



# Cloud-Based Big Data Governance Frameworks for Digital Public Service Platforms

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**ABSTRACT:** Governments are often viewed by citizens and businesses as the natural owners of public data that are generated or collected in their jurisdictions. It is expected that such data assets, if governed properly, can facilitate the provision of better services, enable data-driven policymaking, foster innovation, and drive new economic opportunities. However, big data present new and complicated challenges. Recent studies indicate data governance has become one of the most puzzling issues for governments pursuing digital transformation, which necessitates the establishment of a governance framework. Indeed, evidence-based guidance to inform the establishment of a big data governance framework for digital public service platforms on cloud infrastructure using a governance-as-a-service model is needed.

An analysis of the different stakeholders that contribute to the operation of digital public service platforms on a cloud infrastructure reveals that the primary goal is to establish the data governance framework. This framework aims to protect information security and ensure data can be reused and shared with low risk. Following a formal structure, four cloud-based big data governance frameworks adopted by governments are presented: the Cloud-Based Big Data Governance Framework, which targets big data ecosystems; the Cloud-Based Big Data Governance White Paper, which informs the operation of data exchanges; the Cloud-Based Smart City Data Governance Framework, which addresses the establishment of key data resources; and the Cloud-Based Data-Driven Economy Toolkit, which supports the proactive sharing of public data. Together, they form a roadmap for establishing a complete big data governance framework for digital public service platforms in a cloud environment.

**KEYWORDS:** Big Data Governance, Digital Public Services, Cloud-Based Governance, Data Governance-as-a-Service, Government Data Platforms, Public Data Sharing, Smart City Data Governance, Data-Driven Policymaking, Public Sector Digital Transformation, Cloud Data Ecosystems, Data Security and Reuse, Government Data Exchange Frameworks.

## I. INTRODUCTION

Research indicates that the public sector envisions the development of a digital public service platform that provides integrated services derived from various systems of records built by different government agencies for the sake of enhancing the quality and efficiency of service delivery. Along with significant funds being invested in the development of digital government service platforms during external disasters, the focus is not only on quality service provision but also on effective operations by making use of an appropriate governing mechanism, the role of which is emphasised in the literature. The primary aim is to examine how big data governance can be utilised in public-sector big data management on cloud-based digital public service platforms deployed as a hybrid model. Cloud-based big-data architectures offer advantages such as pay-per-use and do-not-build capabilities that reduce operation costs. Moving towards a hybrid model enables government agencies to deploy services or applications on the public cloud while retaining services or applications with strict control constraints on the business continuity of operation in a private cloud.

In a hybrid model for digital public service platforms hosted in a cloud environment, government agencies share resources and infrastructure, thereby gaining economic benefits for service deployments. Data used in public-sector agencies, however, is either closed or sensitive and comes under security and privacy constraints. Economic evidence in Big Data management is useful for the governance of service delivery and not only data for data analytics. Big Data associated with a digital public service platform in the public sector carries higher risk factors that hinder economic benefits, making Cloud [data] Governance System Design and Plan an essential mechanism. A Cloud Data Governance System Design Roadmap, adopted in the Cloud Data-Agnostic Governance System Design, recommends a Clear Governance Roadmap and Checklist to provide a Live-Business Continuity Governance Power Copy System and to



make Cloud Data Economically Viable in supporting Big Data Public-Good Service Delivery and Digital Public Service Platform operations.

### 1.1. Understanding the Context and Importance of Big Data Governance

Governance focuses on the interaction of people, processes, and information within an organization. It is required to achieve the effective collection, storage, and use of data based on delimiting principles, policies, and rules governing data management throughout its life cycle. The concept generally extends to the notion of stakeholders—the groups most directly affected by the inclinations and decisions of the organization. In the case of big data, a distinguishing characteristic is the large number of separate organizations that generate, collect, and store the data for diverse purposes. Some build large digital data reservoirs but retain only public access to the data. Others use data to analyze and research, benefiting from others' investment in gathering data but remaining data consumers. Others exploit the availability of public data to bring new products and services to the market. An added layer comes from those who use these private services, often for free, but in return provide their own data.

Stakeholders have various goals relating to big data—from simply allowing safe public access to actively encouraging the integration and analysis of data. All these goals involve risk, both for the parties directly generating and using the data and for many wider stakeholders. Hence, just as governance is needed to align the inclinations and decisions of the various parties, big data governance is needed to achieve the specific goals surrounding big data while managing risk effectively. The digital public service platform, as the key to cloud-based digital public services, is a major enabler of the alignment of public and private interests in the use of big data while offering the effective mitigation of risk and compliance with government obligations.

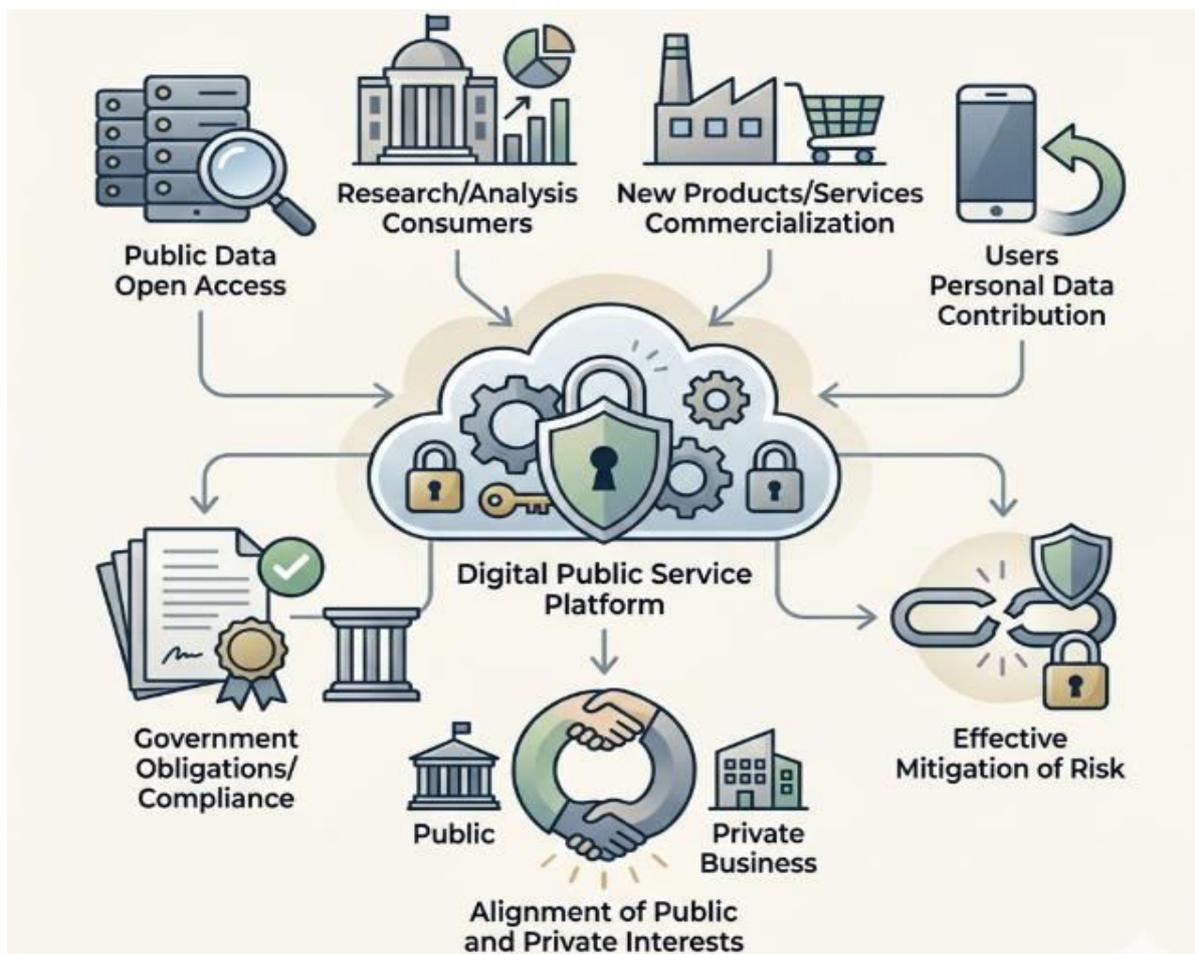


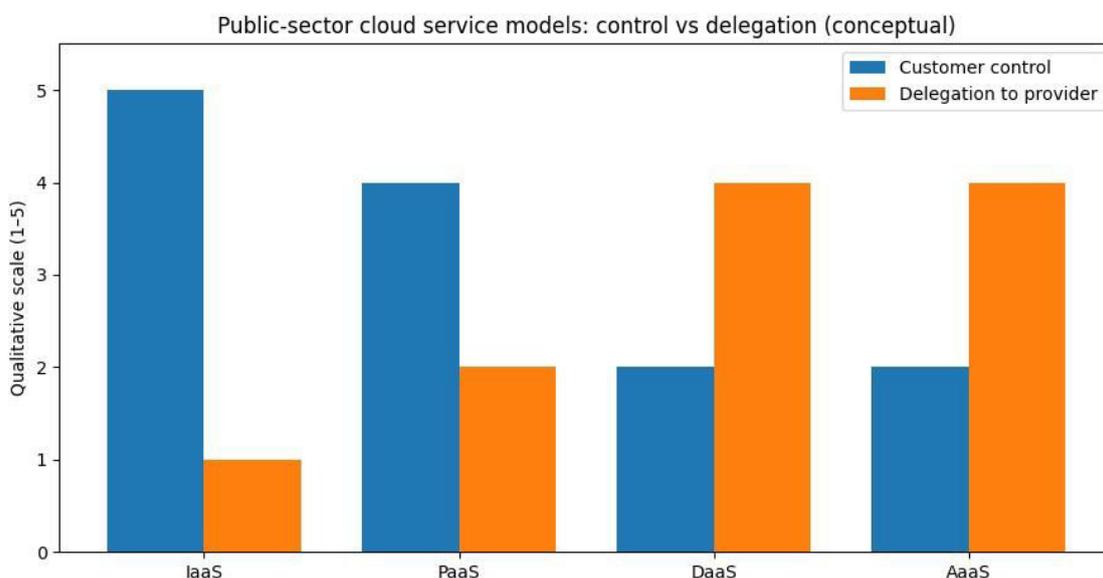
Fig 1: Big Data Governance and Risk: The Digital Public Service Platform as an Enabler of Multi-Stakeholder Alignment and Compliance



II. THEORETICAL FOUNDATIONS OF BIG DATA GOVERNANCE

Three schools of thought provide a foundation for understanding the governance of big data in a public sector context. Governance theories address the articulation of policy objectives, the instruments deployed to pursue these objectives, and the methods by which they are coordinated. In a broad sense, big data governance is principally concerned with developing and sustaining social trust, as determined by data quality and information policy, including data stewardship and commons theories. The greater the quality and integrity of any public or private information, the more effectively it can be used to predict the results of courses of action. Data stewardship builds on concepts of a common pool resource to develop a risk-based model that addresses the issues of data ownership and allocation of decision rights. Thirdly, the concept of governance maturity models, long applied to information technology, now finds a new home in big data, tracking increasing capability across five core dimensions—governance and strategy; people and culture; processes; technology; and data.

In light of significant differences between public and private organizations, accountability, transparency, privacy, and security preside over other governance principles in the public sector; public sector platforms must remain focused on the needs and preferences of a broad range of citizens and constituents; access to public assets must be nondiscriminatory; support for the common good must trump commercial advantage; real-time access to information produced and consumed by the public and private sectors is critical; innovations must simplify the interaction with government; future resources must be leveraged; and unsuccessful projects must be rapidly transitioned out of the portfolio. Big data governance must also embrace the improved integration and cross-agency sharing of data, standardized semantic interoperability of core data across the public sector, secure and ethical frameworks for sharing citizen and business data with trusted third-party organizations, appropriate data-sharing policies and legislation governing the release and reuse of data, standards and frameworks for limiting the risk of bias in deriving insights from data, and development of a privacy-enhancing identity management framework that enables trusted data sharing.



Equation A) Risk-governance model (formalized from the “governance manages risk + builds trust” logic)

Step1— Define a risk register

Assume the platform faces a set of risks:

$$\mathcal{R} = \{r_1, r_2, \dots, r_n\}$$

Step2 — For each risk, define likelihood and impact

For each  $r_i$ :

- $p_i \in [0,1]$ : probability (likelihood) of occurrence
- $I_i \geq 0$ : impact (harm magnitude: privacy, security, service disruption, trust loss, etc.)



**Step 3 — Define inherent (pre-control) risk**

$$\text{InherentRisk}_i = p_i \cdot I_i$$

**Step 4 — Controls reduce risk (control effectiveness)**

Let  $e_i \in [0,1]$  be the effectiveness of governance controls on that risk (0 = no reduction, 1 = full mitigation). Then residual risk is:

$$\text{ResidualRisk}_i = (1 - e_i) \cdot p_i \cdot I_i$$

**Step 5 — Overall residual risk across the platform**

$$\text{ResidualRisk}_{\text{total}} = \sum_{i=1}^n (1 - e_i) p_i I_i$$

**Step 6 — Map “governance principles” to control effectiveness**

The identifies **seven principles** as the core governance levers: data quality, accountability, transparency, privacy, security, interoperability, lifecycle management.

Let the principle maturity levels be:

$$m_j \in [0,5], \quad j = 1..7$$

(0 = nonexistent, 5 = optimized)

Normalize:

$$\hat{m}_j = \frac{m_j}{5} \in [0,1]$$

Now define risk-control effectiveness as a weighted sum of principle maturity:

$$e_i = \min \left( 1, \sum_{j=1}^7 w_{ij} \hat{m}_j \right)$$

where  $w_{ij} \geq 0$  and  $\sum_j w_{ij} \leq 1$ .

**2.1. Understanding Key Principles of Big Data Governance**

Seven principles guide the governance of big data assets supporting digital public service platforms. These principles support officials’ decisions about the implementation of an appropriate big data governance framework to enable the design, development, and delivery of data services; expand data-driven decision making and policy responses; realise the legal, ethical, and operational potential of the data ecosystem; and mitigate risks. Data quality, accountability, transparency, privacy, security, interoperability, and data lifecycle management are explored here. While the principles are defined separately, respondents recognise the inherent interdependencies between them and collectively refer to stakeholders’ ethical conduct as the cornerstone of big data governance.

High-quality data is crucial to support efficient, effective, and trustworthy decision making, policy responses, and service delivery. Decision makers must be held accountable, and central governance oversight and controls must be complemented by controls built into data services, platforms, and analytics models. Transparency of data-related processes, business and analytic models, and data-driven decision making and policy responses builds public trust. Legal provisions and ethical principles safeguarding data privacy are essential to ensure citizens’ trust in online service delivery. Digital service providers, partnership agencies, and other data custodians must ensure comprehensive data security. Interoperability between systems and services facilitates the linking of data sets from different sources. During the data assets’ ongoing collection life cycle, operations supporting successful data management initiatives, risk assessments, and testing procedures must ensure that the data meets business and operational requirements.

**III. CLOUD-BASED ARCHITECTURES FOR DIGITAL PUBLIC SERVICE PLATFORMS**

Cloud services support major data lifecycle stages and functional operations, but the roles of Infrastructure as a Service, Platform as a Service, Data as a Service, and Analytics as a Service differ in accordance with two key factors: control over the underlying resources offered in the architecture and data configuration and management requirements. The degree of control is important for compliance with legal requirements that differ by jurisdiction, especially concerning data provenance and cross-border data exchange to countries posing risks with respect to privacy, security, or cybersafety. Data stewardship and ownership models must therefore take into account compliance requirements based on the location of the infrastructure and the provenance of the data being offered. Resource configuration and

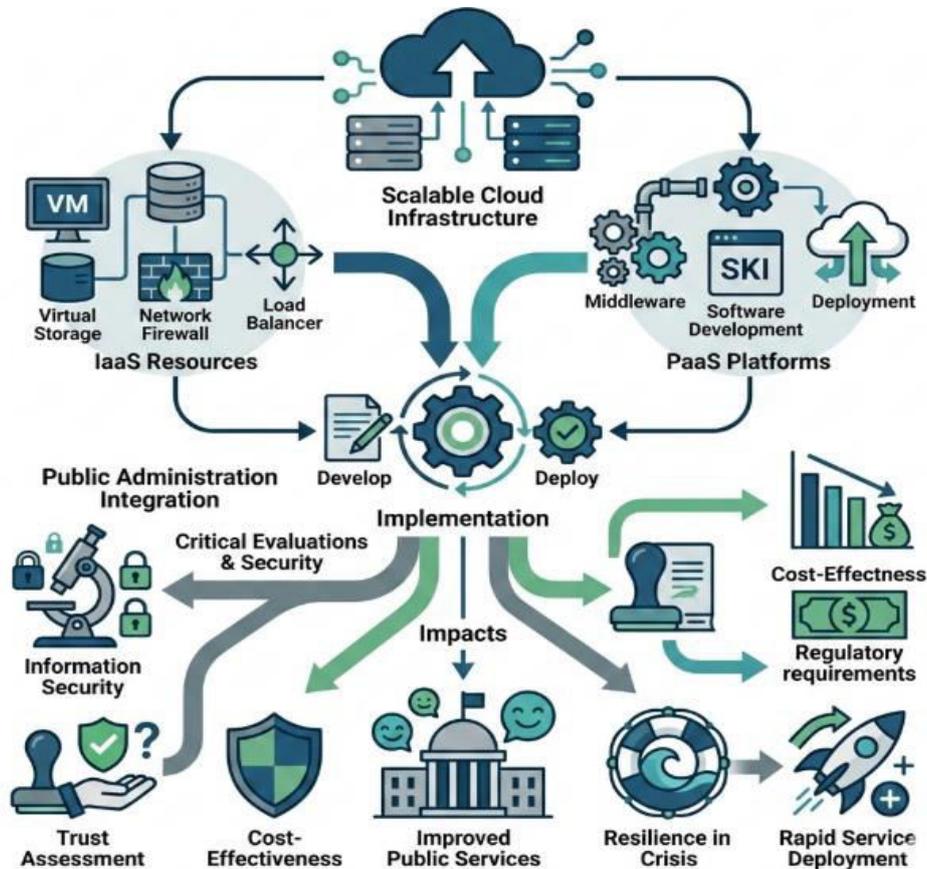


management are critical for ensuring that data assets are adequately provisioned, governed, and secured so as to mitigate risks associated with data use and data processing.

The provisioning of infrastructure, platform, analytic, and data services enables Cloud Service Providers (CSPs) to offer services that can lower the overall financial burden of big data analytics for government organizations, either by enabling the outsourcing of data processing or permitting more cost-effective and more tuned resource operation under spikes in analytic demand. IaaS services afford customers the highest degree of control and governance over their resource use, although these come at the cost of the customer being responsible for their correct configuration in terms of privacy, security, and other adequacy grounds. PaaS also enables resources to be operated at a higher level of abstraction, with Cloud Service Consumers (CSC) capable of delegating some levels of resource management to the CSP, but also entails a lower level of control and governance over resources when compared to IaaS. Conversely, DaaS enables the CSC to delegate the management of their data to the CSP, which is expected to take care of data privacy, data ethicality, and data quality in terms of the services being catered.

**3.1. Infrastructure as a Service and Platform as a Service in public sector contexts**

Infrastructure as a Service (IaaS) provides scalable computing resources over the internet, enabling organizations to provision and de-provision networks, firewalls, virtual machines and VMs, load balancers, and storage without the need to invest in the hardware required. IaaS is typically combined with Platform as a Service (PaaS), which provides middleware and tools for developing, testing, and deploying applications, software and services without maintaining hardware and software layers. The use of IaaS allows organizations to focus on developing organizational capabilities and strategically utilizing the required technology. Integrating these capabilities into public administration and the entire public sector facilitates the development and provision of better public services, both during times of normal operation and in crisis situations, while ensuring cost-effectiveness and compliance with public policies.



**Fig 2: Synthesizing IaaS and PaaS Frameworks in Public Administration: Balancing Scalability and Agile Deployment against Regulatory Compliance and Sovereign Data Control**



Unlike the private sector, the public sector is subject to stricter regulatory requirements, many of which relate to information security and the management of personal and sensitive data. These requirements impose additional costs and, in many cases, limit the possible use of the IaaS architecture, as the service provider must remain under the government's administrative control and have the resources to prove technical compliance with laws, regulations, and standards. Therefore, when considering IaaS and PaaS, the level of confidence in the specific supplier's ability to comply with regulations and security demands has to be adequately evaluated; nevertheless, the availability of PaaS from IaaS suppliRES can give public sector organizations significant flexibility and speed in adding new public services.

### 3.2. Data as a Service and Analytics as a Service for governance

The Data as a Service (DaaS) and Analytics as a Service (AaaS) capabilities of cloud-based architectural models can benefit governmental big data governance initiatives in several ways. Data consumption capabilities are likely to be provided in a compliant and controlled fashion. Data consumers should be able to access cloud-hosted data sets that are provisioned for DaaS use. These offered data sets will likely be publicly available but may also fall under the category of government information that is not personalized for public consumption but provided to third parties for further analysis and decision-making. Such information will be accessible from a centralized location via the Internet. Furthermore, DaaS capabilities will enable governments to set up data catalogs or marketplaces that serve as Cloud-First or Cloud-Only policies for data, information, and analytics.

Cloud-hosted AaaS platforms that provide analytics, AI, and machine learning capabilities with broad adoption will also ease the governance burden. With many of the governmental analysis requirements being similar, these platforms will likely have optimized algorithms that cover issues such as public safety and accident vulnerabilities. These platforms offer data catalogs and discovery layers that can assist all governmental agencies to search for relevant data sets to consume for decision-making and planning processes. Such AaaS platforms will also benefit from metadata detection capabilities that help capture data lineage and clearly indicate data quality. Furthermore, with a large pool of data being hosted by the government, these AaaS platforms will also have access to a pool of data and metadata to work on bias detection and correction, aiming to enable fairness and inclusivity in AI predictions.

## IV. DATA GOVERNANCE FRAMEWORKS IN THE PUBLIC SECTOR

A growing number of public sector organizations are implementing formal Big Data Governance Frameworks with the aim of defining suitable governance arrangements for data assets, including Development Data, Open Data, and the data produced, shared, and consumed within and across government entities and agencies. A review of available frameworks and guidelines reveals four types of governance framework typically examined: (1) Control Frameworks offer a structured representation of the type of controls that need to be implemented and provide guidance to data custodians on the design and implementation of adequate data controls. In the Big Data context, they provide information on controls that need to be implemented at the level of Information Technology (IT) operation and support; (2) Data Management Frameworks outline the required organisational and decision-making structures, data stewardship roles and responsibilities, management processes, and technology infrastructure to effectively manage data, acknowledge data as a core enterprise asset, and ensure data availability, quality, usability, and security; (3) Data Governance Guidelines, usually issued by Chief Data Officers (CDO) or equivalent roles, are high-level documents intended to enable the successful management and regulation of the enterprise-wide data ecosystem; and (4) Maturity Models define the desired characteristics of a governance domain for different levels of maturity and provide guidance for data management capability improvement planning and implementation.

The creation of an appropriate data governance framework for a jurisdiction is critical to determining the success of Big Data initiatives. The objectives considered in this initiative represent only a subset of a more comprehensive list of goals that governments usually aim to achieve when implementing a data governance framework. As the goals expand and the risks increase, governments will develop the controls, processes, people, structures, and overall governance framework to support their objectives.

### 4.1. Data stewardship and ownership models

In any organization, data ownership is typically assigned to individuals who are responsible for the overall quality and fitness-for-use of specific datasets. However, the stewardship model that makes sense in a business context may not be appropriate for the public sector. Different approaches to data ownership and stewardship have been proposed: the lone data owner, the distributed data owner, and the data governance council. The first model rests on the business context of the organization and assigns data ownership to the business unit that generates or is the major consumer of the data.



In a distributed-data-owner model, individual data quality and fitness-for-use responsibilities are shared by all data custodians with the business-technology partnership playing a key role in the governance, quality surveillance, and remediation of data. The council-type model emphasizes that public-sector data are collectively owned by citizens and for citizens and assigns specific legal rights to internal custodians and external data customers.

Regardless of the ownership model, systems for managing and controlling access to sensitive data remain essential. These ensure that users with the appropriate rights can access only the information they need without compromising the data assets of the organization.

In democracies, the legal right to access data generated and collected by the government is enshrined in freedom-of-information laws. These laws also specify the time frame within which the request must be fulfilled. In many jurisdictions, data created and maintained through public funding are accessible and reusable for commercial and noncommercial purposes with few or no restrictions. At the same time, such data may contain private, sensitive, or otherwise confidential information whose disclosure would compromise citizens’ rights or well-being, endanger the security of the state, or jeopardize international relations.

**Equation B) “Control vs delegation” model for cloud service layers (IaaS/PaaS/DaaS/AaaS)**

**Step 1 — Define two axes**

For a service model  $s$ :

- $C(s)$ : customer control (higher means agency has more control)
- $D(s)$ : delegated management to provider (higher means CSP manages more)

**Step 2 — Normalize to [0,1]**

$$\hat{C}(s) = \frac{C(s)}{C_{max}}, \quad \hat{D}(s) = \frac{D(s)}{D_{max}}$$

**Step 3 — Compliance adequacy as a function of control and jurisdiction constraints**

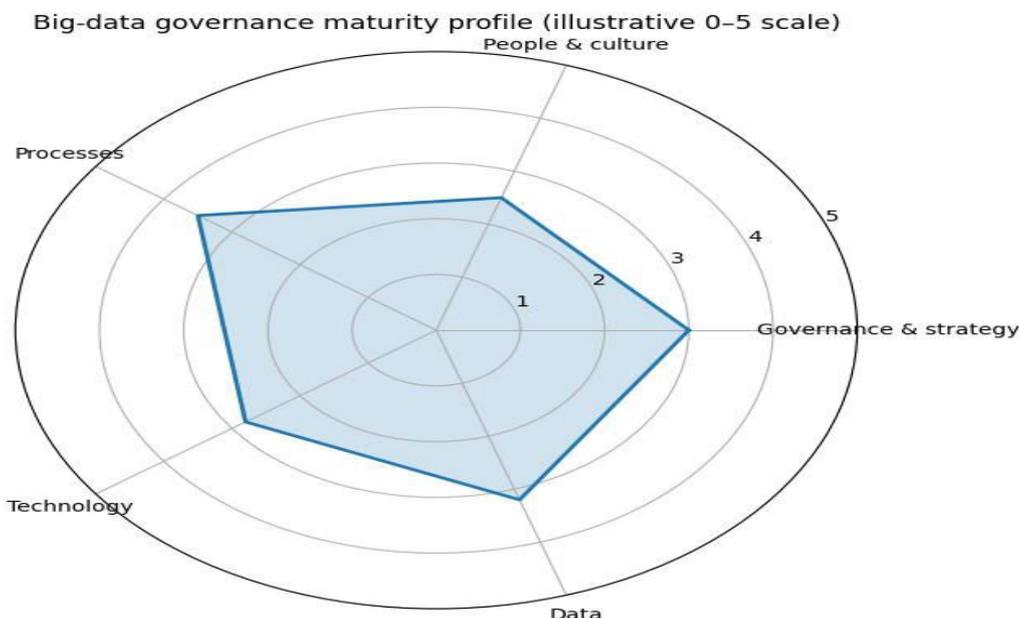
Let:

- $J \in [0,1]$ : strictness of legal/regulatory constraints (1 = very strict, e.g., strong localization, high sensitivity)

A simple formalization consistent with the paper’s logic is:

$$\text{ComplianceScore}(s) = \alpha \hat{C}(s) - \beta \hat{D}(s) \cdot J$$

- When  $J$  is high, high delegation can increase compliance risk (unless the provider is sovereign/qualified).
- When  $J$  is lower, higher delegation may be acceptable and operationally beneficial.





## 4.2. Metadata governance and data cataloging

Metadata—data about data—supplies the context that makes any form of data understandable and thus usable. Metadata specifies the structure, format, and description of the data content and makes it easy to find, access, manage, and use data assets effectively. Metadata is used throughout the data lifecycle by providers, processors, and end-users. In order to automate the processes around data, metadata also needs to be machine-readable. In addition to data assets, metadata for processes, scientific models, and for the language of logical reasoning also have to be created and made available.

Governments follow a set of relevant international metadata standards that are aligned to their country's requirements, including those issued by standards-developing organizations such as the International Organization for Standardization and the Open Geospatial Consortium. The Government of Canada's metadata profile for digital data sets is an exhaustive set of minimum data elements to be created. Metadata catalogs contain metadata about data sets from one or more data providers. Each catalog entry for individual data sets will include standard metadata elements and additional elements such as the name of the process that created the data set, the language of the data set, and expected changes within a specified time frame. Common catalog workflows conforming to the Open Data Catalog Vocabulary include the publication and registration of the meta-catalog itself, addition of new collections and data sets, modification of existing data sets, update of data set physics and semantics, and deletion of data. Maintaining data lineage across the full continuum of data management—collection, processing, storage, and analysis—is essential, especially in the context of data quality, forensics, and impact and risk analysis. Metadata's role in lineage capture is to supply the means to know when and how each asset has changed over time, where its data and processing come from, how it has been used, and its impact and risk.

## V. BIG DATA MANAGEMENT PRACTICES FOR DIGITAL PUBLIC SERVICE PLATFORMS

Governance over big data assets encompasses more than assigning decision rights regarding the use and application of data. Data management practices also determine the level of operational quality and the consistency with which data are provisioned, accessed, and consumed. Poor management can stymie any ambitions to deploy a principled model of data governance, nullifying progress already made by thoroughly undermining the reliability of the data served. The lack of rigorous quality controls increase the likelihood of erroneous data entering the pipelines, lower confidence in the outputs of analytical models and lead to repeated churn and work duplication associated with fixing past mistakes.

Data integration and interoperability rank among the most important operational practices to manage data assets on a digital public service platform. Government agencies are among the most prolific creators of data. They gather data from a multitude of sources, including social media, public sensors, public contact registers, citizen surveys, third-party suppliers and service providers, and foreign government data sources in order to better understand the public's needs and to improve public decision-making. Cloud-based DaaS and NaaS capabilities can provide timely and scalable access to external data sources. However, high demand from different user groups can create contention bottlenecks, which suggests that government entities should supplement these possibilities with improved internal data-sharing setups. Designing a coherent set of internal ETL capabilities can discretely integrate key data assets originating from disparate sources and repeatedly provide these assets to different users, consuming resources only once.

These internal assets should also be designed to minimize the number of distinct data models being published and actively serve as a pivot between diverse schemas. Deployment-related decisions can further enhance data integration. System installations from external vendors can use translation software to enable the import and processing of data from alternative vendors' systems. Employing the same vendor can mitigate these translation needs, provided the internal schema is designed for interoperability with the external vendor's recognized schema. On a cloud-based model, constituting the data asset as a public-facing DaaS NaaS offering allows external data suppliers to automatically feed data directly into the government NwD-use system. Effective operational procedures and controls can also facilitate data integration and interoperability across international boundaries. Establishing and applying a consistent assessment framework for DWD companions can explain the potential function of the companion data and highlight similarities and differences compared with the country's own local data

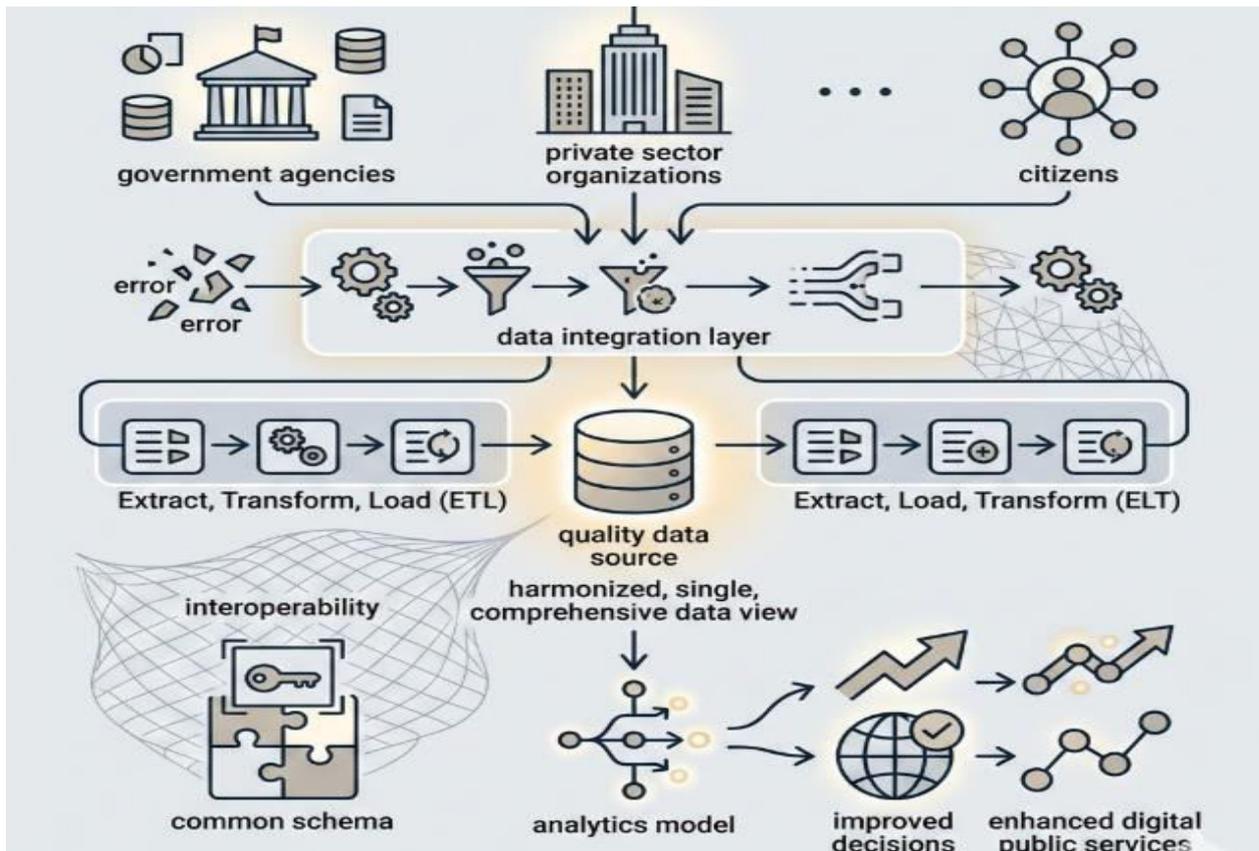
Principle	Operational intent on a digital public service platform
Security	Protect systems and data against threats and misuse.
Interoperability	Enable linking/harmonization across agencies and systems via shared schemas.
Data lifecycle management	Manage collection→use→archiving with risk assessment, testing, and controls.



**5.1. Data integration and interoperability**

Digital public service platforms will be increasingly integrated with various other sources of data, such as other government agencies, private sector organizations, and citizens. As a result, a major governance challenge is ensuring that the data accessed are suitably transformed, harmonized, and integrated before being made available. Data ingestion and preparation processes must incompletely remove errors from the data and enable different data sources to be combined into a single, comprehensive, quality data source. These processes, which represent the data integration layer of the architecture, can be structured around data sources within the data ecosystem, using Extract, Transform, Load (ETL) or Extract, Load, Transform (ELT) processes. Data sources for the integration layer mainly comprise the transactional databases supporting the various digital service delivery platforms engaged in high-frequency transactions with citizens.

Data integration is the process of combining data from different sources into a unified view. Data integration encompasses data ingestion and preparation for analytics, enabling analysis of data from multiple sources simultaneously. Data integration supports the deployment of analytics models. Data from different sources must, therefore, be harmonized to enable seamless use in the same or a combined analytics model. Interoperability enables data harmonization by specifying a common schema for a data set, thus acting as a shared model for all data providers and consumers. The schema can represent a single data source or a combination of multiple data sources for particular data elements. Data from non-interoperable sources must be transformed at the point of integration to enable their combination with other data sources.



**Fig 3: Architecting Interoperability: A Governance Framework for Integrated Data Harmonization in Digital Public Service Ecosystems**

**5.2. Data lineage and traceability**

Provenance tracking, impact analysis, and auditing mechanisms are central to establishing data lineage and ensuring traceability. Tracking the origin and history of datasets enables users to ascertain whether they are fit for use and fulfill compliance obligations associated with regulatory or certification regimes. Impact analysis—throughout the data



lifecycle, from production through to use and archiving—further strengthens effective governance by addressing potential liability concerns and enabling quality-control measures.

Automated data lineage analysis is thus an essential element of production and consumption processes, and should ideally be incorporated into the data provisioning system and analytics platform, ensuring that appropriate information is collected at the required granularity and detail for timely, informed, and responsible data use. Such automation can reduce manual effort, promote persistence and continuity in metadata governance activities, and broaden end-user participation. A dedicated team or individual nevertheless remains important for proactively monitoring, managing, and assuring correctness.

## VI. COMPLIANCE, ETHICS, AND ACCOUNTABILITY IN CLOUD-BASED GOVERNANCE

Cloud computing is susceptible to cyber threats, hence establishing an elaborate regulatory regime is critical to mitigate risks. Normative and legal imperatives delineate the regulatory landscape that governs the development of digital public service platforms. Sectoral regulations within sensitive domains are developed to safeguard citizen's rights and mitigate risks. The regulatory framework in the hosting country needs to be examined when procuring cloud services. For instance, the surveillance regimes of the United States, China, and Russia require additional considerations when processing personally identifiable information within their legal jurisdiction. Cross-border or jurisdictional legal regimes such as GDPR deals with the movement of data across country/region boundaries. Cloud service providers that provide hosting outside the home country must ensure that the concerned regulations permit such movement of data. Such models escalate the cost and operational complexity of cloud-based systems. The risk of exposing sensitive data while processing within high-risk countries requires the deployment of strict data protection mechanisms, limitation on data movement, and strict accountability on cloud service providers.

Though the cloud computing ecosystem offers elasticity in scaling resources, restricting demand-based changes is the best strategy to prevent adverse consequences. The use of low-cost Infrastructure-as-a-Service and Platform-as-a-Service models in the public sector enhances control and compliance at the expense of increased operational cost and efforts. Consequently, cloud computing for digital public service platforms ensures effective resource utilization, governmental compliance, secure citizen data access and control, and auditability. Automated mechanisms that ensure the sharing of all types of data with authorized users can be incorporated into the Data-as-a-Service and Analytics-as-a-Service requirements to enhance convenience and user-friendliness while promoting compliance. All identified requirements should be examined at regular intervals and incorporated into governance mechanisms to ensure holistic governance of data assets.

Cloud service model	Customer control over underlying resources (1=low, 5=high)	Delegation of management to provider (1=low, 5=high)
IaaS	5	1
PaaS	4	2
DaaS	2	4
AaaS	2	4

### 6.1. Legal frameworks and cross-border data transfer considerations

Cloud-based architectures hosting digital public services must satisfy legal requirements established by normative frameworks addressing stakeholder needs. Data localization requirements that limit data transfers to specific jurisdictions are common, as organizations must be accountable for personal data use and adhere to the legal frameworks applicable to citizens being served. Recognizing that cross-border data flows present a risk to national security and having jurisdiction over the data can assure citizens that their data is only shared when necessary, can be used to address actual risks, and that any sectoral laws designed to correct online harm are effectively enforced. Requiring all data to be hosted in-country, however, tends to impede sustainable data sharing across jurisdictions.

Cross-border transfers of data must balance the imperative to meet these requirements with the practical realities of multi-jurisdictional collaborations and participations. Principles of privacy by design embedded directly within Multi-Party Machine Learning Offerings create assurance that data will not be revealed to other parties, and Multi-Party Computation avoids sharing the trained model with any participant based on the data being used. Organizations must therefore evaluate the external legal regimes applying to the data they use, understand the details of the legal



framework to which they are bound, particularly as it relates to cross-border transfers, and put in place mitigating or follow-on actions to reduce risk.

**Equation C) Governance maturity model (5 dimensions) as a measurable score**

**Step 1 — Define maturity dimension scores**

$$g, p, r, t, d \in [0,5]$$

**Step 2 — Normalize**

$$\hat{g} = \frac{g}{5}, \hat{p} = \frac{p}{5}, \hat{r} = \frac{r}{5}, \hat{t} = \frac{t}{5}, \hat{d} = \frac{d}{5}$$

**Step 3 — Weighted maturity index**

$$M = \sum_{k \in \{g, p, r, t, d\}} a_k \hat{k} \quad \text{where} \quad \sum a_k = 1, a_k \geq 0$$

**Step 4 — Link maturity to expected residual risk (conceptual coupling)**

A common governance interpretation is: higher maturity reduces residual risk:

$$\text{ResidualRisk}_{\text{total}} \propto (1 - M)$$

More explicitly:

$$\text{ResidualRisk}_{\text{total}} = \gamma(1 - M)$$

**6.2. Ethical governance and bias mitigation**

Fairness, inclusivity and transparency are core principles for decision-making processes involving AI-based systems. These systems need to be carefully monitored to detect and mitigate algorithmic bias. Furthermore, model- and algorithm-agnostic approaches should be used for auditing commercial automated decision-making systems, and the explanations for algorithmic outcomes should be structured with respect to the understanding of the population affected by the decision. Digital Public Service Platforms play a crucial role in promoting fairness in AI development and use, particularly in the European context. As a fairness-preserving decision maker, the government should incentivize the development of fairness-aware AI systems in both technical and non-technical dimensions while providing advanced monitoring and auditing tools and procedures.

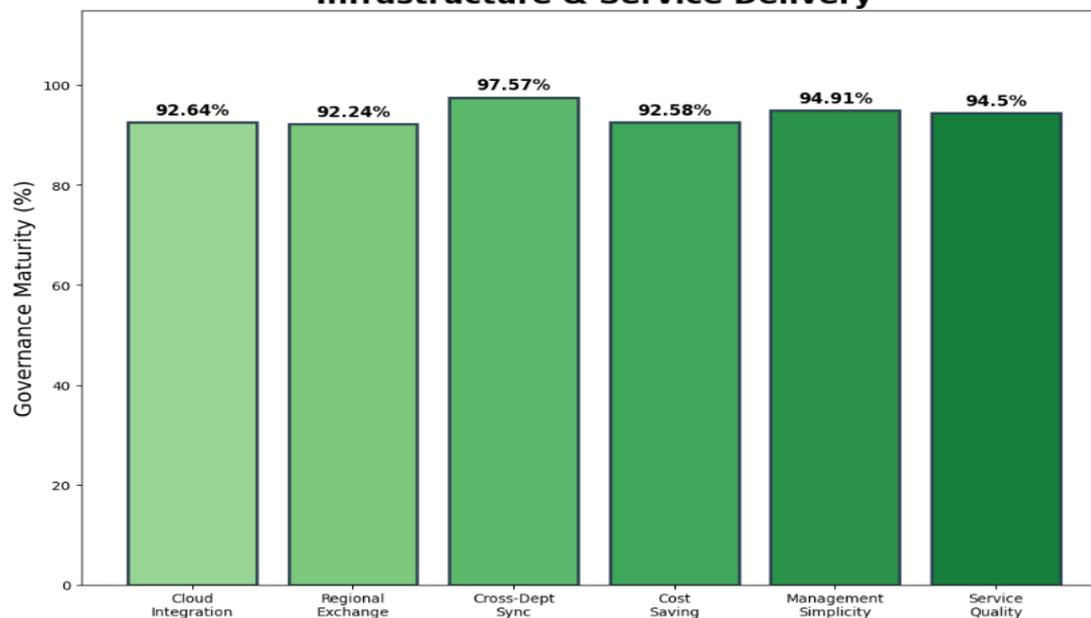
The government should also ensure that its own automated decisions are fair. Fairness-aware AI decision models should be developed and adopted to serve the general public. Legislation should be enacted to ensure that fairness, inclusivity, and transparency are included as primary objectives in the public sector's AI strategy and reflect the needs and views of affected groups through citizen participation. Algorithms adopted by the public sector should be under effective audit and supervision mechanisms, supplemented by the establishment of a bias monitoring system. The capability to mitigate algorithmic bias should be considered when selecting commercial AI systems, and fairness-preserving explanations for algorithmic outcomes should be provided. Furthermore, AI models and systems supporting administrative processes should be adopted after they have been externally evaluated from a fairness perspective.

**VII. CONCLUSION**

Providing good government services is a crucial aspect of a country's development, and digital public service platforms support delivery, information exchange, data integration, and other interactions. To achieve this, governments use all kinds of cloud-based big data infrastructure and services, which can help save costs, simplify management, reduce the overall burden, and improve service quality. The integration and application of various data across departments, regions, and levels also poses a challenge for government data management and cloud-based big data governance frameworks. Therefore, cloud-based big data governance for digital public service platforms should be established. A mature evaluation model can be used to determine the level of government platform cloud-based big data governance.



### Infrastructure & Service Delivery



**Fig 4: Infrastructure & Service Delivery**

The findings of the research are beneficial in practice. First, the work outlines the basic content of cloud-based big data governance for digital public service platforms; then, it proposes a cloud-based big data governance framework for digital public service platforms, involving enterprise supervision and social participation, describing in detail the seven control objectives of risk governance in digital public service platforms; finally, it proposes a dynamic governance capability evaluation model for digital public service platforms, running a case analysis using the new energy vehicle platform data governance capability evaluation model combined with a cloud-based architecture design to achieve governance capability evaluation, providing a basis for continuous improvement of governance capability.

#### 7.1. Final Thoughts and Future Directions in Big Data Governance

Although cloud-based digital public service platforms increasingly enable authorities to collect, integrate, and analyze cross-border data for evidence-based decision-making, formal governance frameworks for these big data assets remain elusive. Drawing on authoritative literature and expert sources, the discussion highlighted key support activities, content dimensions, operational management practices, and normative obligations shaping cross-border big data governance. A roadmap is proposed to guide the establishment of a cloud-based big data governance framework.

Emerging frameworks such as the National Institute of Standards and Technology AI Risk Management Framework, EU Commission Guidelines on Trustworthy AI, and Ethical Guidelines for Trustworthy AI provide invaluable guidance. However, given the dynamic nature of AI and its operating environment, organizations must continually monitor and examine their practices. To mitigate the bias resulting from differential wealth distribution and differing capacities to produce evidence, evidence-based public policy must move beyond economic efficiency and consider fairness, inclusiveness, and justice.

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