RETHINKING DATA GOVERNANCE: A VIABLE SYSTEM MODEL

Completed Research Paper

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Abstract

Data governance is a prerequisite for organizations wanting to harness the strategic potential of data. Although the conceptual foundations of data governance have reached a sound level of clarity, research still does not explain how data governance unfolds in large and complex organizations. To address this gap, we introduce the Viable System Model as theoretical lens and examine data governance at five multinational companies with varied organizational structures. We find that data governance orchestrates data practices on multiple, interconnected levels, through sub-systems. The interplay between these sub-systems facilitates the establishment of a dynamic balance, enabling (1) the delineation of responsibilities, distinguishing between global and local data governance that orchestrates data practices, and (2) the implementation of data practices at the operational level that simultaneously emphasize control and foster innovation. Our research contributes to rethinking data governance and addresses previous calls for research that accounts for its dynamic nature in practice.

Keywords: Data governance, Data practice, Viable System Model, Systems thinking.

1 Introduction

Successful organizations recognize the strategic potential of data for sustainable competitive advantage (Jones, 2019) and its vital role in creating business value, such as cost efficiency or better market positioning (Günther *et al.*, 2022). A prerequisite for unlocking the potential of data is data governance, i.e., the specification of "*a cross-functional framework for managing data as a strategic enterprise asset*" (Abraham, Schneider and vom Brocke, 2019, p. 425). Grover *et al.* (2018) even argue that "*without appropriate organizational structures and governance frameworks in place, it is impossible to collect and analyze data across an enterprise and deliver insights to where they are most needed*" (p. 417). Data governance has long been concerned with the quality and protection of data assets and the adherence to regulatory requirements (Weber, Otto and Österle, 2009; Otto, 2011). Today, data is at the heart of value creation in enterprises, resulting in data governance having the dual purpose of simultaneously balancing control and innovation (Vial, 2023).

Data governance research has mainly focused on clarifying the basic understanding and defining the scope and overall framework of data governance (Khatri and Brown, 2010; Abraham, Schneider and vom Brocke, 2019). Building on IT governance literature, it conceptualizes data governance as an ensemble of mechanisms (Tallon, Ramirez and Short, 2013; Abraham, Schneider and vom Brocke, 2019; Vial, 2023) encompassing structural mechanisms (e.g., roles, responsibilities, locus of decision making), procedural mechanisms (e.g., processes, monitoring), and relational mechanisms (e.g., communication, training). While the foundations of data governance are increasingly clear, criticism has emerged from practice claiming that data governance cannot be viewed only "*as series of mechanisms implemented in organizations, at the expense of understanding the process of governing data*" (Vial, 2023, p. 6). Concretely, research still mainly lists *what to do* and does not explain *how to do* data governance, i.e., data governance in practice (Alhassan, Sammon and Daly, 2016; Aaltonen, Alaimo and Kallinikos, 2021; Vial, 2023). Moreover, given global firms' complex organizational structures, establishing data governance for them remains a challenge (Otto, 2011). In order to be effective, data governance must reach many different parts of an organization and shape the situated data practices through which data acquires its value (Parmiggiani and Grisot, 2020). Federated data governance models, which combine global and local data governance responsibilities, have been proposed as a solution in rolling out data governance in accordance with the primary organizational structure (Grover et al. 2018; King 1983). However, so far, no link has been established for understanding how data governance mechanisms materialize at local and global levels. Further, the rather static view of data governance mechanisms does not properly explain the dynamic nature of data governance which must evolve in symbiosis with strategy and operations (Benfeldt, Persson and Madsen, 2020). As markets, regulations, and organizational culture are continuously evolving, data governance obviously has to adapt (Tallon, Ramirez and Short, 2013; Abraham, Schneider and vom Brocke, 2019).

In such a context, we ask the following research question (RQ):

RQ: *How does data governance unfold in multinational companies?*

In our study, we apply systems thinking to data governance and use the Viable System Model (VSM) as theoretical lens. The VSM explains a system's viability, i.e., its ability to maintain its existence in a changing environment (Beer, 1985), and it has been used to explain IT governance setups (Peppard, 2005; Huygh and De Haes, 2019). Our study is embedded in a collaborative practice research (Mathiassen, 2002), with 17 multinational companies. It is informed by insights from nine focus groups, as well as in-depth case studies. To understand how governance mechanisms are implemented in large and complex organizations, we analyzed the cases of five companies that have developed global and local data governance responsibilities. Our findings reveal that data governance orchestrates data practices on multiple, interconnected levels, through sub-systems. The interactions between data practices happening at operational, governance, and strategic levels make it possible to establish an appropriate balance that mediates (1) between global and local data governance, and (2) between data governance activities that seek control on the one hand and innovation on the other. Overall, closing this research gap advances the academic understanding of federated governance, paving the way for a new angle in investigating data practices at strategic, governance, and operational levels. Our research offers practitioners guidelines on how to set up a data governance framework that aligns with their overall strategy and organizational structure.

In the remainder of the paper, we first give information on prior data governance literature and highlight the research gap. Second, we motivate the relevance of systems thinking and the applicability of VSM as a theoretical lens. Next, we present our methodology, and finally, we summarize and discuss our findings, and also provide an outlook on future research.

2 Theoretical Background

2.1 Data governance

Data governance is seen as a framework describing cross-functional efforts for maximizing the value of data as strategic enterprise assets and ensuring the compliant and strategic use of data (Tallon, Ramirez and Short, 2013; Abraham, Schneider and vom Brocke, 2019). It thus fosters the contribution data makes to achieving organization goals and generally aims to improve firm performance (Mikalef *et al.*, 2020). Data governance is shaped by both external environmental antecedents, such as legal and regulatory, industry, or regional conditions, and internal ones, such as business strategy, corporate culture, or organizational structure (Baijens, Huygh and Helms, 2021; Tallon, Ramirez and Short, 2013).

To set up data governance, firms should clearly identify its scope along three dimensions (see Figure 1). First, organizational scope refers to "*expansiveness of data governance*"(Abraham, Schneider and vom Brocke, 2019, p. 430), which can be intra-organizational or inter-organizational. Second, firms define the data scope and identify the relevant data objects, data types, and data domains to prioritize for data governance. For instance, master or transactional data objects are usually governed first, but other big data-related types such as media data and sensors can come in scope later to support new data applications (Abraham, Schneider and vom Brocke, 2019; Fadler, Lefebvre and Legner, 2021). Third, the "depth" of the data governance program is defined by its domain scope, i.e., the different data decision domains, such as data quality, data security, data architecture, data lifecycle, metadata, data storage, and infrastructure (Khatri and Brown, 2010; Abraham, Schneider and vom Brocke, 2019).

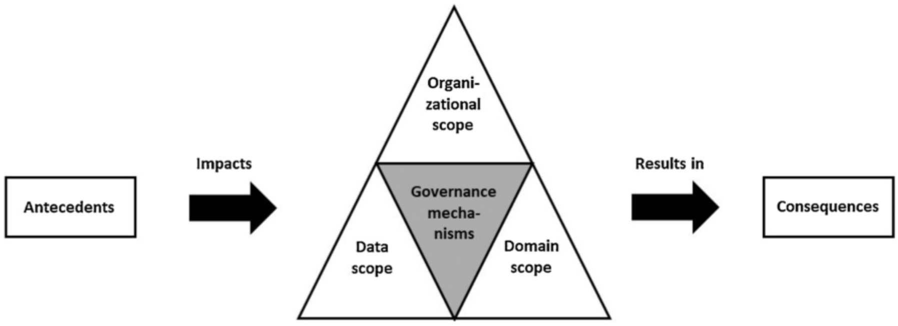

Figure 1. Conceptual framework for data governance by Abraham et al. (2019).

Three mechanisms—structural, procedural, and relational—constitute the core of data governance, drawing from established IT governance frameworks (Tallon, Ramirez and Short, 2013; Abraham, Schneider and vom Brocke, 2019; Vial, 2023). These mechanisms should be combined and not addressed separately for maximum efficiency (Tallon, Ramirez and Short, 2013), and can typically be bundled into archetypes aligned on the strategic context and scope for data (Fadler, Lefebvre and Legner, 2021).

Structural mechanisms focus on specifying roles (e.g., data owner, data steward) and responsibilities in line with the organizational structure, and on allocating decision-making authority. This entails defining where the different data teams are positioned and their reporting lines (Otto, 2011). The literature differentiates between centralized, decentralized, and federated data governance designs (Brown, 1999; Sambamurthy and Zmud, 1999; Weber, Otto and Österle, 2009). A strict centralized data governance model implies that a central data unit has global authority and responsibility regarding data. Such a model is convenient for company-wide control, efficiency, and reliability in the (re)utilization of data assets because it leverages lateral organizational capabilities between units. However, it decreases local units' flexibility and capacity to innovate (Velu, Madnick and van Alstyne, 2013; Grover *et al.*, 2018). Conversely, in a fully decentralized model, business units hold local responsibility for their data, each with their respective governance principles which enable rapid adaptation to changing requirements (Velu, Madnick and van Alstyne, 2013). In this model, the lacking standardization leads to coordination challenges, compliance concerns, data quality issues, limited collaboration, and complex data access management. Federated (also called hybrid, or Hub-Spoke) models combine the two forms in a global hub responsible for enterprise-wide standards, policies, methods, and tools, with business units as spokes taking care of responsibilities closer to the relevant data operations (e.g., data creation, data quality, data maintenance) (King, 1983; Grover *et al.*, 2018). While offering numerous benefits such as greater local autonomy, faster issue resolution, and improved agility, a federated model generally requires better coordination mechanisms and acknowledged data ownership by respective business units (Velu, Madnick and van Alstyne, 2013).

The procedural and relational mechanisms instantiate the structural mechanisms. *Procedural mechanisms* describe decision-making related to data activities and processes, and thereby "*emphasize the operational means that are put in place to ensure compliance with governance principles"(Vial, 2023, p. 4)*. These include data strategy; policies, standards, and procedures; contractual agreements; performance measurement; compliance monitoring; and issue management (Abraham, Schneider and vom Brocke, 2019). *Relational mechanisms* ensure alignment, collaboration, and knowledge sharing between stakeholders. To expand the reach and understanding of data governance principles, these mechanisms usually comprise both formal (e.g., working groups, collaboration platform, training events) and informal (e.g., job rotation, corporate events, communities) means of coordination (Abraham, Schneider and vom Brocke, 2019). For instance, communities of practice foster knowledge sharing and data literacy among both data experts and non-experts (Lefebvre and Legner, 2022).

The above view on data governance has attracted criticism because the governance mechanisms do not explain data governance in practice (Alhassan, Sammon and Daly, 2016; Aaltonen, Alaimo and Kallinikos, 2021; Vial, 2023). Recent research suggests "*a shift from data governance as a matter of asset management to data governance as a matter of work practice*" because data governance is enacted as part of local actors' sense-making processes, such as during data curation tasks (Parmiggiani and Grisot, 2020, p. 3). Therefore, firms naturally evolve toward federated data governance that accommodates both global and local needs (Benfeldt, Persson and Madsen, 2020), thus pragmatically reflecting the organizational complexity of the organization, specifically in multinational companies (Velu, Madnick and van Alstyne, 2013; Khatri and Brown, 2010). This shift is also reflected in the emerging data mesh paradigm which emphasizes data management responsibilities close to data creators because they know the context the best (Machado, Costa and Santos, 2021). Further, data governance should be addressed as a "*dynamic element that is implemented and should evolve in conjunction with strategy and operations"* to maintain its dual purpose of balancing control and data-driven innovation (Vial, 2023, p. 9). However, the literature neither explains how data governance responds to growing operational needs (e.g., data requests in business) nor clarifies data governance's role in assimilating strategic decisions. This gap calls for further investigation of how data governance unfolds in practice.

2.2 A systems thinking approach to address data governance in practice

We argue that systems thinking, and especially the VSM, offers a promising lens to study data governance as a system dynamically shaped by antecedents and composed of a set of interrelated sub-systems. The VSM introduces the concept of viability, suggesting that a system is able to remain functional despite a dynamic and fluctuating environment (Beer, 1985). It provides a framework for describing organizations and how they process information between different entities, including internal departments, external partners, and the broader environment which represents surrounding external factors that could influence the system (see Figure 2). This framework emphasizes the continuous interactions and information exchanges (symbolized by the arrows between each element), both critical aspects of organizational decision-making, adaptation, and innovation.

To achieve viability, the VSM posits self-organizing systems as composed of five sufficient interconnected sub-systems (Systems 1 to 5) that each have a role in maintaining the viability of the system (Beer, 1985), i.e., all sub-systems must be active and continuously exchange information:

- System 1 represents the *Operations* element of the VSM. As system-in-focus, it describes the different local operative units that execute the necessary tasks (i.e., work practices) that maintain the entire system's purpose. These operative units are typically embedded in the organization's primary structure and have their own local management. They can communicate with one another.
- Systems 2 to 5 – coordination, control, intelligence, policy – together form the *Management* element of the VSM, which acts as meta-system determining System 1. Thereby, they ensure smooth operation delivery (e.g., scheduling, strategic planning).

By applying the VSM as theoretical lens we can gain a thorough understanding of how data governance practices are arranged to assimilate and accommodate changes (e.g., in data scope). This lens also illustrates how data governance is embedded in the organizational structure. This approach has been employed to investigate IT governance (e.g., Peppard (2005), Huygh & De Haes (2019)) and, more recently, to examine analytics governance, which emphasizes the contextualized output of data utilization (Baijens, Huygh and Helms, 2021). The latter authors notably argue that analytics governance is part of a meta-system for the totality of data analytics activities (e.g., data analytics projects). However, data use depends on input data and, consequently, on data governance practices (Aaltonen, Alaimo and Kallinikos, 2021; Legner, Pentek and Otto, 2020). Thus, we argue for data governance – as a separate VSM – because "*the actual work tasks carried out by individuals to curate and set up the data are typically downplayed*" (Parmiggiani, Østerlie and Almklov, 2022, p. 139).

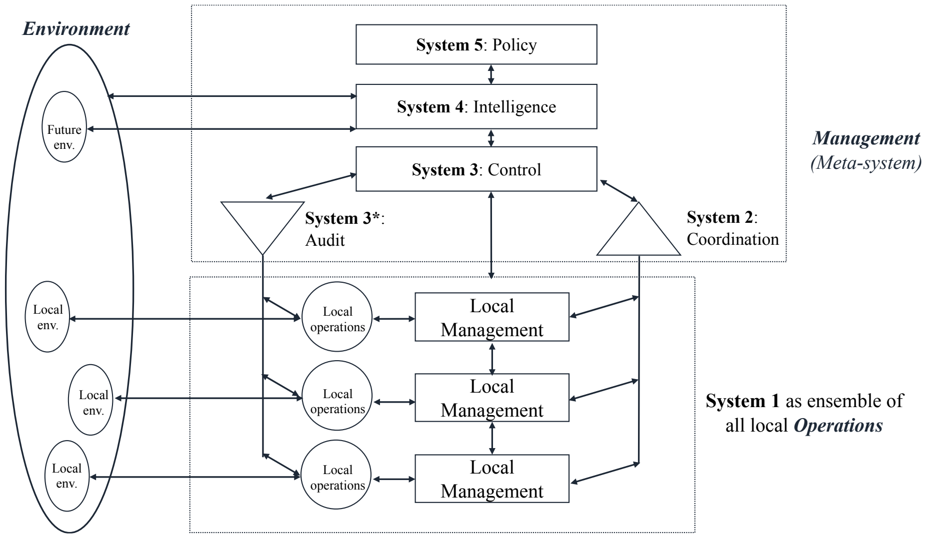

*Figure 2. Structure and relationships in the Viable System Mode*l *(simplified representation based on Beer (1985)).*

3 Methodology

3.1 Research design

Considering our research question (*How does data governance unfold in multinational companies?*) and our theoretical proposition (that data governance in multinational companies can be observed through the VSM lens), we follow a qualitative research design (Dubé and Paré, 2003). Our study spanned the period from September 2020 to November 2023. It was embedded in a collaborative practice study (Mathiassen, 2002) and informed by insights from focus groups of 17 multinational companies, as shown in Figure 3. To further deepen our analysis, we conducted five in-depth case studies (Yin, 2018).

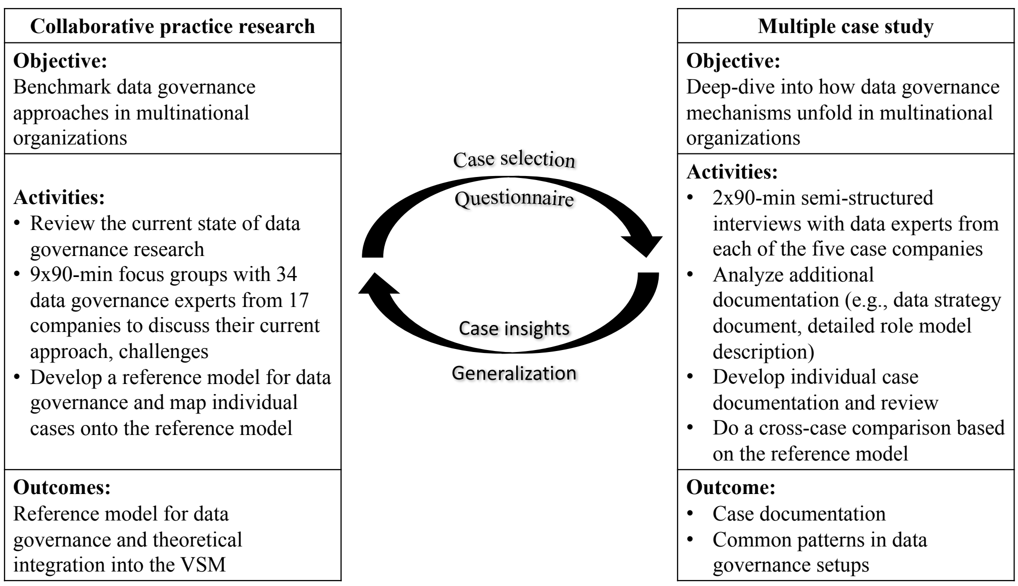

Figure 3. Overview of the research design.

3.2 Collaborative practice research

In our collaborative practice research, we partnered with 17 companies seeking to benchmark their data governance approaches. We organized nine 90-min focus groups with 34 high-profile data experts, where participants provided an overview of their data governance approach, as well as describing its evolution over time, which gave all participants a first understanding of their data governance mechanisms. Besides the focus groups, we undertook research activities to review the literature on data governance and develop a reference model as basis for the benchmarking study. This study was used to map and compare individual companies' governance approaches. Using purposeful sampling (Patton, 1990), we identified five companies' data governance approaches for the subsequent case study analysis (see Table 1 and section 3.3). Our interactions with the five case companies informed the subsequent focus groups iteratively. The final focus group consisted of 22 data executives from the 17 companies who discussed the findings, i.e., the reference model and the benchmarking study with illustrations from the five cases.

3.3 Case studies

To be able to generalize a VSM, we opted for multiple cases as this supports better analytical generalization (Yin, 2018). We selected companies with diverse characteristics regarding their industry, the goal and scope of their data governance, and different organizational structures influencing the design of global and local data governance teams. The case companies had implemented federated data governance design decisions, e.g., they had complete role and process models at global and local levels.

Case, Industry	**Revenue/ Employees**	**Key informant**	**Data governance's goal and scope**	**Global data governance**	**Local data governance**
ManufCo *Automotive manufacturing*	\$1B–\$50B/ ~90,000	VP Data & Analytics Governance	Enterprise-wide data governance on 44 data domains to stimulate data use in all business units and address all strategic areas of digitalization.	Data and analytics governance team (13 people) reporting to the Chief Digitalization Officer.	Data and analytics coordination in each of the 12 organizational areas, i.e., functions, divisions, regions (100 people for data management).
BeautyCo *Adhesives & Beauty products*	\$1B–\$50B/ ~20,000	Director Master Data & Product Lifecycle	Enterprise-wide master data governance on two domains (products, finance) to improve operational processes and to improve value generation from data.	Master data team (35 people) split between business (supply chain, finance) and IT with respective reporting lines.	Three regional data hubs close to the markets and overseeing data lifecycle in different countries (25 people).
PharmaCo *Pharma, Chemicals*	\$1B–\$50B/ ~100,000	Head of Data Framework & Stewardship	Enterprise-wide analytics-driven data governance supporting Analytics & AI innovation, enablement, and solutions.	Data Framework and Stewardship (30 people) in the Data & AI Competence center reporting to Global Digital Services.	20 divisional digital offices with about 200 data stewards.
EnergyCo *Energy*	\$100B-\$500B/ ~100,000	Chief Data Officer	Enterprise-wide data governance on 16 data domains defined according to the business model to drive data use into operational processes.	Small chief data office focusing on data foundation (5 people).	35 Chief Data Officers allocated to divisions with a small team each (70 data architects in total).
SoftCo *Software*	\$1B-\$50B/ ~110,000	VP - Head of Data Management	Enterprise-wide master data governance on two business-critical data domains (products and customers) to improve operational processes.	Intelligent data management (IDM) team (98 people) in the Chief Data Office reporting to COO.	Three regional hubs (20 people in Europe, APAC, South America), Outsourced (80 people in India).

Table 1. Cases overview.

To gain in-depth insight on the five companies' federated data governance approaches, we conducted semi-structured interviews with key informants who had been mandated to oversee enterprise-wide data governance in the case companies. We selected only interviewees who had worked at the company for an extensive period (>3 years), who knew the history of data governance initiatives, and had experienced the issues and challenges associated with implementing data governance, such as involving business stakeholders across different regions and divisions or assigning roles and responsibilities. We designed our interview questionnaire to capture the strategic context and scope for data at the company, and we complemented it with questions that address the three generic data governance mechanisms (see Table 2). Two researchers conducted the interviews via MS Teams video conferencing. Each lasted, on average, 90 minutes as planned. The interviews were recorded and documented according to a pre-filled template structured around guiding questions. After the interviews, we asked the informants to review our interview reports and to confirm our documentation (e.g., key statements), and to address remaining questions. The continuous interaction within the focus groups raised additional data requests, which we addressed in follow-up discussions. After each interview, we performed an additional search for secondary materials that could add to our documentation (e.g., a data strategy document, a detailed role model, the structure of the primary organization), sometimes guided by the expert himself, e.g., to look something up on the company website. To ensure construct validity and reliability of our findings, we triangulated our interview data with further documentation (e.g., company presentations) that we had collected during our research program or from public sources (e.g. presentations at practitioner conferences, annual reports). The final set of data allowed us to obtain granular and complete details on each data governance approach covering all three governance mechanisms. Overall, we obtained a rich case study database built on a chain of evidence composed of primary and secondary data.

Protocol areas		**Guiding questions**
Strategic context and scope	Strategic context	What are the drivers for data and analytics in the company? Do you have a data and/or analytics strategy? If yes, since when and what is its focus? What business value and benefits do data and analytics create? What are your top five data projects?
	Scope	Which data domains do you distinguish? How do you define them? Which data types are established or emerging? Which data and analytics products do you deliver?
Governance framework	Structural	What organizational form has been chosen (e.g., line function, shared service)? Is the global team/department part of the primary organization and, if so, where is it located in the organizational structure? What are the responsibilities, headcount, structure, and composition of data and analytics teams? Are there any boards and committees for data and analytics? What is their role?
	Procedural	Which data management processes have you established? Which steps/tasks are taken over by the global/ local data organization? Which analytics processes have you established? Which steps/tasks are taken over by the global/local data organization? How do you monitor data governance progress and success? Which metrics do you use and how do you report them?
	Relational	How do you align and collaborate with business stakeholders? How do you align and collaborate with IT stakeholders? How do you align and collaborate between data and analytics? Which data/analytics communities exist? How do you engage with them?

Table 2. Semi-structured interview protocol.

In analyzing our data, we applied abductive reasoning because it allows for embedding empirical findings into an existing theoretical model (Ketokivi and Mantere, 2010). This approach facilitated theorization through a detailed examination of the data by employing inductive coding for categorizing interview data and deductive coding for incorporating the VSM perspective. Figure 4 presents the coding process and illustrates the data analysis process with illustrative quotes from one of the cases. First, using inductive coding, the same two researchers labelled the statements following a bottom-up approach to derive open codes (Gioia, Corley and Hamilton, 2013). Next, they identified relationships, connections, and patterns between open codes, thus bringing a more comprehensive understanding of the underlying concepts. This led them to a set of axial codes reflecting data practices. Last, they used selective coding to derive core themes that describe clusters of these practices. They then used deductive coding to apply the VSM lens. They focused their analysis on assigning data practices for each of the five sub-systems so that they could clarify how the practices are distributed at various levels in the organization. Eventually, they obtained the grouping of the data practices into larger themes that map onto VSM sub-systems.

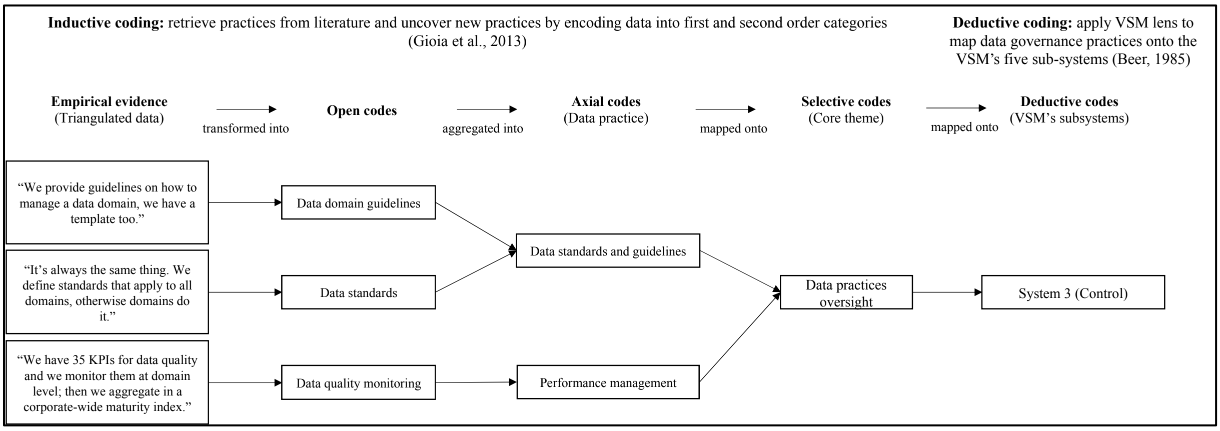

Figure 4. Data analysis process exemplified with quotes from ManufCo case.

We did our cross-case analysis in the form of a comparative analysis of the five cases. A cross-case analysis is particularly relevant to this research as it supports the aggregation, simplification, and generalization of complex cases (Miles, Huberman and Saldaña, 2014). For this, we leveraged a granular understanding of each data governance approach. We searched for differences and commonalities between cases by iteratively searching for similarities between codes. From the emerging patterns, we were able to generalize a VSM for data governance by reviewing common data practices (axial codes) and core themes (selective codes) necessary to describe each of the five sub-systems.

4 A Viable System for Data Governance

From our cross-case analysis, we theorized a VSM for data governance that addresses both global and local data governance activities. We find that data governance should occur at multiple, interconnected levels, i.e., in sub-systems (see Table 3): S2, S3, S4, and S5 together form a metasystem of data practices performed in operational units (S1). While S2, S3, and S3* represent the data governance layer (i.e., the data governance teams) and orchestrate data practices, S4 and S5 form the strategy layer (through boards and committees) and shape data governance practices. In the following sections, in describing the different systems, we exemplify the VSM with examples and quotes from our cases (e.g., regional data governance at BeautyCo, divisional data offices at EnergyCo). We also clarify the notion of recursion in the VSM using ManufCo's federated data governance as a critical case (Yin, 2018).

4.1 Operations – Perform data practices

System 1 has a set of **operative units** which are typically business functions that embed data in their work practices. These units provide data to their members and to other units, and consume data provided by their members or by other units, for instance in creating dashboards, reports, and increasingly also feeding advanced analytics/machine learning models. Two key data practices enact data provisioning, namely *data creation* and *data curation*. ***Data creation*** involves the intentional and systematic generation of data through various processes, for instance if the account manager in a regional sales team creates a customer record. ***Data curation*** involves the deliberate and systematic maintenance of data throughout its lifecycle to ensure that the data is processed in compliance with regulations and is fit for purpose (data quality). As EnergyCo stated, "*No-one owns the data lifecycle other than the data domains themselves.*" To support operative units, all five cases use shared service centers that handle a part of the data curation tasks, as shown at SoftCo: "*We have a team called 'data operations' that executes data processes. For this, we have a three-level classical shared services setup. We have a follow-the-sun approach with two regional teams in Prague and Manilla, it's about 20 people. We also consider a third offshore team in Brazil. We have a first level outsourced to a consulting company in India, which works with ticketing. There we have another 80 people. It seems really big but actually this is where we provide data maintenance services for all market units at the firm worldwide.*" Business functions are also responsible for addressing data consumption requests and should ensure that data quality follows both standards and consumer expectations. Hence, operative units take ownership of their data and manage data accessibility and data sharing in accordance with data access rights, as articulated by EnergyCo: *“We try to make data discoverable for possible usage through our data catalog, Collibra. We have started working with the business to define the key curated data products that we would like to see in place.”* ***Data usage*** practice implies that business units use the data for operational and analytics purposes (e.g., in analyzing the data to create a sales forecast). Data can be consumed within the business functions or by outside units that need it to perform their own data analysis or to enrich their own business function’s data.

Systems		**Theory** (Beer, 1985)	**Description**	**Key data practices**	**Layer**
System-in-focus	S1	Describes the different operative units that execute the tasks expected to fulfil the system’s purpose.	Represents all business units where data practices are embedded in work practices and performed by providers and consumers of data.	• Data creation • Data curation • Data usage	Operations: *Perform data practices*
Meta-system	S2	Handles coordination and communication across the different S1s, especially during disturbances affecting the VSM (e.g., environmental fluctuations).	Ensures coordination between data governance teams by assigning data roles and responsibilities and distributing the latest governance principles to the entire network. It also provides data management support, training, and data applications to data providers and consumers.	• Definition of data roles and responsibilities • Data enablement • Data management support • Data documentation and architecture • Data applications specification	Governance: *Orchestrate data practices*
	S3	Oversees the activities of the system-in-focus (S1) through “day-to-day management” to ensure the smooth delivery of data operations against strategic goals.	Oversees all data practices in the system-in-focus (S1) and ensures that they are performed in line with strategic goals and according to standards and guidelines (e.g., for data collection, storage, use, documentation). Monitors the execution of the data strategy and provides periodic strategic reporting.	• Definition of data standards and guidelines • Performance monitoring and improvement	
	S3*	Complements System 3 act as a compliance system of operative unit (S1).	Performs data-related audits of operative units to ensure compliance with laws, regulations, and standards.	Data compliance auditing	
	S4	Senses threats and opportunities to the system by scanning the environment.	Senses data opportunities (e.g., trends) and threats (e.g., compliance) that could impact the data organization.	Data threats and opportunities sensing	Strategy: *Shape data governance practices*
	S5	Maintains the system’s identity by describing the system’s norms and purpose.	Provides strategic direction for the entire data activities in alignment with company strategy.	Data strategy definition and monitoring	

Table 3. VSM sub-systems and their application to data governance.

4.2 Governance – Orchestrate data practices

System 2*,* taking care of **coordination**, is managed by the data governance team, be it at global or local level. Its role is to communicate about data governance and to coordinate the network of data providers and consumers (S1). Thereby, it ensures alignment at enterprise-wide level, be it between data providers and data consumers within an operative unit (S1), or between several operative units (e.g., in data sharing between customer and sales data domains). We identify five key data practices enacted by S2, which are *definition of data roles and responsibilities*, *data enablement*, *data management support*, *data documentation and architecture,* and *data applications specification*. ***Definition of data roles and responsibilities*** is an established data governance practice that involves defining, assigning, and communicating data-related roles and responsibilities, such as those of data stewards or data editors. This practice also clarifies the role-players’ interaction and the collaboration models. For BeautyCo, “*the role definition is central, but the execution happens in regions. For this, we set up the regional hubs* *and the roles have solid reporting lines to regional offices. But they also have a functional reporting line to me.*" ***Data enablement*** comprises an emerging set of data governance practices focused on empowering individuals and teams to harness the full potential of data by providing the necessary tools and skills. Typically, as the number of employees in data roles grows, increasing data literacy, for instance through training programs, is a priority. Firms also initiate global data culture initiatives, as EnergyCo explains: *"We have a company-wide initiative called 'The year of data,' which is about raising data awareness by showcasing three things: what you can do with data in general, where the company stands and what it struggles with, and what can be done. We also follow up with a data mood survey.*" Executives at ManufCo drive data-driven culture with axioms such as "*Data belongs to all employees, and all can benefit from knowledge of the data*", "*We acknowledge the value of data for the company", "We pay attention to error-free data and thereby guarantee a high level of customer satisfaction."* However, due to the growing business ownership of data, *data enablement* must also reach locally, as BeautyCo states: *"Data enablement is central and regional. In the future, we want most regional hub interactions to have local functions. For instance, our hub in Poland is quite active and does a lot in this instance. They have built their own way of communicating with newsletters and so on. They are very good. We are learning from them."* ***Data management support*** involves all data governance practices aimed at coordinating business and project support (e.g., compliance with data strategy, data needs), coordinating requirements with technical teams (e.g., data engineering), and generally ensuring functional communication across the different units. ***Data documentation and architecture*** practice involves systematically creating and updating comprehensive metadata documentation. Thereby the organization creates transparency regarding its data. This is achieved by designing and evolving the data architecture, and by how data is collected, stored, processed, documented, and used. ***Data applications specification*** aims to define the supporting applications for data provision and consumption. Applications with data governance in scope are typically related to master data management (e.g., SAP MDG), data quality, and data cataloging. As PharmaCo explains: "*I am responsible mostly for the content part. Our task is to translate the technical data into meaningful content. To make the data understandable and consumable for the entire organization, we manage the company-wide data catalog, and along with our divisional stakeholders we are filling it in. We also use a tool to build ontologies and knowledge graphs."* Governance practices around data applications are performed in collaboration with IT (especially for the platform side). This involves defining the functional requirements, change management, workflows, and UI modelling.

System 3, taking care of **control**, monitors all data practices in S1 and ensures that they are performed in line with strategic goals and according to set standards and guidelines. At the interface of operations and strategy, System 3 plays a pivotal role in standardizing data practices, as well as in strategy delivery and reporting. It displays data governance practices identified as (i) *definition of data standards and guidelines,* and (ii) *performance monitoring and improvement.* The ***definition of data standards and guidelines*** involves creating a data governance framework, developing a local data ownership concept, data process documentation, and data access rights. Control is typically exercised by both global and local data governance teams, as ManufCo highlights: "*Standards and guidelines mainly come from us and are enriched in the specific domains. For instance, we do not give the guidelines for maintaining payment conditions; this is the task of the finance data domain."* ***Performance monitoring and improvement*** is an emerging data governance practice that pertains to the structured methods and tools an organization employs to monitor, measure, and enhance data quality and data-related processes, through, for instance, maturity assessments. While firms traditionally monitor data quality, they now progressively integrate data consumption in their metrics framework (e.g., in the growing number of data objects available on the data catalog at ManufCo and BeautyCo). At BeautyCo, "*we measure the increasing number of data objects on the data catalog. For success, we measure time-to-market in regional hubs. We also monitor how the number of GTIN violations decreases.*"

System 3*, the **audit**, complements *System 3* by auditing data practices of operative units, thereby ensuring that they agree with legal requirements, industry standards, internal policies, and data standards and guidelines. It is mainly enacted through *data compliance auditing* practices which enforce adherence to rules, regulations, and standards that govern the collection, storage, processing, and sharing of data.

For instance, at ManufCo, "*data management is a mandatory, auditable process in the quality management system. To support IT security and data protection, delicate data objects are flagged as sensitive in the data model. Data domains that contain intellectual property are also closely monitored to address potential risks and to initiate risk mitigation.*"

4.3 Strategy – Shape data governance practices

System 4**,* related to **intelligence**, ensures that the whole system can adapt to disturbances by scanning the environment to detect changes (e.g., new data trends, use cases) and by proposing mitigation plans. It is mainly performed through the strategic practice of ***data threats and opportunities sensing and involves actively monitoring, identifying, and responding to potential risks or beneficial situations in the organization's data landscape. This proactive approach enables timely mitigation of threats, such as to data security, and exploiting opportunities, such as new use cases for emerging technologies (e.g., Generative AI). A new local regulation can also impact the data activities, as raised by ManufCo: "*Let's say we want to react to the EU data governance act. It will be discussed in the data council but due to the effects on other enterprise areas we would also put it to the digital coordination council and to the board. We also take it to the global risk and compliance committee, and to several other committees that I am not going to list right now. So, it impacts way more than just data*." For this reason, and due to the critical role System 4 plays in the system's viability, companies might use ambassadors at executive level to help with communication and collective acknowledgement. As SoftCo observed: "*We have a super senior executive coms person in our team. This is one of my biggest assets. Yes, I sit in the organization at level three, but I communicate with everybody, including senior executives and the board. This is sometimes challenging, especially if you want to discuss data topics at a business and strategic level. The role is called 'executive communications lead' and helps us neutralize emotions and politics that come with data topics at strategic level.*"

System 5**,* dealing with **policy**, provides strategic direction for all data activities aligning with the corporate strategy and business priorities. Strategic data practices introduced here revolve around the enterprise-wide ***data strategy definition and monitoring customs and consist in planning, implementing, and optimizing systematic approaches to create value from data. It also involves identifying and assessing the data capabilities required to enable the business model. For instance, the opportunities Industry 4.0 offers and the C-level's recognition of data's strategic value led to ManufCo updating their integrated data and analytics strategy in 2022. In fact, all cases had recently updated their data strategies with a shift toward innovation and value creation from data. As PharmaCo explained: "*We are still working on our enterprise-wide data strategy. In such a big company, this is a long-term project. Our team manages it because it is not about technology; it is about communities, change, culture, this seamless data experience we want to bring. We also propose shifting to a kind of global data office in combination with larger domain responsibilities*."

4.4 Federated data governance as recursive system

Consistent with existing literature, we note that global firms adopt a federated governance model, albeit with various, sometimes subtle, distinctions. Using the VSM, we find that these federated data governance practices unfold through several systems-in-focus (i.e., multiple System 1). Consequently, global data governance practices can be distributed by being embedded, and often enriched, in local systems which mirror the primary organization's existing regional, divisional, and functional structure. This indicates a recursive logic with two (possibly more, depending on organizational structure) systems-in-focus: (1) at level "n", the totality of corporate data practices governed by global data governance practices, and (2) at level "n+1", local data practices governed by local data governance practices. Above, in describing the different systems, we have already exemplified the recursion in the VSM, giving various examples and quotes from our cases (e.g., the regional data governance at BeautyCo, divisional data offices at EnergyCo). Following here, we clarify the notion of recursion in the VSM by providing a vignette that illustrates ManufCo's federated data governance approach.

Our analysis disclosed that ManufCo's approach is the most advanced of the cases in that its data operating model covers data governance practices at a global level and on a local level operates in regions, divisions, and functions. The board's publication of the so-called "digital agenda" was an important contribution to securing the company's long-term competitiveness, marking a paradigm shift in the role of data, which now forms a "core component of value creation." Consequently, ManufCO launched in the project "Data Domain Management in all Data Areas," working with the global data governance team to remove bottlenecks and to establish a network of data roles spread globally (across functions, divisions, and regions). This shift triggered an extension of the data scope from key master data objects (such as suppliers and customers) to 44 data domains relevant for digitalization. Examples of these domains are "R&D Engineering", "Sales", "Manufacturing Planning", and "Finance Accounting".

ManufCo's VSM displays a patent example of recursion, showing that most data practices enacted in the five sub-systems are replicated at data domain level. Each data domain is itself a viable system that strategically self-organizes, independently from other domains. Data domain governance controls and coordinates domain data practices (e.g., data creation, usage, and maintenance in the data domain only), and interacts with the local environment (e.g., correlating function, division, region, and outside world). Figure 5 shows the role of each sub-system and highlights how key structural mechanisms (e.g., boards, teams, roles) can be mapped onto them. Next, we describe the five sub-systems, thereby showing the interplay between data strategy, data governance, and data operations.

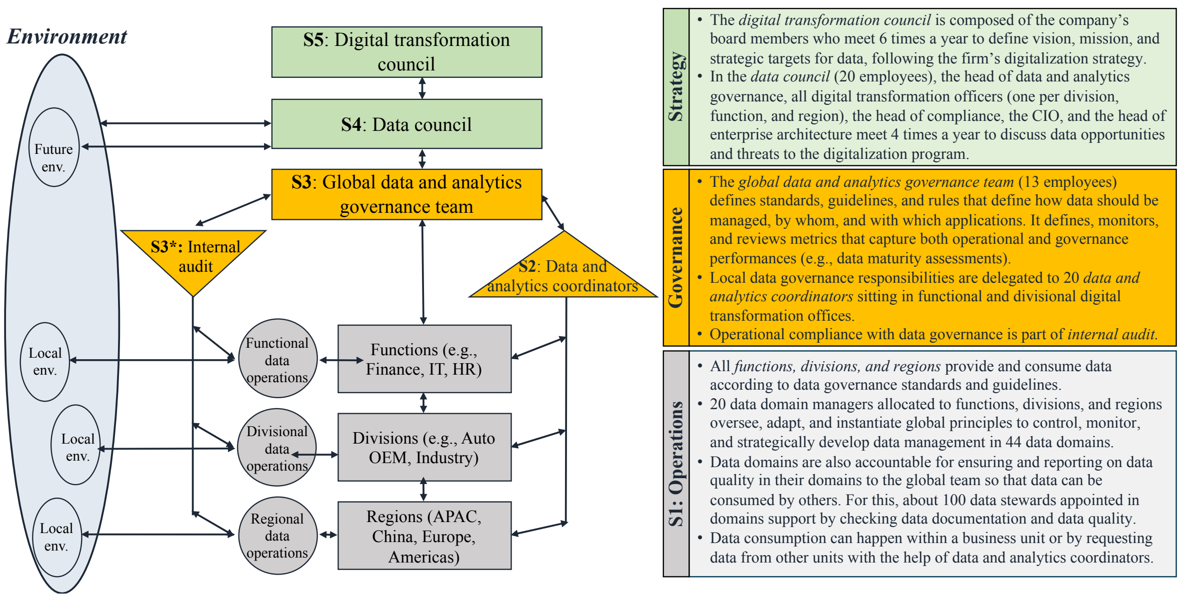

Figure 5. Viable System Model for data governance at ManufCo.

System 5 is enacted through the Digital Transformation Council (DTC). It is composed of six company board members who meet bi-annually to monitor the progress of the so-called "digital agenda," which is the digital arm of the company's strategic goal to be the technology leader in the "mobility of tomorrow." More specifically, the DTC aims to secure the company's long-term competitiveness through a paradigm shift in the role of data, which now forms a "core component of value creation." Concretely, having discussed data vision (e.g., data monetization), key drivers (e.g., data democratization, data economy), and associated KPIs, the DTC formulates the data strategy.

System 4 is enacted through the Data Council, the organizational body responsible for the underlying data-related activities, their prioritization, oversight and alignment, and possible implementation issues (S4). It is composed of 20 members that include the head of data and analytics governance, all digital transformation officers (one per division, function, and region), the head of compliance, the CIO, and the head of enterprise architecture. During quarterly meetings they discuss topics such as how to react to new regulations (e.g., the EU data act), or how data can support the different business processes in creating business value (e.g., where to find trustworthy data, what count as dependencies, as key vocabulary, as important security and privacy aspects, and as business processes' requirements). The data council also manages the data domains portfolio that currently includes 44 data domains. Eligibility questions for opening new data domains typically include: Which business processes or other principles would justify a new domain? Does the corresponding function or division generate its own data (e.g., specific data entries)? Would the domain be temporary or sustainable in the long term? Would data be useful in all departments? Would the domain be cross-functional? Are there synergies with other domains that could justify an integration/merger? Would setting up a regional satellite for this domain be wise? Based on lean templates, each data domain's profile is documented (e.g., in a description of its content and data objects, sensitive data, relevant business processes).

S*ystem 3* is enacted through the global data and analytics governance team. Composed of 13 experts who control all corporate data operations, the team provides the general data standards and guidelines applicable to all domains, and it monitors various metrics to demonstrate progress on the data strategy, such as data quality improvements, the data documentation rate, data tools use, and data literacy assessment. The team also gets support from internal audits to assess various data domains' compliance with global standards and guidelines.

System 2 is enacted by 20 data and analytics coordinators who act as counterpart in division, functions, and regions, who sit in the respective digital transformation offices. They communicate the global standards provided by *System 3* to all domains. This way, the entire network builds knowledge of the data strategy, data roles and responsibilities, data processes, data applications, data model, and data quality. Further, they provide data management support, for instance by coordinating data provisioning and data consumption requests across operational units. This is facilitated by the "Data Domain Manager Round Table" that enables cross-domain practice exchange.

System 1 represents all operational data practices across functional, divisional, and regional units. Each corresponding data domain takes ownership for creating, curating, and using their data or using other domains' data. Recursively, in each domain, *data domain managers* adapt global principles and define their own data domain principles, i.e., they control, monitor, and strategically develop data management in their data domain. These managers are also accountable to the global team for data quality in their domains, ensuring the quality and reporting on it. For instance, the Finance Accounting domain gets contributions from other domains, e.g., gaining inventory data that belongs to the Storage and Shipping domain or costing data that belongs to the Sales and Marketing domain. The *regional data domain managers* are responsible for coordinating the data domains in a given region, thus linking the data domain manager to the operative business units (e.g., helping to define the access authorization concept in compliance with local regulations). *Data stewards* support the data domain manager in documenting data (e.g., metadata) and maintain data quality in each domain by integrating business knowledge in data curation tasks. They are also responsible for responding to data users' data access requests, in- or outside the domain.

Since implementing their federated data governance model in 2021, ManufCo has observed substantial improvements in business performance. The duration of both the "Initial Order" and the "Request for Quotation" processes were significantly reduced thanks to data quality improvements. Further, the recorded cycle time of the business partner approval process was reduced by 30%, the cycle time of intercompany service requests by 45%, and ManufCo could achieve a striking 97,3% duration reduction in all processes within the 24-hour timeframe agreed in the service level agreement. These results show the critical role of data governance in enabling innovative local data practices.

5 Contribution, Discussion, and Implications

Although the foundations of data governance have reached a sound level of clarity, much of the research to date remains conceptual and proposes generic, static mechanisms. This study is among the first to focus on the implementation of data governance mechanisms and their adaptation in large and complex organizations. Our results explain how data governance unfolds in practice in multinational companies through a viable system composed of multiple, interconnected levels, i.e., sub-systems with their own sets of data practices. The application of the VSM in this study demonstrates that data governance cannot be seen only as a static framework that shapes structural, procedural, and relational mechanisms; rather, it needs a dynamic framework that supports the expansion of data practices in all areas of the organization. This is in line with Vial (2023, p. 6) who stresses that "*the instantiation of this design in practice is important to understand how an organization protects and leverages data for digital innovation.*" Overall, the use of the VSM supports a better understanding of such seemingly paradoxical activities by explicating both the dynamics of control (e.g., data protection) and the dynamics of value creation (e.g., from data use).

Our results confirm and extend prior research, arguing that global firms adopt federated (also called hybrid) models for data governance (King, 1983; Grover *et al.*, 2018). Through the lens of the VSM, we show how companies thoughtfully merge and maintain global responsibilities, such as universal standards, protocols, and methodologies, with local responsibilities that are uniquely tailored to individual business units, including data quality monitoring and project execution. This model involves transferring certain data governance responsibilities from the global data governance unit and assigning new responsibilities to local roles in business (e.g., data steward). Data access is mainly managed by business experts (i.e., data managers) themselves, following corporate policies set by the global data team (*System 3*). This obliges the audit function (*System 3*)* to take on additional responsibilities that will mitigate data management risks. Overall, while global data governance fosters uniform enterprise-wide data management principles, standards, and methods, federated data governance practices favor local business expertise. *System 2* is then crucial for cross-functional projects and network enablement.

We find that data governance practices are enacted according to an organizational hierarchy, thus not at the same level. The recursion highlighted in our VSM demonstrates that federated data governance is enacted through a cascading system that assign data governance responsibilities across multiple hubs typically aligned on the organization's primary structure (e.g., corporate, functional, regional). This model further branches out through "spokes," representing the data creators and users within the business, ensuring that governance reaches all levels of operation. Hence, unlike a hub-spoke model that centralizes data governance responsibilities at a corporate level, hub-hub-spoke models, which can embed more than just one recursion, offer numerous benefits such as greater local autonomy, use of domain knowledge, faster issue resolution, and improved agility. For their respective sectors, each hub sets strategic data objectives, defines data standards and guidelines, creates transparency on data, and fosters data enablement. In return, a hub-hub-spoke model generally requires better coordination mechanisms (e.g., a data council, data communities, local hub monitoring). However, coordination mechanisms (*System 2*) generally "*do not arise prior to coordinating but are constituted through coordinating*" and they typically follow a system's disruption (Jarzabkowski, Lê and Feldman, 2012, p. 907). This highlights the pivotal role of environment sensing on both a corporate and on local levels to continuously update data coordination mechanisms. For instance, the strategic need to develop new analytics use cases (e.g., Generative AI) might enlarge the scope of data governance (e.g., extending to new data types) and trigger an update on the role and board model. Future research could investigate hub-hub-spoke models in greater detail, and especially how they unfold into different organizational structures. In this regard, the study of global-local coupling in federated data governance systems could be an interesting starting point, for example, by examining the impact of external turbulences based on the responsiveness and specificity of the system in focus (Weick, 1976; Orton and Weick, 1990). This avenue could investigate how to build modularity, the right level of redundancies, adaptability, and resilience into federated models.

From an academic perspective, the VSM perspective paves the way for investigating data governance from a new angle. It contributes to the previously neglected dynamic nature of data governance and addresses the need to investigate data governance in practice (Vial, 2023). The insights developed in this study further provide valuable guidance on how to design the organizational counterpart to technical data mesh principles by showing, for instance, how different business units enact ownership of their data. Besides data creator and data user roles, our study shows that data steward and data (domain) owner roles, which are seldom clearly distinguished and are often misunderstood (Vial, 2023), are essential to the execution of domain-level data governance practices thanks to their knowledge of the business context. Future research could further investigate the interaction between the technical architecture and the operating model for data governance, especially considering the difficulty of knowledge integration and the data literacy gap between business and analytics teams (Kollwitz, Mengual and Dinter, 2018; Someh *et al.*, 2023). From a practical perspective, our findings support decision makers in global firms to define, adapt, and implement data governance. They can leverage the VSM to build their own federated data governance framework, that addresses both global and local levels.

Since this study takes a new, systems theory approach to examining data governance, it is inherently prone to first mover limitations, and we strongly encourage future research in this area. Beyond the potential future research activities mentioned above, the understanding of data governance as a self-organizing system could be further deepened. As this study focused mainly on elucidating the five sub-systems, our findings also open avenues for further research into how antecedents affect data governance as a system. For instance, researchers could investigate how different industries' strategies and operating environments impact the system's viability. In such a case, certain principles from VSM theory, like variety and transduction (Beer, 1985) with which this paper could not deal extensively, provide interesting possibilities for refining the model.

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