

# Orchestrating and Designing Data Collaboratives: What Governance Model is Fit for Purpose?

Dr. Stefaan Verhulst

## Abstract

As data sharing and reuse become central to scientific discovery, artificial intelligence, and public decision-making, the challenge of data governance has shifted from a primarily technical problem to one of institutional design. Over the past decade, a wide range of governance models for data collaboration have emerged—including data trusts, data commons, data cooperatives, data intermediaries, data unions, data sandboxes, and data spaces. These models are often presented as competing institutional solutions to the problem of responsible data sharing. This paper argues instead that such models represent distinct governance responses to different structural challenges within data ecosystems.

Building on the concept of *data collaboratives*—which I introduced in 2017 as cross-sectoral arrangements for responsible data reuse in the public interest—I propose a purpose-driven typology that identifies seven governance archetypes and the specific coordination problems they address, including transaction costs, power asymmetries, legitimacy deficits, collective governance needs, ownership inequality, systemic uncertainty, and scaling complexity.

I argue that the question is not which governance model is normatively superior, but rather which model is *fit for purpose* within particular institutional contexts. The paper concludes by introducing a functional theory of data collaboration centered on *institutional orchestration*, whereby multiple governance arrangements coexist and evolve within polycentric data ecosystems. In this framework, strategic data stewardship becomes essential for diagnosing governance needs and sequencing institutional responses that enable responsible and sustainable data reuse.

## 1. Introduction

Data governance has moved in recent years from a predominantly technical question toward an institutional and even societal one. As data sharing and reuse become increasingly central to artificial intelligence, public decision-making, and societal innovation, the core challenge is no longer simply one of enabling access but rather to determine the [legal, ethical, and normative](#) conditions under which data should be accessed, stewarded, and governed.

In this context, the role of [data collaboratives](#), a concept that I introduced in 2017, has grown increasingly foundational. Data reuse today requires new forms of cross-sector cooperation that redistribute roles, responsibilities, and risks across stakeholders. Data collaboratives offer a

framing for such cooperation—all without prescribing a single institutional form, and while leaving open a landscape upon which diverse governance mechanisms and forms can emerge.

Over the past decade, this landscape has diversified into a growing ecosystem of governance models: [data intermediaries](#), [data trusts](#), [data unions](#), [data commons](#), [data cooperatives](#), [data sandboxes](#), [data spaces](#), and more. These concepts are often treated as competing alternatives, different pathways toward the same goal. In fact, such a framing obscures the reality that each model addresses distinct governance challenges and includes different models of authority, participation, value distribution, and risk.

In what follows, we propose a purpose-driven typology for different data collaborative models. Describing seven different approaches, we argue that institutional governance arrangements for data reuse should be understood not as normative choices or preferences but as functional responses to specific coordination and governance challenges. As such, the key analytical question facing policymakers becomes: Which institutional form is fit for which purpose? We explore this question in Section 4, where we argue for a new theory—and practice—of orchestrated institutional governance.

Section 2 describes the contemporary data reuse landscape and some key benefits offered by data collaboratives. Data collaboratives, we argue, are best understood as a meta-framework for data reuse and sharing, offering broad guidance rather than any specific institutional form. In Section 3 we outline some of the most common models that have emerged, and explain the different needs and challenges to which they respond.

## 2. Data Reuse and Data Collaboratives

The contemporary data landscape is increasingly characterized by bifurcation. On the one hand, there are growing concerns about [privacy violations](#), [unauthorized scraping](#), [commercial extraction](#), [opaque algorithmic](#) uses, and the [concentration of data power](#) in a small number of actors. On the other hand, there is growing recognition of the societal costs of [not sharing data](#). Responsible data reuse has become central to advances in a range of sectors, including artificial intelligence, science, public health, agriculture, and mobility. [Cross-sector collaboration](#) in these fields and others can unlock insights and public value that no single actor—or siloed data set—could generate alone.

This bifurcation is often framed as a tension between the perils of *misuse* and the lost potential of *missed use*. Yet such a binary framing is too simplistic. The challenge is not to choose between restriction and openness—or regulation and innovation—but rather to design institutional arrangements that enable [responsible data reuse](#). Such arrangements would recognize both the risks and benefits of data sharing, and would embed safeguards, accountability, and participatory governance into an increasingly datafied world.

In other words, the questions surrounding data reuse are fundamentally related to governance and institutional design. The problem is not whether data should be shared, but under what conditions, through what structures, and with what allocation of authority and responsibility.

Within this context, data collaboratives have emerged as a particularly promising avenue. Broadly conceived, [data collaboratives](#) can be conceptualized as an umbrella category describing cross-sectoral arrangements, through which data is made accessible and potentially reused to generate public value. Their defining characteristics include:

- cross-organizational responsible data sharing;
- public-interest orientation;
- novel governance arrangements;
- negotiated allocation of benefits and responsibilities.

Importantly, the concept of data collaboratives is *institutionally agnostic*. Describable as a meta-framework rather than any specific structure, it does not prescribe for instance whether governance should be centralized, participatory, independent, or market-based. Instead, it invites experimentation and context-sensitivity, with institutional design that responds to the [specific challenges and circumstances](#) of particular data or data-sharing endeavors.

In what follows, we examine several models of data collaboration that have emerged in recent years. Each of these models, we argue, is suited to addressing different constraints or concerns pertaining to data sharing and reuse within data ecosystems.

### 3. Seven Governance Archetypes

As noted, recent years have witnessed a proliferation of models for data collaboratives. Seven approaches have gained particular prominence:

- **Data intermediaries**, which act as brokers to reduce transaction costs and facilitate trusted exchange between data holders and users.
- **Data unions or coalitions**, which aggregate participants to strengthen collective bargaining power in data markets.
- **Data trusts**, which delegate decision-making authority to independent fiduciaries acting on behalf of defined beneficiaries.
- **Data commons**, which establish participatory governance structures for shared stewardship of pooled datasets.
- **Data cooperatives**, which embed democratic ownership and member control directly into data governance arrangements.
- **Data sandboxes**, which create controlled experimental environments to test governance rules and data uses before scaling.

- **Data spaces**, which provide federated infrastructure and shared standards to enable interoperability across sectors or jurisdictions.

This proliferation of models may at first glance create an impression of conceptual—or operational— fragmentation. Yet this diversity becomes more intelligible when viewed in the context of specific risks and opportunities in the data reuse landscape. Rather than representing competing models, these arrangements in fact embody distinct governance logics that emerge in response to different forms of failure within data ecosystems.

In other words, form follows function. Each governance structure emerges to address particular governance challenges, and provides a specialized focus that solves an underlying imbalance in data reuse partnership. As described further below, these imbalances include coordination failures, power asymmetries, legitimacy deficits, uncertainty, and scaling constraints. Because each governance archetype represents a response to one or more of these problems, a successful data collaborative implementation relies on the leadership and insights of established data leaders empowered to think systematically about needs and context—a role we call *strategic data stewardship*.

**Table 1. Problems, Collaborative Models, and Institutional Purpose**

| Problem                                                                                                                       | Collaborative Model                | Institutional Purpose                                                                                            |
|-------------------------------------------------------------------------------------------------------------------------------|------------------------------------|------------------------------------------------------------------------------------------------------------------|
| <b>Coordination failure:</b><br>Difficulty partners have in working together due to lack of capacity, trust, or understanding | <b>Data Intermediaries</b>         | Brokerage and transaction-cost reduction through negotiated rules and <a href="#">operational intermediation</a> |
| <b>Bargaining asymmetry:</b><br>Difficulty partners have in guaranteeing their interests due to power imbalances              | <b>Data Unions (or Coalitions)</b> | Bargaining and collective negotiation to <a href="#">rebalance power</a> and improve terms of data use           |
| <b>Legitimacy deficit:</b><br>Difficulties in operating that stem from a lack of community or stakeholder support             | <b>Data Trusts</b>                 | Independent <a href="#">fiduciary stewardship</a> to ensure neutrality and credible commitment                   |
| <b>Collective governance need:</b> Difficulty in                                                                              | <b>Data Commons</b>                | <a href="#">Participatory rule-making</a> and shared stewardship for collective benefit                          |

|                                                                                                              |                          |                                                                                                                  |
|--------------------------------------------------------------------------------------------------------------|--------------------------|------------------------------------------------------------------------------------------------------------------|
| operating due to a lack of stakeholder involvement                                                           |                          |                                                                                                                  |
| <b>Ownership inequality:</b><br>Difficulty in operating due to a lack of community or stakeholder agency     | <b>Data Cooperatives</b> | <a href="#">Democratic ownership</a> and member agency to redistribute control and value                         |
| <b>System Uncertainty:</b><br>Difficulty in operating due to a lack of knowledge about how tools can be used | <b>Data Sandboxes</b>    | Experimental governance to <a href="#">test rules</a> , <a href="#">safeguards</a> , and institutional viability |
| <b>Scaling complexity:</b><br>Difficulty in operating across a larger space or in a different context        | <b>Data Spaces</b>       | Federated coordination and <a href="#">interoperability across actors and jurisdictions</a>                      |

### 3.1. Data Intermediaries for Coordination Failures

The most immediate challenge facing many data collaborations is operational friction. Data holders and users often lack the trust, capacity, or shared frameworks needed to exchange data directly. Data intermediaries emerge to address this [coordination gap](#).

The role of data intermediaries is to reduce transaction costs by managing the practical negotiations that enable data reuse: handling data access permission, data provenance, privacy safeguards, downstream rights, and accountability arrangements. Thus the defining feature of intermediaries is to act as facilitators of trust and set “rules of the road” for data-sharing relationships.

This type of data collaborative is especially effective in early-stage or multi-actor settings, where collaboration is possible but cannot yet be operationalized without a neutral coordinating actor.

### 3.2. Data Unions or Coalitions for Bargaining Asymmetries

As data markets mature, coordination can prove challenging for addressing power asymmetries. Certain actors—especially individuals or smaller organizations—face structural power asymmetries vis-à-vis dominant platforms or AI developers. Bargaining institutions, such as data unions or [coalitions](#), emerge as a response to this imbalance.

Unlike cooperative structures (see below), which emphasize governance and shared ownership, data unions focus on collective leverage and negotiation. By aggregating participants, they allow small institutions to better exercise leverage in relation to larger counterparts. They are able to work together to negotiate terms of access, compensation, or restrictions on use that benefit them and other similar small institutions. In short, data unions and coalitions offer collective bargaining power.

Such arrangements are most relevant in situations where data is treated as an extractive asset and where governance mechanisms alone cannot rebalance incentives.

### **3.3. Data Trusts for Legitimacy Deficits**

In many cases, the key challenge facing data collaboration is legitimacy. This is particularly true when data reuse involves sensitive domains or contested interests, and when stakeholders may distrust arrangements where data holders retain control over decision-making. In this context, [data trusts](#) respond to the legitimacy deficit by introducing independent stewardship.

Here, authority over data access is delegated to trustees whose responsibility is to act on behalf of defined beneficiaries. Independence becomes the institutional mechanism through which credibility and trust are generated. The need data trusts fill is thus institutional. They separate governance authority from ownership.

These structures are particularly well suited to domains where credible commitment and neutrality are essential for collaboration to proceed.

### **3.4. Data Commons for Collective Governance Needs**

Where legitimacy depends not only on independence but also on participatory governance, collective stewardship models such as data commons are well suited. Inspired by [commons theory](#), these arrangements emphasize [shared governance](#), collective rule-making, and the distribution of benefits across participants.

Recent work on [data commons for AI](#) illustrates how such ecosystems pool datasets to enable public-interest innovation while incorporating stakeholders as active decisionmakers. Commons models recognize that data governance is both a technical question and a social one, requiring ongoing negotiation among communities. Indeed, data commons approaches may be particularly suited to managing competing interests among heterogeneous stakeholder groups, particularly where data sharing spans institutional, cultural, or national boundaries and requires sustained [social license](#).

As models for data sharing, data commons arrangements tend to be particularly useful in contexts where public legitimacy, inclusiveness, and shared benefit are central to success. These

contexts can include scientific collaboration, cultural data initiatives, inter-communal or inter-cultural interaction, or public-interest AI development.

### ***3.5. Data Cooperatives for Ownership Inequality***

A further institutional response emerges when participants seek durable control over how data is used and how value is distributed. Data cooperatives draw on long-standing cooperative traditions to embed democratic ownership into data governance itself.

In such arrangements, contributors are both members and beneficiaries. [Democratic control](#) and economic participation transform data subjects into decision-makers. Data cooperatives allow those providing data to determine how it is used and what long-term goals they want their data to support. They ensure agency by institutionalizing it, requiring those demanding or using data to seek the approval of data providers prior to acting.

These models are particularly relevant in domains where contributors seek sustained influence over downstream value creation. Such domains include health, agriculture, and worker- or producer-led ecosystems.

### ***3.6. Data Sandboxes for System Uncertainty***

Not all governance challenges can be resolved through permanent institutional arrangements. In contexts characterized by high uncertainty—such as when actors want to test new tools like AI, experiment with a dataset, or assess some other resource—actors often need mechanisms for short-term experimentation before committing to long-term systems or mechanisms. [Data sandboxes](#) are useful tools in such situations.

Sandboxes function as bounded experimental environments in which governance rules, technical safeguards, and compliance pathways can be tested under controlled conditions. Their primary contribution is to generate knowledge about what forms of governance are viable before initiatives are scaled. As such, they may also help identify key risks and opportunities, helping stakeholders design better scaled-up data sharing initiatives.

Sandboxes typically precede more stable institutional forms, enabling ecosystems to learn before institutionalizing. As such, they are well suited to pilot projects and the very early stages of data sharing projects.

### ***3.7. Data Spaces for Scaling Complexity***

As data collaborations expand across sectors or jurisdictions, there is an added need for interoperability and systemic coordination. Data spaces address these scaling challenges through federated governance.

Examples of such federated governance include [shared standards, rulebooks, data sharing agreements](#) and governance frameworks that allow actors to exchange data while maintaining autonomy over their own systems. By enabling such mechanisms, data spaces put control in the hands of the community that generates data, ensuring they preserve control and can exercise agency. Governance in this context incorporates multiple perspectives and integrates technical, legal, organizational, and ethical dimensions within a shared infrastructure.

Data space arrangements are particularly suited to large-scale data ecosystems—such as [health](#), mobility, or industrial sectors—where interoperability and federation matter as much as access itself. They allow many different kinds of data to be collated and used toward a common purpose.

### ***3.8. Cross-cutting layer: strategic data stewardship***

Across all seven archetypes described above runs a common thread: the need for responsible, responsive, and strategic data stewardship. Regardless of the specific institutional structure, successful data collaboration requires alignment on purpose, desired outcomes, and an understanding of how to balance risks and opportunities. This alignment—as well as the specific institutional structures chosen—can only be achieved if there is a person or institution whose dedicated role it is to shape strategy and define practical steps toward achieving the desired objectives.

Governance models do not select themselves; they must be matched to context. In short, the ability to identify and operationalize a model of data collaboration depends significantly on the existence of experienced and empowered data stewards. Stewardship acts as the connective tissue linking diverse possible governance arrangements within a polycentric ecosystem that contains diverse goals, challenges, and opportunities. Data stewards ensure that organizational goals—as well as societal norms and values—are embodied in data collaboratives, and that the interests of all stakeholders are adequately balanced.

**Table 2. Comparing Governance Archetypes: Fit for What Problem?**

| Archetype / Model          | Institutional function                              | Primary addressed                                                 | Decision-maker                           | Value orientation                                 | Optimal use cases                                                                     |
|----------------------------|-----------------------------------------------------|-------------------------------------------------------------------|------------------------------------------|---------------------------------------------------|---------------------------------------------------------------------------------------|
| <b>Data intermediaries</b> | Brokerage, coordination & negotiated rules          | High transaction costs; low trust; limited capacity               | Intermediary organization                | Mixed (public/sectoral)                           | Early-stage collaboratives; multi-party reuse with complex permissions                |
| <b>Data unions</b>         | Bargaining and collective negotiation               | Power asymmetry in data markets                                   | Union entity / representatives           | Redistributive (terms/ compensation/ constraints) | When leverage against dominant platforms/AI developers is the priority                |
| <b>Data trusts</b>         | Fiduciary and independent stewardship               | Conflicts of interest; legitimacy deficits                        | Trustees with legal duties               | Beneficiary-focused                               | Sensitive data; contested ecosystems; credibility/neutrality/independence is required |
| <b>Data commons</b>        | Participatory governance and collective stewardship | Collective action + legitimacy; data scarcity for public interest | Multi-stakeholder / community governance | Public/collective benefit                         | Public-interest AI; knowledge institutions; culturally sensitive datasets             |
| <b>Data cooperatives</b>   | Democratic and member based ownership               | Sustained control + empowerment                                   | Cooperative members                      | Member benefit + equity                           | Member based organizations, worker/producer data; long-term member agency             |
| <b>Data sandboxes</b>      | Controlled experimentation                          | Uncertainty; risk before sharing and scale                        | Regulator / consortium                   | Learning & risk reduction                         | Novel AI and analytics use cases; governance prototyping                              |
| <b>Data spaces</b>         | Federated interoperability and infrastructure       | Scaling & cross-border coordination                               | Governance authority + participants      | Ecosystem efficiency + compliance                 | Sector-wide ecosystems; interoperable exchange with sovereignty preserved             |

## 4. Toward a Functional Theory of Data Collaboration: From Institutional Choice to Institutional Orchestration

A central insight emerging from the above typology is that governance models respond to distinct governance challenges. While contextual and organizational factors influence the suitability of different models, institutional variation can also be understood along three analytical dimensions: authority, value distribution, and coordination scale.

- First, institutional forms differ in how authority is organized—whether decision-making power rests with independent trustees, intermediaries, communities, or member-owned structures. For example, early-stage collaborations may rely on centralized intermediaries to coordinate exchange; as legitimacy and agency concerns grow, authority may shift toward data trusts, data commons, or member-owned cooperatives that distribute decision-making more broadly.
- Second, data collaboratives diverge in how value is distributed, ranging from public-interest orientation to member-centered or ecosystem-based benefit-sharing. Initial arrangements may prioritize access and innovation, while more mature models—such as unions, trusts, or cooperatives—formalize mechanisms to rebalance power, protect beneficiaries, or institutionalize more equitable value sharing.
- Third, they vary in scale, from localized collaborative arrangements to infrastructural systems designed for interoperability across sectors or jurisdictions. Thus, while sandboxes often operate at limited scope, more mature data spaces emerge when coordination extends across sectors or borders.

Considered together, these dimensions suggest that institutional structures are not simply diverse but also developmental. As data ecosystems mature, governance challenges shift, and institutional responses evolve accordingly. Seen in this light, governance models should not be interpreted as competing alternatives but as stages or layers within a broader institutional lifecycle. Mature ecosystems rarely rely on a single model. Instead, they combine multiple institutional forms, each addressing different governance failures simultaneously.

This perspective reframes the central question of data governance. Rather than choosing “the right model,” the real task is to understand how different arrangements can be developed—and coexist—within a polycentric ecosystem of strategic data stewardship. Data collaboratives remain

a useful overarching conceptual frame because they foreground purpose and public value while allowing institutional flexibility. Within this context, the practical challenge lies in developing methodologies capable of matching governance models to contextual needs—all the while balancing legitimacy, innovation, coordination, and sustainability over time.

Ultimately, the future of data governance may depend less on inventing new institutional labels than on cultivating institutional fluency. A key responsibility—indeed, the overarching responsibility—for data stewards is to diagnose which governance arrangement is appropriate for which purpose, how data collaborative structures should evolve as ecosystems mature, and when hybrid or layered configurations are required. In this sense, strategic data stewardship becomes less a question of institutional choice and more a practice of institutional orchestration: the capacity to sequence, combine, and adapt governance models as data ecosystems evolve over time.

The notion of institutional orchestration will be developed further in a subsequent paper. Overall, it represents an effort to move beyond static institutional design toward a more dynamic and layered understanding of data governance. It flows from a recognition that, as data ecosystems grow in complexity, the challenge is not merely to establish responsible arrangements, but to sustain them through shifting risks and opportunities. Institutional orchestration thus marks a new frontier in the theory and practice of strategic data stewardship, offering a pathway toward resilient and adaptive responsible data reuse in the public interest.

*(Thanks to Nadiya Safonova, Andrew Zahuranec, Adam Zable and Hannah Chafetz for reviewing earlier drafts)*

## References

- Acemoglu, D., Fallah, A., Makhdoumi, A., Azarakhsh Malekian, & Asuman Ozdaglar. (2023). *How Good Are Privacy Guarantees? Platform Architecture and Violation of User Privacy*. National Bureau of Economic Research. <https://doi.org/10.3386/w31413>
- Benhamou, Y., & Dulong, M. (2025). Open Licensing and Data Trust for Personal and Non-Personal Data: A Blueprint to Support the Commons and Privacy. *IIC* 56, 1553–1589. <https://doi.org/10.1007/s40319-025-01636-y>
- Bühler, M. M., Calzada, I., Cane, I., Jelinek, T., Kapoor, A., Mannan, M., Mehta, S., Micheli, M., Mookerje, V., Nübel, K., Pentland, A., Scholz, T., Siddarth, D., Tait, J., Vaitla, B., & Zhu, J. (2023). Data Cooperatives as Catalysts for Collaboration, Data Sharing, and the (Trans)Formation of the Digital Commons. *Preprints*. <https://doi.org/10.20944/preprints202304.0130.v1>
- Chafetz, H., Zahuranec, A. J., & Verhulst, S. V. (2025). *A Blueprint to Unlock New Data Commons for AI*. Open Data Policy Lab. <https://incubator.opendatapolicylab.org/files/data-commons-for-ai-blueprint.pdf>
- DataCollaboratives.org – A New Resource on Creating Public Value by Exchanging Data*. (2026). The Living Library. <https://thelivinglib.org/datacollaboratives-org-a-new-resource-on-creating-public-value-by-exchanging-data/>
- Datasphere Initiative. (2025). *Sandboxes for AI: Tools for a new frontier*. <https://www.thedatasphere.org/datasphere-publish/sandboxes-for-ai/>.
- Granell, C., Mooney, P., Jirka, S., Rieke, M., Ostermann, F., Den, V., Sarretta, A., Verhulst, S., Dencik, L., Oost, H., Micheli, M., Minghini, M., Kotsev, A., & Schade, S. (2022). Emerging approaches for data-driven innovation in Europe. *JRC Publications Repository*. <https://doi.org/10.2760/630723>
- Henderson, J., & Prewitt, M. (2023, June). *Data coalitions & escrow agents*. RadicalxChange Foundation. <https://www.radicalxchange.org/updates/blog/data-coalitions-and-escrow-agents/>.
- Kalkar, U., & Alarcón, N. G. (2023). Facilitating Data Flows through Data Collaboratives: A Practical Guide to Designing Valuable, Accessible, and Responsible Data Collaboratives. *IDB Publications*. <https://doi.org/10.18235/0005185>
- Kalkar, U., Saxena, S., & Verhulst, S. (2023). *Data Sandboxes: Managing the Open Data Spectrum*. Open Data Policy Lab. <https://incubator.opendatapolicylab.org/files/DataSandboxesPrimer.pdf>

- Letteriello, N. (2025, June 12). *Companies are missing the chance to improve the world with their data*. Forbes.  
<https://www.forbes.com/councils/forbestechcouncil/2025/06/12/companies-are-missing-the-chance-to-improve-the-world-with-their-data/>
- Marinotti, J. (2022). Data Types, Data Doubts & Data Trusts. *SSRN Electronic Journal*.  
<https://doi.org/10.2139/ssrn.4058529>
- Mendonca, F., Di Marzo, G., & Abdennadher, N. (2025). Data Cooperatives: Democratic Models for Ethical Data Stewardship. *ArXiv (Cornell University)*.  
<https://doi.org/10.48550/arxiv.2504.10058>
- Micheli, M., Farrell, E., Bruno, C. S., Posada, S. M., Signorelli, S., & Vespe, M. (2023). Mapping the landscape of data intermediaries. *JRC Publications Repository*.  
<https://doi.org/10.2760/261724>
- Price, T. C. (n.d.). *Data unions: people-powered data control*. Future Signals 2026.  
<https://www.nesta.org.uk/feature/future-signals-2026/data-unions/>
- Roose, K. (2023, July 15). *They wrote the A.I. chatbots' voices. Now they're out of a job*. The New York Times.  
<https://www.nytimes.com/2023/07/15/technology/artificial-intelligence-models-chat-data.html>
- Sacasas, L. M. (2023). *Outsourcing virtue*. The Point Magazine.  
<https://thepointmag.com/criticism/outsourcing-virtue/>
- The GovLab. (2025). *Data Commons For GenAI Case Studies* [Data set]. Google Sheets.  
[https://docs.google.com/spreadsheets/d/\[unique-ID\]/edit?usp=sharing\[1](https://docs.google.com/spreadsheets/d/[unique-ID]/edit?usp=sharing[1)
- Turow, J., Lelkes, Y., Draper, N. A., & Waldman, A. E. (2023, February 15). *Americans can't consent to companies' use of their data: They admit they don't understand it, say they're helpless to control it, and believe they're harmed when firms use their data—making what companies do illegitimate* [Report]. Annenberg School for Communication, University of Pennsylvania.  
[https://www.asc.upenn.edu/sites/default/files/2023-02/Americans\\_Can't\\_Consent.pdf](https://www.asc.upenn.edu/sites/default/files/2023-02/Americans_Can't_Consent.pdf)
- Verhulst, S. (2025, April 3). *The Future of Health Is Preventive — If We Get Data Governance Right: Unlocking the Potential of the European Health Data Space*. *Data & Policy Blog*.  
<https://data-and-policy.medium.com/the-future-of-health-is-preventive-if-we-get-data-governance-right-a60a3d86a145>
- Verhulst, S., Chafetz, H., & Zahuranec, A. (2024). Data Commons: Under Threat by or The Solution for a Generative AI Era? Rethinking data access and re-use. *SSRN Electronic Journal*.  
<https://doi.org/10.2139/ssrn.4836354>

- Verhulst, S. G. (2025, June 29). *A New Social Contract for AI?* Medium.  
<https://sverhulst.medium.com/a-new-social-contract-for-ai-bc14ee215a30>
- Verhulst, S. G. (2024, June 26). *Innovative Datenpolitik: Potenziale und Herausforderungen* [Testimony]. Ausschuss für Digitales, Deutscher Bundestag.  
<https://www.bundestag.de/resource/blob/1009976/Stellungnahme-Verhulst.pdf>
- Verhulst, S., Young, A., & Srinivasan, P. (n.d.). *An Introduction to Data Collaboratives*. Data Collaboratives; The GovLab. Retrieved March 5, 2026, from  
<https://datacollaboratives.org/introduction.html>
- World Economic Forum. (2022). *Advancing digital agency: The power of data intermediaries*.  
<https://www.weforum.org/publications/advancing-digital-agency-the-power-of-data-intermediaries/>
- World Economic Forum. (2019). *Data collaboration for the common good: Enabling trust and innovation through public-private partnerships*.  
[https://www3.weforum.org/docs/WEF\\_Data\\_Collaboration\\_for\\_the\\_Common\\_Good.pdf](https://www3.weforum.org/docs/WEF_Data_Collaboration_for_the_Common_Good.pdf)
- Wu, D., Verhulst, S., Pentland, A., Avila, T., Finch, K., & Gupta, A. (2021). How data governance technologies can democratize data sharing for community well-being. *Data & Policy*, 3.  
<https://doi.org/10.1017/dap.2021.13>
- Zorrilla, M., & Yebenes, J. (2025). Architecture Building Blocks for Data Governance in Data Spaces. *Information*, 16(11), 927. <https://doi.org/10.3390/info16110927>