans and Whyte, 2017, p.3). OCLC Research also developed a three-part research data management service guide in 2018 covering how to understand local needs, identifying incentives for various services, and whether to create or buy identified services (Bryant, 2018). Additional institution-specific case studies and frameworks regarding the development of research data management services were also developed. Examples include Oxford University, Central Washington University, and the University of Toronto (Chiarelli et al, 2022; Fu et al, 2022; Perrier & Barnes, 2018). While these guides and frameworks address similar issues of institution-level needs assessment, service maturity, and the costs versus benefits of various services; the model presented in this paper offers a new framework for categorizing and evolving services over time by utilizing multiple styles of governance.

This paper will rely on my experiences as a research data librarian at the University of Utah. As such, generalizability of this work is limited and requires further research and application at other institutions. For context, the University of Utah is an R1 research university with approximately 26,827 undergraduate students and 8,409 graduate students as of 2023. There are 1,592 full-time tenure-line faculty and 1,863 full-time career-line faculty. In the 2023 fiscal year, the institution received \$768 million in research funding (University of Utah, 2024). Prior to August of 2023, there was a brief gap in research data support from the library which was filled by myself and one other research data librarian faculty member. These hires and subsequent reinstatement and expansion of research data services were a direct result of the [OSTP memo of 2022](#) and an increased focus on open science across campus. In addition to the library, research data infrastructure comes from the Center of High Performance Computing, guidance from the Vice President of Research Office, and data science initiatives.

Methodology

At its core, this is a conceptual article which utilizes theory adaptation to expand upon Gartner's adaptive data governance model, wherein four styles of data governance are used simultaneously to meet variable needs. Because of this, the paper relies on Gartner Research's methodology. Gartner states that they "offer a full range of research methods such as in-depth proprietary studies, peer and industry best practices, trend analysis and quantitative modeling" (Gartner, 2024). Their proprietary

methodology was developed and utilized by their global experts numbering over 2,000. In regards to their objectivity, Gartner cites their strict code of conduct and guidelines to ensure neither the company nor its employees are in a position to benefit from any one company, industry, or technology (Gartner, 2024). In addition, they were ranked by Forbes as #92 on their America's Best Companies list for 2025 (Forbes, 2024).

Theory adaptation as a methodology “develop[s] contribution by revising extant knowledge—that is, by introducing alternative frames of reference to propose a novel perspective on an extant conceptualization” (Jaakkola, 2020, p. 23). According to Jaakkola, this necessitates identifying a theory of interest, adjusting or expanding the original theory's scope, and justifying why the shift is needed, including why the selected theory is the best fit (2020). In keeping with these requirements, I will first identify and explain the theory of interest, which will be Gartner's Adaptive Data Governance framework. Next, I will justify why the shift is needed by identifying shared core challenges of Data Governance and Research Data Management, as well as how these challenges are addressed by the framework. Finally, the shared core challenges along with the mapping of research data management services and their iterative development into the framework will be used to argue the efficacy of this theory adaptation. As with all conceptual articles, the work has not been empirically proven “but rather build[s] on theories and concepts that are developed and tested through empirical research” (Jaakkola, 2020, p. 19). As such, this paper will also include limitations and a call for further evaluation and critique.

Data governance overview

Data Management Association International (DAMA) defines data governance as “the planning, oversight, and control over management of data and the use of data and data-related sources” (DAMA, 2017), typically within companies and government organizations. This includes a wide range of activities, including data architecture, data modeling and design, data storage and operations, data security, data quality, metadata, data warehousing, reference and master data, document and content management, and data integration and interoperability (DAMA, 2017). It also includes collaborating with data scientists, data analysts, and business leaders to coordinate efforts and align goals. In a fast-paced business environment, particularly those motivated by growth, data governance can often be seen as a block to progress rather than an enabler of it. This is due to a tendency in traditional governance towards reactivity and a top-down approach. However, if data is not properly organized, managed, and protected, there will be larger complications down the line whether they be from legal action resulting from not adhering to policies, data breaches, or consistent duplication of effort and poor resource management (Abraham et al, 2019).

Adaptive data governance is an approach to data governance created to alleviate some of the issues with traditional governance styles described above. At the heart of the approach is agility, which allows data governance to accomplish its goals while encouraging innovation and growth (Gulzar and Kopcho, 2024). Adaptive governance is achieved by combining multiple styles of governance, which will be outlined in the following sections. The use of multiple styles also allows for data governance teams to handle more complexity and disparate needs across an organization (Rama, 2013). In addition, this approach is complementary to the rapid changes and development in organizations, enabling efficiency rather than preventing it.

Gartner, a leader in data and IT management research, defined an adaptive data governance framework that incorporates four governance styles; control, outcome, agility, and autonomous (Gartner). Each style builds upon the last in maturity and enables an organization to handle increasing complexity. Control is at the heart of the model and closely resembles the traditional approach to data governance in which compliance with policies and rules guides all work (Gulzar and Kopcho, 2019). In data governance at a corporation, this would take the form of data policies such as sensitive data policies and data access policies, along with government regulations and company or industry standards. The outcomes style of governance still incorporates the control of the previous style, but introduces analytics as a way to balance priorities and make informed decisions (Gulzar and Kopcho, 2019). Here, standards and rules may be altered so business performance goals may be met while still adhering to policies and regulations. The agility style introduces increased flexibility by distributing empowerment to dispersed groups in an organization to accelerate decision making by placing power in the hands of subject matter experts (Gulzar and Kopcho, 2019). This stands in stark contrast to control where decisions are made from the top down and policies are created and managed at the upper levels of management. In this bottom-up approach, decisions can be made that balance individual teams' needs and policies to move away from the 'one size fits all' approach. The final governance style in the model is autonomy, including distributed authority from the autonomy style, along with input from AI and other automated tools (Gulzar and Kopcho, 2019). The use of AI and algorithms increases the ability for complex decision-making by incorporating a variety of factors and real time data while still adhering to policies.

The model is not designed to be unidirectional. Rather, the goal is to situate services and tools for given data management activities within the governance style that best meets the needs of an individual organization at a given point in time. The governance style employed for a given activity, such as monitoring data quality can progress from one style to another as needs and overall data maturity of an organization change. For example, an organization may use the agile approach to monitor data quality wherein responsibility is dispersed to departments within a large organization. As the organization's data strategy matures, they may pivot to the autonomous style of governance by utilizing an algorithm to monitor data quality instead. On the other hand, the introduction of novel policies such as the OSTP memo in 2022 could necessitate moving data management practices that were previously governed with an outcomes or agile style to the control style because more oversight is needed to comply. At the University of Utah, this was the case with data sharing practices. Therefore, success of implementing the model depends on whether the organization is able to accurately understand the level of data maturity across the organization at a given time and what governance style is needed for data-related activities.

Shared core challenges: Research data management and data governance

Research data is defined as “ the outcome of experiments or observations that validate research findings, and can take a variety of forms including numerical output (quantitative data), qualitative data, documentation, images, audio, and video” (National Library of Medicine, 2022). Research data is similar to industry or government data in that it comes from a variety of sources, contains a combination of sensitive and non-sensitive data, and is used for a variety of purposes. It is unique in that there are additional variations in the data types and formats, including video, audio, code, and simulations. Additionally, policies and processes come from a variety of sources such as government, funding agencies, and institutions. This means internal regulations, or lab-specific regulations and

processes, tend to be looser and more disparate, even between research labs within the same discipline (Reichmann et al, 2020).

Data management, similar to research data, is a very broad concept that encompasses "data management planning, documenting your data, organizing data, improving analysis procedures, securing sensitive data properly, having adequate storage and backups during a project, taking care of your data after a project, sharing data effectively, and finding data for reuse in a new project," (Briney, 2015, p.7). The scope of data governance is slightly larger than data management, as data management activities are seen as a component of data governance. However, each works to achieve similar goals where proper data management improves usability of data while managing risks such as security breaches, data loss, and poor data quality.

Several core challenges are shared by research data management and data governance that can be improved with the adaptive approach. Complexity and context create challenges due to a variety of data sources and types. Variation in these areas creates difficulty in developing policies and practices that fit across data types. Internal and external policies introduce complexity as they may have conflicting requirements. Disparate standards and processes can be a barrier when introducing new policies or best practices, and can also create challenges for instruction development for a wide audience. Additionally, understanding all of these differences across disciplines is unfeasible for many organizations.

Another shared challenge is a lack of awareness among data creators and users of policies, standards, and best practices. Lack of awareness arises from training gaps, either within a research group or across an institution. There are also multiple sources of guidance from professional organizations, groups within institutions, and government and funding agencies. Lastly, it is difficult to reach all applicable audiences, especially in a decentralized organization where data management is not seen as essential.

Finally, constant developments and changes across the data landscape contribute to the above challenges of lack of awareness and handling complexity and context. Updates to policies and regulations may go unseen by affected parties unaware of what applies to them. This includes the development of data sharing requirements, either from states like California issuing the California Consumer Protection Act, or from research funders and publishers. In addition, the introduction of new tools, systems, and methods may make current policies and instruction inadequate.

Adaptive data governance for research data management

In order to explain how the adaptive data governance model, as laid out by Gartner, can be applied to research data management, each of the four governance styles described earlier will be re-contextualized for research data management within an academic institution. As described in the introduction, this will primarily stem from the library perspective and examples from the University of Utah.

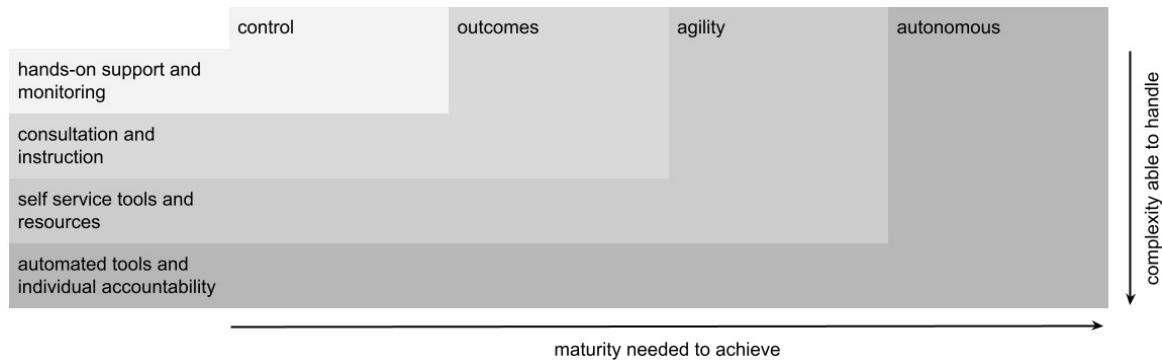


Figure 1: conceptual map of linear relationship between service modality complexity and maturity needed to achieve each adaptive governance style

Control

In data governance, the control style is defined by policies and adopts a passive, compliance-based approach (Judah, 2023). To re-define this style for research data management; the control style of research data management seeks to mitigate risks by monitoring compliance to applicable research data policies and standards arising from funding organizations, publishers, government, and institutions. A core drawback to this approach is strict adherence to policies that are often not defined by those in the library or other academic offices supporting researchers. However, these policies and laws create the jumping off point for service development and resource acquisition. Clear requirements for research data management in the form of policies create clear service priorities and an opportunity to perform outreach to researchers. Additionally, control establishes the need for a compliance and policymaking body within an organization, which can serve as the basis for further infrastructure and support staff for researchers.

The research office serves as the primary policymaking and compliance group on campus. However, in contrast to a company, institutions have more disparate compliance processes built in. For example, grant offices assist researchers in reporting on compliance to their funders and researchers are also accountable to comply with policies on data sharing set forth by publishers. Regardless of this slight decentralization, the main mechanism driving data management in this context is compliance with policies and regulations created in a top-down manner. At the University of Utah, examples include assisting researchers developing data management plans, selecting appropriate repositories for data sharing, and advising on infrastructure development to support these requirements.

In terms of benefits, interfacing with researchers under this style has the dual benefit of incentivizing researchers to seek support from the library to comply with policies regardless of their origin and gives the library insight into key support needs of researchers. Assisting researchers complete data management plans (DMPs), selecting appropriate repositories, and storing data securely opened conversations on common needs and questions. Some examples included difficulty describing data and generating metadata, difficulty selecting a repository or knowing what characteristics to look for, and confusion over where to seek guidance on research data management. These conversations prioritized service and resource development in the following governance styles and created educational opportunities that matured many researchers' understanding of research data management.

Outcomes

The outcomes style relies on balancing risk and performance to meet the policies outlined in the control style while still prioritizing efficiency and business goals (Judah, 2023). In the context of research data management, this style supports research data management through the development of services and resources across multiple modalities, informed by the needs and gaps of an institution's researchers as well as relevant standards and requirements. Utilizing learnings from the previous section, or from a more structured approach such as a survey, serves as the foundation for service and resource development within this governance style. Understanding certain departments' level of need for services, as well as the modalities most requested, can guide the need for additional support teams. Additionally, resources and standards aimed at meeting the goals of data policies should be introduced. For example, the FAIR principles assist researchers in meeting data sharing policies while improving the findability, accessibility, interoperability, and reusability of those shared datasets.

At the University of Utah, there was a clear value to and need for developing an institutional data repository to assist researchers in meeting data sharing requirements quickly and freely. This gives researchers greater flexibility when depositing data and we are able to adapt different aspects of the deposit process and standards to meet their needs. For example, researchers fill out a Qualtrics form when requesting to deposit which we use to generate a readme on their behalf. Usually, one section of the form is writing out a codebook. Defining variables in a codebook is essential to future users understanding a dataset, which is complimented by methodological information included in a readme document. However, we have had several researchers with over 100 variables who we allowed to upload a codebook separately which is referenced in the readme file. Remaining open to these small adjustments is essential for research data management as the amount and format of data (and metadata) vary widely.

For this and the following styles, it is important to focus as much on what an institution's researchers don't need as what they do need. A key part of the outcomes style is recognizing what efforts and resources are not yet necessary and would take away from needed support. On the flip side, analysis of current offerings may show a gap in services. For example, the University of Utah's research data repository recently increased its retention period from five to ten years due to longer retention requirements in federal funding and publisher policies. Going forward, analytics on downloads and citations metrics will be used to make deaccessioning decisions at the end of that period. Other examples include deciding whether or not to hire additional staff for data curation support, paying for additional storage space for data deposits, offering coding or software support, and providing in person or on demand workshops. Given the ample online resources from academic institutions, professional organizations, and other groups, investigating free and already available content should be top of mind.

Agility

The agility governance style emphasizes placing decision making power in the hands of subject matter experts to allow decisions to be made efficiently. It also prioritizes on demand resources and services to support individuals and teams. In the context of research data management, agility empowers researchers and supporting staff to perform research data management using self service tools that align with their individual needs. As shown in the model, additional data management maturity is

needed at an institution to enable localized decision making and the use of self service tools. Some challenges referenced earlier, particularly addressing training gaps, will need to be addressed by the following styles prior to introducing agile approaches.

At the University of Utah, this is the stage when research data management responsibilities were dispersed across the university between the libraries, research office, IT, and researchers and research labs. Structurally, the library provides access to training and resources while the research office handles policy making and compliance, IT handles data security and classification policies along with data storage for in-progress research, and researchers along with grant officers are accountable for compliance and reporting for any policies affecting their work. In this system, various groups are able to decide what gaps on campus they have capacity to fill and how those resources are made available. Collaboration and pooling of resources can also be done to complete larger projects, such as the Center for High Performance Computing offering additional storage space that the library-managed repository cannot accommodate.

The library specifically offers several self-service tools to support agility and empower researchers who are more comfortable with the data management process. DMPTool is an online tool that allows users to access data management templates and guidance based on the institution they belong to or their funder. LibGuides are another on demand resource with comprehensive information on the research data lifecycle and reusing research data, including a repository selection tool. While the ultimate goal is to provide self service resources when possible, it is important to consider areas where this may not be the best fit. For example, we have noticed many researchers are unfamiliar with building readmes and generating metadata using controlled vocabularies or standards. As such, it makes sense to retain control of the deposit process in our institutional data repository rather than a self-deposit model. This is a great example of not having the required level of maturity on campus for an agile or autonomous style for this service. It is also an example of how a blended style approach meets institution-specific needs.

Autonomy

Autonomy requires the highest level of maturity but is able to handle the most complexity by combining the power of automated tools and agile decision making. This style allows practitioners to manage research data via individuals and automated tools attuned to the researcher's needs while complying with relevant policies and regulations. Many tools and services that fit within this approach are novel and not yet widely used. Examples include machine readable data management and sharing plans that will allow easier compliance monitoring after the grant cycle, additional automation for our repositories deposit process which would greatly speed up the process and reduce data-entry type tasks, and dataset curation or metadata creation done by AI to allow for more efficiency and a more discipline specific approach than we are able to provide currently. Thus far, The University of Utah has not reached the automation level. Implementing autonomy style tools will require resources and technical expertise in addition to data management knowledge across campus. Utilizing use cases from data management savvy researchers and possibly the assistance of grant funding to develop services will be key mechanisms for implementing this style.

Conclusion

The primary purpose of this model is to guide research data librarians and related practitioners at research institutions on the development and prioritization of research data management services

and resources over time. The model may also be useful to adjust services and resources as the landscape of research data management changes due to increased data literacy at a given institution, the introduction of new policies, and/or an increased commitment to open science. While existing case studies, guides, and frameworks provide helpful guidance in research data management service development, this adaptive data management approach provides a novel strategy to blend multiple approaches and scale services up and down over time. Therefore, it provides the benefits of flexibility, continuous improvement, and efficiency and empowerment.

Flexibility is a core benefit of the adaptive approach to research data management. Combining multiple styles facilitates institutions meeting the needs of as many researchers as possible. Practically, this can look like offering training and informational content in multiple modalities such as videos, text, consultations, and live presentations and workshops. It also takes the form of accommodating individual needs in various processes such as depositing in an institutional repository. As mentioned in a previous section, research data varies even more widely than industry data with fewer standard practices within disciplines. This variation requires a flexible approach to assisting researchers in meeting policies and requirements rather than one size fits all processes and resources. The adaptive approach allows for that flexibility while maximizing the support provided through a mixture of internal and external services, information offered in multiple modalities, and prioritization based on the most pressing needs.

Continuous improvement is achieved through the adaptive approach by having a gradually maturing model built in. As training gaps are closed and more individualized services are requested across campus, more agile and autonomous management styles can be implemented. Ensuring basic policies and requirements are met as a first priority creates an opportunity to educate researchers on a host of other topics including standards like FAIR, the use of metadata schemas and standardized vocabularies, how to select a data repository, and how to handle sensitive data. That knowledge can be built upon over time resulting in the use of self service tools like DMPTool, freeing up time and resources to be put to developing additional tools or automating processes. Receiving regular input and concerns from researchers also results in agility and re-prioritization over time.

Finally, efficiency and empowerment are encouraged through self service resources, automation wherever possible, and dispersed accountability. Managing research data through a compliance-based mindset is often reactionary and can hamper innovation. Moving away from this style to decentralize over time as expertise with data management grows across key groups such as grant offices, research administrators, and researchers themselves reduces the need for command and control efforts. Investing resources across each style gives researchers more options for managing their data and aligns with the 'teach a man to fish' ethos common in libraries and academic institutions. The power of the adaptive data management approach comes from the centering of the researcher and striving to mold a set of practices and policies around their knowledge and the resources available. As stated at the beginning of this paper, this synopsis of the adaptive data governance approach and its application to research data management arise from my experience in both fields as well as the referenced articles, which are primarily from Gartner. Adapting research data management tools, services, and resources exists along two axes. The first is the chosen tools, services, and resources offered to support activities across the research data lifecycle. The second is the level at which those tools, services, and resources are offered. Examples include synchronous or

asynchronous, virtual or in person, self service or mediated, and informational or hands-on. As these decisions are further complicated by resource limitations and staff expertise, this adaptive model re-imagined for research data management can assist in guiding and prioritization over time. Additional research on how institutions with varying characteristics situate services and resources within the model shared in this paper would be instrumental in validating and understanding this application of adaptive data governance to research data management.

Limitations

The primary limitations of this paper are its conceptual nature, reliance on Gartner's proprietary methodology, and use of examples derived from only one university. A conceptual article is inherently non-empirical, and therefore does not meet the requirements of a paper based on empirical research. Further application by other institutions would be necessary to fully evaluate the effectiveness of this theory adaptation. Secondly, while Gartner claims to have high standards for independence and objectivity in their research, those methodologies are proprietary and were therefore not fully evaluated in this paper. Finally, the examples and experiences used to adapt Gartner's Adaptive Data Governance framework were based on one university. Generalizability of this work relies on future application, evaluation, and critique by other institutions.

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Endnotes

¹ Madison Golden, Assistant Research Data Librarian, University of Utah. madison.golden@utah.edu
<https://orcid.org/0009-0004-4993-3503>