On Domain Information Governance

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Abstract
This paper introduces concepts of domain information governance and domain specificity. It aims to establish a critical perspective on specificity in operating models, using the well-known Data Mesh socio-technical method as an example of a localized, domain-specific approach. It employs a relative, reflexive, qualitative analysis, building upon earlier work on information governance at an enterprise level, and draws a distinction between tactical and strategic notions of governance that should inform practitioners with respect to the design of business architectures that enable governance.

Keywords
Domain Specificity, Enterprise Information Governance, Data Mesh, Data Product, Data Object.

1. Introduction

This paper introduces and explores the concepts of domain information governance and domain specificity. It builds upon an earlier definition of Enterprise Information Governance (EIG) [1] and shows how key concepts can be framed in terms of information assets within areas of knowledge, activity, and accountability. The notion of specificity introduced here corresponds in practice to tactical governance and serves as a counterpoint to that of strategic or enterprise governance.

The paper begins with a brief account of the research methodology employed: the relevant literature on data and information governance. This paper includes definitions of data objects and data products. It is about the exploration of the governance of domains, and the specificity of governance. The paper brings out novel parameters with respect to governing domain, business unit, process, and decision-point bases alongside Data Mesh to support design of domain-specific regulatory business architectures for governance.

2. Research Methodology

Our exploration of the existing literature was based around a clear differentiation between the *management* and *governance* of data and between the concepts of *data* governance versus *information* governance [2]. We find it useful to distinguish between the software products, tools, and techniques employed in data management and the framing of the regulations that

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embody data governance [3, 4]: although there is a clear intersection in operational terms, we see data governance as sitting above management.

We have adopted a qualitative approach, with analysis undertaken iteratively against an evolving list of references, within the limits of thematic saturation, indicated by the keywords "data governance", "information governance", and "Data Mesh". Analysis progressed by determining themes, or categories, using a textual matrix of source versus theme. Results are presented partly in a tabular form, drawing an immediate comparison between domain and enterprise governance.

We followed Creswell's recommendations [5] regarding inductive and deductive analysis to establish patterns and themes; researcher reflexivity, and interpretation of a problem and triangulation between sources via structured literature review and simulation of "prolonged time in the field", drawing upon actual case studies grounded in consultative fieldwork [6], with data generated between 2005 and 2022.

3. Data Objects and Governance

A domain in our context is a *locus* (Otto [7]) and maps both to the consideration of Khatri and Brown's [8] *data decision domains,* and to their similar and parallel concept of locus, which we consider later. A domain may most commonly be seen as a department or team—project, or business-as-usual-or an "office", the group of people who perform a definite business or technical function. We define a domain in this paper as being a "governed" domain, that is, one to which governance applies. Our definition also borrows from Evans' [9] domain-driven definition. We define "domain" in our context here, drawing on Otto, Khatri and Brown, Evans, and upon the definition of Enterprise Information Governance [1] as, *"a bounded or scoped organizational, functional, or sociotechnical area of knowledge, activity, and accountability, within which information assets may be created, utilized, managed, and governed according to a defined authority."*

Brous, *et al.* [10] see data as a set of characters, their meaning defined by context and usage, held in operational data stores, varietal components, and "systems of systems" (Tekinderdogan, *et al.* [11].) Ackoff [12] saw data as symbols representing properties of objects, events and environments. Boisot and Canals [13] argue that data, information and knowledge differ. Omnès [14] sees data as, "an essential intermediary for reaching a result". Considering the life of data, they can be said typically to follow what might be called "a lifecycle" [15] in context in an organization. Part of the essential management thinking around data is a concept propounded by Corrado, *et al.* [16]: treating them as intangible assets, a "storable factor input", or things that contribute to final production in an economy. Weber, Otto, and Österle's [17] research showed that, "Data is often distinguished from information by referring to data as 'raw' or simple facts and to information as data put in a context or data that has been processed." They are satisfied that the terms data and information can be used interchangeably.

Ackoff [12] saw information as "contained in *descriptions,* answers to questions that begin with such words as *who, what, where, when,* and *how many*", and that "information… is extracted from data by analysis." Building directly upon Ackoff's perspectives, Hoppe, *et al.* [18], use as a definition, "Information is data that has been given meaning," arguing that, "data, information and knowledge [are] concepts building on each another." Buckland [19] introduces the concept of "Information as Thing," and that it might take forms as a process, as knowledge, and ("as thing") attributively for objects such as data and documents that are informative. Information is, by implication, a superset of facts represented by data. Buckland sees "data" as implying information-as-thing that has been processed in some way for use.

Madison [20] distinguishes data-as-form and data-as-flow. In considering the data lifecycle that is essential to information architectures, and through which they flow, are held, and are

stored; also, in the lifecycle of data as they pass around an ecosystem, Madison sees data as simultaneously form and flow. Zins' [21] comprehensive study, including a consideration of definitions of data, information, and knowledge, initially defines data as, "basic individual items of numeric or other information, garnered through observation; but in themselves, without context, they are devoid of information."

The European Union's Data Governance Act [22], sees data as, "any digital representation of acts, facts or information and any compilation of such acts, facts or information, including in the form of sound, visual or audiovisual recording." This sees data and information as semantically distinct, though offers no consideration of any differentiation in terms of relationship between them: facts and information seemingly equate. In consideration of the regulation and control of data, both their fluidity, and "thingness", will require regulatory governance as well.

Madison [20] sees data as intangible, and pools or collections of data as not depletable; but also that data-as-flow captures the fluidity of data. Friké [23] observes that, "Seeing information in terms of a data-information-knowledge–wisdom (DIKW) hierarchy or pyramid is commonplace", and quotes Rowley [24] in noting that this is often quoted, used implicitly, "in definitions of data, information and knowledge in the information management, information systems and knowledge management literature." If this were a criticism of such models, we might also note that Friké has argued [23] that DIKW should be abandoned completely, reasoning that, "some information is universal in form and as such could not have been derived from data."

Other scholars have considered DIKW deeply. Hoppe, *et al.* [18]; Pop, Talpos and Prisac [25]; Jennex [26]; and Müller and Masdoorp [27], quoted by Friké. These authors suggest, respectively, contraction of DIKW, expansion of DIKW, differing bases of analysis, or an extension more into an analysis focused upon organizations. These criticisms are valid but offer little help to the real-world corporate practitioner or to the scholar of data governance: in framing an operational understanding of information and data or establishing a pragmatic, canonical, framework.

It could be determined from these analyses that "information" could be viewed in a practical technology landscape as a superset of "data". "Information" can be seen as an overarching term, more strategic and encompassing; more aligned with (and align-able to) a defined strategy and to the IT context. "Data" could be seen usefully as more operational, processable, resources: Things–assets-to be governed and controlled at a lower level, perhaps; and more associated with delivery, with software interaction and day-to-day activities in departments and teams.

IBM® Consulting's (2021) information governance field and education artefacts conceived of "data objects", defined as, "the information or data owned within the scope of ownership". This introduced concepts of *ownership* of data, of their *stewardship* and *custodianship*, also of *bounding of ownership,* a domain or scope, by named individuals. They make decisions, *undertake* the ownership, define security and related procedures, and perform the management of data. A *data object* may physically relate to one or more data items. It can be constituted from a single byte, or many petabytes or zettabytes of data, or more. The storage mechanism related to a data object is not relevant to its governance but may be to its ownership. This is very much of the essence of the governance of data and the conceptualization naturally recalls Buckland's "information-as-thing" and implies data have been processed in some manner. Synthesizing from Humby's idea about context, Gartner, Luisi, Boisot and Canals, Weber, *et al.,* Omnès, Buckland, and Madison, there appears to be clearly emerging a concept of "enterprise information." This is encapsulated by Lockwood, *et al.* [28] in their observations that enterprises need to achieve enterprise agility through leverage of trusted information as a strategic asset, and develop a comprehensive, enterprise-wide approach, an enterprise information strategy. Today, facts are held as the information and data, with "data" typically

held in operational data stores and varietal components that constitute such information technology systems and "systems of systems", Tekinderdogan, *et al.* [29].

As we have seen, scholars have viewed data and information in various ways. That IBM definition of data objects introduced concepts of ownership, stewardship, custodianship, and of *bounding ownership of data,* via a domain or scope definition. The concept determined a data object as physically relating to one or more data items, themselves constituted from any scale. There have been many other conceptualizations of data objects. These include: Dray, Guthery, and Schwarzhoff [30] who saw them as, "an item of information… for which are specified a name, a description of logical content, a format and a coding. Each data object has a globally unique name called its object identifier." The authors note that, "The *content* of a data object is the sequence of bytes that are said to be *contained in* or to be the *value of* the data object. The number of bytes in this byte sequence is referred to as the *length* of the data content and also as the *size* of the data object." Gehrke [31] saw data objects as constants and variables. Booch, *et al.* [32] defined the data object as, "Something to which you can do things" and that each one will have a state, an identity, and behaviors, with commonality between objects determined by category. Microsoft™ define data objects variously, for example: Microsoft [33] sees data objects defined as pairs of data and format identifiers, supporting multiple formats; secondly, the corporation also defines them [34] as the destination side of a data transfer; thirdly, in the context of their Databricks platform [35], they say that "every asset you govern is modeled as an object", though this relates to objects identified as "securable" within the software set's governance context. SAP® [36] see data objects in a similar manner within a software context, defining them as "a type of artifact that allows you to store process related data." And we recall Zins' [21] study which, by contrast, flips around the concept from data objects to *information objects,* to posit its (initial) definition that, "Data can be defined as a class of information objects, made up of units of binary code that are intended to be stored, processed, and transmitted by digital computers".

Given that the IBM context was specifically that of the *governance of information and data,* we could use that definition here most straightforwardly for a consideration of domains, though others might be as appropriate for our consideration, and Zins' concept, or even Booch, *et al.'s,* would arguably work just as well here, if with slightly different perspectives. In any case, in business terms a data object could live and be owned by a grouping with some *scope of ownership,* such as an accounts payable team, human resources team, sales team, or any other unit, group, or division. Equally, a data object could physically exist within an operational data store, a database, data warehouse, or a bucket within Amazon's AWS™ S3, their "simple storage service." Of course, by implication, a data object need not in fact be owned by a definite team, in which case ownership might be assumed to be that of "the company" in general, the organization in whose ownership the data or file system or operational data store containing the data subsists.

EIG is defined as encompassing both information governance and data governance [1]. It was adduced as a corporate-wide strategic framework, differentiated from pure information technology governance and data management. This vision cascades to operational levels. The definition sees such governance as framing actions to ensure trust and compliance by determining strategic, tactical, and operational policies, standards, guidelines, and processes. Alhassan, *et al.* [37] define governance of data and management of data as differentiated: *Governance* refers to decisions, whereas *management* involves implementation. Hence, management is influenced by governance. The EIG framework itself supports management of shared resources and is delivered through rules —or other control mechanisms- that co-ordinate, integrate, direct, monitor and allocate tasks. These exercise authority, control, and accountability in order to manage decision rights over data [3]. The pursuit of EIG by an enterprise, prosecuted by an executive sponsor [3], would be undertaken to achieve value-

maximization of data assets. It would need to be consistent with organizational strategy, mission, values, norms, and culture. The EIG framework is scoped and bounded through the design and definition of a *business architecture* [38]. This brings together organizational leadership's strategic vision for governance (however that has been defined) with day-to-day operations, the tactical activities undertaken by individuals and teams. As an essential aspect of the EIG definition, "information" is viewed as a superset in a technology landscape; "data" semantically a subset. This construct enables consideration of information and data as terms at relative levels within and across an enterprise. "Information" is more strategic and encompassing. Data represents operational, processable, resources: Assets to be governed and controlled at a lower level contextually subsumed by the scope and boundary of "information" [3]. The EIG definition encompasses organizational components, business capabilities, and functions, in the form of an (initially new) *target business architecture.* Such an architecture will include definitions of a variety of classic operational governance roles, and topics that intersect with operational C-Suite (CIO, CTO, etc.) and divisional portfolios [1]. This perspective and definition of EIG form the basis for our consideration of the Data Mesh perspective with respect to *domain specificity* in the governance sphere.

Target business architectures (Hadaya and Gagnon [38]; and Easton [62]) are essential both to design governances and to support the transformation of organizations to encompass them. Such alterations of organizational schema are usually undertaken as part of a Change program or project, driven by a Transformation Plan [38]. Such business architectures need to make sense to individuals operationally, such as in teams, in departments, in projects (for example) and in other organizational structures; in defining functional and non-functional requirements and backlogs; delivering artefacts and software, and in the activities related to, and the equitable management of, data and information. We can determine based upon this thinking, and upon the concepts of strategy (Ein-Dor and Segev [39]; Gartner; Weber, *et al.*; Lockwood, *et al.*; Brous, *et al.*) that in the enterprise information governance concept, there are both *strategic* and *tactical* modes of governance. Whilst there is clearly an enterprise, more macro or strategic, level of governance there will also exist a set of constructs and a framing for policy, standards, guidelines, and procedures, a version or element, that ensures these regulatory aspects can govern data day-to-day and proactively in relation to a lower level than the strategic. External laws and regulations could be represented indirectly or implicitly in the design of individual *policies* within the scope of governance. Given the definitions of strategy in relation to such governance, we might appropriately call this "day-to-day", then, *tactical governance.* Considering our EIG definition, it can be deduced that there will need to be a finer-grained aspect of governance, or extension to regulatory framing, to support this tactical activity. There exists an emergent systemic approach that we can consider an example with respect to such tactical governance. It encompasses this finer-grained level of definition, embracing both tactical practice and a way that organizations can be transformed to consider data more particularly, looking directly at *domain and localized regulation or governance.* The method crosses the data management and governance boundary and perhaps challenges the concept of "enterprise" information governance itself. In fact, it can be seen as a type of governance that may be made specific to business or technical *domains* within an organization. The approach, perhaps methodology, is known as "Data Mesh." The concept was developed from the work of Dehghani in their well-known introductory paper in 2019 [40]. Data Mesh has become significant in leading socio-technical thinking across the IT industry, with its prominence exemplified by the growing number of organizations using it, such as PayPal®, AstraZeneca®, ABN AMRO™, Disney™, HSBC™, Michelin™, and J.P. Morgan™.

4. Data Mesh and Data Products

The concept of Data Mesh had been developed by Dehghani in 2018. The main argument was that the prevailing method of trying to force data into a single monolithic architecture, such as a data warehouse, was fundamentally limiting [51]. The new Data Mesh paradigm offered a way to resolve this *monolithism* through organization transformation, with a focus upon the *tactical* management of data assets. Data Mesh arguably aligns with perspectives, such as those of Trist [41] and of Baxter and Sommerville [42], as a *sociotechnical* paradigm, also aligning with Prodan, *et al.'s,* [43] *people, process, and technology* concept. It can be framed as supporting implementation of Bodendorf and Bayer's "Flexible Digital Platform" [44] or potentially meet some of their definitions for a (localized variant of a) "Corporate Data Broker". A variety of IT industry practitioners, however, have confused Data Mesh with data fabrics [45], with which it may align, but from which it differs substantially by virtue of not being a pure technology solution, platform, or necessarily an IT architecture, *per se.*

Dehghani's definition calls Data Mesh a "paradigm shift" in data management, one that attempts to resolve the typically monolithic nature of traditional data warehousing and data lakes, centralized, managed and governed by the IT team. The methodological aspect is founded upon four principles, those of: "domain-driven ownership of data", "data as a product", the "self-serve data platform", and "federated computational governance" [46]. The following (2021) framing of Data Mesh is most concise contextually: *"…a domain-driven analytical data architecture where data is treated as a product and owned by teams that most intimately know and consume the data"* [47]; although this has recently been updated (2026) to, *"a mature socio-technical paradigm, where Data Products and Self-Service Data Platforms have become foundational commodities"* [48].

The concept of Data Mesh relies upon *data domain owners,* or as the method defines them, "data product owners", as responsible for determining definitions of the data products they own. This conceptualization of "data-as-product" (latterly, "DaaP" [49], a slight conceptual variant) is similar to Buckland's ("information-as-thing" [50]). Data products recall the concept of *data objects.* The definitions of Data Mesh offered by Dehghani [51] see the analytical data of "domains" treated as a product and that its consumers are seen as "customers". Data in the paradigm become definitively "things"–along, in Data Mesh terms, with a set of attributes-and therefore governable because such parameters are *knowable, quantifiable, determinable,* according to Data Mesh concepts, and a lifecycle for them might be construed and thus theoretically controllable. Data Mesh's version of *data products,* as opposed to the comparator *data objects* we met earlier, has a more precise definition in that they are seen as individuated by virtue of being required by the method each to conform to a coherent model. In this variant of the product paradigm, data products had originally to be secure, discoverable, addressable, understandable, trustworthy (or truthful), accessible, interoperable, and valuable [40]. In 2024, this was revised by Thoughtworks™, the consultancy in which Dehghani originated the concept, to, "Discoverable, Addressable, Trustworthy, Self-Describing, Interoperable, and Secure (DATSIS)" [48]. The original "discoverable", "accessible", and "interoperable" parameters' conceptualization echoes that of Wilkinson, *et al.'s* [52] paper on *FAIR Data,* now used internationally in the pharmaceutical and wider scientific community, which requires that data is in and of itself: "Findable", "Accessible", "Interoperable", and "Re-usable".

Data Mesh relies on the structure of an organization being transformed such that localized domain groups take charge of the creation and provision or delivery of data products in specific relation to that department. The rationale is that interested parties are "close to" the data they use day-to-day. We could call this set of observations those that define the nature of the individuated business or functional *domain,* or bound or scope its *domain specificity.* It is in the domain that the data product itself subsists. The knowledge of and about the data in each

domain is seen as specific to it, too, and the Mesh model advocates the decentralization of data specialists associated with each of these domains. These individuals become identified more with the team, group, or department (domain) in which they work rather than with any *centralized* corporate function. Such centralization is seen as anathema according to the methodology. In practice, these data specialists might be data scientists, AI or data engineers, working as part of the domain or of data product teams. Data Mesh is predicated on the idea that it enables the delivery of customized data products to meet the demands and requirements of different interests within and across an organization.

In Data Mesh terms, the definition of a data product is determined by matching the criteria for such an object as defined by Dehghani [51]. It is a *set of all of the components* of which it is composed. For example, the product must be **secure**: The security protocols and parameters are defined: for example, database or data warehouse roles, users, and access. The product must also be **discoverable**: the information will include details such as relevant metadata (data defining the data product), product ownership, its origin, lineage, and versioning. The product must be **addressable**: it has a permanent and unique address for access via software or manually, with accessible records ("tuples") available via a "window" for the accessing program or viewer to see them. The product must be **understandable**: this is part of the Data Mesh concept of self-service: each data product must provide semantically coherent data, with a specific shared meaning, readily apparent to its user. Ideally, relationships and adjacent data products are apparent, too [51]. Common concepts such as "entity" and "relationship" are borne of Relational Theory. The product must be **trustworthy** (truthful): it assures the trustworthiness of data through defining Service Level Objectives ("SLOs") [51] with respect to the Data Product, at the same time as assuring data provenance and lineage and supporting data quality metrics. This aligns with ITIL® concepts of SLAs (Service Level Agreements) and OLAs (Operational Level Agreements), per Jouravlev, *et al.* [53]. In Data Mesh terms these actually relate to parameters such as timeliness, change interval, and operational qualities such as data "freshness." The data product must be "natively" **accessible**: a data product should be capable of its data being read ("accessed") by the standard ("native") software tooling used by a variety of users. The data product must also be **interoperable**: it must be easy to link it across domains, that is, to other data products and for uses other than, say, a single software artefact in the current domain. Lastly, a data product must be **valuable** (on its own): it must have inherent value in the *service* of the organization [51]. The *Data Mesh* conceptualization of a data product is therefore a particular one and assumes that Mesh has been supported and introduced to service by a significant organizational transformation, and that would ensure that the data product itself is *produced* via utilizing a Data Mesh.

5. A Localized Data Patois

Information Technology as a knowledge domain has inevitably spawned terminology and a jargon of its own. Given that we have established Data Mesh as sociotechnical [41, 42], this observation warrants some further investigation, not least as we can determine that such governance clearly includes cultural aspects in its development and application and these will be of moment to delivery and to design, particularly to the program of transformation.

Amirbekova, *et al.* [54] refer to "a rich and dynamic layer of informal language–commonly referred to as IT slang." An IBM Consulting (2022) analysis found that linguistic variants will be likely across enterprises with multiple *business domains.* Budiyanto, *et al.* [55] see jargon as only really understood by a profession's "insiders", it cannot be understood by outsiders. In terms of localized jargons, Preetha R. and Senthamarai [56] write of their finding a "rich and expanding lexicon that supports ongoing development" in their paper on evolving technical

language. Swales' [57] review work, building upon Nystrand's [58] concept of a socio-rhetorical "discourse community", defines such communities as, "groups that have goals and purposes, and use communication to achieve their goals." As one of his eight criteria scoping such groups, Swales notes that they typically acquire a "specific lexis", that is, "abbreviations and shorthands of all kinds"; that they "[utilize] an evolving selection of genres in the furtherance of [their] sets of goals and as a means of instantiating… participatory mechanisms." Such "genres" include different types of meetings, roles, agendas, minutes, and so on. Data Mesh terminology and conceptualization, considered in these analytical contexts, can be understood as both enabling and constraining: It permits distributed varietal enterprise actors to co-ordinate their activities around shared artefacts, notably data products.

At the same time, Data Mesh as a method seems likely to create boundaries of localized expertise: teams, groups, departments' data terminology, not un-akin to that of a discourse community. They require translations between business, technology and governance communities; therefore potentially with *individuated* governances, local to domain, and potentially local definitions of semantics and meanings. We could characterize this, perhaps, as a *localized data patois,* that is, relative, rather than absolute semantics, terminology; a "patois" being a dialect, jargon, or informal speech. Without careful, centralized or holistic, management across boundaries and teams within an organization, it seems likely that such a *patois* may substantively conduce towards encouraging *silos* (siloed, separated, and disjointed domains) and the reverse of monolithism, technological diversity, something at odds with a tenet of Dehghani's Mesh method.

6. Domain-Centric Governance

The EIG framework can be used as a model with which to dissect the Data Mesh perspective, as an example of looking at domain specificity in the governance sphere; also supporting development of the novel concept of *domain governance* versus corporate or enterprise, *centralized governance.* Using it, we can more clearly differentiate EIG (enterprise) from DIG (domain) governance.

Data Mesh in its very first 2019 incarnation seemed from one reading to eschew classical information and data governance [40]. Dehghani [51] felt the term "governance", exemplified rigidity, authoritarianism, and presented characteristic systemic bottlenecks. From a research perspective, what we consider the "Data Mesh view" of governance appears not so much to be regulatory, which EIG is —driven as it is by policies, standards, guidelines, and procedures, the framing of vision and mission- but more a data-centric, data mechanistic, one, reliant upon software mechanisms.

A data product is seen as integrative across data, code and (governance) policy [51]. Governance is seen as manual, as minimally supportive of change; as frequently engaged-with too late in the systems lifecycle. The Mesh paradigm intends to move responsibility and authority over data close to its source, to a specific domain. It *automates* governance. There is a conundrum here, one that sparks disagreement. This arises because the Data Mesh view of governance, of policy compliance, seems not to accord entirely with the more holistic view of EIG, adduced from the work of diverse scholars. DeMaine [59] finds that information governance is *holistic.* The Data Mesh paradigm seems to imply, by comparison, it is very much not holistic, but localized, or *siloed* even. Data Mesh is driven mechanistically, more from the "shared resources" tactical aspect, with an emphasis upon stated technology models such as data lakes and data warehousing, discursive references to which, in Data Mesh literature, are legion.

Seiner [60] sees governance as formalized execution and enforcement of data management. Smallwood [3], as ensuring high quality of data at its root level. It would be possible to see Data Mesh as aligning with these perspectives. Information Governance, taken as a discipline, is itself neither inherently primarily mechanistic nor software-centric, but can be seen as more *regulatory* in nature [1, 2, 3]. The primary Data Mesh approach, by comparison, considers data products governed by programmatic code *("computational instructions")* as the representational form of policies: The code is intended to be embedded in each of the data products, with each programmatic policy validated and emplaced as part of the product's lifecycle [51]. This is a tactical, more clearly domain-bound, rather than a strategic, approach. Thinking of the tactical nature of Data Mesh, we can note that Tallon, *et al.* [61] see factors that *inhibit* information governance as including departmental silos, low process integration, a "pack-rat" culture, and decentralization. Decentralization is a cornerstone of Mesh, though, but it is also a method that actively supports *localization,* albeit with caveats. The data-productized view seems at first to exclude the concept of enterprise, of *holism*, of holistic, cross-functional, cross-domain governance, though Data Mesh is described as requiring "business-driven execution" and being a "component of a larger data strategy" [51]. Dehghani also describes here delivery of governance via a "mesh experience plane," or "multiplane platform", which could in program delivery take the form of a data platform, equating (for example) to a cloud-based environment. Again, we may see this perhaps as more *mechanistic* than a regulatory paradigm.

Summarizing, we can determine that there are a set of *explicit* assumptions inherent within Data Mesh, in terms of localized, decentralized paradigm proposed. Policies are naturally implemented in a programmatic manner; policies are versioned; policies are tested, implicitly like software; policies are executable and executed (i.e., run); and they are time-variant and change with time. The assumptions that appear *implicit* here, and that can be clearly inferred from Data Mesh literature, include that: Policies are *capable* of programmatic representation and assertion (Data Mesh likes the idea of *"policies as code"* [51]*;* policies will be *embedded programmatically* within a data product in some manner; the embedding of a programmatic policy within a data product is not itself problematic; policies are always necessarily mechanistic, software-centric, and programmatic in nature; Data Mesh, and any governance within its scope of transformation, *relates only (realistically) to data products (i.e. the Data Mesh definition of them,* so "data objects" in and of themselves could not fall within the scope of governance); and data products, to be valid, must accord with a *prescriptive scoping* rather than (say) to that concept of *data objects,* which might accord with a wider and less proscribed parameterization.

Regulatory enterprise information governance policies in themselves are, of course, not necessarily able to conform to these implicit assumptions. It may be suspected that the Data Mesh view of policies is more purely mechanistic for exactly this reason. We can see a significant divergence between the Data Mesh concept of domain specific "governance" policies, and by extension standards, and an enterprise information governance concept of them as external to the system in question, for example laws, regulations, defined or mandated from outside the organization. Dehghani writes of organizational shifts from centralized ownership of data by specialists who run data platforms, but in many modern organizations, data is already available using localized cloud instantiations (e.g. AWS, Azure™.) These instances are owned—though not necessarily paid for-by local departments, teams, or groups anyway.

We can now summarize in Table 1, below, observations about Data Mesh, as follows, and use this summary to consider it as an approach to Domain Information Governance, DIG, using components taken from the definition of EIG [1], as a guide for the analysis:

Table 1
Domain versus Enterprise Information Governance

Element	DIG: Domain Information Governance (Data Mesh)	EIG: Enterprise Information Governance (Generic)
Lowest "Unit" of Governance	Explicitly Data Product [40, 51].	Conceptualized as information effectively a superset of data [1]. Data Object, or with unit as defined by governance specification (e.g. standard, policy.)
Strategy and Mission	*Tactical* in terms of operation, less strategic *("a component of a larger data strategy"* [51]). Sees localized policies as being essential to the model, and effectively de-prioritizes or reduces focus upon enterprise policies; it espouses localized, domain specificity with respect to data product ownership, management, and policies.	*Strategic:* Driven from "top down"; independent of any particular department or division [3]. Governance encompasses both information governance and data governance [13, 17]. A corporate-wide strategic [10, 17] framework [1].
Vision, Mission, Goals	Introduction of Data Mesh is a strategic choice, but vision is focused by domain and domain expertise [51]. Mesh relies upon data domain owners, *"data product owners."* It is not primarily a whole-enterprise method, eschewing centralized governances.	Defined against a vision for end-to-end governance [1]. A cross-functional framework for managing data as a strategic enterprise asset [2] and the componentry of the business architecture that determines actionable descriptions of the elements.
Culture, Values, Norms	Data Mesh requires organizational transformation and culture change to a model of more localized, domain-specificity: *"Distributed Domain Driven Architecture, Self-serve Platform Design, and Product Thinking with Data"* [40]. The approach eschews cross-organizational governance.	Pursues value-maximization of organization's data assets [1, 3, 7] and operation will be consistent with its strategy, mission, values, norms, and culture [1, 17].
Terms, Language, Jargon	Can be surmised as possessing potential for significant localization, development perhaps of a localized "Data Patois" [54, 55, 56, 57]. *Tactical* in terms of operation, less strategic.	Can be surmised as possessing potential for significant generalization: Driven from "top down"; independent of any particular department or division [1, 3.]

Operating Model (Business Architecture)	Decentralized data specialists, associated with each separate domain. Less regulatory, more software-centric (mechanistic) in terms of programmatic policies: *"Data mesh shifts this responsibility close to the source of the data"* [51]; and *"This is a new architectural construct that autonomously delivers value."*	Tends to be more centralized. More regulatory, less software-centric; less mechanistic. Planned using a business architecture to bridge strategy and tactical operations [7]. Design developed via the concepts of business architecture [4]. Target operating model (Business Architecture) may be similar to CBM™-BoIT [62]. Brings aspects of governance into an operational whole.
Governance versus Technology	More data management, less data governance: *"domain-driven ownership of data", "data as a product", "self-serve data platform" and "federated computational governance"* [51].	Less data management, more data governance. Differentiated from Information Technology governance, *per se,* [1, 3] and data management [39].
Policies or Standards	*Mesh "encodes all the behavior and data needed,"* and uses "*computational instructions"* [51] to do so. Thus, programmatic, more mechanistic, tactical, domain specific.	Frames actions that ensure trust and compliance with strategic, tactical, and operational policies, standards, guidelines, and processes [4, 10]. Laws and regulations represented indirectly or implicitly; or explicitly, directly, in design of policies to incorporate aspects of external regulation.
Shared Resources	More mechanistic; aligning more with technology than with the governance domain: *"business-driven execution"* [51]. Data Mesh becomes embedded in localized teams with individuated governances, local to domain; likely local semantics, a localized *data patois,* and silos of data or information.	Supports management of shared resources [20]; is circumscribed by rules or control mechanisms that help to co-ordinate, integrate, direct, monitor and allocate tasks [1, 8], exercising authority, control, and accountability in managing decision rights over data [1, 2, 18, 39].
Information and Data Assets	Data Mesh is *data-product-focused* [40, 46, 51.] Must be: secure; discoverable; addressable; understandable; trustworthy; "natively" accessible; interoperable; and valuable. Latterly (from 2022), "DATSIS".	Where defined, might be characterized more as *data-object-focused.* May have varietal definitions [31, 32, 33, 34, 35, 36], with definition framed by governance design (e.g. policy, standard.) No implied limit to size, volume, or scale.

7. Domain Specificity

We can now turn towards *domain specificity* with some greater clarity. Following our review and Table 1, it would be possible to see Data Mesh as aligning with more holistic perspectives. Likewise, in considering Boisot and Canals' information in the physical world, Buckland's information-as-thing, Weber, *et al.,* IBM's, and Dray, Guthery, and Schwarzhoff's data objects (as examples), Madison's form-like data, and Dehghani's Data Mesh data products, these concepts seem to have some conceptual alignment.

In the corporate world, the term "governance" appears often in the management of companies and boards of directors as *corporate governance*; or, more broadly, of institutions in what could be referred to as *institutional governance.* Smallwood notes that *"IG programs are driven from the top down but implemented from the bottom up,"* [3] and The Sedona Conference® determines that, *"An [Information Governance] program should maintain sufficient independence from any particular department or division to ensure that decisions are made for the benefit of the overall organization"* [3]. Independence is significant, avoiding localized silos. In these cases, the conceptual link is some form of location, of denoted area, of scope, of *placement,* that defines in what way or by what means such *office, function, or power, or authority* is both determined organizationally and delimited in terms of its sphere of dominance and influence. Thinking of this, earlier in this paper we referred to "an unresolved tension" in governance between a definition of holistic (whole organization or cross-organization) and localized regulations.

Otto [7] brings out the idea of location and scope, writing of the concept of *"locus of control",* and a variety of authors' views with respect to *"hierarchical positioning"* of the locus, for example in different functional business departments versus IT/IS department versus a shared responsibility. Otto finds no clear trend across the differing opinions and observes that centralized and decentralized organization is effectively a continuum. Khatri and Brown [8] determine a similar concept to Otto's, with what they call a *"locus of accountability."* They quote co-author Brown [63] in saying, *"In designing data governance, the assignment of the locus of accountability for each decision domain will be somewhere on a continuum between centralized and decentralized".*

The Data Mesh paradigm, then, aligns with some of the strategic and tactical thinking in seeing organizations as needing top-down communication of vision; bottom-up enablement of technology [51], correlation of data across domains and harmonization of rules, which it is argued should belong to global governance [40]. However, Data Mesh places operational governance in the hands of practitioners localized to domain. It relies on organization structure transformation such that domains take charge of *data products*, even as it espouses the balancing of *"local data sharing with global interoperability"* [51]. However, the paradigm interweaves enterprise information governance and its regulatory nature with a mechanistic approach, a federal governance operating model, but automated policies embedded in data products [51].

Roles, typical of other models of governance, such as data owner, steward and custodian, are absent in Data Mesh, though the concept of *ownership of data products* does exist, tied to domain ownership. The IBM Consulting concept of ownership of data, for example, is more nuanced because it is *object-centric* where Mesh is *product-centric.* But ownership of data, of *data objects,* rather than *data products* is a driver in information governance terms according to IBM. These concepts align with Boris Otto's concept of *"locus of control"* and Khatri and Brown's *"locus of accountability."* An IBM (2021) field consulting concept held that governance "must mean something in the context of the business ecosystem", and included consideration of core ownership of data, escalation points, (IT) management, (ITIL) service lifecycles, and data lifecycles. It determined four perspectives, or using Otto's concept, *locus* definitions: Respectively, **domain-based** (that is, scoped by data domain); **Business Unit-based** (scoped by named business or operational unit); **Process-based**, process-centric (bounded by a determined, named, process set, driven by function or business); and, **Decision-Point-Based**: Scoped by the components required to take "a decision", for example produce a user visualization, such as a dashboard. Aligning IBM's and Otto's concepts—and recall that we selected the IBM approach here, but we might equally posit another in place of IBM for our analysis. It might be posited, then, that Otto's *locus* [7] could be represented in these, being domain-based, unit-based, process-based, or decision-point-based: each locus offers a governance *control point,* but with differentiated scope boundary. Introducing Khatri and Brown's "locus of accountability" [8], the positioning here would depend upon the way in which

the operating model of the organization supports (or fails to support) *enterprise* governance and ownership. If we consider the *data object* definitions of Data Mesh that we met earlier against those of *data products,* it becomes apparent that a data object is defined to enable the widest possible category of data to be governed or brought within the scope of defined ownership, stewarded and in custody of a nominated custodian. By comparison, the only concept of which Data Mesh admits is that of the data product, an artefact which is itself originally defined precisely by being required to match criteria as secure, discoverable, addressable, understandable, trustworthy, accessible, interoperable, and valuable. This would also preclude, considering the reverse, objects or products that do not conform to these criteria.

Data Mesh attempts to shift data governance from a centralized, top-down, federated model with "computational policies" embedded in "nodes" on the Mesh: The concept of enterprise, of strategy, seems lost in this localization. The model focuses upon *each separate domain's* data products and upon governance-as-programmatic-policy. It assumes many policies are effectively software-based and fundamentally mechanistic in nature. We might see that certain programmatic rules (which might indeed reasonably be called "policies") could be represented in code or in terms of, say, data warehouse parameters or settings, and could—depending upon scope, technology and architecture-potentially be encapsulated in a data product. In fact, Data Mesh does admit to having a centralized governance team as part of what the paradigm calls *"federated computational governance."* This is intended to establish principles, guide decision-making, and determine global versus domain governance policies. They operate during an operating model adoption phase described as "explore and bootstrap" in the method, and are intended to establish "patterns" and "sensible practices" collaboratively, whilst sharing knowledge [51]. We might argue critically that Mesh conceives of policies as being automated only, and to support "interoperable and secure" data products, leaving as an obvious gap the hanging question of how to govern data effectively. We could say that Data Mesh is clearly domain-based with ownership scoped by *data domain.* In many instances within a complex organization, therefore, we can imagine that domain-specificity as synonymous with **Business-Unit** based ownership (locus) because under Data Mesh, data owners are synonymous with product owners and sit within domains. The locus of control would lie within the domain and with respect to and around data products. The locus of accountability would lie with those who are operationally "closest" to the data. Data Mesh is actually neither Process-based (process-centric) nor Decision-Point-Based. We can recall Smallwood's observation that governance should, "focus on breaking down traditional functional group 'siloed' approaches" [3]. Abraham, *et al.* see governance as cross-functional [2]. DeMaine, that a top-down governance implementation is particularly effective in taking a holistic view of information" [59].

8. Conclusion

Whilst the choice of Data Mesh deployment is clearly a strategic one in and of itself, it is difficult to characterize Data Mesh *as strategic* or, because of its particular *modus operandi,* as a paradigm that would necessarily *break down* silos; it might rather perform the reverse. Recalling Alhassan, *et al.'s*, summation [37] that governance is about decisions and management about implementation, Data Mesh looks decidedly like a *data management paradigm,* and far more that than a *data governance* one: it has effectively developed its own meaning; it represents determined domain specificity in governance, but in a way that is mechanistic.

Moura, *et al.* [64] offer a criticism of Data Mesh in terms of three "challenges" with respect to: cultural change and organizational pushback; holism in governance; and the definitive lack of an off-the-shelf implementation. They find the independence of teams in terms of maintaining their own data products potentially straining and difficult to achieve without significant cultural change. Likewise, coexistence of data inconsistencies arises because of

independence (lauded under the Data Mesh method) and the impossibility of establishing cross-domain co-ordination where the Data Mesh paradigm is utilized. Lastly, technically, they find the effective requirement for multiple technologies to interconnect, a key real-world one, is unrealistic in Mesh without determined enterprise standardization, itself a complex, separate, transformation activity.

Bode, *et al.* [65] find that Data Mesh has lacked empirical field insights. Their study determines via expert interviews that issues raised included complexities in shifting to a federated governance model from a more traditional, centralized one; management of the responsibilities that come with decentralized data ownership; ensuring high-quality metadata; and, similarly to Moura, *et al.* addressing the organizational resistance that can accompany significant changes in data management practices related to introduction of the paradigm.

In considering Data Mesh, we may determine that where an organization has been transformed sufficiently —that is, to the point at which its staff can viably operate it in a manner according with its principles- and it can be implemented, there could yet be a significant tendency towards development of varietal, diverse local governances, and even a localized semantic *data patois,* to supplant canonical enterprise definitions due to siloed development and domain isolation. It would also likely supplant cross-enterprise policies and standards. That localized patois is not helpful from an enterprise information perspective.

We might call this "domain specific data governance", the case where local policies, standards and procedures have been defined locally to a team, project, or department rather than being driven, defined, or directed predominantly by *enterprise* information governance. This would be distinct from it, not least by virtue of having escalation paths and enterprise decision-making and operational bodies, and an executive sponsor, all differentiated from localized versions. This would, then, exemplify domain specificity.

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References

[1] McCullough, A. (2024), 'Defining a new perspective: Enterprise Information Governance', paper presented at NXDG, NeXt-generation Data Governance workshop, workshop within Semantics 2024 conference. Amsterdam, Netherlands: September 17. doi: https://doi.org/10.48550/arXiv.2409.14388.

[2] Abraham, R., Schneider, J. and vom Brocke, J. (2019), 'Data Governance: A conceptual framework, structured review, and research agenda', in: International Journal of Information Management. Liechtenstein: Institute of Information Systems, University of Liechtenstein, Vol.49, December. doi: https://doi.org/10.1016/j.ijinfomgt.2019.07.008.

[3] Smallwood, R. F. (2020), Information Governance: Concepts, Strategies and Best Practices. Hoboken, NJ: John Wiley and Sons, Inc. 2nd ed. December. E-Book PDF and URL: https://learning.oreilly.com/library/view/information-governance-2nd/9781119491446/.

[4] British Academy, The and Royal Society, The (2017), Data Management and Use: Governance in the 21st century?—A joint report by the British Academy and the Royal

Society. London: The British Academy. URL: https://www.thebritishacademy.ac.uk/publications/data-ai-management-use-governance-21st-century/.
[5] Creswell, J. W. and Poth, C. N. (2018), Qualitative Inquiry and Research Design: Choosing Among Five Approaches. London: SAGE Publications, Inc., 4th Ed., p. 8.
[6] Creswell, J. W. and Creswell, J. D. (2022), Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. London: SAGE Publications, Inc., Sixth Edition. 24 October. p.199.
[7] Otto, B. (2011), 'A Morphology of the Organisation of Data Governance'. Paper published in: ECIS 2011 Proceedings, 272. European Conference on Information Systems, Summer.
[8] Khatri, V. and Brown, C. V. (2010), 'Designing Data Governance', Proceedings of the Association of Computing Machinery (ACM), January. doi: https://doi.org/10.1145/1629175.1629210.
[9] Evans, E. (2015), Domain-Driven Design Reference: Definitions and Pattern Summaries. Carmel, NY: Domain Language, Inc. URL: https://www.domainlanguage.com/wp-content/uploads/2016/05/DDD_Reference_2015-03.pdf.
[10] Brous, P., Janssen, M., and Vilminko-Heikkinen, R. (2016), 'Coordinating Decision-Making in Data Management Activities: A Systematic Review of Data Governance Principles,' in: Scholl, H.J., et al., Electronic Government. EGOV 2016. Lecture Notes in Computer Science, Vol.9820. Cham, CH: Springer. doi: https://doi.org/10.1007/978-3-319-44421-5_9.
[11] Tekinderdogan, B., Ali, N., Grundy, J., Mistrik, I. and Soley, R. (2016), 'Quality Concerns in Large-Scale and Complex Software-Intensive Systems', Mistrik, I. (2016), Software Quality Assurance: In Large Scale and Complex Software-Intensive Systems. Amsterdam: Morgan Kaufman. 1st Edition, Chapter 1.
[12] Ackoff, R. L. (1989), 'From Data to Wisdom,' in: Journal of Applied Systems Analysis. Lancaster, UK: University of Lancaster, Department of Systems. Vol.16, pp.3-9.
[13] Boisot, M., Canals, A. (2004), 'Data, Information and Knowledge: Have we got it right?', in: Journal of Evolutionary Economics, Vol. 14, No. 1, pp.43-67.
[14] Omnès, R. (2002), Quantum Philosophy: Understanding and interpreting contemporary science (trans. Arturo Sangalli). New Jersey: Princeton University Press.
[15] Joint Task Force, National Institute of Standards and Technology, US Department of Commerce (2018), Risk Management Framework for Information Systems and Organizations–A System Life Cycle Approach for Security and Privacy. NIST Special Publication 800-37, Revision 2, December.
[16] Corrado, C., Haskel, J., Jona-Lasinio, C., and Iommi, M. (2022), Intangible Capital and Modern Economies. Journal of Economic Perspectives. Nashville, Tenn.: American Economic Association: Vol.36, No.3, Summer, 2022.
[17] Weber, K., Otto, B., and Österle, H. (2009), 'One Size Does Not Fit All—A Contingency Approach to Data Governance', Journal of Data and Information Quality. New York, NY: Association of Computing Machinery – ACM Journals, Vol.1, No.1, pp.1-27. 1 June. doi: https://doi.org/10.1145/1515693.1515696.
[18] Hoppe, A., Seising, R., Nürnberger, A., and Wenzel, C. (2011), 'Wisdom - the Blurry Top of Human Cognition in the DIKW-model?', in: Proceedings of the 7th conference of the European Society for Fuzzy Logic and Technology (EUSFLAT-11), Galichet, S., Montero, J., and Mauris, G. (Eds): Advances in Intelligent Systems Research 17. Paris:

Atlantis Press (Springer Nature), pp.584-591. doi: https://www.doi.org/10.2991/eusflat.2011.91.
[19] Buckland, M. K. (1991), 'Information as Thing', in: Journal of the American Society for Information Science, Vol. 42, Issue 5, June, pp. 351-360.
[20] Madison, M. J. (2020), 'Tools for Data Governance', in: Leenes, R. and Martin, A. (2020) Technology and Regulation 2020. Tilburg: Tilburg University, Vol.2., pp.29–43.
[21] Zins, C. (2007), 'Conceptual Approaches for Defining Data, Information, and Knowledge,' in: Journal of the American Society for Information Science and Technology. Hoboken, US: Vol.58, No.4, February. pp. 479–93. doi: https://doi.org/10.1002/asi.20508.
[22] European Union, The (2022), Article 2, 'Definitions', Para.(1), REGULATION (EU) 2022/868 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724 (Data Governance Act). Official Journal of the European Union, EUR-Lex. Brussels, BE. 30 May. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32022R0868.
[23] Frické, M. (2019), 'The Knowledge Pyramid: the DIKW Hierarchy,' in: Knowledge Management. Singapore: IMR Press. Vol.46, No.1, pp.33-46. doi:10.5771/0943-7444-2019-1-33.
[24] Rowley, J. E. (2007), 'The Wisdom Hierarchy: Representations of the DIKW hierarchy,' in: Journal of Information Science. Vol.33, pp.163-80.
[25] Pop, I. G., Talpos, M-F., and Prisac, I. (2016), 'A Transdisciplinary Approach on the Advanced Sustainable Knowledge Integration,' in: Balkan Region Conference on Engineering and Business Education: Joint meeting of 3rd International Engineering and Technology Education Conference (IETEC'15) and 7th Balkan Region Conference on Engineering and Business Education (BRCEBE). URL: https://www.researchgate.net/publication/283451017_A_Transdisciplinary_Approach_on_the_Advanced_Sustainable_Knowledge_Integration#fullTextFileContent.
[26] Jennex, M. E. (2009), 'Re-Visiting the Knowledge Pyramid,' in: Proceedings of the 42nd Annual Hawai'i International Conference on System Sciences, Sprague, R.H. (Ed). Los Alamitos, CA: IEEE Computer Society. doi: https://doi.org/10.1109/HICSS.2009.361.
[27] Müller, H. and Maasdorp, C. (2011), 'The data, information, and knowledge hierarchy and its ability to convince,' in: Proceedings - 2011 FIFTH INTERNATIONAL CONFERENCE ON RESEARCH CHALLENGES IN INFORMATION SCIENCE. Gosier, France. pp.1-6. doi: https://doi.org/10.1109/RCIS.2011.6006851.
[28] Lockwood, S., Godinez, M., Hechler, E., Koenig, K., Oberhofer, M., and Shroeck, M. (2010), The Art of Enterprise Information Architecture - A Systems-Based Approach for Unlocking Business Insight. Upper Saddle River, NJ: IBM Press, Pearson plc. 1st Edition.
[29] Tekinderdogan, B., Ali, N., Grundy, J., Mistrik, I. and Soley, R. (2016), 'Quality Concerns in Large-Scale and Complex Software-Intensive Systems', Mistrik, I. (2016), Software Quality Assurance: In Large Scale and Complex Software-Intensive Systems. Amsterdam: Morgan Kaufman. 1st Edition, Chapter 1.
[30] Dray, J. F., Guthery, S. B., and Schwarzhoff, T. (2005), Interfaces for Personal Identity Verification. NIST Special Publication 800-73. Gaithersburg, MD: National Institute of Standards and Technology (NIST), April. p.18.
[31] Gehrke, W. (1997), 'Data Objects,' In: The F Language Guide. London, UK: Springer, pp.25-40. doi: https://doi.org/10.1007/978-1-4471-0989-1_4.

[32] Booch, G., Maksimchuk, R. A., Engle, M. W., Young, B. J., Conallen, J., and Houston, K. A. (2007), Object-Oriented Analysis and Design with Applications, 3rd Edition. Addison-Wesley Object Technology Series. Upper Saddle River, NJ: Addison-Wesley.
[33] Microsoft (2025), Data and Data Objects. Seattle, WA: Microsoft Corporation, 5 July. URL: https://learn.microsoft.com/en-us/dotnet/desktop/wpf/advanced/data-and-data-objects.
[34] Microsoft (2026-a), Data Objects and Data Sources (OLE). Seattle, WA: Microsoft Corporation, 23 February. URL: https://learn.microsoft.com/en-us/cpp/mfc/data-objects-and-data-sources-ole?view=msvc-170.
[35] Microsoft (2026-b), What is Unity Catalog? Seattle, WA: Microsoft Corporation, 23 February. URL: https://learn.microsoft.com/en-us/azure/databricks/data-governance/unity-catalog/.
[36] SAP (2024), Explaining Data Objects. Walldorf, DE: SAP SE, October. URL: https://learning.sap.com/learning-journeys/developing-business-processes-with-sap-process-orchestration/explaining-data-objects_d544c7a1-02f8-4168-8f86-af10fe0b5fc7.
[37] Alhassan, I., Sammon, D. and Daly, M. (2016), 'Data governance activities: an analysis of the literature', in: Journal of Decision Systems. Abingdon, UK: Taylor & Francis. Vol.25, No.1, pp. 64–75, 16 June.
[38] Hadaya, P., and Gagnon, B. (2017), Business Architecture: The Missing Link in Strategy Formulation, Implementation and Execution. Montreal, Canada: ASATE Publishing Inc.
[39] Ein-Dor, P., and Segev, E. (1978), 'Strategic Planning for Management Information Systems', in: Management Science. Institute of Management Sciences, November, Vol.24, No.15, pp.1631-1641.
[40] Dehghani, Z. (2019), 'How to Move Beyond a Monolithic Data Lake to a Distributed Data Mesh', Articles. Chicago, IL: ThoughtWorks, 20 May. URL: https://martinfowler.com/articles/data-monolith-to-mesh.html.
[41] Trist, E. (1981), The Evolution of Socio-Technical Systems: A Conceptual Framework and an Action Research Program. Toronto, Ontario: Ontario Ministry of Labour, Ontario Quality of Working Life Centre. Occasional Paper No.2, June.
[42] Baxter, G. and Sommerville, I. (2011), 'Socio-technical systems: From design methods to systems engineering,' in: Interacting with Computers, The Interdisciplinary Journal of Human-Computer Interaction. London, UK: British Computer Society (Oxford University Press); Vol.23, No.1, January. pp.4–17. doi: https://doi.org/10.1016/j.intcom.2010.07.003.
[43] Prodan, M., Prodan, A., and Purcarea, A. A. (2015), 'Three New Dimensions to People, Process, Technology Improvement Model'. In: Rocha, A., Correia, A., Costanzo, S., and Reis, L. (Eds): New Contributions in Information Systems and Technologies. Advances in Intelligent Systems and Computing. Cham, CH: Springer, Vol.353, pp.481-490. doi: https://doi.org/10.1007/978-3-319-16486-1_47.
[44] Bodendorf, F. and Bayr, C. (2025), 'Shaping platform governance principles to manage interorganizational data exchange.' In: Information Systems Journal, Vol.35, No.5, pp.12-13. 17 March. Available at: https://onlinelibrary.wiley.com/doi/10.1111/isj.12592.
[45] Informatica (2025), 'Data Mesh vs Data Fabric: 3 Key Differences, How They Help and Proven Benefits.' Redwood City, CA: Informatica. URL: https://www.informatica.com/blogs/data-fabric-vs-data-mesh-3-key-differences-how-they-help-and-proven-benefits.html.

[46] Dehghani, Z., Sato, D., Ford, C. and Jahan, S. (2024), 'The four principles of Data Mesh'. Chicago, IL: ThoughtWorks. URL: https://www.thoughtworks.com/en-gb/about-us/events/webinars/core-principles-of-data-mesh.
[47] Thoughtworks (2021), 'Data Mesh'. Chicago, IL: Thoughtworks, 14 December. URL: https://www.thoughtworks.com/what-we-do/data-and-ai/data-mesh.
[48] Werner, S., Prakash, K., Aliyeva, L., Sato, D., and Spens, J. (2026), The state of Data Mesh in 2026: From hype to hard-won maturity. Chicago, IL: Thoughtworks, 16 January. URL: https://www.thoughtworks.com/en-gb/insights/blog/data-strategy/the-state-of-data-mesh-in-2026-from-hype-to-hard-won-maturity.
[49] Lamury, R. (2024), Leveraging data as a product: A strategic imperative for business leaders. Chicago, IL: Thoughtworks, 13 February. URL: https://www.thoughtworks.com/insights/articles/leveraging-data-as-a-product-a-strategic-imperative-for-business-leaders.
[50] Buckland, M. K. (1991), 'Information as Thing', Journal of the American Society for Information Science. Hoboken, NJ: Wiley-Blackwell: Vol.42, No.5, June, pp.351-360.
[51] Dehghani, Z. (2022), Data Mesh – Delivering Data-Driven Value at Scale. Sebastopol, CA: O'Reilly Media inc., March.
[52] Wilkinson, M., Dumontier, M., Aalbersberg, I., et al. (2016), 'The FAIR Guiding Principles for scientific data management and stewardship,' in: Scientific Data. London, UK: No.3, Art.160018, 15 March. DOI: https://doi.org/10.1038/sdata.2016.18.
[53] Jouravlev, R., Anand, A., Carmona Orbezo, J., Casteel, E., Corona, M., DuMoulin, T., Hearsum, P., Hunnebeck, L., Leach, M., Rae, B., Rance, S., Yagi, T., and MacDermid, K. (2019), ITIL® 4 Foundation: ITIL 4 Edition. Norwich, UK: Williams Lea Tag: The Stationary Office (TSO).
[54] Amirbekova, A., Kulmanov, S., Fazylzhanova, A., Bissengali, A., and Omarova, A. (2025), 'Slang Terms in the Field of Information Technology and Their Standardization.' Singapore: Bilingual Publishing Group. Forum for Linguistic Studies, Vol.7, No.6, pp.452–467. doi: https://doi.org/10.30564/fls.v7i6.10091.
[55] Budiyanto, D., Mayrita, H., Aprillitzavivayarti, Indrayana B., Rahmawati, S., Roni, R., and Mukminin, A. (2019), 'Jargons Used in "PC World" Magazine,' in: International Journal of Recent Technology and Engineering (IJRTE), Vol.8, No.4. Blue Eyes Intelligence Engineering and Sciences Engineering and Sciences Publication – BEIESP, pp.2198–2205. doi: https://10.35940/ijrte.d7881.118419.
[56] Preetha R., G., and Senthamarai, T. (2024), 'The Evolution of Technical Jargons in Communicative English Among Bachelor of Engineering and Bachelor of Technology Students,' in: Frontiers in Health Informatics. Ghaziabad, UP. Vol.13, No.7, pp.1040-1052.
[57] Swales, J. M. (2016), 'Reflections on the concept of discourse community,' in: ASp. la Revue de GERAS. Gif-sur-Yvette, Paris: GERAS–Groupe d'étude et de recherche en anglais de spécialité: Vol.69, pp.7–19. URL: http://journals.openedition.org/asp/4774. doi: https://doi.org/10.4000/asp.4774.
[58] Nystrand, M. (1982), What Writers Know: The language, process, and structure of written discourse. New York, NY: Academic Press.
[59] DeMaine, S. (2016), 'Preparing Law Students for Information Governance', 35 Legal Reference Services Quarterly, 16 May. URL: https://ssrn.com/abstract=2781130.
[60] Seiner, R. S. (2014), Non-Invasive Data Governance. Basking Ridge, NJ: Technics Publications.

[61] Tallon, P., Short, J., and Harkins, M. (2013), 'The Evolution of Information Governance at Intel,' in: MIS Quarterly Executive: Vol.12, No.4, Article 5. doi: https://aisel.aisnet.org/misqe/vol12/iss4/5.
[62] Easton, J. (2012), 'The Future of the IT Department – Exploring the impact of Cloud on IT roles and responsibilities.' London, UK: SmartCloud Thought Leadership White paper: IBM United Kingdom Limited, January. URL: https://public.dhe.ibm.com/software/uk/itsolutions/cloud-circle/Cloud_-_The_Future_of_the_IT_Department.pdf.
[63] Brown, C. V. (1999), 'Horizontal mechanisms under differing IS organization contexts', MIS Quarterly, No. 23, pp.421-454. Cited in: Khatri, V. and Brown, C. V. (2010) 'Designing Data Governance'. Proceedings of the Association of Computing Machinery (ACM). New York, NY: Association of Computing Machinery. January.
[64] Moura, C., Sotta, E., and Rubinov, K. (2023), 'Pros and Cons of Data Mesh.' Switzerland: PwC. Tech, Data & AI Insights, 3 May. URL: https://www.pwc.ch/en/insights/digital/data-mesh-challenges.html.
[65] Bode, J., Kühl, N., Kreuzberger. D., and Holtmann, C. (2024), 'Toward Avoiding the Data Mess: Industry Insights From Data Mesh Implementations,' in: IEEE Access, Vol.12, pp.95402-95416. doi: https://doi.org/10.1109/ACCESS.2024.3417291.