Navigating the Everchanging Research Landscape and Maximizing the Impact of Academic Data Science and AI Organizations

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Abstract
In the past decade, many universities have established university-wide data science (DS) research organizations to enable the development of DS methods and their transformative use in disciplinary and interdisciplinary research, enhance institutional research capacity, advance responsible innovation, and advance DS education and training. With the emergence of artificial intelligence (AI), many such organizations are incorporating AI as a new focus area in research and education. However, such organizations vary vastly in their mission, mandates, funding model, reporting structure, organizational structure, resources, and stakeholders. This reality makes it challenging for these organizations to learn from each other and to collaborate. In 2024, the Academic Data Science Alliance (now the Alliance for Data Science and AI) and the Michigan Institute for Data and AI in Society jointly hosted a workshop for leaders of 13 university-wide data science, AI and computing organizations and initiatives. The workshop focused on understanding how these organizations address challenges that come with evolving mandates, resource constraints, the need for clarity on organizational roles, and impact measurement, especially in the face of the rapidly advancing AI technologies and its adoption in academic research. This article synthesizes insights from the workshop and highlights strategies for positioning these organizations on campus, addressing unfunded mandates, and developing AI strategies aligned with institutional goals. Our findings provide actionable frameworks for leaders in research universities to improve organizational effectiveness and long-term sustainability.

In this article (and the workshop that this article is based on), we focus on institutes, centers, initiatives, or other academic units that provide broad support for a university or a significant part of it. We will refer to these organizations and programs as “DS / AI organizations” in the remainder of the article. We will not discuss organizations whose primary responsibility is either to advance data science and AI methodology and research (that is typically the charge for computer science or statistics departments) or to run educational programs.

Introduction

In the past 10-15 years, campus-wide data science (DS) initiatives, institutes, programs, and schools have sprung up at many research universities. Such organizations vary greatly in their mission, strategic focus, reporting and organizational structure, and funding models. A major source of this variability stems from the differences in the needs across universities that led to the initiation of such an organization or program at these universities. Some focus on advancing data science methodology through original research, while others focus on building institutional research capacity through enabling the application of data science methods in a wide range of research domains, and yet others focus on preparing the next generation of data-literate workforce. Such differences in strategic focus, combined with variations in organizational structures and funding models, make it challenging for these organizations to learn from each other and collaborate, and to benchmark themselves against peers at other universities. The first goal of our workshop was to provide a snapshot of the wide range of goals, structures, and operations of our organizations in order to facilitate understanding and collaboration.

The second goal of the workshop was to examine the impact of artificial intelligence (AI) and the demand for its adoption in academic research in these organizations. Many universities have charged their data science organizations, formally or informally, to develop AI capacity at the university for research and training (Liu & Jagadish, 2024). Such new mandates come at a time when every university is exploring how to adopt AI, but with few examples of campus-wide guidance or AI policies. These new mandates are also often unfunded, with no new resources or staff time allocated to the effort. Many data science organizations (now data science and AI organizations) are trying to grapple with such “unfunded mandates”, identify strategic directions and challenges, seek resources, refine their value propositions, and design measurements of success.

The issues of value proposition and measurements of success have been persistent for many such organizations since their inception, and the addition of AI to their mandates makes these challenges even more salient (Huebner et al., 2024; Ribes & Lee, 2010). DS / AI organizations can be inherently different from stereotypical interdisciplinary research institutes that are abundant on university campuses. Typically, interdisciplinary research institutes exist to advance research defined by a grand challenge, such as sustainability or health equity, that requires contributions from researchers across disciplines and departmental boundaries. Such interdisciplinary institutes may draw several hundred researchers across a university, but there is a very clear distinction between those who do research aligned with the grand challenge and those who do not. Data science and AI are methodologies that can advance almost all disciplines in addition to being fields of research in their own rights (Donoho, 2017; Cao, 2017; Gao & Wang, 2024; Gil et al., 2014; Wang et al., 2023; Xu et al., 2021). DS / AI organizations, therefore, can be charged with a broad set of research missions depending on a university’s specific needs, including some combination of advancing data science and AI core research, and advancing research in many fields through the application of data science / AI. In addition to a mission of growing research, DS / AI organizations often also provide technical services and support, develop new interdisciplinary teams and team matching, offer educational programs, and provide public service.

Our article will focus on DS / AI organizations’ structures, evolving mandates and strategic alignment, funding models, sustainability, value propositions, and performance metrics. We hope the observations and insights that this paper shares can help our peer DS / AI organizations navigate the following questions:

- How do they structure themselves to serve faculty, students, and the university as a whole?
- How do their mandates evolve and how do they respond to requests for AI leadership, especially in the landscape of national policy shifts?
- How can they build sustainable financial models for work that rarely fits traditional research funding?
- How do they measure success beyond the easy-to-count research outputs?

Organizational Models and Structures

Organizational models and reporting structures

The inherent cross-disciplinary nature of data science and AI, as well as the science that they enable, has led to the establishment of DS / AI organizations at many institutions. They serve an important role in enabling researchers from a multitude of domains and research areas and often provide academic and operational support across broad ecosystems (Earnshaw, 2019). Some of these organizations also provide a formalization of interdisciplinary research programs, such as the data science and AI postdoctoral training program at the Michigan Institute for Data and AI in Society and the Data Science Institute at Brown University. Another example is Texas State University Center for Analytics and Data Science, which facilitates interdisciplinary research by administering seed-funding initiatives and delivering shared training and curriculum modules. These programs help reduce silos within a university and alleviate the fear of data science or AI being “owned” by a particular college or department.

There is no single “correct” home for a DS / AI organization -some reside in research divisions, some within academic units, and some under one or multiple executive offices. Each reporting line influences an institute's authority, access to funding, and ability to coordinate across campus. In addition to a reporting structure, many organizations also have a formal board and / or an executive committee.

Many universities also have multiple DS / AI programs, each with more focused functions or research fields. University-wide DS / AI organizations may collaborate with these focused DS / AI programs, in which case an additional federating structure may be needed. For example, regular meetings amongst leadership bring together multiple programs and organizations within a university, such as at the University of Arizona and the

University of Utah. However, not having a formal model of coordination within a university is not indicative of a lack of need for such coordination. There is often a great deal of overlap in expertise and effort amongst various programs, so regular communication and coordination is necessary to avoid conflict and duplication of effort.

University-wide research organizations. A single campus-wide DS / AI organization is the most common. It often provides broad research support and can include resources to support proposal development, project execution, software development, researcher training, data curation and cleaning, and research infrastructure development. Examples include the Translational Data Analytics Institute (TDAI) at The Ohio State University, the Tufts Institute for Artificial Intelligence at Tufts University, the Data Science Institute (DSI) at the University of Arizona, the Michigan Institute for Data and AI in Society (MIDAS) at the University of Michigan, the One-U Responsible AI Initiative (RAI) within the Scientific Computing and Imaging (SCI) Institute at the University of Utah, the University of Washington eScience Institute, the Center for Analytics and Data Science (CADS) at Texas State University and the Data Science and AI Hub at the University of Minnesota. The Institute for Computation and Data Enabled Insight (ICDI), also at the University of Arizona, is a slightly different example that focuses on leveraging data science across the university in connection with external communities (e.g., economic development for Arizona).

Another characteristic of these organizations is that most of them are not academic homes of faculty. This creates a unique challenge for building a strong faculty community because tenure-and-promotion criteria rarely reward sustained center service and many faculty engage only when they seek resources.
The university-wide organizations mostly use a sole reporting model. Due to their focus on research, typically these institutes directly report to the Vice President, Vice Chancellor, or Vice Provost for Research. Examples of this type of reporting include the DSI, MIDAS, The Institute for Data Science at New Jersey Institute of Technology, the TDAI, and the National Center for Supercomputing Applications (NCSA) at the University of Illinois.

Sole reporting structures may also include reporting directly to leadership of academics, including the Vice President of Academic Affairs or the Provost. These organizations often have a combined purpose of supporting research growth and integrating with faculty across campus. Examples include the Data Institute at University of San Francisco, North Carolina State University (NCSU) Data Science & AI Academy, One-U RAI, and University of Pittsburgh Responsible Data Science.

Some organizations report to multiple campus structures to ensure representation across campus. This could include reporting to leadership for research, academic affairs, specific domains such as health sciences, and also the Deans of specific colleges. For instance, ICDI reports dually to the Provost and the Vice President for Research, reflecting the fact that emerging data science technologies span instruction and research. Similarly, CADS at Texas State University reports to the Vice President for Research but also provides regular updates to the Provost's Office due to partial funding support, and to its internal advisory board composed of campus partners. A more distributed example is the DSAI at the University of Minnesota, which reports to the Vice President for Research & Innovation, the Provost, and three academic deans representing colleges deeply associated with data science. Similarly, eScience at the University of Washington reports to three Deans (Arts & Sciences, Engineering, and Libraries) and the eScience Director also holds the title of Associate Vice Provost for Data Science reporting to the Vice Provost for Research.

Domain-specific Research organizations. Some DS/AI organizations focus on a specific grand challenge or application area, such as precision medicine or environmental resilience, and bring together experts from a subset of domains. Examples include the Center for Biomedical Informatics and Biostatistics (CB2) at the University of Arizona; the Data Exploration and Learning for Precision Health Intelligence (DELPHI) Initiative at the University of Utah; the Institute for Health Informatics at the University of Minnesota; the Institute for Data Intensive Research in Astrophysics and & Cosmology (DiRAC) at University of Washington; and Data Science & Environment (DSE) at University of California at Berkeley. The domain-specific institutes tend to report to the leadership of that specific domain at the university, such as the Vice President of Health Sciences.

Multi-university organizations. Another type of DS/AI organizations bridges across multiple universities and institutions. These often provide services, especially cyberinfrastructure, that can be shared across universities. One example is the Renaissance Computing Institute (RENCI), which leverages collaboration amongst Duke University, NCSU, State of North Carolina, and University of North Carolina at Chapel Hill to catalyze data-driven discoveries for healthcare research, environmental science, and economic and business successes. Another example is Arizona Research Computing (ARC) that is being established as a dynamic collaboration between Arizona's three state universities (Arizona State University, University of Arizona, and Northern Arizona University) in partnership with the Sun Corridor Network, working to advance the research landscape through cutting-edge computational infrastructure and data stewardship, empowering innovation and community growth.

Other workshop participants noted similar emerging models. For example, Arizona and Utah are attempting a consortium approach to support state-wide technology and data science needs (leveraging the missions of the University of Arizona and the University of Utah to serve their states), and universities in New York are collaborating on data science initiatives with support from the Simons Foundation (CUNY, 2024). These regional efforts suggest that some DS / AI organizations see their role not only as campus hubs but also as nodes in broader networks, convening partners across institutions to tackle large-scale data and computing challenges.

Official boards are more common in multi-institution or external-facing organizations, such as RENCI or ICDI. RENCI has an oversight board representing multiple universities that administratively resides at the University of North Carolina at Chapel Hill.

Evolving structures: The organizational and reporting structures also evolve as new research needs emerge. Some DS / AI organizations started as a single, centralized unit, but over time have grown into multiple affiliated centers or programs, with the need of an "umbrella" structure for coordination. The workshop participants noted that such growth, while reflecting success and expansion, can lead to challenges in clarity of oversight and resource allocation. NCSA's experience is illustrative: rather than aggregating everything under one organization, NCSA operates as a hub that coordinates projects across campus without direct control of all of them. This coordination-without-control model works to the extent that the university incentivizes it (for instance, sharing indirect cost returns or providing central funding for joint projects). It also means that NCSA focuses on enabling others' research rather than owning all data science activities. This model highlights considerations about responsibility and accountability, which are concerns that many organizations are addressing as they expand. The increasing impact of data science and AI on all academic disciplines is also motivating significant organizational changes at many universities. For example, the University of Arizona recently created the position of Chief Data Science and AI Officer to provide a single point of entry. This has led to the creation of a new Arizona Institute for AI and Society (AI2S), integrating the existing DSI and ICDI into a more coherent structure.

Summary and recommendations

In summary, organizational models for academic DS / AI organizations range from highly centralized to distributed, and from single-university to multi-institutional, each with its own trade-offs. The workshop discussions underscored not only that an organization's structure should align with the university's needs and culture, but also that intentional coordination (through governance boards, multiple reporting lines, or collaborative agreements) is vital when responsibilities are spread across multiple organizations or universities. In developing or refining a DS / AI organization, it is important to develop clear governance models that align its goals with university priorities. These models should include clear reporting and administrative structures, along with measures of success that are both concrete enough to measure the specific value of the organization and flexible enough to ensure that the organization can be responsive to changing needs across the campus. The DS / AI organizations carry out their work in an ever-changing research landscape due to the emerging nature of data science and now AI. In addition, coordination is a constant challenge as new academic departments / institutes are established with missions partially overlapping with those of the DS / AI organizations. For this reason, regular reviews of the organizational structure are also highly recommended.

Regardless of the formal structures, successful DS / AI organizations understand the importance of having strong champions or advocates among the university leadership who understand the organization's role for the university. Without a senior champion (be it a provost, vice president, or dean), campus-wide organizations can struggle for visibility and sustained support (Parker et al., 2021). This is a unique challenge rarely faced by traditional academic units.

Evolving Mandates and Strategic Alignment

The definition of a DS / AI organization's responsibilities and successes is often the combined result of top-down vision and bottom-up faculty input. For some organizations, the mission was initially set by university leadership (e.g. a Provost or President's charge to "make us a leader in data science") and then refined through faculty committees or a strategic planning process. In other cases, the need for these organizations was first identified by faculty in data science or related fields, such as statistics, computer science, or mathematics, or from another domain with high demand for data analytics, such as genomics, medicine, or business.

Similarly, the initial scope of the DS / AI organizations is often the result of some combination of internal and external input and closely tied to the funding source. For example, organizations established through federal funding are often expected to serve a national research ecosystem. NCSA, for example, funded by the National Science Foundation, was established to develop and deploy advanced cyberinfrastructure to support growing capabilities in computational science for the national ecosystem. Such organizations may also provide unique support to their local community, especially during development of their service model. In contrast, internally or state funded organizations may have a similar scope of service and activities but are more likely to serve a community equivalent to their funding source. Tufts Institute for AI, OSU's TDAI, and U. Michigan's MIDAS, for example, were established by the university administrations and serve as focal points for data science and AI activities and services for their respective universities.

DS / AI organizations are typically created with a relatively clear scope; often balancing research, education, and service (e.g., consulting or infrastructure support); and supporting communities ranging from a part of the campus to a broad regional or national community. The scope is often directly related to the organizational model and structure and the source of funding. However, even when the financial and administrative support of an organization is consistent, the scope often needs to evolve to match the emerging needs of the research community and the rapid advancement of data science and AI technologies. A unique challenge that they must also address is how they fit alongside departments, libraries, central IT, and other entities. A question discussed in the workshop was: Is the DS / AI organization primarily a provider of services (e.g. data infrastructure, consulting, training) or a driver of new research (through its own projects and faculty)? Each university strikes a different balance but most strive for both. In practice, the institute's scope is continually negotiated.

Initial scope

While the specific make-up of each DS / AI organization varies, their work shares much similarity. Typically, it fits into critical areas of research, education, service, community and collaboration, and broader impact. Typical activities within each of these areas include:

- Research:
    - Funding to support pilot projects;
    - Research development support, including team building and proposal development;
    - Consultation and intensive project support;
    - Developing data science / AI tools and software packages;
    - Supporting major research initiatives at schools / colleges / departments or in response to faculty demands;
    - Enabling research rigor, reproducibility, and trustworthiness.
- Education and training:
    - Degree or certificate programs;
    - Postdoctoral training programs;
    - Student research programs;
    - Short courses and workshops;
    - Development of guidelines for AI use in research.
- Service:
    - Cyberinfrastructure, including storage, compute, training and support for users;

    - Software and algorithm development support;
    - Access to data and AI models.
- Community building and collaboration:
    - Faculty hiring;
    - Distinguished visitor programs;
    - Broadening participation in data science and AI-enabled research;
    - Increasing industry internship opportunities for students
    - Research collaboration with industry, non-profits, and government.
- Broader impact:
    - Collaboration with policy makers and regulators;
    - “Data and AI for social good” programs;
    - Upskilling, reskilling, and K-12 education programs.

The evolving mandates

One of the most pressing challenges discussed at the workshop was how DS / AI organizations adapt to rapidly evolving mandates, most notably the expectation to lead campus efforts in AI adoption. AI’s rise to prominence has been breathtakingly fast, with new tools and breakthroughs emerging at “warp speed.” Universities everywhere are grappling with how to support AI research and its adoption across research fields, and incorporate AI into curricula. In many cases, the DS / AI organizations are tapped (officially or unofficially) to spearhead these efforts. As one participant put it, “Helping researchers adopt AI is now one of the most urgent demands in our institute.” Universities are also grappling with the issue of how to transform the existing data science organization into an AI unit, or how to set up new AI units side-by-side with data science units. All such efforts face significant uncertainty: technologies change quickly; best practices (and governance policies) are in flux;’ and no institution has a tried-and-true roadmap for academic AI integration.

One specific challenge is that universities are in a rush to develop AI visions without a template or guidance. Many AI visioning exercises are not well coordinated with data strategies or software strategies. Bottom-up and top-down strategies also need to align. Strategies also cannot stay at the level of defining outcomes but must provide a roadmap for how to achieve the desired outcomes. The DS / AI organizations are involved to various degrees in such visioning exercises, but sometimes not at all. This makes it difficult for the DS / AI organizations to gain clarity on how to spearhead the AI adoption effort.

Another equally daunting challenge is that DS / AI organizations often receive new mandates without commensurate resources (“unfunded mandates”). Several leaders described scenarios of being asked to “coordinate AI across the campus” or “ensure our faculty have AI training.” These organizations need to train their researchers to enhance institutional research capacity, grow external partnerships and engagement, ensure that the university remains connected to cutting-edge AI developments, and secure major funding for AI. As a result, many organizations are supporting their AI activities by reallocating existing funding and staff effort. While this bolsters an organizations' value proposition, this model cannot scale with increasing demands and often detracts from important data science work. Furthermore, the focus on current AI trends (namely Large Language Models and generative AI) can cause the loss of resources for other equally fundamental work. These organizations face enormous pressure to simultaneously seek new resources and jumpstart AI efforts.

Being nimble and strategic

One statement that we often hear is that the academic research model and research universities are not built to be nimble in response to the rapidly changing landscape of technology advancement. However, organizations within a university can be nimble and proactive.

In some cases, DS / AI organizations can shift resources and capabilities to grow in scope. MIDAS, for example, was able to proactively launch programs in AI literacy, demonstrate use cases for AI in research, develop AI use guidelines and training for rigor and reproducibility in AI-enabled research, and establish formal postdoctoral training programs focusing on AI for domain research. These programs provided critical research support across the campus and extended the role of support that MIDAS plays at the University of Michigan (Liu & Jagadish, 2024). The ICDI worked with the Provost’s office to create a campus-wide AI for Access and Integrity Working Group to address the emerging impacts of AI and to facilitate conversations on the potential impacts of AI on instruction, research, and operations. In each of these examples, a broader campus need was addressed by an established DS / AI organization.

To cope with the evolving and unfunded mandates, our central guiding principle is prioritization and focus. Organizations must identify which new demands align with their core mission and strengths. For example, some organizations have chosen to focus their AI efforts on a particular need on campus, such as developing AI training programs for faculty and students. Several workshop participants emphasized the importance of coordination. The DS / AI organization should clarify roles rather than duplicate efforts happening at the Library, central IT, an AI-focused department, or a high-performance computing center. One institute leader described an arrangement where their data science institute leads human capital development for AI (training people and fostering interdisciplinary research teams), whereas a separate campus computing center manages hardware and the library manages data governance. A DS / AI organization may provide coordination with these parties to ensure an integrated campus-wide AI strategy through advisory councils or task forces. For instance, CADS provides user support and training to expand the effective use of AI computing resources managed by central IT, ensuring that these efforts align with and reinforce a coordinated, campus-wide AI strategy.

Another important strategy is seeking external partnerships and funding specifically for AI initiatives. Given limited internal funds, several organizations have looked to industry or foundation partners to kickstart new AI programs. For example, MIDAS leveraged a philanthropic grant to launch campus-wide AI policy research seed grants as a component of their effort to meet the mandate. Such partnerships, when aligned with the university's goals, can fill resource gaps for AI.

Keeping pace with the evolving mandates

Workshop participants acknowledged that no DS / AI organization can keep pace with every AI development. One practical approach is to focus on foundational capacity: ensure that the campus has the expertise and ethical framework to use AI tools, rather than trying to train researchers to master every cutting-edge algorithm. Some DS / AI organizations have started offering short courses or bootcamps on using popular AI tools to quickly raise the baseline competency of researchers. Others have formed working groups on responsible AI to develop guidelines for their campus on issues such as data privacy, bias, and generative AI use. Through such approaches, the DS / AI organizations position themselves as enablers of and guides on AI. They are also connectors-connecting faculty and researchers to form interdisciplinary AI research teams; connecting administrators with faculty to inform policy; and connecting the university to external partners.

Workshop discussions also touched on other emerging mandates associated with AI. DS / AI organizations frequently find themselves involved in campus-wide initiatives around data governance, open science, and research computing. As data policies evolve (for example, new federal mandates for data sharing or reproducibility (The White House, 2025), the DS / AI organizations may be asked to help the campus respond. Here again, the challenge is to be effective with limited resources, collaborating with other campus units (such as the library for data management plans), and demonstrating the added value of the DS / AI organization. Organizations that successfully navigate evolving mandates are those that maintain a clear focus on their mission (i.e., supporting research, education, or both) and communicate to leadership what they cannot deliver without additional support.

Recommendations

The mandates of DS / AI organizations are not static. They continually evolve in response to new technologies, institutional needs, and societal expectations. What begins as a focused mission (such as catalyzing interdisciplinary data analytics) can quickly expand into additional roles such as spearheading campus-wide AI initiatives. These broadened responsibilities reflect the rising strategic importance of data science and AI across all domains, but they also introduce significant tensions. A recurring theme is the challenges of balancing breadth and focus as the organizations fulfill their original objectives and accommodate new demands.

We recommend that university leadership regularly revisit a DS / AI organization's mandate to ensure it remains aligned with both the university's changing priorities and the organization's core strengths. The organization's resource allocation, authority, and structural support need to ensure that new initiatives succeed.

It is equally important to define boundaries and foster coordination to prevent inefficient redundancies and turf conflicts. For leadership of DS / AI organizations, agility is essential when exploring emerging areas such as ethical AI, data policy, or novel interdisciplinary collaborations. However, DS / AI organizations need to keep sight of their foundational mission, proactively guide and support the evolving mandates, creatively seek resources and partners, and coordinate with the rest of the campus.

Funding Models and Sustainability

The long-term sustainability of DS / AI organizations is tightly linked to their funding models, which should reflect their scope of activity and position on campus. However, both the breadth of mandates and the novelty of the data science / AI fields pose funding challenges that require creative approaches.

Funding portfolios

Almost all organizations rely on a mix of funding sources, each with advantages and limitations (Figure 1). Common sources include: direct university allocations (central funds or support from the Provost or VPR), federal grants (for research projects, research centers, and training programs), philanthropy (gifts or endowment), industry partnerships, and occasionally state government appropriations. Indirect cost revenues from grants, tuition income and service recharge are sensitive issues because invariably such income streams are already highly valued by traditional research and teaching units.

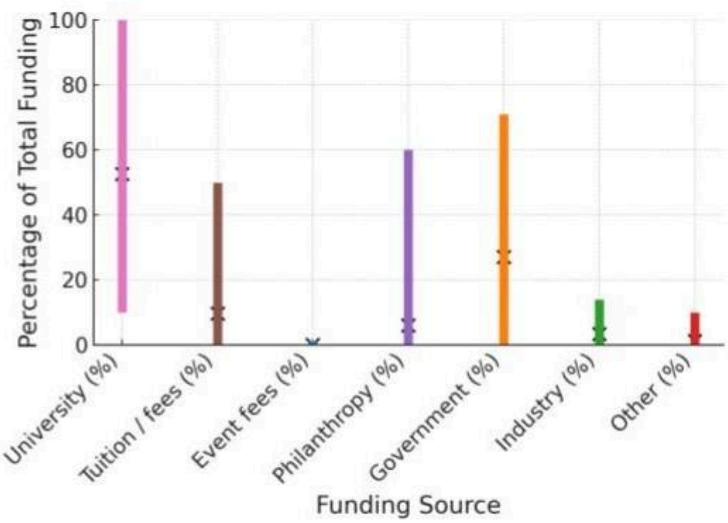

Figure 1. Funding models of the DS / AI organizations. The x axis represents the different types of funding. The y axis represents the distribution and the mean of percentages for each type of funding. For example, the range of industry funding (0 - 15%) indicates that the institutes in our survey received as little as none, and as much as 15% of their total funding from industry sources.

An informal survey of ten DS / AI organizations showed that most organizations patch together multiple sources to cover their operations (Table 1). This can be a strength. As one participant noted: “having multiple funding streams provides resilience.” Current funding models rely heavily on university investment, with all organizations receiving university funding ranging from 10% to 100% of their budget. This is supplemented by:

- Federal or government funding with six of ten organizations reporting support of up to ⅔ of overall funding,
- Tuition revenue or certificate fees were reported by five organizations, from a small percentage of the organization’s total budget to 50% for more academic-focused institutes,
- Philanthropy was reported by two organizations, and
- Industry funding accounts for a small percentage of the budget for five organizations.

Some funding model examples showcase the results of a combination of deliberate planning, leveraging institutional strengths and connections, and opportunities.

- MIDAS supplements its base university budget with gifts and grants, with the largest being funding from Schmidt Sciences for its AI in Science postdoctoral training program.
- NCSA balances a large portfolio of federal research grants with recurring state funding, with internal coordination over the allocation of credit and indirect cost revenue among collaborating academic departments.
- RENCI receives state funding and pursues a range of federal grants for research infrastructure and data science outreach.

- The Texas A&M Institute of Data Science (TAMIDS) draws from university funding, state agency funds, and industry-sponsored projects.
- The School of Data Science at the University of North Carolina at Charlotte has a strong teaching component and relies heavily on tuition revenue, in addition to state funds.
- The eScience Institute is supported by a mix of state and university funds, federal research grants, and philanthropic support notably for the university's Scientific Software Engineering Center (SSEC) which sits under the eScience umbrella.

Each organization's sources of funding are unique. The common thread is that success requires tapping into as many avenues as possible and aligning each with parts of the organization's mission.

Expenditures and investment priorities
The use of funding within a DS / AI organization includes several major categories of expenditure, as identified by workshop participants:

- Administrative and program staff: These may include an organization's directors, business administrators, event coordinators, communication and marketing staff. Most institutes operate with lean administrative teams, but even a small team needs stable funding.
- Faculty appointments: A number of DS / AI organizations jointly appoint faculty members with other campus units or provide the administrative home for a small number of faculty members.
- Technical and research support staff: Technical staff provide research consultation, coordination, and provide grant and project support. They can be research software engineers, data scientists, data curators, certified project managers, grant writers, or AI specialists. In addition, they often bring in grants to cover part of their salary. Hiring and retaining such staff members is a significant expense, especially because of strong competition from industry. Yet they are increasingly crucial in academic research and are a distinctive feature of DS / AI organizations. Given the fast evolving nature of the AI landscape, these personnel also need time and resources for upskilling and professional development (Van Tuyl et al., 2023).
- Training programs and teaching staff: They serve as instructors and managers for knowledge sharing programs such as data science and AI summer schools, workshops, bootcamps, semester-long courses, and faculty development sessions. These programs spread expertise and often require funds for instructors, curriculum development, and participant support.
- Seed funding: Internal grant programs stimulate new interdisciplinary research projects and support students, researchers, and faculty. They are especially important for adapting to the fast-evolving AI technologies in the current landscape when the competition for federal funding is fierce. With clear expectations (such as expanding the seed grant project to secure external funding) and structured reporting, seed funds can be highly effective in catalyzing larger grants in the long-term.
- Students and postdoctoral fellows: Salary and stipends are needed to support postdoctoral fellows, graduate student fellowships, or undergraduate research experiences (e.g., summer internships).
- Community building and outreach: Events and support for communities of practice bring together researchers across the university as well as external partners. Many organizations host seminar series, research mixers, annual summits, working groups, and industry showcases.

These expenditures highlight how DS / AI organizations must invest in personnel and programming on a limited budget. One workshop attendee wryly noted that running a DS / AI organization feels like "funding a mini-university within the university" because there are teaching elements, research elements, and infrastructure elements, and each of these elements needs support.

Challenges in funding and sustainability
A candid workshop discussion of challenges revealed common issues that make sustainability precarious. The work at DS / AI organizations often has an opportunistic element because the types of programs that can be developed or expanded upon often depend on funding opportunities. Each type of funding source presents unique challenges. For example, heavy reliance on time-limited grants and gifts is challenging for long-term strategic planning and can limit commitments to multi-year initiatives or personnel appointments. Federal grants are mostly project-driven and focus on producing original research outcomes instead of building or expanding research capacity. University funds are limited and often non-recurring, especially when coming from one-time initiatives. Industry funding may come with constraints due to intellectual property rights and

may quickly shift with market trends. And, as already mentioned, indirect costs, tuition, and service charges can become contentious issues among institutes on campus. In addition, the unique position of the DS / AI organizations poses challenges that traditional departments do not usually face, such as:

- Fragmentation and competition for resources: Many major universities have multiple departments and institutes with DS / AI as part of their focus and they may compete for the same internal funding or philanthropic donors. This can lead to confusion about who should be funded to do what and the overall fundraising effort can be diluted if uncoordinated.
- Stakeholder alignment and advocacy: Workshop participants noted that they are often confused about who advocates for them on campus. DS / AI organizations often serve many masters (central administration and multiple colleges). With distributed stakeholders, everyone can value the organization in principle, yet no single entity feels responsible to fund it robustly or even to allocate campus fundraising support. Additionally, competing priorities among stakeholders can dilute funding impact. For instance, if an organization is expected to develop research grants, support teaching, drive industry partnerships, and improve research infrastructure, it may receive modest contributions from each area rather than a concerted investment from one source. Clarity and strong advocacy at the leadership level is critical to overcoming this challenge.
- Demonstrating return on investment (ROI): Because the impact of DS / AI organizations can be indirect (facilitating other people's research rather than producing research outputs within the organization), quantifying ROI is a major challenge. Traditional metrics, such as the number of publications or the dollar amount of grants, often underestimate the organization's impact. Success stories and engagement data are additional metrics that demonstrate how DS / AI organizations deliver value in traditional or non-traditional ways. This idea will be expanded upon in the next section.

Recommendations for sustainable funding

The workshop participants recommend several strategies:

- Diversify funding streams: While obvious, it bears repeating that a diversified portfolio is healthier. Beyond the usual federal and university sources, our organizations are exploring industry partnerships, state government programs, and fee-for-service models. Industry partnerships can range from corporate-sponsored research projects to membership consortia where companies pay an annual fee to access university expertise. State funding might be available if an organization's work aligns with economic development or workforce goals (e.g., a state initiative in AI workforce training). Some organizations have started offering specialized services (e.g., data analysis support or professional education courses) on a recharge or fee basis to generate income; this can work if there is demand, though it can be perceived as detracting from core academic activities.
- Build shared accountability for resources: Create joint funding mechanisms where multiple stakeholders invest together. For instance, one successful model is a matching program, with the central administration matching the funds from colleges or external sponsors, thus ensuring that everyone has vested interest and shared commitment. Another approach is establishing a governance board including representatives from key colleges and central offices, which not only guides the organization but also helps secure co-funding from those constituencies.
- Align funding requests with institutional goals: When seeking funding (internally or externally), the organization's role in addressing pressing institutional or regional needs is critical. If the university's strategic plan calls for growth in AI and data-enabled research, explicitly tie the organization's budget request to those goals (e.g., "This funding will allow us to train X number of faculty in AI, leading to Y increase in grant activity").
- Invest in long-term capacity building: It can be tempting to allocate funds only to immediate needs or to claim immediate wins, but dedicating some resources to capacity-building (e.g., staff professional development, improving data infrastructure, or seeding risky interdisciplinary ideas) adds important value in the long-term. The concern about sustainability should not preclude us from investing in the strategic efforts for the long term. What we need to do, instead, is to always improve how we can articulate the value of such long-term strategic investments to stakeholders to win their support.
- Track downstream results and gather user stories: For example, to justify faculty training programs, the organizations should document how participation in these programs can lead to larger grants or significant publications. These downstream metrics help make a compelling argument for continued funding. In addition, the participants mentioned the power of qualitative evidence. Collecting testimonials from faculty who achieved a breakthrough because of the organization's support, or from

students who launched careers due to the organization's academic programs, can influence funders and donors. These narratives can complement quantitative metrics and make a strong case for the organization.

Ensuring financial sustainability is a complex but critical aspect of leading a DS / AI organization. There is general agreement that a mixed funding model is unavoidable and preferred, and the organizations must be adept at both entrepreneurial fundraising and internal budgeting. When this workshop took place in 2024, no one anticipated the drastic change of the federal funding landscape for scientific research that unfolded in 2025. DS / AI organizations now need to be even more nimble to incorporate new funding streams. It will likely be more difficult for DS / AI organizations to receive funding from their universities (including schools and colleges). They will need to rely more on the direct charge model for services that they provide to the university research community, as well as developing stronger value propositions for industry and philanthropy funding. They will need to secure their universities' support to intensify fundraising efforts and seek more flexible and creative approaches. University leaders should consider providing stable baseline funding to cover key staff and programs, advocating for them in resource allocation discussions, and encouraging collaborative funding approaches that bring multiple stakeholders together. When the organizations are well-funded and secure, they become engines of innovation and interdisciplinary success that benefit the whole university.

Articulating Our Values and Measuring Success

Challenges in articulating values and metrics

The DS / AI organizations sit in traditional academic research institutions but their role is very different from a traditional academic unit or even an interdisciplinary research institute. By design, DS / AI organizations play a vital role in enabling interdisciplinary research, fostering collaboration, and advancing the integration of cutting-edge technologies into a wide range of academic and real-world applications. They support a diverse research ecosystem by providing the necessary infrastructure, expertise, and resources. As such, success is not just the sum of individual faculty achievements (which traditional metrics capture) but the added value generated by the organization's programs and collaborations as well. Many of the standard metrics for academic research, such as grant awards and publications, are ill-suited for capturing the broader, transformative impacts of these DS / AI organizations. For example, many DS / AI organizations offer seed funding programs, faculty training, in addition to applied data science and/or software engineering support. But causality between these programs and a research project's success is not easy to determine because an interdisciplinary project can receive a range of initial support before it takes off and the time required for a project to succeed can be long, thus diluting any causal effect.

Therefore, we need metrics to demonstrate how we may contribute to broader academic, research, and societal goals; promote the use and integration of DS / AI technologies into diverse fields; and support long-term interdisciplinary transformation. Some examples of important measurements might include:

- Depth of impact: Are researchers increasingly adopting data science and AI methodologies in their work in more sophisticated or novel ways and what research outcomes have resulted?
- Long-term transformation: How are data science / AI becoming more integrated into research across the university?
- Infrastructure effectiveness: Do researchers find the organization's computing resources, data access, and consulting services up-to-date, appropriate, and adequate for research purposes, and usable?
- Interdisciplinary integration: How much more interdisciplinary research and innovation are happening through the organization's work and how does this result in better and more significant research discoveries or inventions?
- Policy and ethics leadership: Is the institute influencing discussions and practices of responsible data science and AI, open science, and the trustworthiness of research?

Such measures of deeper and longer-term impact are difficult to quantify in meaningful terms and compare across organizations. It is also very difficult to know the counterfactual: if a DS / AI organization did not exist, how much could have been accomplished through the traditional units and faculty's own efforts? Another complication is that expectations vary by stakeholder. University leadership might care about high-profile outcomes (e.g. major grants or reputational gains), whereas faculty might value more concrete research benefits (e.g. access to computing resources or seed funding), and external funders might look for societal impact or workforce development outcomes. Thus, an organization might need a portfolio of metrics to satisfy different audiences. The workshop participants stressed the importance of aligning metrics with the organization's mission and the definition of success agreed upon with the university. Clarity in mission drives the ability to measure progress effectively. For example, if the mission is "to build campus-wide data science capacity," then measures of how many people are getting trained or adopting data science are central. If the mission is "to spur interdisciplinary data-intensive research," then tracking interdisciplinary grants and publications is key.

Defining metrics for the DS / AI organizations is a serious challenge (Blake et al., 2024). But we need to show our success to our stakeholders, including funders, university leaders, and our research community. In addition, metrics serve as an internal learning function. They inform strategic decisions and help determine whether an organization is truly making a significant, meaningful impact. Moreover, having a clear definition of success, grounded in the organization's mission and the university's priorities, allows the organization to communicate its story compellingly to potential supporters and enable additional funding and resources.

Current metrics

The workshop participants shared a number of metrics that they currently track or have found useful, including:

- Community building: The numbers of faculty, trainees, staff and external members engaged with the organization and the research units and disciplines they represent; and the number and variety of programs / activities that support the community.
- Training and workforce development: The number and variety of workshops, bootcamps, and tutorials offered, and the number of attendees and their unit and disciplinary representations.
- Grant funding: External research funding that the organization helps to secure. This can be measured as the number of grants or funding amount that the organization or its personnel serve as leads or co-PIs, as well as grants received by affiliates that the organization significantly supported (e.g., by providing pilot data or matchmaking collaborators).
- Publications and knowledge outputs: Publications from projects or collaborations supported by the organization, as well as datasets, software tools, or open educational resources the organization helped create or fund.
- Career trajectories: For postdoctoral fellows and/or student trainees these can be a measure of the success of the program in setting up participants for future career success.
- Interdisciplinary collaboration metrics: Some organizations count the number of new interdisciplinary teams or projects formed via their events or programs. A related metric is the number of grant proposals submitted that involve cross-departmental teams that met through the organization.
- Long-term outcomes and success stories: Tracking downstream results such as subsequent grant success rates for seed-funded projects or participants of summer schools provides evidence of sustained impact.
- Adoption of best practices (e.g., responsible AI): The number of researchers that adopt certain frameworks or guidelines introduced or championed by the organization, including ethical or open science approaches. For example, an organization might train faculty in an ethical AI toolkit and later assess how many incorporated those practices in their research.
- Resource usage indicators: Some organizations manage or provide access to computing resources, so another straightforward metric is utilization of those resources by the campus community (e.g., percentage of the university's high-performance computing hours used for data science / AI research, the number of datasets hosted and actively used, and the number of departments included in the user base). High utilization can demonstrate demand and impact, though as we discuss later, it should be contextualized by how those resources further research goals.
- External partnerships and broader impact: The number and scope of partnerships with industry, government, or community groups. This might include joint research projects, tech transfer outcomes, joint events, or "data and AI for social good" projects and their outcomes.

It's evident that the above list is broad. Not every organization tracks all of them; metrics need to be selected to reflect each organization's mission and activities. Importantly, the group emphasized that metrics should not just be collected, but actually used to evaluate and adjust strategies. If certain programs are not yielding the expected outcomes (e.g., lots of workshops held without an increase in interdisciplinary research output), that insight should feed back into decisions on where to invest time and money.

Rethinking metrics for institutional impact
The workshop participants delved deeply into brainstorming innovative metrics that capture impact and research transformation. We collectively identified several dimensions of impact that metrics should cover, and examples of creative metrics that some organizations are experimenting with.

Transforming the Research Landscape Through Methodology Adoption. AI and data science methodology adoption rates represent a fundamental indicator of an organization's success in transforming the research landscape. Does the organization increase data science and AI skills and activities across campus? How many researchers, departments and research disciplines are integrating AI or data science into their work who previously were not? Are these methods spreading beyond the early adopters into the wider faculty body?

The DS / AI organizations are starting to experiment with metrics for this dimension. For instance, MIDAS has implemented post-workshop surveys conducted 6-12 months after training events to track how participants have incorporated new methods into their research workflows and if they have shared those methods with colleagues. RENCI has been creating communities of practice around specific methodologies (for instance, a regular working group on data management or an interest group on AI in healthcare). These groups provide a natural mechanism for tracking continued engagement and methodology adoption, and a place where participants self-report their progress and challenges, which can be qualitative metrics of how their capabilities are growing over time.

Documenting research enablement and acceleration. Is the organization shortening the time to discovery or enabling research breakthroughs that wouldn't happen otherwise? Are projects being completed faster due to the organization's support? Are there notable discoveries or innovations where the use of data science / AI (supported by the organization) was a key factor? Tracking major discoveries or breakthroughs enabled by data science / AI methods provides compelling evidence of an organization's impact. One concrete metric could be the number of major research results (e.g., publications, patents, prototypes) where the organization's resources or expertise are acknowledged. Another could be tracking if data science / AI involvement leads to follow-on activities such as commercialization of research outputs or new interdisciplinary centers being formed.

Workshop participants emphasized the importance of building systems to capture these outcomes rather than relying on *ad hoc* reporting. The University of Arizona's ICDI has compiled a series of research spotlights or "research case studies" that highlight instances where data science / AI techniques enabled a breakthrough in various disciplines. Each spotlight details the problem, the data or AI approach used (with the organization's support), and the outcome. These narratives serve as compelling qualitative evidence of impact. TDAI at The Ohio State University has developed a structured interview protocol to capture the specific ways in which its resources and expertise contributed to research breakthroughs, thus creating an impact archive. The interview asks questions such as: What was the unique contribution of TDAI (expertise, tools, funding) to your project? Would this project have been possible without TDAI? Did it lead to new interdisciplinary relationships or follow-on projects? Similarly, Tufts Institute for AI also collects researcher testimonials.

Measuring Depth and Sustainability of Interdisciplinary Impact. Interdisciplinary research impact should be assessed not just by counting collaborations, but also by examining their depth and sustainability. For example: How many faculty from different departments began collaborating because they attended a program at a DS / AI organization, and continued to work together thereafter? If an institute hosted an interdisciplinary postdoc who works with two mentors from different fields, did that team stay connected and perhaps create a long-term research partnership? The number of new collaborations formed across departments due to the institute's facilitation serves as a starting point, but tracking how many cross-disciplinary grants and centers emerged from these connections, what research they are able to do, and how they in turn inspire more collaborations and research breakthroughs offers greater insights into lasting impact.

RENCI, TDAI, and MIDAS are exploring social network analysis to measure interdisciplinary impact. By analyzing co-authorship networks or team compositions in grant proposals, they aim to quantify changes in connectivity over time and with various programs / activities at the organization. If over a few years one sees a significant increase in cross-department connections in the network graph, that can be presented as evidence that the organization’s presence is knitting the campus together in new ways. Several organizations also reported success in tracking "second-generation" collaborations: where researchers who initially connected through the organization went on to form additional collaborative relationships. These organic extensions of the collaborative network represent a powerful indicator of sustainable impact. The Tufts Institute for AI has begun tracking how many departments adopt joint hiring practices or create shared curricula following collaborations initiated through the organization’s activities as evidence of structural changes.

Promoting Responsible AI and Open Science. Measuring how many researchers adopt ethical AI practices after engaging with the organization can demonstrate leadership in responsible research. Similarly, tracking the organization's role in fostering open data and open software development shows its contribution to building research capacity beyond traditional academic outputs. Metrics could include the adoption rate of ethical guidelines promoted by the organization (e.g., number of projects using its data ethics checklist), or counts of researchers undergoing ethics training. More qualitatively, it could involve documenting cases where the organization helped avoid an ethical pitfall or improved the rigor of a study.

The University of Utah's Responsible AI Initiative has developed a rubric for assessing how research projects incorporate responsible AI principles, and can track changes in practice over time. Several other organizations have begun monitoring the inclusion of ethical considerations in grant proposals and publications following engagement with their resources.

Open science practices provide another dimension for measuring impact. Several organizations track the number of researchers who transition to open data repositories or adopt reproducible research workflows following their training activities. These metrics capture the institute's contribution to improving research transparency and reliability, which are outcomes that benefit the entire academic community but might not be reflected in traditional productivity measures.

Reframing Infrastructure Usage Metrics. Sustainable infrastructure usage requires a shift from measuring computing resources consumed to assessing how effectively these resources enable new research. This approach acknowledges that the value of computing infrastructure lies not in its utilization rate but in its ability to support transformative research. Hence, institutes should develop metrics that capture the relationship between infrastructure investments and research outcomes.

Workshop participants noted success in tracking how computing resources facilitate new methodological approaches or enable researchers to work with previously intractable datasets. NCSA has developed "impact stories" that trace the connection between computational resources and specific research outcomes. By documenting examples where advanced computing capabilities enabled researchers to pursue questions that would otherwise have been infeasible, they demonstrate the transformative potential of infrastructure investments. DSI at the University of Arizona measures how many researchers transition from desktop computing to high-performance computing environments following training, which represents a qualitative shift in research capabilities. At Texas State University, CADS monitors both the extent and depth of researcher engagement with data science computing infrastructure following participation in CADS-led workshops and use of their training materials.

Societal and External Impact. This dimension looks at how research enabled by the DS / AI organizations translates beyond the campus. Are solutions developed with the organization’s support being deployed in real-world settings (industry, healthcare, government, community)? Measures might be: The number and impact of collaborative projects with direct societal impact, or case studies of research that influences policy or business practice. For instance, an organization might highlight that its data scientists helped city governments use data to improve services, or that research it facilitated on climate data informed an environmental policy. These measurements show that the organization is not only advancing academic goals but also contributing to the university’s public mission.

Challenges and recommendations

Articulating value through thoughtfully chosen metrics is now as much a part of an organization’s job as anything else. Our workshop reinforced that the DS / AI organizations must hold themselves to the same innovative spirit in assessment that they apply in research: be data-driven, experimental, and open to new ways of measuring success. By doing so, they can more convincingly demonstrate their critical role in transforming the university's research enterprise in the era of data and AI. Workshop participants also emphasized the importance of sharing metrics frameworks and assessment tools so that the community can benefit from collective experience.

A strong message from the workshop was that metrics should not be purely quantitative bean-counting. We need to measure what matters even if it is not easy. Some aspects of an organization's impact will always be qualitative or hard to quantify (such as "culture change" or "increased interdisciplinary mindset" on campus). The key is to collect narratives systematically and tie them to the bigger picture. At the same time, having some concrete numbers lends credibility and allows year-over-year tracking. The recommendation was to use quantitative metrics to show scale and reach, and qualitative examples to show depth and meaning.
The workshop discussions highlighted how qualitative evidence can be particularly effective when communicating with university leadership and potential funders. One approach discussed was to pair every traditional metric with a narrative or a "so what" explanation. If you claim 500 people attended your workshops this year (a quantitative metric), complement that with a follow-up result: for example, 50% of them had applied the new skills in their research, and 10% initiated new interdisciplinary projects. That translation from activity to outcome is what truly demonstrates impact.

Finally, the participants cautioned that implementing new metrics can be challenging. Long-term tracking requires consistent effort and sometimes cooperation from other campus units in order to gather data. In addition, not everything that an organization would like to measure is currently recorded at an institutional level. The university may also lack a system or resources for institution-level long-term tracking. Despite these hurdles, the consensus was that investing in better metrics is worthwhile. It not only helps justify the organization's existence, but also sharpens its own understanding of where it is effective and where it needs to improve. The workshop participants identified several approaches to addressing these challenges. Some organizations have developed lightweight but consistent data collection methods that can be sustained over time without creating undue burden on staff or participants. Others have partnered with university assessment offices to incorporate impact tracking into existing institutional processes.

Conclusion

The evolution of academic DS / AI organizations offers important lessons for research university leaders. These organizations have emerged as engines of interdisciplinary innovation and technology adoption, but their success depends on strategic alignment with university priorities and supportive institutional frameworks. Based on the workshop insights, we provide several recommendations for university leadership.

1. Aligning organizational structure with university mission to empower the DS / AI organizations. Universities should intentionally design the organizational placement and reporting structure of DS / AI organizations to fit their mission. Whether an organization reports to a VPR, the Provost, or multiple offices, clarity of authority and purpose is essential. Leaders must then empower the organization within that structure by advocating and championing for it during budget and strategy discussions, and giving it a seat at the table in campus-wide initiatives. An empowered organization can act as a catalyst across silos.

2. Providing resources that are appropriate for the mandates. When asking an organization to take on new priorities such as leading the university's AI strategy, university leadership should consider the resource implications. Unfunded mandates risk overextending the organization. Leaders should strive to at least partially resource new initiatives (through funding, additional positions, or reallocation of existing support) or help the organization secure external funds. If budget constraints make that impossible, then expectations should be managed and phased. Additionally, creating coordinating structures such as AI advisory councils can signal that implementing the AI mandate is a shared responsibility and not solely on the organization's shoulders.

3. Encourage sustainable funding strategies. University leaders overseeing these organizations need to adopt a long-term view on funding. These might include committing stable core funding for the organization's critical operations and supporting its efforts to diversify revenue. Leaders can open doors to potential donors, advocate for state or federal support, and facilitate industry engagements by leveraging their networks. Where appropriate, integrate the organization into capital campaigns or strategic investment plans of the university.

DS / AI organizations can fall between traditional budgetary units. Therefore, a collaborative funding model (multiple colleges or offices contributing) can be very effective. The returns on such investment manifest in research competitiveness and campus modernization that benefit all contributors. Also, if multiple units are addressing similar domains, consider consolidating efforts or clearly delineating roles to avoid redundant funding requests and to present a unified vision to external sponsors.

4. Institutionalize effective metrics. Leadership should support organizations to develop robust evaluation frameworks. This could involve investing in data infrastructure to track cross-department collaborations, or tasking institutional research offices to help gather data. More importantly, once good metrics are in place, use them in decision-making. For instance, if an organization's metrics show high demand for researcher training, allocate additional resources or joint hires to address that area. Use annual reports from the organization not just as retrospective documents but as planning tools. University leaders might also consider asking the organization to present its progress and challenges using both metrics and stories, and then engage in strategic adjustments. This practice changes the conversation from "here's what we did" to "here's what we learned and what we should do."

5. Embrace the organization as a strategic partner. The rise of data science and AI touches every corner of the university. A campus-wide organization can be a strategic asset in navigating this transformation, but only if it's leveraged effectively. University leaders should integrate the organization into their broader strategy. For example, if the university is developing an AI ethics policy, it should involve the organization. When pursuing a major interdisciplinary grant or initiative, a university should leverage the DS / AI organization's network and expertise. The organization is a vehicle to achieve the university's ambitions in research innovation and societal impact.

In conclusion, academic data science and AI organizations are crucial hubs of interdisciplinary collaboration and innovation and help universities stay at the cutting edge of research. The workshop reaffirmed that while these organizations face significant challenges from rapid technological change to building sustainability and demonstrating impact, they are meeting those challenges with creativity and resilience. The strategies outlined in this article provide a roadmap for both organization and university leaders. By aligning structure to mission, resourcing mandates wisely, fostering sustainable funding, measuring what matters, and developing strategic partnership, university leadership can position these organizations to play a central role in the transformation of the entire academic enterprise to thrive in the era of data and AI.

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