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# DATA & AI FOR POLICY INNOVATION

## Learning from Global Practice

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# Table of Contents

# Introduction

## Idea behind this guide

Across the world, public administrations are experimenting with data and artificial intelligence (AI). In many cases, these efforts are driven by a shared ambition: to generate better evidence, design more effective policies, and deliver public services that respond more closely to citizens' needs. In this sense, data and AI are increasingly understood not just as technical tools, but as key contributors to policy innovation. Yet when ambitions meet everyday practice, the reality is often more complex. Promising pilots stall. Legal and organisational uncertainties surface. Capacity gaps emerge. And approaches that work well in one setting may prove difficult to translate to another.

At the same time, the context in which governments operate is changing rapidly. Governance is never static – but in the case of data and AI, change is happening particularly fast. Technologies evolve quickly. Public expectations rise. Rules and regulations shift. And there is no settled model for how data and AI should be used in government. Practices are very much in the making, with many administrations learning by doing.

This guide starts from that reality. It brings together practical insights from diverse national contexts, with a focus on public administrations in the Global Majority[1]. It captures key success factors, common pitfalls, and ways how governments have adapted as they move towards more data- and AI-driven policymaking.

The guide builds on the work of the global programme "Learning from Experience – Data for Evidence-Informed Policy (Data2Policy)" implemented by Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) – the German Agency for International Cooperation – and was developed in close partnership with the Open Data Institute (ODI). It responds directly to the most pressing challenges and learning areas identified by data labs across German Federal Ministries through a survey that forms the baseline of this work.

**By bringing international experience and domestic priorities into dialogue, the guide aims to foster peer learning across contexts.** It examines recurring challenges administrations face in becoming more data- and AI-driven, highlights champions who are finding ways through them, and distils lessons that others can adapt to their own work – in Germany and beyond.

Overall, the guide is designed to support reflection and decision-making in practice. It translates lived experience into actionable insights that can inform how data and AI are embedded in policymaking processes.

## Who this guide is for

This guide is written for people working inside or closely with public administrations who are shaping how data and artificial intelligence (AI) are used in practice. This includes:

- › policymakers and policy advisors,
- › staff in data labs and digital units,
- › legal, IT, and governance teams,
- › leadership responsible for digital transformation, and
- › partners from civil society, academia, and the private sector.

Whether you are developing strategy, managing pilot projects, setting up governance structures, or translating political priorities into operational practice, the guide aims to offer reflections and examples that resonate with your day-to-day work. Given the commonality of the challenges and learning areas covered, insights are intended to be transferable to diverse national and local contexts.

Rather than assuming a single starting point, the guide speaks to practitioners at different stages of their journey – from early exploration to more institutionalised use of data and AI in policymaking. It is designed as a shared learning resource: one that aims to support learning with and from peers. It encourages readers to see their own work as connected to a broader, evolving community of practice, in which insights can travel across institutions and contexts, and where progress often emerges through exchange rather than isolated experimentation.

1 We use the term Global Majority as a descriptive alternative to Global South, emphasising population size rather than primarily developmental distinctions.

## How to use this guide

The structure of this guide reflects the realities of practice of data and AI-driven policymaking and the learning processes many administrations are currently navigating:

› **Background**

Provides context on the Data2Policy initiative and the Data Labs of the German Federal Government. It introduces a survey among the Data Labs that served as the baseline for this guide and explains why peer learning is particularly relevant in the context of data and AI in policymaking.

› **Part I – Challenges and Champions**

Explores recurring challenges in data and AI adoption in policymaking, including data governance and legal uncertainty, lack of in-house data and AI skills, limited data quality, organisational maturity gaps, and limited data availability. Each chapter pairs a key challenge with "champions" – administrations from around the world that have found practical ways to navigate these obstacles.

› **Part II – From Barriers to Learning Pathways**

Focuses on concrete learning areas in data and AI adoption, such as using data and AI in political decision-making, applying AI tools in administration, improving data quality and availability, developing internal data and AI strategies, and strengthening collaboration between technical units and policy experts. The section highlights practical examples and learning pathways that others can adapt to their own institutional contexts.

› **Part III – Challenge Cards for Data & AI for Policy Innovation**

The Challenge Cards complement the guide with interactive, discussion-based exercises. They translate themes from "Challenges and Champions" (Part I) and "Learning Pathways" (Part II) into formats suitable for team meetings, workshops, and peer exchange. Participants can step into different roles to explore challenges from multiple perspectives and surface underlying assumptions.

Each card includes reflection questions, a fictional scenario with suggested roles and discussion prompts, and QR codes leading to optional resources for further learning. The aim is to foster dialogue, collective reflection, and shared problem-solving across teams and institutions.

You can read the guide from start to finish or dip into specific sections depending on your interests and current challenges and learning areas. Each chapter stands on its own while contributing to the broader narrative of learning from experience for data- and AI-driven policymaking.

# Background › Institutional Context and Guiding Principles for Peer Learning

## The Data2Policy initiative

In this section, we intend to give an insight into the structures and experiences that are the foundation and inspiration for this guide. The guide was issued by the Data2Policy initiative of Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) as part of its outlook to make learnings on data and AI globally accessible and share knowledge on data for policymaking among governments worldwide.

Data2Policy was launched in 2023 as a follow-up to the Data4Policy initiative (2021). It supports partner governments in making more evidence-based decisions by developing and testing data- and AI-based solutions. These approaches help policymakers move beyond opinions and gut feelings towards more durable, fact-based decision-making.

The initiative takes a sector-agnostic approach, recognising that data and AI can support fairer, more inclusive, and more efficient outcomes across government when applied with care and critical scrutiny. In its current phase, Data2Policy works with government entities in countries such as India, Mexico, South Africa, Egypt, Peru, Armenia, and Iraq. Through innovative pilot projects, it supports the use of data and AI across areas including social security, employment, gender equality, nutrition, and climate policy.

To ensure that pilot projects have a lasting impact, Data2Policy places a strong emphasis on learning from experience – commonly referred to as peer learning. Insights from pilot use cases are systematically analysed to identify which technical solutions work well in specific contexts and where organisational, regulatory, and data and AI governance challenges tend to arise across partner countries. To make these learnings accessible and enable synergies across governments, the project has partnered with the United Nations Development Programme (UNDP) to establish the Data to Policy Navigator. This platform brings together methods and practical guidance for integrating data and AI into the policy cycle, alongside concrete use cases – from Data2Policy, UNDP's in-country work and from open submissions.

**The aim of the Data2Policy initiative is not only to advance the use of data and AI in government through exchanges within the Global Majority,but also to generate insights that can inform practice in high-income countries.** In particular, it seeks to transfer learnings back to the German data ecosystem – especially the Data Lab of the Federal Ministry for Economic Cooperation and Development (BMZ), the commissioning party for Data2Policy, as well as to counterparts across other federal ministries.

## The Open Data Institute

This report was co-created by the Open Data Institute (ODI), a non-profit organisation that works towards building open and trustworthy data ecosystems as well as advancing trust in data culture. Founded in 2012, the ODI helps organisations, governments, and communities use data in ways that are fair, responsible, and impactful. Through research, policy engagement, training, and practical tools, the ODI champions better data practices that unlock social, environmental, and economic value while protecting people's rights and interests.

Over the course of the Data2Policy initiative, ODI has contributed with technical expertise and capacity-building support for policymakers in partner countries. Their tools provide the basis for various methods outlined on the Data to Policy Navigator and used by Data2Policy during their in-country work, e. g. the Data Ecosystem Mapping methodology. Combined with its longstanding expertise and insights gained from consulting on numerous data- and AI-related projects, the ODI was able to bring together a wide range of expertise and relevant resources for this guide.

## The Data Labs of the German Federal Government

The Data Labs are an innovative approach of the German Federal Administration financed by the European Union to improve data use and data competencies across the Federal Government in Germany. When the COVID-19 crisis struck, the European Commission set out to invest in digital infrastructure and digitalisation through its Next Generation EU initiative, instated in 2021. The German Federal Government translated this into the German Recovery and Resilience Plan (GRRP) in 2021. The GRRP included the foundation of the Data Labs as an instrument to advance data-driven innovation and significantly increase the availability and responsible use of data for political decision-making.

The German Federal Government further issued its first ever data strategy in 2021, underpinning the importance of strategic data use. The Data Labs play an important role in the implementation of this strategy, often serving as the main dedicated data units within their respective Federal Ministries.

The Data Labs are designed as a structure that fosters both peer learning and innovation. With 17 Data Labs in total – across 16 Federal Ministries and the Federal Chancellery – this setup enables government-wide coordination, shared learning, and the creation of synergies, while still allowing data and AI solutions to be tailored to the specific needs of each ministry. Each Data Lab has four goals fixed in the GRRP:

- Establishing a Data Lab, including the role of a Chief Data Scientist
- Developing data infrastructures both in terms of data bases and tools
- Enhancing data competencies within the Federal Administration
- Institutionalising a viable data culture

Main activities of the Data Labs therefore include the development of data products such as dashboards, or cloud-based AI assistants that interact with government knowledge sources. In addition, the Data Labs provide capacity-building trainin to strengthen government staff's understanding of data, AI, ethics, data analysis and visualisation, as well as practical LLM use.

The Data Labs represent a particularly innovative institutional setup, as their design enables fast, needs-driven solutions. Because teams largely consist of data scientists, technical products can be developed using in-house expertise. Positioned at the intersection between administrative structures and implementation, Data Lab teams have a strong understanding of their ministries' daily needs. Their agile project management allows them to rapidly validate data and AI product concepts by assessing both technical feasibility and anticipated value.

The innovative character of the Data Labs further lies in their collaborative learning approach. Through regular exchange formats and demonstration days that showcase technical solutions and approaches to other Data Labs, they create synergies and efficiencies. This culture also shapes their approach to learning, fostering an open culture of experimentation, failure, and learning.

## Assessing the needs of policymakers – Survey of the Data Labs of German Federal Government

Building on Data2Policy's experience with partner countries, we explored how these examples can inform the German data ecosystem and where peer learning can create synergies across public administrations internationally. To tailor this guide to the needs and real-world challenges of policymakers, we conducted a survey among the Data Labs of the German Federal Government in collaboration with PD, the in-house consultancy of the German public sector. The Data Labs were identified as a particularly valuable sample group, as their work sits at the intersection of developing data and AI applications and strengthening data culture. This position gives them insights across all stages of the data policy cycle.

In the survey, respondents were asked to indicate the challenges they face in using data and AI in their work, as well as areas where they would like to learn from international counterparts. Both questions were designed as multiple choice with the possibility of multiple selection and adding open answers. In total, 18 respondents representative of the 16 Data Labs shared their opinions in the survey.

Almost all survey respondents commonly cited two key challenges in their work with data and AI: a lack of in-house data and AI skills and legal uncertainty. Around half of respondents also commonly cited issues related to data quality and data availability. In addition, gaps in organisational structures and challenges related to data governance were cited by a majority of respondents (see Graph 1).

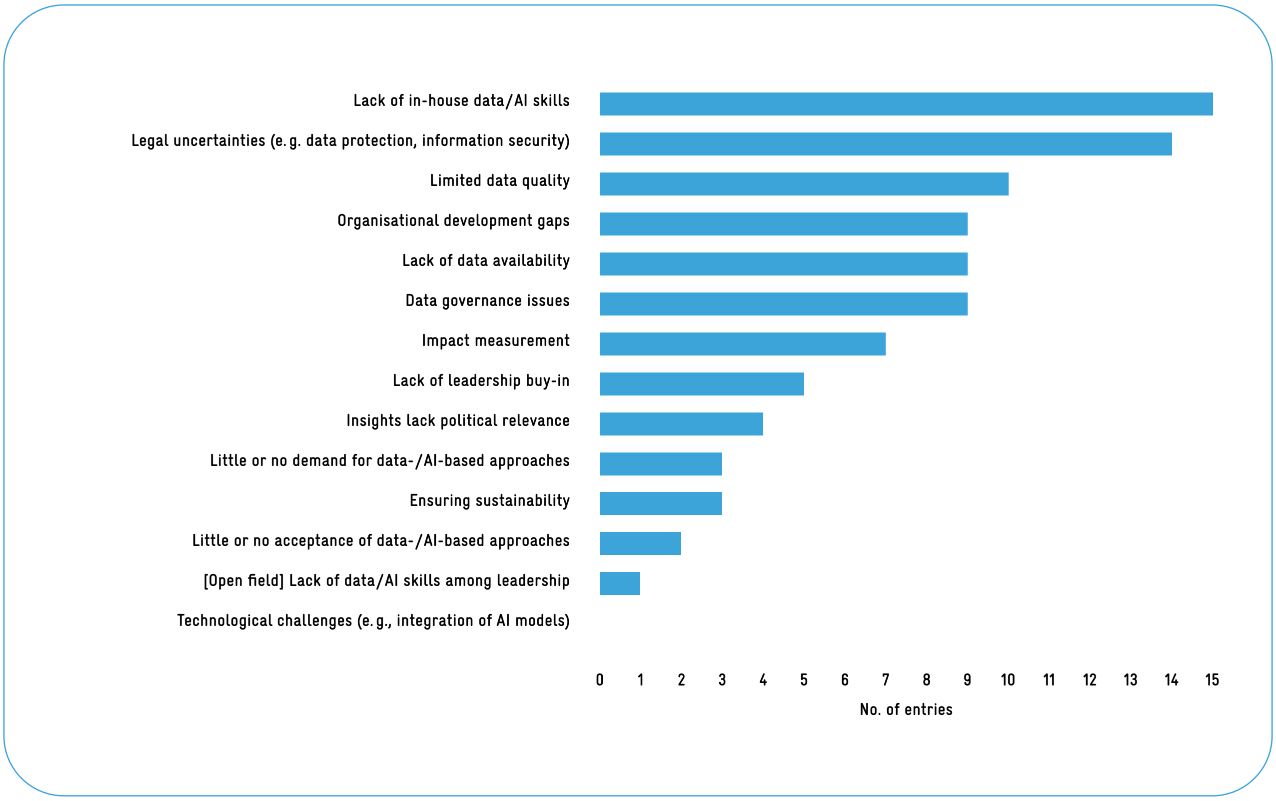
With regard to learning areas where Data Labs seek input from international counterparts (see Graph 2), the most frequently stated needs were practical examples and guidance on using data and AI in political decision-making processes and on applying AI tools in administration, with each option selected by ten respondents. Other commonly cited learning areas reflected the challenges identified above, including improving data quality and availability and developing internal data and AI strategies. Several respondents also cited challenges related to cooperation across internal units, further underscoring the relevance of peer learning and exchange.

Part I of this guide addresses the five most commonly cited challenges, while Part II focuses on the five most commonly listed learning areas.

Overall, the challenges and learning needs identified through the survey align closely with Data2Policy's experience from exchanges with government partners and international organisations, where similar issues in data and/or AI for policymaking are frequently encountered.

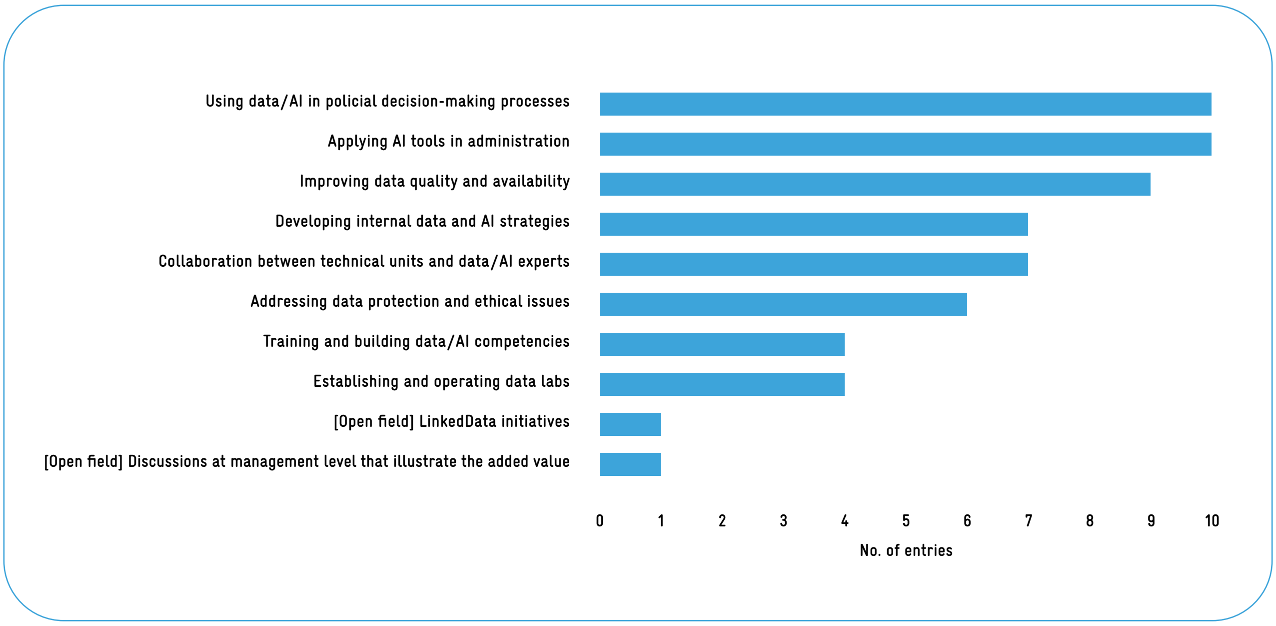
## Results of survey among Data Labs

Challenges in the use of data and AI
Multiple answers possible




› Chart 1: Challenges

Areas in which learning experiences from international partners are desired
Multiple answers possible




› Chart 2: Learning areas

## Defining peer learning – the backbone of this guide

The following sections of this guide build on a central insight from our work: no public administration that seeks to use data and AI is clearly ahead in everything.

Across contexts, governments are navigating similar challenges. They experiment, encounter obstacles, adjust their approaches, and learn along the way. Progress is rarely linear but rather emerges through trial and error, small successes, and course corrections in response to new technological and institutional realities.

Peer learning connects these experiences. It enables institutions to learn from each other's successes and failures, avoid repeating mistakes, accelerate reform processes, and build confidence in situations of uncertainty. In this sense, peer learning is more than a method used in this guide – it is its underlying logic. The guide itself is designed to foster shared reflection, exchange, and collective problem-solving in data and AI for policymaking.

In this guide, we understand peer learning as the ways in which institutions and policymakers in public administration learn from and with one another. It is about exchanging experiences on an equal footing and jointly developing better questions and, over time, better answers.

This understanding builds on Pisano and Berger's (2016) conceptualisation of peer learning as an umbrella concept encompassing different mechanisms that enable learning among peers. One such mechanism is the existence of comparable reference systems, shaped by similar experiences (e.g. similar institutional constraints). These similar experiences make it easier to relate to one another's challenges and to translate insights across contexts. Peer learning is also an active process. Participants in peer learning deepen their understanding by articulating their own ideas to others, working collaboratively on shared challenges, giving and receiving feedback, and reflecting on their own learning along the way (Pisano & Berger, 2016). Learning, in this sense, is not only about absorbing external input, but about collectively making sense of experience.

This strongly resonates with our experience at Data2Policy In our work, we repeatedly see that practitioners in public administration in Germany and internationally face similar challenges, bottlenecks, political dynamics, success factors, and pitfalls when trying to leverage data and AI for policymaking. It is precisely this shared reality that makes peer learning so valuable. But its impact depends on contextual translation: to not simply exchange solutions but unpack the reasoning behind decisions and explore why an approach worked in a specific context, also by looking at how obstacles were navigated in practice (see Part II of this guide).

Drawing on our experiences at Data2Policy, shared challenges matter more than geography. Common responsibility, not necessarily national or local context, underpins effective peer learning. Experiences of peers, however, become most meaningful once they are translated into one's own national, local, or institutional realities.

From our perspective, learning from each other's experiences in the context of data and AI for policymaking is therefore not just useful, but a necessity. In a field where standards are still emerging and risks remain uncertain, peer learning helps administrations make informed decisions under conditions of complexity and limited precedent.

What we see in practice closely mirrors how UNESCO (2022) conceptualises effective peer learning. Their framework captures the elements that repeatedly prove crucial in our own exchanges. In particular, UNESCO (2022) highlights:

- On-demand support: learning responds directly to concrete needs identified by practitioners in their own national or local contexts.
- Capacity-building and policy development: learning is oriented towards real governance challenges.
- Multi-stakeholder approaches: involving actors from government, civil society, and the private sector to broaden perspectives and expertise.
- Partnership and collaboration: knowledge is co-produced rather than transferred in a one-directional way.
- Openness and safe environments: spaces that allow for honest reflection without reputational risk.
- Continuity: peer learning is understood as an ongoing process rather than a one-off intervention.

These principles provide an important reference point for how we work with our partners at Data2Policy and also shape the logic of this guide. Accordingly, this guide is designed as a facilitation tool for peer learning on data and AI for policy innovation. It includes a dedicated chapter focusing on challenges (Part I) and learning pathways (Part II) and aims to stimulate reflection on shared challenges and emerging good practices. The guide builds on the work of Data2Policy and ODI, and in particular on the experiences of countries from the Global Majority. It seeks to foster exchange and collective reflection on how data and AI can be leveraged for better policymaking.

**Sources:**


- Pisano, U., & Berger, G. (2016). Exploring peer learning to support the implementation of the 2030 Agenda for Sustainable Development (ESDN Quarterly Report No. 40). European Sustainable Development Network.
- UNESCO. (2022). Peer-to-peer learning toolkit: Promoting policy and cooperation to support creativity (Brochure). United Nations Educational, Scientific and Cultural Organization.

## Why peer learning matters for data and AI in government

Around the world, governments are exploring how data and AI can help them to better understand societal challenges, design more effective policies, and deliver public services in new ways. Practitioners grapple with questions such as how data can inform policy responses to (youth) unemployment, how AI can improve how governments listen to and serve citizens, and how digital tools might amplify underrepresented voices in decision-making.

**What characterises the current moment is not only the pace of technological change, but also the lack of well-established approaches for data and AI use in government. Practices in this area are still taking shape, with many administrations learning through experimentation.**

Through our pilot projects with partner governments, we observe institutions testing how to manage data access and collection, as seen in a project on nutrition security in India, how to integrate AI into everyday workflows, e. g. to support women's economic participation, and how to build internal capacities to serve the public interest, e. g. through multistakeholder workshops as conducted in Peru to improve health interventions

Parallel experimentation turns data and AI use in government into a shared learning space – one with many pioneers and no single pathway. Therefore, peer learning plays a central role. It provides a setting for collective sense-making at a time of rapid technological change and persistent uncertainty.

Across our work, we also see that progress rarely comes from technology alone. Leadership, governance mechanisms, institutional change, and a strong focus on public interest matter just as much. Learning from how others have dealt with obstacles helps administrations adapt ideas to their own realities.

Our experience shows that peer learning for data and AI in government matters most when complexity emerges during implementation, when rules and expectations shift, and when similar approaches are applied in very different institutional contexts. The following sections explore these three aspects in more detail.

### 1 NAVIGATING COMPLEXITY BEYOND THE TECHNICAL

Introducing data- and/or AI-based initiatives rarely remains a purely technical exercise. In practice, new projects often raise political and legal questions, as well as issues of organisational responsibility and ethics. In our work, we have seen data pilots unexpectedly encounter privacy concerns, AI prototypes prompt debates about bias and fairness, and data-sharing initiatives stall because systems across organisations cannot be aligned.

While some of these dynamics are anticipated early on, many only become visible as projects progress and move beyond the planning phase. It is often at this stage that new challenges emerge. At this point, peer learning becomes particularly valuable.

**By drawing on how similar situations unfolded elsewhere, governments gain insight into how challenges were handled – how resistance emerged, which governance mechanisms proved helpful, and what safeguards were introduced along the way.** This supports anticipatory governance: learning from others' experiences to proactively prepare for comparable dilemmas in one's own context.

### 2 KEEPING UP WITH EVOLVING RULES AND SHAPING NORMS

Data and AI governance are moving targets. Regulatory frameworks, political priorities, institutional guidance, and public expectations evolve rapidly, making it difficult for static guidelines to remain useful for long. Peer exchanges offer policymakers a way to navigate this shifting landscape together, for example by jointly reflecting on emerging grey areas from a public-interest perspective. Where formal guidance is lacking or still developing, it is through these interactions that shared norms begin to take shape. Policymakers develop common reference points for what "good practice" looks like in concrete situations. Over time, these informal understandings start to guide everyday decision-making, often well before they are translated into formal rules or regulations. In this way, peer learning does not only help administrations respond to changing governance frameworks but actively contributes to shaping how data and AI governance evolves in practice.

### 3 CONTEXT MATTERS: ADAPTATION TO NATIONAL, LOCAL, INSTITUTIONAL REALITIES

Experience from Data2Policy's pilot projects shows that data- and AI-driven initiatives rarely work the exact same way everywhere. A decision-support system may run smoothly in a highly digitised ministry, but struggle in an administration where records are still kept on paper. A chatbot designed to answer citizens' questions might be widely used in cities yet barely reach people in rural areas with limited connectivity or digital access.

Peer learning helps make these differences visible. When administrations compare their experiences, they begin to see which assumptions are built into their solutions and ways of working, for example about data quality, staff capacity, digital infrastructure, or organisational processes. They also gain a clearer understanding of the conditions that enabled an approach to work elsewhere.

This comparison often triggers very practical reflection. What would need to change for this initiative to work here? Which elements could be adapted, and which would not translate? Practices that appear "standard" in one setting may cause issues in another. It is precisely through this shared reflection that peer learning enables meaningful adaptation, and supports administrations in making more informed choices to foster data- and AI-driven policymaking.

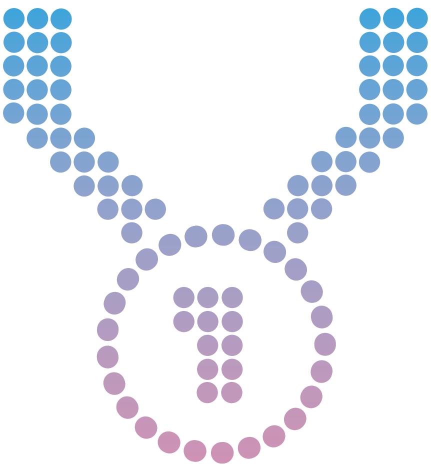
# PART I

# CHALLENGES AND CHAMPIONS

# Part I › Challenges and Champions

Using data and AI is no longer a distant prospect for governments – they are already shaping service delivery, decision-making, and citizen engagement. Yet turning ambition into impact is far from simple. Many administrations encounter recurring obstacles: unclear governance and legal frameworks, shortages of in-house skills, unreliable or incomplete data, weak organisational maturity, and persistent gaps in data availability. These are not isolated issues, but interconnected barriers that often prevent promising pilots from becoming systemic reforms. The challenges addressed in the following section are a result from the most pressing issues raised in the survey conducted among the Data Labs of the German Federal Government (see Chart 1).

The purpose of this first part of the guide is to examine these challenges head-on and, crucially, to highlight the champions who are finding ways through them. Our champions are the administrations, labs, and innovators who are showing how to overcome barriers with creativity, collaboration, and reform. Their stories reveal not only what holds governments back, but also the sparks of leadership and innovation that point to new ways forward.



In the chapters that follow, we look at:

› **Data governance and legal uncertainties** – and how Estonia and Peru show that embedding governance into infrastructure and clarifying the law can unlock trust and innovation.

› **Lack of in-house data and AI skills** – with lessons from Tanzania's Data Lab and Ghana's accelerator programmes on how training translates into real-world outcomes.

› **Limited data quality** – illustrated by Ghana's coaching model and Rwanda's systematic audits, proving that practical interventions can transform reliability.

› **Organisational development gaps** – addressed through Bangladesh's a2i programme and Colombia's national AI policy, both showing how reform and coordination matter as much as technology.

› **Lack of data availability** – tackled in Sierra Leone's digitisation and India's AI sowing app, demonstrating that equity and usability must be designed in from the start.

Together, these champions show that progress is not only possible but already happening. The stories underline three central lessons. First, challenges in data and AI are not unique to any one region: administrations everywhere face similar obstacles. Second, solutions rarely depend on technology alone. They require leadership, governance, institutional reform, and a relentless focus on citizen outcomes. Third, by examining how others have navigated these barriers, governments can see how to adapt the lessons to their own context – building more trustworthy, sustainable, and inclusive uses of data and AI.

# Data Governance and Legal Uncertainties

## Challenge

Governments often face uncertainty in how to manage, share, and regulate data for AI and policy purposes. Weak governance structures create confusion over roles and responsibilities, while rapidly evolving legal frameworks (data protection, cybersecurity, cross-border flows) can discourage innovation. Without clarity, administrations risk either paralysing innovation or exposing citizens to harm.

## Champions: Who's Tackling This?

### Estonia > Embedding Governance into Digital Infrastructure

Following independence in the 1990s, Estonia confronted fragmented institutions, scarce resources, and low public trust. Rather than bolting on regulation later, Estonia designed governance into its digital transformation from the start. Its X-Road interoperability platform was developed with clear principles for data ownership, accountability, and security, alongside the "once-only" principle that spared citizens from repeatedly providing the same information. GDPR and national data protection law were integrated into the system's architecture, while oversight bodies and a national digital ID ensured transparency and accountability. Today, over 99 % of public services are available online, including voting, healthcare, and taxation. Citizens benefit from reliable, trusted services, while the government benefits from reduced transaction costs and greater efficiency. Estonia's approach has become a global reference point, with its e-Governance Academy supporting digital reforms in countries such as Ukraine, Rwanda, and also in Germany where the Association of Statutory Health Insurance Physicians in Hesse launched a pilot project for video consultation hours and digital prescriptions in April 2020.

#### Source:


- Nortal. (2022, June 10). X-Road: Estonia's digital backbone. Nortal. Retrieved December 22, 2025, from https://nortal.com/insights/x-road-estonias-digital-backbone


### Peru > First AI Law in Latin America

Across Latin America, lack of legal clarity around AI made ministries and businesses hesitant to invest. Public agencies faced uncertainty over data protection, algorithmic accountability, and human rights safeguards. In response, Peru passed Law 31814 – the law that promotes the use of artificial intelligence in favour of the economic and social development of the country[2] – in 2023, the region's first AI-specific law. The legislation established a multi-sector governance framework, set requirements for human oversight, and embedded ethical principles into AI adoption.

The law created confidence for both government and private actors, enabling expansion of AI initiatives in areas such as digital taxation and smart cities. It also positioned Peru as a regional leader in AI governance, attracting international cooperation and raising its profile in global digital governance rankings.

#### Sources:


- OECD.AI. (2025, July 9). Law 31814, law that promotes the use of artificial intelligence in favor of the economic and social development of the country. OECD.AI. Retrieved December 22, 2025, from https://oecd.ai/en/dashboards/policy-initiatives/law-31814-law-that-promotes-the-use-of-artificial-intelligence-in-favor-of-the-economic-and-social-development-of-the-country-3047
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2 Original in Spanish: Ley N. 31814, Ley que promueve el uso de la inteligencia artificial en favor del desarrollo económico y social del país

### KEY SUCCESS FACTORS

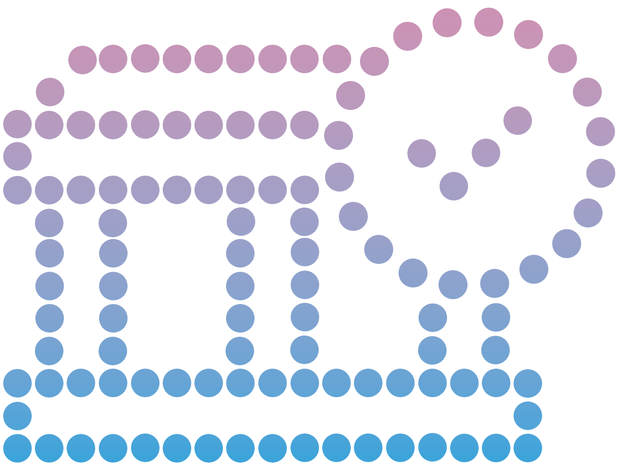
- **Governance by design:** Estonia shows that embedding legal safeguards (privacy, security, data ownership) into technical architecture creates durable trust.
- **Early legal clarity:** Peru's AI law demonstrates how legislative frameworks can reduce uncertainty, attract investment, and accelerate adoption.
- **Independent oversight:** Clear institutional roles — data protection authorities, chief data officers – strengthen enforcement.
- **Global knowledge sharing:** Estonia's export of governance expertise and Peru's regional leadership both highlight the value of cross-country learning.

### PITFALLS TO AVOID

- **Copy-pasting models:** Legal frameworks must be adapted to local institutional realities; Estonia's model works because it grew from its context.
- **Over-bureaucratisation:** If governance is seen as compliance red tape, it risks slowing innovation instead of enabling it.
- **Unclear roles:** Fragmented responsibilities dilute accountability and leave grey areas in enforcement.
- **Citizen exclusion:** Without transparency and engagement, governance reforms risk eroding rather than building trust. Without explicit attention to rights and fairness, governance reforms may reinforce existing inequities.

## Putting it into practice

Estonia and Peru illustrate two pathways for reducing governance and legal uncertainty. Estonia demonstrates governance-by-design, embedding trust into digital systems and institutions. Peru shows how legal clarity through AI-specific legislation can provide confidence for innovation while protecting citizens. Together they highlight that governance and law, far from being barriers, are critical enablers of sustainable and trusted AI adoption.



# Lack of In-House Data/AI Skills

## Challenge

Developing the skills to use data and AI effectively is a challenge for governments everywhere. Public administrations often struggle to retain expertise, connect technical specialists with policymakers, and ensure that training leads to institutional change rather than one-off projects. Governments across the world are pioneering innovative models to build sustainable talent pipelines – linking training directly to real-world applications, fostering inclusive participation, and creating ecosystems that bridge government, academia, and startups. These approaches offer valuable lessons for administrations within governments worldwide seeking to strengthen their in-house capacity for working with data and AI.

## Champions: Who's Tackling This?

### Tanzania > Building Capacity through dLab

Prior to 2018, Tanzania's data ecosystem was fragmented, and data literacy across government and civil society was low. Policymakers struggled to interpret evidence for planning, while open data policies lacked traction. The Tanzania Data Lab (dLab) was established as a hub for skills training, ecosystem development, and applied data innovation.

dLab combined capacity building with applied innovation. More than 1,700 people were trained in data literacy, management, and visualisation, including through a dedicated Women in Data programme. Partnerships with the University of Dar es Salaam and others created a pipeline of local trainers, embedding expertise in national institutions. Applied projects such as the Data Zetu initiative mapped 22,000+ households in underserved areas, feeding directly into health and education interventions. dLab also supported national policy, helping double the number of datasets on Tanzania's open data portal and shaping the national Open Data Policy.

At the community level, data-driven investments transformed healthcare outcomes – for example, facility upgrades at Iyunga Dispensary reduced emergency referrals and doubled the number of safe births. Institutionally, dLab grew into an independent NGO, hosting annual Data Tamasha festivals and funding innovation challenges for local entrepreneurs. Internationally, it became a reference point for ecosystem building, recognised by the World Bank and IEEE as a blueprint for national data hubs.

**Sources:**


› Open Data Institute. (2018, October 3). Case study: Tanzanian Data Lab (dLab). The ODI. Retrieved December 22, 2025, from https://theodi.org/insights/impact-stories/case-study-tanzanian-data-lab-dlab/

› Millennium Challenge Corporation. (2021, March 8). Investing in local data use pays off as women #ChoosetoChallenge in Tanzania. Millennium Challenge Corporation. Retrieved December 22, 2025, from https://www.mcc.gov/blog/entry/blog-030821-investing-in-local-data-use-pays-off/

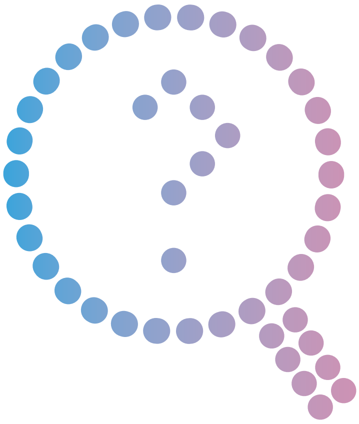

### Ghana > From Training to Applied AI in Health

Ghana faced an acute shortage of applied AI talent, with training limited to academic contexts and little hands-on exposure. This gap was especially stark in healthcare, where there was just one radiologist for every 800,000 citizens, creating dangerous delays in diagnosis of treatable conditions. To tackle this, two complementary initiatives emerged: the Africa AI Accelerator (AAA) and the homegrown startup MinoHealth AI Labs.

AAA, launched in 2020 by GIZ, Ghana Tech Lab, and partners, combined technical training with mentoring, incubation, and entrepreneurship support. This built a pipeline of practitioners capable of developing and scaling AI innovations. MinoHealth AI Labs, supported by such accelerators, developed AI diagnostic systems for 14 chest conditions, training local teams in AI development and integrating tools into clinical practice.The twin approach of training and application created a sustainable ecosystem. AAA graduates entered government, private, and health sectors, boosting Ghana's AI workforce. MinoHealth's diagnostic tools are now deployed in 20+ countries across Africa, with clinical trials showing performance exceeding individual radiologists. Together, these initiatives showcase how skills development linked to applied use cases can deliver life-saving impact while positioning Ghana as a regional AI leader and increasing the pool of digital skills talent within the country.

**Source:**


› Akogo, D., Sarkodie, B. D., Samori, I. A., Jimah, B. B., Anim, D. A., & Mensah, Y. B. (2022). Minohealth. ai: A Clinical Evaluation of Deep Learning Systems for the Diagnosis of Pleural Effusion and Cardiomegaly in Ghana, Vietnam and the United States of America. arXiv preprint arXiv:2211.00644.

## Ghana > Partnering to Develop Statistical Data Science Skills

When the Ghana Statistical Service (GSS) established its Data Science Unit in 2021, gaps in critical digital skills undermined its ability to deliver timely statistics for policymaking. The team struggled with technical challenges such as inadequate IT infrastructure to handle vast census data and insufficient computing power, as well as skill gaps in advanced analytics and data science concepts. These challenges compromised GSS's capacity to produce statistics with the level of granularity required in order for government departments to do their jobs more effectively.

Through participation in the Global Partnership for Sustainable Development Data initiative, GSS sought to overcome both the technological and skills obstacles that were faced. Infrastructural support was provided through hardware made accessible by several companies through the initiative, while the UK's Office for National Statistics provided weekly mentoring sessions covering version control, project management, and quality assurance that helped GSS restructure their Consumer Price Index code into maintainable, reproducible analytical pipelines.

The initiative helped transform statistical production. GSS deployed machine learning to automate industrial classification, created an online platform accessing over 300 million census statistics, and developed a Digital Census Atlas with geospatial overlays. Staff then applied the new skills they had acquired across multiple surveys, passing knowledge to colleagues organisation-wide. A key takeaway demonstrated through the case study of Ghana's Statistical Service is that building data science capacity in resource-constrained settings requires combining technology infrastructure with sustained mentorship on real production systems.

**Sources:**


› Ohuruogu, V., Mugo, M., Seidu, O., & Arkafra, K. L. (2024, October 7). Ghana Statistical Service harnesses data science and machine learning for better statistics. Data4SDGs. Retrieved December 22, 2025, from https://www.data4sdgs.org/blog/ghana-statistical-service-harnesses-data-science-and-machine-learning-better-statistics

› Data Science Campus. (2023, December 14). Transformation in the Ghana Statistical Service. Office for National Statistics. Retrieved December 22, 2025, from https://datasciencecampus.ons.gov.uk/transformation-in-the-ghana-statistical-service/


### KEY SUCCESS FACTORS

› **Learning by doing:** Linking training directly to applied projects (healthcare in Ghana, community services in Tanzania) ensures lasting skills and institutional adoption. In governmental departments, this could include the development of learning opportunities where staff can immediately apply new digital skills to actual government challenges, such as mapping underserved populations and improving service delivery.

› **Hybrid training models:** Training combined with mentoring, business incubation, and partnerships creates longer-lasting pipelines of talent.

› **Inclusive workforce development:** Targeted initiatives like Women in Data and SheCanCode can help reduce gender imbalances in the AI workforce. Within government units, this could include focused cohort-based learning where government staff learn together through the formation of peer networks.

› **Ecosystem approaches:** Effective skills development emerges when governments move beyond transactional procurement relationships and instead engage universities, civil society, and the private sector as collaborators in shared problem-solving. When partners are involved in co-designing, delivering, and learning from projects – rather than simply supplying services – skills, knowledge, and ownership are far more likely to be retained within public institutions, while the government remains firmly in the lead role.

› **Demonstrable outcomes:** When data and AI skills clearly improve service delivery, health outcomes, or policy effectiveness, they generate organisational buy-in and political support.

### PITFALLS TO AVOID

› **Over-reliance on external expertise:** When core analytical or technical functions remain dependent on consultants or external partners, knowledge often fails to transfer into government, limiting long-term capability and institutional memory.

› **Measuring only outputs:** Measuring success only by numbers trained, rather than by how skills are applied in day-to-day work, risks producing capacity that is underused or quickly lost.

› **Political volatility:** Shifts in government support (as seen in Tanzania's open data push) can undermine momentum.

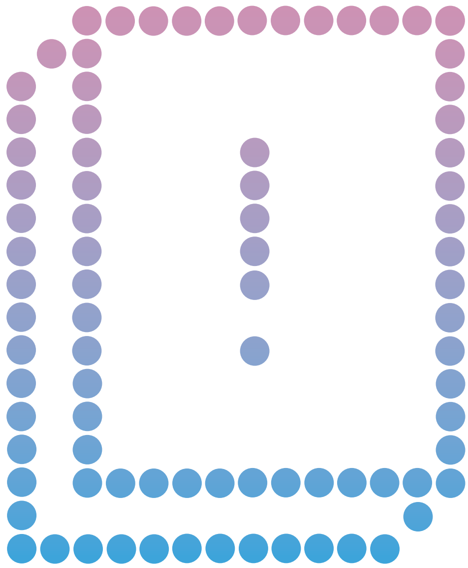
## Putting it into Practice

The experiences from Tanzania and Ghana show that building in-house data and AI capacity is most effective when skills development is tied directly to real-world applications that deliver visible public value. Training alone is rarely sufficient. Capacity sticks when it is reinforced through sustained mentorship, access to appropriate technology, and opportunities to apply new skills within live government systems and services.

A recurring lesson is the importance of changing how governments engage with external actors. Rather than relying solely on short-term procurement of expertise, administrations that treat universities, startups, and civil society as collaborators – co-designing solutions, working alongside civil servants, and transferring knowledge through delivery – are more likely to retain skills internally. This shift from supplier relationships to shared problem-solving helps ensure that expertise does not disappear when a contract ends, and that public institutions remain in the lead.

Creating mixed ecosystems that connect government teams with academic institutions, innovators, and communities also helps build sustainable and contextually relevant talent pipelines. Inclusivity must remain central to these efforts, for example through targeted programmes supporting women in data or initiatives that open pathways for early-career professionals to work on real public challenges.

Finally, building in-house capacity requires long-term commitment. Skills development needs to be embedded into workforce planning, role design, and career progression, rather than treated as a one-off initiative. When governments invest in people, tools, and collaborative ways of working over time, data and AI capability becomes a durable institutional asset rather than a temporary project outcome.



# Limited Data Quality

## Challenge

High-quality data is the backbone of trustworthy AI and evidence-based policymaking. Yet, across governments worldwide, ensuring that data is complete, accurate, and reliable remains a persistent challenge. Errors or inconsistencies can undermine trust, reduce the effectiveness of services, and slow down innovation. Countries across the globe are showing how targeted interventions from staff mentoring to system-wide quality assessments can create lasting improvements in data foundations.

## Champions: Who's Tackling This?

### Ghana > Marine Litter Citizen Science Data Collection

Until recently, Ghana lacked any official data on marine plastics, reflecting a wider global challenge: oceans are vast, and collecting reliable data on litter is both difficult and costly. To address this gap, a coalition of government agencies, researchers, NGOs, and citizen groups came together to pilot a new approach. The project integrated citizen science into official statistics by aligning methodologies, building partnerships, and applying common standards for data collection. A three-phase data validation process was introduced to ensure the quality and reliability of the information gathered. The initiative enabled Ghana to generate accurate, cost-effective, and timely data on marine litter for the first time. This information is now being used to inform environmental policy and international reporting, while also demonstrating the value of participatory approaches in tackling complex sustainability challenges. By embedding validation and standards into citizen-led data, Ghana turned a data blind spot into actionable evidence.

**Source:**

› United Nations Development Programme. (2025). Using citizen-generated data to tackle marine pollution: Ghana. Data to Policy Navigator. Retrieved December 22, 2025, from https://www.datatopolicy.org/use-case/ghana

### Rwanda > Data Quality in Community Health Systems

Rwanda has invested heavily in community-based healthcare, supported by digital systems such as mUzima, built on the open-source platform OpenMRS. Community health workers (CHWs) collect data on non-communicable diseases, feeding into national planning. To test the reliability of this system, researchers conducted a large-scale quality assessment of 231,799 patient records entered between April 2023 and March 2024.

The study evaluated core dimensions such as completeness of variables and uniqueness of patient identifiers – both critical for accurate diagnosis and follow-up.

The results showed strong performance: more than four-fifths of variables were complete, and nearly 90 % of patient records were uniquely identified. These findings suggest that when digital tools are designed to support the workflows of CHWs, data capture can achieve a high standard. The assessment also highlighted opportunities to embed further quality controls for continued improvement.

**Source:**

› Uwase, M., Ntakirutimana, I., Kayiranga, D., Mugisha, E., Twizere, C., Tumusiime, D., & Mugisha, M. (2025). Data Quality Assessment in mUzima-OpenMRS: A Mobile Application Used by Community Health Workers for Screening Hypertension and Diabetes in Rwanda. Studies in health technology and informatics, 328, 387–391. https://doi.org/10.3233/SHTI250744

### KEY SUCCESS FACTORS

- **Partnership approaches:** Ghana's case demonstrates how multi-stakeholder collaboration can integrate unconventional data sources, such as citizen science, into official systems.
- **Routine measurement and monitoring:** Rwanda demonstrates how systematic assessments can reveal both strengths and areas for improvement.
- **Embedding quality at the source:** Designing systems around user workflows – whether frontline CHWs or citizen volunteers – encourages accurate capture and reduces errors.
- **Culture of data use:** When data entry clerks see the value of data for planning, quality becomes part of daily practice.
- **Intentional data collection:** Focusing on targeted and controlled data collection by collecting what is needed, to an agreed standard, for a clearly defined purpose improves data reliability, reduces noise, and strengthens trust among both users and citizens.

### PITFALLS TO AVOID

› **Limited scalability:** Hands-on models, whether coaching or citizen science validation, can be labour-intensive to expand.

› **Sustainability threats:** Once coaching ends, data practices risk slipping – so embedding routines and supervision systems is vital.

› **Partial metrics:** Quality assessments may omit critical dimensions like timeliness or data use – limiting holistic understanding.

› **Building data swamps:** Governments increasingly invest in data lakes, central repositories designed to store data in a structured, well-documented, and reusable way. However, when data is collected without clear purpose, ownership, quality controls, or plans for use, these lakes can quickly become data swamps: large volumes of poorly curated, duplicated, or outdated information that are difficult to navigate or trust. Data swamps bury valuable signals under noise, make analysis harder rather than easier, and increase operational and ethical risks. Citizens can become disengaged or distrustful when large amounts of data are collected without a clear, explainable rationale or demonstrable public benefit.

› **Standards ≠ quality:** Conforming to a schema or technical standard does not automatically make data high quality. Without examining coverage and representation, even "standardised" datasets can reinforce bias and undermine fairness.

## Putting it into practice

The lessons from Ghana and Rwanda highlight that improving data quality does not require large-scale overhauls. Practical steps, whether validating citizen science contributions through multi-stakeholder coalitions or running systematic quality audits of clinical records, can have transformative effects.

A critical shift for administrations is moving away from indiscriminate data accumulation towards intentional and governed data collection. Collecting more data does not automatically improve decision-making; in fact, it can obscure what matters most. By defining clear purposes for data collection, applying validation at the point of capture, and regularly reviewing whether data is actually being used, governments can avoid the drift from data lakes into data swamps.

When quality assurance, representation, and ethical considerations are built into routine practice rather than treated as technical afterthoughts data becomes a reliable foundation for policymaking and AI. This enables administrations to focus effort where it matters most, while maintaining public trust in how data is collected and used.

# Organisational Development Gaps

## Challenge

Adopting data and AI is not just about technology. For innovations to last, governments need the organisational maturity to sustain them: clear coordination across ministries, embedded leadership structures, and incentives for collaboration. Without these, promising pilots risk fading away instead of becoming systemic reforms.

## Champions: Who's Tackling This?

### Bangladesh > Aspire to Innovate (a2i) Programme

Bangladesh's public services were highly fragmented, with citizens often travelling long distances, facing bureaucratic delays, and paying bribes to access basic services. Institutional silos and low data maturity made coordinated service delivery difficult.

Through the a2i programme (initially supported by UNDP and the Government of Bangladesh), the country pursued whole-of-government digital transformation. a2i consolidated services through the MyGov platform, streamlined workflows, and embedded innovation units in ministries to drive organisational change.

By bringing 209 services into a single online platform, a2i made access faster, cheaper, and more transparent. As of December 2022, a2i has collectively saved citizens 19 billion workdays, USD 22 billion, and eliminated 13 billion visits to government offices.

#### Source:


› Hirdaramani, Y. (2024, March 25). From aspiration to agency: Bangladesh's a2i programme is here to stay. GovInsider. Retrieved December 22, 2025, from https://govinsider.asia/intl-en/article/from-aspiration-to-agency-bangladeshs-a2i-programme-is-here-to-stay/


### Colombia > CONPES 4144 National AI Policy

Colombia had multiple AI pilots but lacked central coordination, strategy, and institutional maturity to scale them. Efforts risked duplication, inefficiency, and weak public trust without a coherent governance and organisational framework.

In 2022, Colombia launched CONPES 4144, its National AI Policy, allocating COP 479 billion (USD 115.9 million) through 2030 across six strategic pillars: ethics and governance, talent development, adoption in strategic sectors, research and development, international positioning, and monitoring. This created shared organisational responsibility across ministries, with central leadership from the Ministry of ICT and National Planning Department (DNP).

One of the key impacts resulted from Colombia's social protection registry, SISBEN, being upgraded with AI-enabled fraud detection, improving the targeting of subsidies to the poorest households. By institutionalising AI within planning processes, Colombia made it more difficult for political turnover to derail progress. The strategy also positioned Colombia as a regional leader in AI governance, attracting international cooperation and partnerships.

#### Sources:


› Gonzalez, G. (2025). Access Alert: Colombia launches National AI Policy. Access Partnership. Retrieved December 22, 2025, from https://accesspartnership.com/general/colombia-national-ai-policy/

› Vargas, F., & Muente, A. (2025). Artificial intelligence framework for the Inter-American Development Group (IDB-LM-00716). Inter-American Development Bank. https://doi.org/10.18235/0013377

### KEY SUCCESS FACTORS

- **Whole-of-government platforms:** Bangladesh's a2i shows how central digital platforms can force silos to adapt, while Colombia's CONPES 4144 demonstrates how a national strategy can coordinate efforts across ministries and embed AI into planning processes.
- **Institutional embedding over projects:** Durable progress comes from embedding innovation capacity within existing public institutions, such as permanent units, mandates, and planning processes, rather than relying on temporary programmes or standalone initiatives.
- **Leadership with authority:** Both cases underline the importance of clear leadership structures with decision-making power, whether through a central digital agency or a coordinating ministry, to move reforms beyond experimentation.
- **Citizen-centred performance measures:** Tracking outcomes that matter to citizens, such as reduced time, cost, or error in accessing services, helps build political legitimacy and keeps reforms anchored in public value rather than internal efficiency alone.

### PITFALLS TO AVOID

- **Pilot fatigue:** Without pathways to institutionalisation, pilots risk stalling as "proofs of concept."
- **Over-centralisation:** Strong central strategies must be balanced with ministerial ownership, otherwise reforms risk being seen as imposed.
- **Accountability gaps:** As responsibilities shift to new digital agencies or cross-ministerial bodies, lack of clear oversight can weaken citizen recourse when systems fail.
- **Dependence on individuals rather than institutions:** When progress relies heavily on political champions or small leadership teams, reforms become vulnerable to turnover. Organisational maturity requires roles, mandates, and incentives that persist beyond individuals.
- **Mismatch between ambition and capacity:** National strategies that move faster than workforce skills or organisational readiness can stall implementation and erode confidence.
- **Technology-first reform:** Introducing new platforms or AI tools without corresponding changes in governance, incentives, and ways of working risks superficial adoption rather than lasting transformation.
- **Exclusion through design:** Organisational reforms that do not actively include marginalised groups risk entrenching inequities at a systemic level; for example, in maturity models that focus on specific behaviours which are biased towards one part of society.

## Putting it into Practice

The experiences of Bangladesh and Colombia show that organisational maturity is as critical as technical capacity in sustaining data and AI reforms. Success requires structures that cut across ministries, stable financing and leadership that embeds innovation into day-to-day governance. Administrations looking to close maturity gaps can begin by linking digital reforms to citizen-centred outcomes, embedding innovation capacity into existing institutions, and ensuring continuity through multi-year frameworks rather than short-lived projects.

# Lack of Data Availability

## Challenge

For many governments, critical data to support decision-making simply does not exist, or is locked away in silos. Administrative data may not be collected systematically, private sector datasets may be inaccessible, and open data initiatives often stall at pilot stage. The result is policymaking conducted with partial visibility, blind spots in service delivery, and a lack of trust in evidence-based approaches.

## Champions: Who's Tackling This?

### India > Agricultural Data and the AI Sowing App

In India, millions of smallholder farmers lacked access to agricultural data, leaving them vulnerable to crop failure and income loss. The government's think tank NITI Aayog, Microsoft, and the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) collaborated to launch the AI Sowing App. Drawing on 30 years of climate data and weather forecasts, the app delivered personalised sowing advisories via SMS, ensuring accessibility for farmers without smartphones or internet access.

The app was piloted with 175 farmers in Andhra Pradesh and quickly scaled to thousands across multiple states. Farmers who followed the advisories achieved yield gains of 10–30 % per hectare. Beyond boosting productivity, the app demonstrated how opening and applying agricultural datasets, combined with AI, could directly improve livelihoods in vulnerable communities while ensuring equity through low-tech delivery.

#### Sources:


- Microsoft Stories. (2017, November 7). Digital agriculture: Farmers in India are using AI to increase crop yields. Microsoft. Retrieved December 22, 2025, from https://news.microsoft.com/en-in/features/ai-agriculture-icrisat-upl-india/
- NITI Aayog. (2018). National Strategy for Artificial Intelligence (Discussion Paper). Government of India. Retrieved December 22, 2025, from https://www.niti.gov.in/sites/default/files/2019-01/NationalStrategy-for-AI-Discussion-Paper.pdf


### Singapore > Government Data Architecture (GDA) and Data Sharing Initiative

When Singapore's government agencies struggled with fragmented data systems in the late 2010s, cross-government collaboration was severely hampered. Officials had to individually request data from multiple departments, slowing decision-making and preventing integrated service delivery. The Government Technology Agency (GovTech) was tasked with breaking down these silos and building a unified data architecture to support the nation's Smart Nation Initiative. GovTech established Topic Catalogues, which are one-stop data hubs located in the Department of Statistics (individuals and businesses), Singapore Land Authority (geospatial), and Smart Nation and Digital Government Group (sensors), that aggregate datasets from across government. Alongside this, an API[3] exchange named APEX was developed as a government-wide data sharing platform, providing shared and reusable software components that enable agencies to build digital services quickly and efficiently.

The infrastructure transformed service delivery, allowing citizens to access everything from birth registration to health records through seamless digital channels. During the COVID-19 crisis, the system proved vital for national resilience and inclusion, while also accelerating Singapore's transition to becoming an advanced digital economy, boosting competitiveness and unlocking new growth opportunities. The World Bank now showcases Singapore's approach as a model for other countries building national digital identity and data sharing platforms. Singapore demonstrated how strategic data availability infrastructure can help overcome data availability challenges and unlock cross-government innovation, without requiring agencies to rebuild their existing systems.

#### Sources:


- Qiang, C. Z., Chan, C. H. (2022, December 21). How Singapore's national digital identity and government digital data sharing platform fosters inclusion and resilience. World Bank Blogs. Retrieved December 22, 2025, from https://blogs.worldbank.org/en/digital-development/how-singapores-national-digital-identity-and-government-digital-data-sharing
- Lim Yew Mao, D. (2019, July). Bringing data into the heart of digital government. Civil Service College Knowledge. Retrieved December 22, 2025, from https://knowledge.csc.gov.sg/ethos-issue-21/bring-data-in-the-heart-of-digital-government/


3 API (Application Programming Interface): A specification of how one system can interface with another

## Thailand > Electronic Transactions Development Agency

In acknowledgment of the profound changes involved in the transition from an analogue to a digital society, Thailand's Electronic Transactions Development Agency (ETDA) was founded in 2011 to play a major role in promoting, supporting and developing electronic transactions (e-transactions) or online transactions under the Electronic Transactions Acts of 2001 and 2019. Since it was founded, access to and the sharing of data across and between government ministries and agencies has been identified as a critical obstacle to the objectives of ETDA.

Together with the ODI, ETDA has sought to partially address this through the co-development of a data sharing framework for Thailand, which identifies the actors necessary to unlock access to data that is critical for government functions.

As part of this initial work to develop the data sharing framework, Thailand's Digital Government Development Agency (DGA) subsequently reviewed practices and processes to incentivise the publication and maintenance of government open data in Thailand.

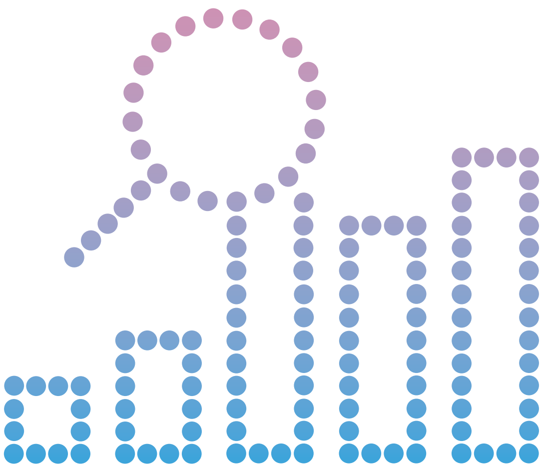
In spite of these efforts, availability of data for the delivery of public services remains obstructed by a number of underlying obstacles. Most notably, this includes apprehension of government staff to share data as a result of concerns surrounding compliance with recent data protection legislation, as well as uncertainty amongst government entities on who is responsible for which activities and where they have the mandate to lead on specific initiatives.

**Source:**


- Moriniere, S., Keller, J. R., & Inverarity, C. (2024, June 5). Empowering Thailand's digital government with open data. Open Data Institute. Retrieved December 22, 2025, from https://theodi.org/insights/reports/empowering-thailands-digital-government-with-open-data/


### KEY SUCCESS FACTORS

- **Clear leadership and mandates:** Singapore and Thailand show the importance of assigning explicit responsibility for data availability and sharing, whether through a central digital agency, a coordinating body, or formal mandates embedded in government structures. Without this, data remains siloed by default.
- **Foundational infrastructure over one-off releases:** Investing in shared data architecture – such as catalogues, registries, and API exchanges – enables reuse across services and crises without forcing agencies to rebuild existing systems.
- **Purpose-driven data opening:** India's agricultural case demonstrates how making specific datasets available for a clearly defined public purpose can unlock rapid value, particularly when data is combined with analytics or AI and delivered through accessible channels.
- **Reducing complexity to enable participation:** Data availability improves when standards, classifications, and technical requirements are proportionate to the use case. Overly complex schemas, specialist terminology, or rigid formats can discourage both internal reuse and external engagement, even when data is nominally "open".
- **Visible public value:** When data availability is clearly linked to outcomes such as higher crop yields, faster service delivery, or improved crisis response it creates sustained demand within government to maintain and improve access.



### PITFALLS TO AVOID

- **"Data dumps" without use:** Simply releasing datasets, without usability or demand in mind, risks undermining trust and uptake.
- **Fragmentation across ministries:** Without shared standards and interoperability mechanisms, data availability initiatives risk duplication, inconsistency, and uneven quality across government.
- **Neglecting sustainability:** Long-term maintenance of platforms and datasets must be budgeted, not left to project cycles.
- **Business-case bottlenecks:** Too often, data is only shared when a specific business case forces it. In a "closed by default" culture, this means valuable information stays locked away. An "open by default" approach asks the reverse, not just 'Is it ethical/legal to share this data?' but also 'Is it ethical/legal not to share it?'. Hoarding data without clear justification can itself undermine fairness, accountability, and trust.

## Putting it into Practice

The experiences of India, Singapore, and Thailand illustrate that improving data availability is primarily an organisational and governance challenge, not a technical one. Progress depends on creating the conditions in which data can move safely, confidently, and routinely across government.

For administrations, this begins with clarifying who has the mandate to lead on data sharing and ensuring that responsibilities for stewardship, access, and maintenance are clearly defined. Investing in shared infrastructure – such as data catalogues, interoperable registries, and API platforms – allows agencies to unlock value from existing data without duplicating systems.

Equally important is adopting a more intentional approach to openness. Rather than waiting for bespoke business cases, governments can benefit from articulating default positions on data sharing and identifying narrow, well-justified reasons for restriction. This shift helps prevent unnecessary hoarding while maintaining legal and ethical safeguards.

Finally, reducing unnecessary complexity is essential. Data standards, terminologies, and formats should support participation rather than exclude it. When data is understandable and usable by a wider range of actors within government and beyond it is far more likely to inform decisions, improve services, and earn public trust.

Taken together, these lessons show that data availability is not about publishing more datasets, but about building the governance, infrastructure, and culture that allow data to be used where it matters most.

# PART II

# FROM BARRIERS TO PATHWAYS

# Part II › From Barriers to Pathways

In the first half of this guide, we looked at the obstacles governments face in using data and AI, and some of the champions who have begun taking steps to overcome them. But challenges are only one side of the story. Governments across the world are not only addressing barriers – they are also learning, experimenting, and shaping new approaches. The pace of development in this space can at times seem overwhelming, however if governments are focused on addressing specific challenges, such as those covered in Part I, this can serve as the platform on which to develop the appropriate solution, whether through new processes and/or new tools.

The second half of this guide therefore explores five learning pathways aligned with learning areas sought by respondents to our survey (see Chart 2) that governments can take forward, drawing from international practice and highlighting practical steps that others can adapt to their own contexts.

In this section we cover:

- › **Using Data and AI in Political Decision-Making** – looking at how to embed AI into daily policy processes, scenario modelling, and evidence-informed governance.
- › **Applying AI Tools in Administration** – moving from pilots to institutionalised use of AI in core government services.
- › **Improving Data Quality and Availability** – how to build the "hard data work" foundations needed for trustworthy AI.
- › **Developing Internal Data and AI Strategies** – how governments can craft their own pathways (leapfrogging vs absorptive capacity[4]) to guide investments and reforms.
- › **Collaboration Between Technical Users and Data and AI Policy Experts** – how to bridge the gap between AI specialists and policy practitioners through co-creation, literacy, and shared governance.

Collectively, these pathways demonstrate approaches that governments can learn from and consider replicating or adapting in order to supercharge their own approaches to developing fair and equitable AI. As the approaches above emphasise, collaboration can have many beneficial outcomes, whether in the development of more robust policies that are fit for purpose, or in ensuring that pitfalls, as outlined in Part I, can be minimalised or mitigated. Collaboration can occur in many forms, and the following chapters illustrate how governments across the world have taken the opportunities offered by the current challenges posed by AI to improve their infrastructure, skills and expertise to meet them.

4 Leapfrogging is the process in which a country skips older, intermediate technologies and instead adopts more advanced solutions. Notable examples include M-Pesa, in Kenya, amongst others. Developing absorptive capacity, on the other hand, focuses on increasing the required skills and technologies to adopt existing fundamental technologies. Examples might include increasing workforce cyberhygiene, to enable safer use of new digital technologies.

# Using Data and AI in Political Decision-Making

## Why This Matters

Every administration faces the same dilemma: how to make complex decisions with limited resources and under conditions of uncertainty. Data and AI offer powerful ways to improve decisions by making evidence more visible, testing policies before they are implemented, and modelling potential consequences. Yet their value only emerges when they are integrated into the rhythms of governance. If used in isolation or as short-term pilots, they risk being seen as novelties rather than becoming part of how policy is made.

## Learning Pathways

Three complementary approaches stand out:

#### 1 SCENARIO MODELLING AND FORECASTING

AI is increasingly used to simulate alternative policy choices. These approaches, often described as digital twins, create virtual environments in which governments can test "what if" scenarios. For example, digital twins of cities can model how road changes affect congestion, or how energy policies alter emissions. Crucially, these systems do not always require perfect "real data". Some models rely on synthetic data[5] that mirrors the world as it is, biases and all, while others construct normative models of the world governments would like to create, helping test reforms against future aspirations.

The strength of scenario modelling lies in its ability to reduce uncertainty. By running hundreds of possible outcomes through the use of computer-enabled modelling, policymakers can better anticipate the trade-offs of their decisions and avoid costly surprises.

Case in point: Karnataka's Bhoomi project in India digitised millions of land records and introduced AI-based simulations. Policymakers could forecast the likely impacts of changes in land-use rules or subsidy allocations before implementing them. This not only cut corruption and waiting times for farmers but also shifted policymaking from reactive responses to predictive, evidence-informed planning.

**Source:**

› Crombie, D., & Engelen, J. (2008, July). Accessible Content Processing Introduction to the Special Thematic Session. Retrieved December 22, 2025, from https://www.researchgate.net/publication/221010251_Accessible_Content_Processing_Introduction_to_the_Special_Thematic_Session

#### 2 DECISION DASHBOARDS AND REAL-TIME DATA USE

Policy decisions are often based on delayed, incomplete, or outdated information. Real-time dashboards change that by consolidating live data flows into a single interface. AI enhances these systems by detecting anomalies, projecting likely outcomes, and flagging where interventions may be needed.

Dashboards work best when connected directly to frontline services. For example, in welfare or tax systems, AI-powered dashboards can highlight patterns of fraud or exclusion in near real-time, allowing course correction before problems scale. But this requires interoperability across ministries, common data standards, and strong quality assurance. Without these, dashboards risk becoming glossy displays without operational value.

Case in point: Colombia's SISBEN IV registry modernised household classification for welfare targeting using AI-enhanced dashboards. The system allowed ministries to monitor eligibility and distribution of subsidies in real time, sharply reducing both under-coverage and leakage. This not only saved resources but also rebuilt citizen trust in the fairness of social programmes – a critical factor for political legitimacy.

**Source:**

› Inter-American Development Bank. (2025). Artificial intelligence framework for the Inter-American Development Group. Retrieved December 22, 2025, from https://publications.iadb.org/en/artificial-intelligence-framework-inter-american-development-group

5 Synthetic data are "Data that have been created artificially (e.g., through statistical computer simulation) so that new values and/or data elements generated." (ODI, 2025)

### 3 CONSEQUENCE AND RISK ASSESSMENT

Decision-making is not only about optimising outputs. It is also about anticipating risks and mitigating harms. Structured consequence assessment frameworks ensure that governments examine unintended effects before policies are scaled.

The ODI's Consequence and Risk Evaluation (CARE) tool is one such approach. CARE combines human deliberation with AI assistance. Participants are guided through structured prompts that surface potential benefits, risks, and trade-offs of a decision. An integrated AI assistant acts as a "critical friend", brainstorming possible consequences or mitigations that might not otherwise be considered. This makes deliberation both broader and more systematic.

Case in point: Global Fishing Watch, an NGO that uses satellite data and AI to track industrial fishing, applied CARE to evaluate its monitoring system. The process highlighted risks such as surveillance misuse, unintended impacts on small-scale fishers, and challenges around data governance. As a result, safeguards were built in before the system scaled further, demonstrating how AI itself can be used to protect against AI's adverse impacts.

## Sources:


- Tarrant, D. (2024, June 11). Consequence and risk evaluation (CARE) tool. Open Data Institute. Retrieved December 22, 2025, from https://theodi.org/insights/tools/consequence-and-risk-evaluation-care-tool/
- Himmelsbach, E., Achenbach, K., & D'Addario, J. (2024, December 17). Embedding data ethics at Global Fishing Watch. Open Data Institute. Retrieved December 22, 2025, from https://theodi.org/news-and-events/blog/embedding-data-ethics-at-global-fishingwatch/


## REFLECTIONS FOR POLICYMAKERS

- **AI helps governments think in futures, not just presents.** Scenario modelling and digital twins allow policymakers to anticipate consequences before they materialise. These tools are not limited to precise forecasts based on perfect data; they can also use synthetic data to model aspirational futures. This opens up space for creativity in policymaking – exploring not only what is likely to happen, but what could happen if governments pursue bold reforms.
- **Real-time visibility builds agility.** Dashboards like Colombia's SISBEN IV show how live data flows can sharpen responsiveness and make programmes more equitable. But they require investments in interoperability, data quality, and institutional capacity. Without these, dashboards risk becoming disconnected from action.
- **AI can be used as a safeguard.** The CARE tool demonstrates that AI is not only about efficiency or optimisation. It can also help surface ethical, social, and long-term risks, making policymaking more accountable and trusted. This flips the narrative: AI can be part of the solution to responsible governance, not just a challenge to it.
- **Citizen-centred outcomes are essential.** Whether it is farmers receiving faster land titles, households gaining fairer access to welfare, or fishers protected from unintended harms, legitimacy comes when citizens see tangible benefits. These are the outcomes that sustain reforms beyond political cycles.
- **Integration is the real challenge.** Pilots prove technical feasibility, but embedding AI into decision-making requires concrete organisational changes, e.g., redesigning workflows, updating guidelines, building leadership capacity, and ensuring cross-ministerial coordination. It also means creating participatory processes so that citizens and frontline staff can give input as systems are rolled out.

# Applying AI Tools in Administration

## Why This Matters

AI, and more recently generative AI, is reshaping public administration. By drafting documents, summarising reports, translating across languages, or providing frontline advice, it promises to free up staff time and make services more responsive. Yet governments face a paradox: adoption is technically easy – a licence key or a cloud API (a way for applications to access services on cloud servers) can unlock world-leading models – but embedding these tools into the heart of administration is much harder.

This is the AI Deployment Paradox: moving from quick wins in pilots to institutionalised use in core government functions requires careful attention to governance, accountability, and integration with official knowledge bases. Governments that succeed are those that treat generative AI not as a novelty but as part of their administrative infrastructure.

## Learning Pathways

Governments' GenAI journey often follows these stages:

### 1 PILOTS AND PROOF OF CONCEPT

The entry point for most administrations is small-scale pilots. Generative AI assistants are tested in safe environments: summarising meeting notes, rewriting reports, or answering simple FAQs. These pilots deliver quick wins, freeing staff time and showing the potential of the technology.

At this stage, data practices are minimal. The models work "out of the box" with general training data. But this also means outputs can be generic, error-prone, or culturally misaligned. Governance here is about monitoring use, preventing sensitive data from being uploaded to third-party tools, and learning what tasks AI is most (and least) useful for.

Case in point: In 2024 the Australian government ran a six-month trial of Microsoft Copilot across 7,600 staff in 60+ agencies. Staff reported saving up to an hour on summarising information, preparing first drafts, and searching for data. The tool was most useful for routine writing tasks, highlighting the efficiency gains GenAI can bring in everyday administration.

## Source:


› Commonwealth of Australia. (2025). Australian Government trial of Microsoft 365 Copilot. digital.gov.au. Retrieved December 22, 2025, from https://www.digital.gov.au/initiatives/copilot-trial/summary-evaluation-findings/cts-executive-summary


### 2 EMBEDDING IN EXISTING PROCESSES

The next step is to embed AI assistants directly into existing government workflows using the tools that civil servants already rely on, such as word processors, code editors, or intranets. Here, AI is no longer an optional add-on; it becomes part of the working environment.

This requires clearer data practices. Governments need rules about what kinds of internal documents can be exposed to AI tools, where outputs are stored, and how staff are trained to critically evaluate AI-generated text or code. Oversight shifts from experimentation to monitoring usage at scale.

Case in point: The UK's HM Treasury has piloted GitHub Copilot as an assistant for software development. Rather than treating GenAI as a stand-alone project, the Treasury embedded it directly in development workflows, helping staff generate code, write tests, and accelerate documentation. The lesson is that adoption succeeds when AI strengthens existing systems instead of creating new silos.

## Source:


› Bruce, D., Fadia, A., Isherwood, T., Marcati, C., Mitchell, A., Münstermann, B., Shenai, G., Vuppala, H., & Weber, T. (2023, December 7). Unlocking the potential of generative AI: Three key questions for government agencies. McKinsey & Company. Retrieved December 22, 2025, from https://www.mckinsey.com/industries/public-sector/our-insights/unlocking-the-potential-of-generative-ai-three-key-questions-for-government-agencies


### 3 CONNECTING TO OFFICIAL KNOWLEDGE

To be useful for citizen services or policymaking, generative AI must go beyond generic answers. This is where Retrieval-Augmented Generation (RAG)[6] and fine-tuning come in. RAG connects the model to curated government knowledge bases with specific domain knowledge, while fine-tuning adapts the model to the language of laws, policies, or technical manuals.

Here, data practices become significantly more complex. Governments need:

- Curated, structured domain specific datasets (laws, regulations, service manuals) that can be indexed and retrieved.
- Metadata and tagging to ensure relevance.
- Version control and audit trails to prevent outdated information creeping into outputs.

When done well, RAG turns a generic model into a trusted government assistant. But it also raises stakes: poor curation can lead to biased or inaccurate advice, and citizens may take outputs as authoritative even when they are not.

Case in point: GOV.UK Chat, launched as an internal experiment in late 2023, applied RAG across 700,000+ web pages to answer citizen queries. Early trials showed that around 70 % of users found responses useful. Crucially, the system was stress-tested with "red teaming" to uncover risks before going live. The case shows how grounding models in official knowledge increases both accuracy and trust.

6 RAG is an AI technique that enhances large language models by connecting them to external, up-to-date knowledge sources (like databases or documents) to provide more accurate, context-specific, and factual answers.

Similar approaches can be seen in India's Jugalbandi chatbot or Kenya's UlizaLlama, where generative AI is tied directly to official scheme manuals or health guidelines, ensuring that answers reflect government positions.

**Source:**


› Gregory, M., Tosi, A., McDonald, S., & Sewell, R. (2024, January 18). The findings of our first generative AI experiment: GOV.UK Chat. Inside GOV.UK. Retrieved December 22, 2025, from https://insidegovuk.blog.gov.uk/2024/01/18/the-findings-of-our-first-generative-ai-experiment-gov-uk-chat/


### 4 API INTEGRATION AND INTEROPERABILITY

Once governments are confident in grounding AI in official knowledge, the next progression is API-level integration. At this stage, AI systems do not just retrieve static documents; they connect to live data sources and operational systems. A chatbot might pull a citizen's case history from a registry, or an assistant might query a tax database to provide tailored advice.

This requires the most advanced data governance practices so far:

- Interoperable APIs across ministries.
- Real-time data flows with safeguards for privacy and security.
- Role-based access controls to prevent overreach.
- Logging and monitoring to track how AI queries are used.
- Model Context Protocols

The payoff is significant: AI can deliver personalised services and automate routine case handling, freeing staff for higher-value tasks. But the risks are equally high – a misrouted case or an unauthorised data access could have major consequences.

Case in point: Singapore's One Service Chatbot has been operating since 2021, handling some 30,000 municipal service cases a month via WhatsApp and Telegram. It automatically extracts case details, predicts categories, and routes issues to the right agencies. The system has saved around 2,000 staff hours and sped up case resolution by two days, showing the efficiency gains of AI once integrated into core processes.

**Source:**


› Government Technology Agency of Singapore. (2024, January 12). How GovTech uses AI to enhance digital public services. Govtech Singapore. Retrieved December 22, 2025, from https://www.tech.gov.sg/media/technews/how-govtech-uses-ai-to-enhance-digital-public-service/


### 5 INSTITUTIONALISATION

The final stage is when generative AI becomes part of the administrative backbone. Here, AI tools are no longer projects or pilots: they are built into budgets, subject to audit, and governed by clear institutional frameworks. Some governments are going further, developing sovereign AI models – like the UAE's Jais LLM – to embed generative AI into state infrastructure on their own terms.

At this stage, data practices must be enterprise-grade: interoperability across ministries, ethical guidelines codified in law, explainability standards, and robust training for staff at all levels. Cultural change is as important as technical change: AI must be seen not as a shortcut, but as a trusted tool for accountable, citizen-centred governance.

## REFLECTIONS FOR POLICYMAKERS

The journey from pilots to institutionalisation is not about technology alone. While technologies can be incredibly helpful, as demonstrated by the examples given above, their adoption should be intentional and with specific objectives in mind that need addressing. Technological adoption within government is also about organisational development, data governance, data maturity, and cultural readiness. It is not only the technology, but organisations that must change for adoption to be successful and achieve the desired results. Lessons from international practice include:

- **Start with the everyday but plan for scale.** Pilots in summarisation and drafting show value quickly. But from the outset, governments must plan how these tools could be embedded, governed, and funded over the long term.

- **Establishment of innovation corridors:** The journey from pilot projects to full institutionalisation of AI is not solely about technology. It requires significant organisational development.

- **Data maturity defines what is possible.** Pilots need little data; RAG and API integration require structured, interoperable datasets. Governments that invest in data quality, metadata, and standards will be the ones able to move fastest.

- **Trust is won or lost on grounding.** Citizens must know that AI answers reflect official policy, not guesses from a model. Linking to authoritative knowledge bases and testing for bias are essential.

- **APIs are levers of the state.** Once AI systems connect to live registries and operational systems, the stakes rise sharply. Permissions, logging, and explainability must be treated as core governance functions, not afterthoughts.

- **Institutionalisation is the milestone.** Real transformation comes when AI is embedded into government systems, subject to audit and law, and resourced sustainably. Without this, pilots risk withering as political fashions change.

Generative AI will not replace human decision-making in administration – but it can augment it, making governments faster, fairer, and more responsive, providing that the right steps are taken. The challenge is not just to adopt AI, but to govern it in ways that citizens can trust.

# Improving Data Quality and Availability

## Why This Matters

In AI development, practitioners often admit: "Everyone wants to do the model work, not the data work." Yet 92% of AI projects experience data cascades, compounding failures that begin with poor data quality and snowball into technical debt, low accuracy, and loss of trust (Sambasivan et al., 2021). The paradox is clear: governments recognise data's importance but rarely invest systematically in the incentives, infrastructure, and skills needed to make it work.

This challenge is universal but acute in resource-constrained environments. Without addressing the foundational "hard data work", ensuring quality, completeness, and governance, even the most advanced AI tools cannot be deployed reliably in government services. The solution lies not in better algorithms, but in better data stewardship.

**Source:**


› Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. (2021). "Everyone wants to do the model work, not the data work": Data cascades in high-stakes AI. In CHI Conference on Human Factors in Computing Systems (CHI '21). Association for Computing Machinery. Retrieved December 22, 2025 from https://storage.googleapis.com/gweb-research2023-media/pubtools/5936.pdf


## Learning pathways

### 1 BUILDING CROSS-DISCIPLINARY DATA TEAMS

The most successful data quality initiatives combine technical expertise with domain knowledge and institutional understanding. Rather than siloing data scientists from policy experts, sustainable systems embed interdisciplinary collaboration throughout data pipelines.

This approach recognises that data quality is not just a technical problem. It requires understanding policy contexts, user needs, and operational realities. Cross-disciplinary teams can anticipate quality issues, design appropriate validation rules, and ensure data systems serve real-world decision-making.

Case in point: Rwanda's DHIS2 implementation created core teams of four to five interdisciplinary members combining technical, organisational, and managerial skills with at least one data scientist. Through cascade training at regional DHIS2 Academies, these teams achieved national coverage of health facilities with real-time validation and integrated quality checks. The model has now scaled to 60+ countries, demonstrating how small cross-disciplinary teams create resilience in data governance.

**Source:**


› DHIS2. (2021, April 26). Rwanda uses DHIS2 as an interactive system for rapid and paperless COVID-19 vaccination. dhis2. Retrieved December 22, 2025, from https://dhis2.org/rwanda-covid-vaccination/


### 2 EMBEDDING QUALITY IN WORKFLOWS

Data quality improves most when validation tools are embedded in everyday workflows, not added as afterthoughts. This means building quality checks, monitoring systems, and feedback loops directly into the tools people use daily, making good data practices inevitable rather than optional.

The key is designing systems where quality checks happen automatically, and errors are caught early. This reduces the burden on frontline staff while ensuring problems are identified before they cascade through the system.

Case in point: Estonia's X-Road data exchange platform embeds data quality protocols across all government digital services. Every data transaction includes validation, logging, and integrity checks, ensuring that the 99% of Estonian govern technical ment services delivered online maintain consistently high data quality. This infrastructure approach makes quality systematic rather than project specific.

**Source:**


› e-Estonia. (n.d). X-Road – Interoperability services.Retrieved December 22, 2025 from https://e-estonia.com/solutions/interoperability-services/x-road/


### 3 CREATING SYSTEMATIC QUALITY FRAMEWORKS

Scaling data quality across large programmes requires systematic frameworks that define standards, measure performance, and create accountability. These frameworks must balance rigor with practicality while being comprehensive enough to ensure quality but simple enough for widespread adoption.

Effective frameworks combine multiple quality dimensions (accuracy, completeness, timeliness, validity) into clear metrics that can guide decision-making and resource allocation. They also create transparency about data limitations and trade-offs.

Case in point: Singapore's Smart Nation initiative developed the Government Data Architecture (GDA) as a whole-of-government data quality framework. The GDA standardises data definitions, quality metrics, and governance processes across all agencies. Combined with automated monitoring tools, this systematic approach enables real-time quality assessment across Singapore's integrated digital government services.

**Source:**


› Chuan, K.E., & Yuxiang, P., (2024). Data Governance and Data Integration in Singapore. Singapore Department of Statistics. Retrieved December 22, 2025 from https://www.singstat.gov.sg/-/media/files/publications/reference/ssn224_pg27-29.ashx

### 4 INCENTIVISING DATA STEWARDSHIP

The fundamental challenge is that data work remains undervalued compared to model development. Without changing incentives in career paths, performance metrics, and project evaluations, organisations will continue to underinvest in data quality, regardless of technical solutions.

This requires elevating data stewardship as a recognised professional path, with clear advancement opportunities and formal recognition. It also means measuring and rewarding data quality outcomes, not just AI model performance.

Case in point: Colombia's Department of National Planning (DNP) introduced data stewardship performance indicators for all major programmes. Officials are evaluated on data completeness, accuracy, and timeliness alongside programme outcomes. This institutional change supported the successful SISBEN IV welfare targeting system, which uses AI-enhanced dashboards to monitor eligibility and reduce both under-coverage and leakage in real-time.

**Sources:**


› Organisation for Economic Co-operation and Development (2018, August). Self-assessment questionnaire on the implementation of the OECD Council Recommendation on Good Statistical Practice. Retrieved December 22, 2025 from https://www.oecd.org/content/dam/oecd/en/toolkits/good-statistical-practice/country-assessments/self-assessment-colombia.pdf


## REFLECTIONS FOR POLICYMAKERS

Improving data quality requires fundamental shifts in how governments approach data work. These initiatives demonstrate that sustainable improvements emerge not from isolated technical interventions, but from systemic changes to institutions, incentives, and workflows. Policymakers should consider these core principles:

› **Data stewardship is infrastructure, not a project.** The most successful initiatives treat data quality as ongoing institutional capacity, not a one-time technical fix. This requires sustained investment, clear governance structures, and systematic approaches that outlast individual projects or political cycles.

› **Collaboration between technical and policy experts:** Bridging the gap between data and AI specialists and policymakers through co-creation, shared governance, and literacy programmes is essential for effective implementation.

› **Quality must be built in, not bolted on.** Retrofitting quality controls to existing systems is expensive and often ineffective. Embedding validation, monitoring, and feedback loops into everyday workflows makes good data practices automatic and sustainable.

› **Incentives drive behaviour.** Without formal recognition, performance metrics, and career advancement tied to data quality, organisations will continue to undervalue the "hard data work". Changing incentives is often more important than changing technology.

› **Standards enable scale.** Ad-hoc, project-specific approaches to data quality create fragmentation and limit learning. Systematic frameworks, shared standards, and interoperable systems enable quality improvements to compound across programmes and agencies.

The key insight is that trustworthy AI requires trustworthy data – and trustworthy data requires systematic investment in the often-invisible work of data stewardship. This may not generate headlines, but it is the foundation upon which all other digital government ambitions depend.

# Developing Internal Data and AI Strategies

## Why This Matters

For many governments, AI is no longer a distant prospect but a present reality shaping agriculture, health, education, and public administration. The challenge is not simply whether to adopt AI, but how to do so in ways that align with national priorities, institutional capacity, and citizen needs.

Internal data and AI strategies are essential: they provide direction, set boundaries, and help administrations avoid over-dependency on external vendors, such as technology and service providers. Without strategy, AI adoption risks remaining fragmented, short-lived, or misaligned with broader development goals.

## Learning Pathways

Research suggests there is no single model for countries to follow. Recent efforts towards the development of national cybersecurity strategies demonstrate that different approaches can be taken, however some general practical steps can be followed. Instead, governments tend to adopt one of two broad pathways, depending on their starting point.

### 1 LEAPFROGGING STRATEGIES

Leapfrogging strategies refer to approaches where public sector institutions bypass traditional, incremental stages of digital transformation in order to adopt advanced technologies directly. Rather than gradually modernising legacy infrastructure, in leapfrogging, governments can skip outdated solutions and implement state-of-the-art digital platforms from the outset.

This is particularly valuable for countries that are building digital capabilities. Some examples include establishing cloud-based national identity systems without paper-based bureaucracies, implementing mobile-first citizen services without desktop portals, or deploying AI-driven systems without intermediate digitisation. Countries like Estonia and Rwanda are often points of reference as countries that have successfully leapfrogged to become digital government leaders.

Key enablers to successful leapfrogging include political leadership, technology partnerships, digital skills investment, and flexible regulations. The absence of legacy systems can also advantage late adopters in some instances. While leapfrogging can result in benefits such as accelerated service delivery and reduced costs, risks when incorrectly implemented can include dependency on external groups or organisations, as well as the possible creation of capacity gaps, where unsustainable assistance has been temporarily secured.

Case in point: India's NITI Aayog partnered with ICRISAT and Microsoft to address unpredictable smallholder farmer yields by using AI-driven climate data for predictive sowing advisories delivered via SMS. This achieved 10–30 % yield increases per hectare without requiring smartphones or major farmer investment, demonstrating how aligning cutting-edge technology with accessible communication tools enables rapid, transformational outcomes.

**Source:**


› Microsoft Stories. (2017, November 7). Digital agriculture: Farmers in India are using AI to increase crop yields. Microsoft News. Retrieved December 22, 2025 from https://news.microsoft.com/en-in/features/ai-agriculture-icrisat-upl-india/


Case in point: Rwanda partnered with Zipline to deploy AI-driven drone delivery for blood and medical supplies in rural areas, reducing delivery times from hours to minutes. This saved thousands of lives and established Rwanda as a global health innovation pioneer, demonstrating that leapfrogging succeeds when governments invest in bold partnerships addressing critical service bottlenecks.

**Sources:**


› World Economic Forum (2024, July 2). Investing in African health tech can transform health systems. Here's how. VaccinesWork. Retrieved December 22, 2025 from https://www.gavi.org/vaccineswork/investing-african-health-tech-can-transform-health-systems-heres-how

› Nisingizwe, M. P., Iyer, H. S., Gashayija, M., Hirschhorn, L. R., Amoroso, C., Wilson, R., Rudusingwa, E., Riviello, R., Shyaka, E., Yirerweho, J. P., Bitton, A., & Hedt-Gauthier, B. L. (2022). Effect of unmanned aerial vehicle (drone) delivery on blood product delivery time and wastage in Rwanda: A retrospective, cross-sectional study and time series analysis. The Lancet Global Health, 10(4), e564–e571. Retrieved December 22, 2025 from https://doi.org/10.1016/S2214-109X(22)00095-X

› Russo, A., & Wolf, H. (2019, January 16). What the world can learn from Rwanda's approach to drones. World Economic Forum. Retrieved December 22, 2025 from https://www.weforum.org/stories/2019/01/what-the-world-can-learn-from-rwandas-approach-to-drones/

## 2 ABSORPTIVE CAPACITY STRATEGIES

Absorptive capacity strategies, on the other hand, are efforts that look to build institutional capability to effectively adopt and utilise digital technologies and data innovations. Unlike leapfrogging, which focuses on adopting entirely new solutions rapidly, absorptive capacity emphasises developing the foundational skills, processes, and organisational culture necessary to sustain and adapt technologies over time. This involves activities such as investing in public servant training programmes, establishing data science units within departments and developing internal technical expertise rather than relying solely on external consultants.

The result of absorptive capacity strategies is that an organisation is better equipped with the fundamental building blocks that enable a smoother adoption of new technologies in an incremental fashion, as opposed to the leapfrogging approach, which often requires an entirely new set of skills to accompany the new technology being adopted.

Key components to such strategies include continuous learning programmes, mentorship structures, knowledge-sharing platforms, and embedding technical expertise within policy teams. Strong absorptive capacity can enable governments to evaluate emerging technologies critically, customise solutions to local contexts, maintain and iterate systems independently, and build on initial implementations. Without it, even successfully adopted technologies may fail to deliver sustained value or adapt to changing needs.

Case in point: Tanzania conducted a UNESCO-aligned AI Readiness Assessment and launched a national AI strategy shaped by the African Union's Continental AI framework, prioritising responsible use, inclusivity, and gradual capacity-building. This positioned AI as a cross-sectoral development tool with embedded ethical principles, demonstrating that readiness assessments and ethical anchoring create trusted foundations for institutional AI adoption.

**Sources:**


- United Nations Educational, Scientific and Cultural Organization. (2025). Tanzania: Artificial intelligence readiness assessment report. Retrieved December 22, 2025, from https://tanzania.un.org/sites/default/files/2025-07/National%20AI%20Readiness%20Report.pdf
- African Union. (2024, July). Continental artificial intelligence strategy: Harnessing AI for Africa's development and prosperity. Retrieved December 22, 2025 from https://au.int/sites/default/files/documents/44004-doc-EN-_Continental_AI_Strategy_July_2024.pdf


Case in point: Kenya partnered with UNDP and Microsoft to launch a public sector AI-skilling centre, standardising training across ministries and agencies to address inconsistent digital skills among government staff. This strengthened digital literacy and fostered cross-government capacity, with ripple effects in policy design and implementation, demonstrating that human capital is essential for institutional strategies to succeed.

**Sources:**


- Omambia, S. (2025, September 23). Kenya's public service stories of change: The faces driving digital transformation. United Nations Development Programme. Retrieved December 22, 2025 from https://www.undp.org/kenya/stories/kenyas-public-service-stories-change-faces-driving-digital-transformation
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## 3 BLENDED APPROACHES

It should be acknowledged that these are not mutually exclusive strategies and that, while it is common for one strategy to be pursued, many governments choose to combine them. This could be within an overall approach, or sectoral, for example it may be appropriate to pursue the leapfrogging approach in health, while using absorptive approaches in finance.

Case in point: Bangladesh's a2i programme provided a central institutional anchor for digital transformation, embedding data-driven and AI-enabled services into government workflows to address slow, fragmented, and inaccessible public services. This saved citizens billions of dollars, digitised dozens of services, and established groundwork for AI-enhanced administration, demonstrating that anchored institutional programmes enable governments to absorb capacity while selectively leapfrogging in service areas.

**Sources:**


- Observatory of Public Sector Innovation. (2023, January 24). Digital Service Design Lab (DSDL). OECD. Retrieved December 22, 2025 from https://oecd-opsi.org/innovations/digital-service-design-lab-dsdl/
- United Nations Development Programme. (2022). Mid-term evaluation of Aspire to Innovate (a2i) Programme. UNDP Evaluation Resource Centre. Retrieved December 22, 2025 from https://erc.undp.org/evaluation/documents/download/22074

## REFLECTIONS FOR POLICYMAKERS

Drawing from these experiences across India, Rwanda, Tanzania, Kenya, and Bangladesh, several key insights emerge for governments developing their own data and AI strategies. Policymakers should consider the following principles when designing approaches suited to their national contexts and institutional capabilities:

- **No one-size-fits-all:** Countries must assess their starting points, including existing infrastructure, institutional capacity, and development priorities, and choose pathways accordingly. What works in one context may not translate directly to another, requiring careful adaptation to local realities.

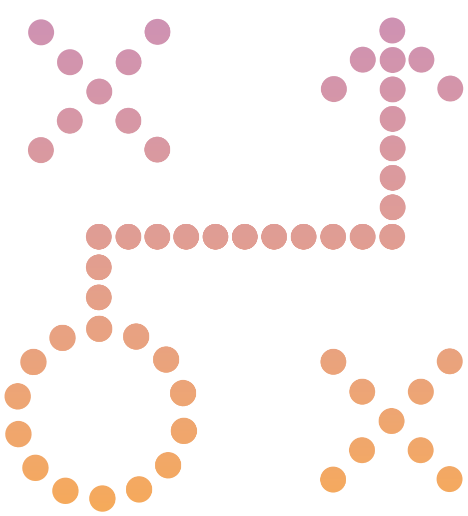
- **Blend leapfrogging and absorptive approaches:** Success often comes from combining bold experimentation in high-need areas with steady investment in institutions and skills. This hybrid approach allows governments to deliver quick wins whilst building sustainable capacity for long-term transformation.

- **Anchor strategies institutionally:** Central entities or taskforces are key for coherence and continuity. Without clear institutional ownership, AI initiatives risk becoming fragmented across departments, leading to duplication, inefficiency, and strategies that fail to outlast political cycles or leadership changes.

- **Ethics and inclusion from the start:** Strategies grounded in citizen rights and ethical principles avoid costly backtracking. Embedding considerations of fairness, transparency, and accountability from the outset ensures AI systems build public trust rather than erode it.

- **Invest in skills and governance as much as technology:** Human capital and institutional strength are the true enablers of long-term AI integration. Technology alone cannot succeed without capable teams, clear governance structures, and organisational cultures that support innovation and adaptation.

Ultimately, successful internal data and AI strategies balance ambition with pragmatism. Whether leapfrogging to address urgent service gaps or building absorptive capacity for sustained transformation, governments must prioritise institutional foundations and human capital alongside technological solutions. The most effective strategies align AI adoption with broader development goals whilst maintaining ethical standards and citizen trust.



# Collaboration between Technical Units and Data and AI Policy Experts

## Why This Matters

When AI enters public service, it sits at the intersection of technical capability and policy responsibility. Yet these communities often speak different "languages": data scientists emphasise model accuracy and performance metrics, while policymakers focus on societal legitimacy, rights, and institutional accountability. This communication gap often creates predictable failures: technically sound systems that ignore policy constraints, or well-intentioned policies that cannot be implemented effectively.

Bridging this divide requires mutual literacy, shared governance, and participatory forums. Without these, AI adoption risks remaining siloed pilots rather than trusted, institutionalised tools in government.

## Learning Pathways

#### 1 BUILDING AND FOSTERING INTERDISCIPLINARY TEAMS

For AI to be adopted successfully within governments and organisations, it is critical that individual expertise is both nurtured and harmonised in a complementary fashion. The challenge that exists is to do so in a manner that prevents siloing and unnecessary upskilling of certain staff. As was the case during the Big Data boom, not everyone needs to be a data scientist. One way in which to foster complementary dynamics that utilise expertise while avoiding silos is through a satellite structure for data science and AI in organisations.

This satellite structure for data science and AI refers to the integration of data competencies where small groups of specialised team members (like data analysts, scientists, engineers) serve as "satellites" in specific domain functions (e.g., finances, agriculture, water, country, region, etc.) while connected to a central "hub" for governance, best practices, and shared resources, offering agility, deep domain expertise, and faster insights compared to a centralised model. This approach is very common in large organisations adopting advanced analytics. As such, a federated governance model is most commonly used, which allows for the balancing of central control on aspects such as data quality and ethics, while giving greater scope for decentralised, tailored execution as necessary, depending on the department.

Key benefits of this approach can include reduced time-to-value, as analysts are close to the domain problem and analysis is directly tied to department goals. The satellite structure can also help foster data literacy and knowledge sharing within domain units.

Case in point: At the intergovernmental organisation level, the UN has attempted to improve decision-making and coordination efforts towards achieving the Sustainable Development Goals through the UN 2.0 initiative. Utilising the hub-and-spoke model articulated above, they have embarked on a process of creating a new network to connect the many stakeholders present within the UN system apparatus to accelerate shifts in training, partnerships and methods. Through this initiative, the UN is looking to unlock and better leverage the data to inform foresight processes of UN member states.

**Source:**


› United Nations (2023, September). Our Common Agenda, Policy Brief 11: UN 2.0 – Forward-thinking culture and cutting-edge skills for better United Nations system impact. UN 2.0. Retrieved December 22, 2025 from: https://un-two-zero.network/wp-content/uploads/2023/09/UN-2.0_Policy-Brief_EN.pdf


#### 2 AI LITERACY DEVELOPMENT

AI literacy means giving non-technical policymakers the skills to understand how AI works, its risks, and limits – while enabling technical teams to understand governance, ethics, and societal impacts. In both instances, it is not essential that each team is expert in the others' domain, but that a requisite level of understanding is attained in order to minimise the likelihood of poor or insufficient regulation being drafted, or models being released that are not compliant with existing regulation.

Beyond compliance, AI literacy strengthens procurement and vendor management capabilities[7] across government. Without foundational understanding, departments risk becoming dependent on external suppliers who may oversell capabilities, understate risks, or lock agencies into proprietary systems. Literate officials can evaluate competing solutions critically, negotiate contracts that protect public interests, and maintain strategic autonomy over technology choices. This prevents the "black box" problem where governments deploy systems they cannot adequately scrutinise, maintain, or adapt to changing needs.

Furthermore, AI literacy enables more effective cross-government collaboration and knowledge sharing. When officials across different ministries share a common vocabulary and conceptual framework for AI, they can identify opportunities for shared infrastructure, avoid duplicating efforts, and learn from each other's successes and failures.

7 Vendor management capabilities are the abilities of a team or organisation to be able to effectively scrutinise the value of the work that has been contracted. Given the highly technical nature of AI work, it is essential that clients, such as governments, and their staff are able to ask the right questions to ensure that solutions that are procured perform as expected and deliver the value intended.

Case in point: Rapid deployment of AI in agriculture, health, and citizen services risked leaving many Indian policymakers unable to evaluate or guide these tools. India's National e-Governance Division launched AI literacy programmes and partnered with universities and industry to train civil servants in both technical fundamentals and governance implications. Initiatives included policy bootcamps, MOOCs, and practical AI labs. Thousands of public officials gained foundational AI understanding, improving procurement, oversight, and policy design. AI literacy is not just technical training; it is a governance capacity. Building it can systemically help reduce the likelihood of "black box" reliance on vendors.

**Sources:**


› Ministry of Electronics and Information Technology. (2025, March). Empowering public sector leadership: A competency framework for AI integration in India. Retrieved December 22, 2025 from https://indiaai.s3.ap-south-1.amazonaws.com/docs/empowering-public-sector-leadership-a-competency-framework-for-ai-integration-in-india.pdf

› Nasscom Insights. (2024, August 19). Advancing India's AI skills: Interventions and programmes needed. NASSCOM. Retrieved December 22, 2025 from https://community.nasscom.in/communities/data-science-ai-community/advancing-indias-ai-skills-interventions-and-programmes


### 3 ETHICS COUNCILS & PARTICIPATORY GOVERNANCE

Independent oversight bodies ensure AI use reflects public values, with input from civil society, academia, and technical experts. By bringing together these varied stakeholders, they can force different disciplinary perspectives and strands of experience and expertise to engage with each other's concerns. In some instances, this might help foster ongoing dialogue throughout the AI lifecycle – the process from start to finish of designing, developing, deploying, maintaining and retiring technologies. This can help technical staff to anticipate governance challenges early, whilst giving policymakers insights into technical constraints and trade-offs that shape what is actually feasible.

Participatory approaches go beyond those working within government itself to include communities that may be potentially affected, as well as experts from civil society groups and academia. Efforts such as public consultations on AI strategies and citizen assemblies on algorithmic decision-making can help create greater opportunities for accountability, while surfacing concerns that might be missed through government discussions alone.

Case in point: Ghana's government and private sectors were integrating AI without coordinated policy direction, risking fragmented adoption that could exclude vulnerable populations and misalign with national development priorities. To counteract this, Ghana's Ministry of Communications and Digitalisation conducted over 40 local stakeholder consultations and four high-level public sector consultation workshops involving government, academia, industry, civil society, and tech innovators to develop its 2023-2033 National AI Strategy.

The resulting strategy established cross-ministerial policies that prioritise health, agriculture and education based on community-raised issues. This goes to demonstrate that participatory governance approaches to AI can help reflect diverse perspectives and local priorities, which can help build legitimacy while incorporating inclusion concerns from the outset.

**Sources:**


› Massey, J., Narayan, V., & Simperl, E. (2024, June 24). How can we empower data communities in the era of generative AI? Open Data Institute. Retrieved December 22, 2025 from https://theodi.org/news-and-events/blog/how-can-we-empower-data-communities-in-the-era-of-generative-ai/

› Lannquist, Y., Miailhe, N., & Alanoca, S. (2022, October 28). National AI strategies for inclusive & sustainable development. The Future Society. Retrieved December 22, 2025 from https://thefuturesociety.org/policies-ai-sustainable-development/

› Archer, T. A. (2025, October 7). Shaping AI governance with African values for global impact. iAfrica. Retrieved December 22, 2025 from https://iafrica.com/shaping-ai-governance-with-african-values-for-global-impact/


### 4 SUSTAINED COMMUNITIES OF PRACTICE

Communities of practice focused on data and AI create vital spaces for cross-disciplinary learning and knowledge exchange between technical practitioners and policy experts. Networks like the Data to Policy Champions and AI4D facilitate peer-to-peer learning across countries facing similar challenges, enabling government officials to access practical guidance, technical resources, and implementation lessons without reinventing solutions. These communities break down the isolation that often characterises government digital transformation efforts, connecting data scientists struggling with ethical frameworks to policymakers grappling with procurement decisions, and linking both to peers who have navigated similar challenges successfully.

The benefits extend beyond knowledge sharing to building collective problem-solving capacity. When technical teams and policymakers engage together in these networks, they develop shared vocabulary and mutual understanding that strengthens collaboration within their own institutions. Communities of practice also provide safe spaces for experimentation and failure as participants can discuss challenges candidly, test approaches through working groups, and refine strategies based on collective feedback before implementing at scale. This reduces risks and accelerates learning curves significantly. Participation in these networks yields critical lessons: sustainable digital transformation requires ongoing learning rather than one-off training; diverse perspectives strengthen solutions; and regional collaboration is particularly valuable as neighbouring countries often face comparable governance contexts, infrastructure constraints, and resource limitations. Communities of practice transform isolated efforts into collective movements, building the institutional confidence and capability needed for responsible AI adoption across government.

Case in point: Rwanda's Ministry of ICT and Innovation sought to develop a comprehensive National AI Policy, however certain obstacles, including technical expertise, were identified as hindrances to the process. The Ministry of ICT therefore sought to engage with several international communities of practice such as GIZ's FAIR Forward initiative and efforts by The Future Society and Smart Africa. Through participation in these initiatives, the Ministry of ICT drew upon international best practices, while working closely with national actors such as the Rwanda Utilities Regulatory Authority, Rwanda Space Agency and AI practitioners. The resulting National AI Policy, which was approved in 2023, established six priority areas organised as Enablers, Accelerators and Safeguards, and included a recommendation to establish a Responsible AI Office within the ministry to coordinate implementation across government.

**Sources:**


› Ministry of ICT and Innovation. (2023, December). National artificial intelligence policy. Government of Rwanda. Retrieved December 22, 2025 from https://www.minict.gov.rw/index.php?eID=dumpFile&t=f&f=67550&token=6195a53203e197efa47592f40f-f4aaf24579640e

› The Future Society. (2023, October 12). Rwanda's national AI policy stakeholder workshop. Retrieved December 22, 2025 from https://thefuturesociety.org/rwandas-national-ai-policy-stakeholder-workshop/

› Gwagwa, A., Kachidza, P., & Siminyu, K. (2024). We know what we are doing: The politics and trends in artificial intelligence policies in Africa. AI & Society. Retrieved December 22, 2025 from https://www.researchgate.net/publication/389595358_We_know_what_we_are_doing_the_politics_and_trends_in_artificial_intelligence_policies_in_Africa


## REFLECTIONS FOR POLICYMAKERS

Collaboration between policymakers with technical experts is essential to the development of successful and inclusive AI initiatives. This, however, requires conscious efforts to ensure coherence between the often conflicting objectives of each group. As we have seen, this can be facilitated through the following actions:

› Developing interdisciplinary teams is critical, given that the success of the adoption of technologies such as AI depends largely on using them appropriately with a specific purpose in mind. Using approaches, such as the satellite structure noted, can help leverage technical expertise and apply it in specific contexts, which can be facilitated through the domain experts from specific departments in a government context.

› Investing in AI literacy for both policy and technical teams to create shared understanding. Building this out through tailored training programmes can strengthen procurement decisions, reduce the likelihood of vendor dependency and bridge essential gaps in understanding between government teams.

› Institutionalising ethics councils and fostering civic co-creation to ensure AI oversight reflects societal priorities. The adoption of AI both within public administration and the private sector is already recognised as having far-reaching implications for all corners of society. Adopting participatory governance approaches can both increase public trust in how AI is used, as well as inform the development of more inclusive policies and deployments.

› Supporting and participating in peer learning to adapt lessons in context. Participation in communities of practice and regional networks can help facilitate knowledge exchange between countries that are facing similar challenges, thus potentially expediting the route to solutions.

Bridging the gap between technical capability and policy expertise is fundamental to responsible AI adoption in government. The experiences from India, Ghana, and Rwanda demonstrate that this requires deliberate investment in mutual literacy, participatory governance structures, and sustained engagement with regional and international communities of practice. Government ministries should prioritise creating formal mechanisms for ongoing dialogue between data scientists and policymakers – not just during crisis moments, but throughout the entire AI lifecycle from procurement to deployment.

# PART III

# CHALLENGE CARDS FOR DATA & AI FOR POLICY INNOVATION

# Introduction to Challenge Cards

This set of challenge cards has been created as an interactive resource for teams of people working inside or closely with public administrations to engage with some of the challenges that are commonly faced when looking to adopt data and AI in policymaking.

These cards are intended as a complementary resource to the guide to promote understanding of how problems can look from different perspectives. Part of the function of these challenge cards is to explore where shared knowledge and understanding can help create equitable solutions and embed good practices.

Each challenge card begins with a series of reflection questions to think about how the challenge looks in the context of your department or team. The card then introduces a scenario, with a background of the situation that will set the scene for discussions, as well as suggested roles to be assumed by participants. In some instances, participants will be encouraged to or can work in groups. A primary "challenge question" is then posed, as well as several discussion prompts, which can be used to encourage conversation amongst participants. In some of the challenge cards, extension activities have also been included, should the group have the time and interest to take the exercise further. Each card also includes a list of relevant resources to be accessed via link or QR code that might be useful for participants to read, whether they are less familiar with the specific subject matter, or are interested in learning more.

Please note that all the scenarios included and associated roles in the challenge cards are fictional, however creation of these examples has been informed by real life challenges and experiences that have been documented.

These challenge cards have been designed to spur discussion and promote interdisciplinary understanding. In some cases, the subject matter or roles may feel unfamiliar, however we encourage you to embrace this and ask questions or raise issues when they arise. Part of the purpose of the cards is to provide practical, context-based learning experiences for participants and to introduce them to concepts or considerations that may be outside of the scope of their usual role.

Challenge >

# Data Data Governance and Legal Uncertainties

## Reflection

- What are some of the obstacles you encounter when considering the use of data for AI applications?
- Where could regulation provide greater clarity on the appropriate and transparent use of data for developing AI applications?
- What do you find to be most useful in maintaining the balance between innovation and citizen protection?
- What existing structures like oversight bodies and ethics boards exist in your organisation, and are you clear on what role(s) they perform?
- What is one concrete step you could take in the next three months to reduce uncertainty for your team or partners?

## Roleplay/scenario

Scenario: **"The AI Procurement Dilemma"**

Setup: Your ministry wants to procure an AI system to automate citizen benefit eligibility assessments. However, there is uncertainty about data protection requirements, algorithmic accountability, and who is responsible if the system makes errors.

Roles:

- **Policy Lead:** Wants to launch quickly to reduce processing times and backlogs
- **Legal/Compliance Officer:** Concerned about data protection violations and lack of clear accountability frameworks
- **Chief Data Officer:** Worried about data quality, interoperability, and long-term governance
- **Citizen Representative:** Representing concerns about transparency, fairness, and the right to appeal automated decisions

Challenge Question: How do you move forward when the legal framework is unclear and stakeholders have competing priorities?

## Discussion prompts:

- What governance structures need to be in place before procurement begins?
- Should legal safeguards be embedded into the system's design from the start, or added through separate oversight processes?
- What specific legal provisions (accountability, transparency, appeals) would help resolve this dilemma?
- What does responsible public engagement look like in this scenario?
- Who should have final accountability if the system causes harm?

Extension: Run the scenario twice – once without any governance framework, then again with clear legal guidelines and oversight bodies. Compare the outcomes and confidence levels.

Click here or scan QR code to access a collection of further resources on the topic.

# Challenge >
# Lack of In-House Data/AI Skills

## Reflection

- What specific data or AI skills gaps are preventing your team from achieving its goals?
- To what extent do you feel you are able to keep up to speed with new developments in data and AI?
- What opportunities exist to link upcoming projects to skill-building opportunities?
- What happens when funding ends or political priorities shift? How sustainable are your current capacity-building initiatives?
- What types of alternative initiatives could be trialled in an attempt to circumvent the typical challenges associated with recruiting and retaining staff with digital skills?

## Roleplay/scenario

Scenario: **"The Stranded Dashboard"**

Setup: Your ministry invested in a powerful data analytics platform 18 months ago. An external consultant built impressive dashboards, trained a small team, and left. Now the dashboards are outdated, the trained staff have moved to other roles, and no one knows how to maintain or update the system. Meanwhile, a new priority initiative desperately needs data analysis capacity.

Roles:

- **Department Director:** Under pressure to deliver results on the new initiative, frustrated by past investments that did not stick
- **HR/Training Lead:** Has budget for training but sceptical after previous failed attempts; wants evidence it will work this time
- **Technical Staff Member:** Eager to learn but overwhelmed by daily tasks; needs protected time and mentorship, not just a one-off course
- **External Partner (university/NGO/consultant):** Offering a training programme but needs government commitment and real projects to work on

Challenge Question: How do you build skills that actually stick this time, while also delivering on urgent policy priorities?

## Discussion prompts:

- What would need to change to ensure skills are retained and applied after training ends?
- Should training be linked directly to the new priority initiative? What are the risks and benefits?
- How can you balance the need for quick results with long-term capacity building?
- What mix of internal mentorship, external partnerships, and dedicated project time would work best?
- Who needs to be involved beyond the technical team (leadership, HR, partner organisations)?

Extension: Map out two scenarios: (1) a traditional training course approach, and (2) an applied "learning by doing" approach linked to the new initiative with ongoing mentorship. Compare costs, timelines, and likelihood of sustainable impact.

Click here or scan QR code to access a collection of further resources on the topic.

# Challenge >
# Limited Data Quality

## Reflection

- How do you currently know/measure whether your data is "good enough" for its intended purpose?
- What dimensions do you assess?
- To what extent are multi-stakeholder partnerships, such as involving citizens, NGOs or community workers, suitable options to support your data collection needs?
- What challenges do you encounter in maintaining critical datasets?
- What processes are you aware of that other ministries use to ensure that they are using good quality data?
- Could these processes be useful for your team to emulate?

## Roleplay/scenario

Scenario: **"The AI That Learned Bad Habits"**

Setup: Your ministry is piloting an AI system to optimise resource allocation for social services, predicting which families might need early intervention support, which elderly citizens are at risk of social isolation, and where preventative services could have the greatest impact. Early results look promising in reducing emergency interventions and improving outcomes. However, an independent audit commissioned as part of your AI governance framework has discovered significant quality issues in the training data: historic records have systematic gaps for immigrant communities and rural areas due to past underreporting and service access barriers; data completeness varies dramatically by region, with affluent urban areas having far richer datasets; legacy IT systems use inconsistent categorisation making it difficult to compare cases across jurisdictions; and socioeconomic proxies embedded in the data reflect historical biases in service provision. The AI has learned from these patterns, potentially directing resources towards already well-served populations whilst systematically underserving vulnerable groups who need support most.

Roles:

- **AI Project Lead (from digital transformation unit):** Under pressure to demonstrate return on investment and scale the system nationally; worried that pausing will undermine confidence in digital government initiatives
- **Data Protection Officer/Ethics Lead:** Has been flagging data quality and bias concerns since the pilot began, citing GDPR Article 22 requirements and national equality legislation; vindicated but needs leadership buy-in to fix systemic issues
- **Social Services Director:** Frontline teams are stretched, and data entry has always been secondary to direct service provision; concerned that fixing data quality will add burden to already overwhelmed staff
- **Equality and Inclusion Representative:** Concerned that the AI is automating and scaling historical discrimination; worried that marginalised groups who are already underrepresented in data will face even worse outcomes if the system scales

Challenge Question: Do you pause the AI rollout to fix the underlying data quality and bias issues, or forge ahead with technical mitigations whilst continuing to scale, risking the embedding of systemic discrimination into automated decision-making?

## Discussion prompts:

- What are the legal and ethical consequences of deploying AI trained on biased data under GDPR, the EU AI Act, national equality legislation or similar regulatory frameworks in your context?
- How do you balance the genuine benefits the system is delivering to some families against the risk of harm to underserved groups?
- What quality checks and bias audits should have been mandatory before the pilot phase, given your existing governance frameworks?
- How can you redesign data collection so that quality and representativeness are built in, rather than expecting overburdened frontline staff to fix it retrospectively?
- What does "fit-for-purpose" data quality mean for AI systems making decisions that affect vulnerable people's access to services?

Click here or scan QR code to access a collection of further resources on the topic.

Challenge >

# Organisational Development Gaps (Maturity)

## Reflection

- Where do coordination breakdowns most often occur: between ministries, levels of government, or within your own department?
- Do you have permanent structures (innovation units, cross-ministerial coordination bodies, dedicated leadership roles) to sustain digital transformation/data- and AI-driven policymaking, or does it rely on temporary project teams?
- How are responsibilities for data and AI initiatives distributed? Is it clear who owns what, or are there gaps and overlaps?
- What incentives exist for different parts of government to collaborate, rather than protect their own territory?
- If you could create one institutional structure or mechanism to improve coordination, what would it be?

## Roleplay/scenario

Scenario: **"Three Pilots, Zero Scale"**

Setup: Over the past two years, three different ministries in your government have each piloted AI solutions: the Ministry of Education and Research used AI for student performance prediction, the Ministry of Food and Agriculture deployed crop yield forecasting, and the Ministry for Transport tested traffic flow optimisation. All three pilots showed promise and received positive media coverage. Now, each ministry wants a budget to scale their solution nationally, but the Ministry of Finance has flagged concerns: there are no common technical standards, no coordination on data sharing, no shared infrastructure, and each ministry has hired different vendors. Meanwhile, a newly elected minister wants to launch a fourth AI initiative in healthcare.

Roles:

- **Ministry of Finance Representative:** Worried about duplicated costs, vendor lock-in, and lack of coordination; wants to see institutional maturity before approving more funding
- **Ministry Representatives (Education and Research, Food and Agriculture and Transport):** Proud of their successful pilot and frustrated by delays; fears that centralisation will slow innovation and impose bureaucracy
- **Chief Digital/Innovation Officer (if one exists, or proposed role):** Wants to create coordinating structures but lacks authority to mandate cooperation across ministries
- **Civil Society/Citizen Representative:** Concerned that without coordination, citizens will face inconsistent experiences and that no one will be accountable when AI systems fail

Challenge Question: How do you move from isolated, successful pilots to systemic, sustainable AI adoption without killing innovation or creating excessive bureaucracy?

## Discussion prompts:

- What institutional structures or governance mechanisms could coordinate efforts without stifling ministerial autonomy?
- Should you pause new pilots until coordination mechanisms are in place, or let innovation continue while building maturity in parallel?
- Which organisations are in the lead for AI coordination?
- How do you balance the need for common standards with the reality that different sectors have different needs?
- What would make scaling easier than piloting in your organisation?

Extension: Map out what organisational maturity would look like at three levels:

1. Current state with isolated pilots
2. Intermediate state with some coordination mechanisms, and
3. Mature state with embedded structures and processes.

What are the concrete steps to move between each level, and what resources, authority, and political commitment would each transition require?

Click here or scan QR code to access a collection of further resources on the topic.

Challenge >

# Lack of Data Availability

## Reflection

- What critical datasets does your organisation need but cannot access? Where are they held, and why are they unavailable?
- Are there datasets you collect that could be valuable to other departments or external partners but are not currently shared?
- Do you have centralised platforms (data catalogues, API exchanges) that make it easy to discover and access data across government?
- How many datasets have you published that no one uses? What would make them more usable?
- To what extent is publishing open data currently a priority of your team/ministry?
- What are some of the challenges to publishing more open data?

## Roleplay/scenario

Scenario: **"The Synthetic Crystal Ball"**

Setup: Your government's planning unit has obtained powerful synthetic data generation tools that can create realistic population datasets by combining fragments of real administrative data with statistical models. They are using this to model future scenarios, such as migration patterns, housing demand, healthcare needs without waiting for actual data from other ministries, which has been stuck in legal reviews for 18 months. The synthetic data is helping ministers make faster decisions and appears in briefing papers as "modelled population data." However, a Data Protection Commission representative has raised concerns: the synthetic data may be reproducing biases from incomplete source data, the models have not been validated against reality, and citizens have no idea their "data" is being synthetically generated and used for policy decisions that will affect their lives.

Roles:

- **Planning Unit Lead from relevant ministry:** Frustrated by data access delays; sees synthetic data as a pragmatic solution that is "good enough" for planning purposes and allows faster decision-making
- **Data Protection Commissioner Representative:** Worried about transparency, consent, bias amplification, and accountability under GDPR and national data protection law. If decisions go wrong, how do you audit synthetic data?
- **Data Owner from relevant ministry:** Refuses to share real data due to legal concerns and lack of resources to properly anonymise it; feels undermined by the synthetic workaround
- **Civil Society/Privacy Advocate:** Concerned that synthetic data is being used as an excuse to avoid the hard work of proper data sharing agreements and that it masks whose voices are missing from the data

Challenge Question: When real data is not available, is synthetic data a pragmatic solution or a dangerous shortcut that could embed bias and undermine accountability

## Discussion prompts:

- Should synthetic data be used for policy decisions when real data exists but is not accessible? What safeguards would be needed?
- Is the synthetic data approach masking the real problem – that data sharing mechanisms are broken?
- How do you balance the need for timely decisions with the risks of using modelled rather than actual data?
- What transparency obligations exist when decisions are based on synthetic rather than real data? Should citizens know?
- Could this scenario have been avoided with better data sharing infrastructure and "open by default" culture?

Extension: Explore two alternative futures: (1) The planning unit continues using synthetic data and makes a major policy decision that later proves to be based on flawed assumptions. Trace through the accountability challenges. (2) The government invests in proper data sharing infrastructure and agreements. Map out what this would require, how long it would take, and what decisions might be delayed. Which risks are more acceptable, and to whom?

Click here or scan QR code
to access a collection of further resources
on the topic.

# Learning Pathway >
# Using Data and AI in Political Decision-Making

## Reflection

- What decisions have been made recently where better modelling, real-time data, or risk assessment could have changed the outcome?
- Have you experimented with scenario modelling, digital twins, or forecasting tools? If so, what happened after the pilot phase?
- How do you currently assess the potential risks and unintended consequences of policy decisions before implementation?
- Can you point to tangible benefits for citizens that have resulted from using data or AI in decision-making?
- How do citizens know when decisions affecting them have been informed by data, models, or algorithms?

## Roleplay/scenario

Scenario: **"The Model Says No"**

Setup: Your government is debating a major housing policy reform that would change zoning regulations to allow more dense development in suburban areas. A newly deployed urban planning digital twin has modelled the proposal and projects concerning outcomes: increased traffic congestion in areas with poor public transport, strain on schools that are already near capacity, and potential displacement of lower-income residents as property values rise. However, the model is based partly on synthetic data (since real-time traffic and demographic data is not fully available) and makes assumptions about future behaviour that some experts dispute. The governing party campaigned on this reform, the minister/political lead for housing is committed to it, and there is intense political pressure to deliver. The model's projections are now creating tension between evidence and political reality.

Roles:

- **Housing Minister/Political Lead:** Believes the reform is the right thing to do and that models cannot capture political and social benefits; worried that "analysis paralysis" will prevent necessary change
- **Digital Twin Project Lead:** Confident in the methodology but acknowledges limitations; wants decision-makers to at least understand and mitigate the projected risks
- **Transport/Education ministry Representative:** Concerned that their services will be overwhelmed and they will be blamed when the model's predictions come true; want the reform delayed or modified
- **Civil Society Representative:** Questions whether the model adequately represents the voices and needs of affected communities; worried about displacment but also desperate for more affordable housing

Challenge Question: When AI models project negative consequences for a politically committed policy, how do you balance evidence, political reality, and democratic legitimacy?

## Discussion prompts:

- Should governments follow what models predict, or are models just one input among many in democratic decision-making?
- How do you handle uncertainty in models – especially when they rely on synthetic data or contested assumptions?
- What is the appropriate response when evidence contradicts political commitments? Modify the policy, reject the model, or proceed with mitigation plans?
- Who is accountable if the government ignores model projections and problems emerge? What about if they follow the model and it turns out to be wrong?
- How do you communicate to citizens that a decision was influenced by AI modelling without undermining democratic accountability?

Extension: Play out two scenarios: (1) The government proceeds with the reform despite the model's warnings. What safeguards or monitoring should be in place? (2) The government significantly modifies or delays the reform based on the model. How do they explain this to the public and maintain trust in both the political process and the use of AI tools? What does responsible use of predictive tools in democratic governance actually look like?

Click here or scan QR code to access a collection of further resources on the topic.

# Learning Pathway >
# Applying AI Tools in Administration

## Reflection

- What AI tools (if any) are colleagues in your organisation already using – officially or unofficially?
- What would it take to move from "proof of concept" to AI being embedded in everyday workflows?
- What rules exist about what information can be shared with AI tools? Do staff know what they can and cannot do?
- How do you ensure AI-generated content is checked before it is used in official communications or decisions?
- Do staff see AI as a helpful tool or a threat? What training and support exists to build confidence and critical evaluation skills?
- How do you balance efficiency gains with the need for human oversight and accountability?

## Roleplay/scenario

Scenario: **"The Chatbot That Knew Too Much"**

Setup: Your ministry has successfully piloted a generative AI chatbot that helps citizens navigate complex benefit applications. It has been grounded in official policy documents using RAG and early trials showed 75% of users found it helpful. Now there is pressure to scale it nationally and connect it via APIs to live case management systems so it can provide personalised advice – checking a citizen's eligibility in real-time and pre-filling applications. However, during internal testing, the chatbot occasionally "hallucinates" information, mixing policy from different schemes or citing outdated regulations. More concerning, when connected to test APIs, it once retrieved and displayed case information for the wrong person due to a similar name match. The minister wants to launch before the election to demonstrate digital progress, but the delivery team is warning that governance frameworks are not yet in place for this level of integration.

Roles:

- **Service Transformation Lead:** Excited about the potential but aware of the risks; worried that rushing could damage public trust if something goes wrong
- **Minister/Political Leadership:** Wants visible wins and faster services; questions whether staff are being overly cautious and slowing down innovation
- **Data Protection/Security Officer:** Alarmed by the API integration plans; insists on strict access controls, audit trails, and testing before any live data connection
- **Frontline Staff Representative:** Concerned they will be blamed when the chatbot gives wrong advice; wants clear guidance on when to override AI suggestions and how to explain AI-generated responses to citizens

Challenge Question: When is an AI tool "good enough" to move from pilot to production, especially when it will handle citizen data and provide official advice?

## Discussion prompts:

- What minimum standards should be in place before connecting AI to live government systems and data?
- How do you balance the political pressure to launch with the technical and ethical need to get it right?
- Who is accountable when an AI system makes a mistake that affects a citizen – the ministry, the technology team, the AI vendor, or the frontline staff?
- Should citizens be told when they are receiving AI-generated advice? How much transparency is appropriate?
- What governance frameworks need to exist before this level of AI integration becomes "business as usual"?

Extension: Map out what responsible scaling would look like: What testing, safeguards, training, and governance mechanisms should be in place at each stage, from pilot to embedded tool, to API integration, to full institutionalisation? Where are the acceptable stopping points if risks cannot be adequately mitigated? Create a "readiness checklist" that could apply to similar AI deployments across government.

Click here or scan QR code
to access a collection of further resources
on the topic.

Learning Pathway >

# Improving Data Quality and Availability

## Reflection

- Do you know what percentage of your ministry's data would be considered "AI-ready" (complete, accurate, properly labelled, accessible)?
- Are quality checks embedded in your data collection workflows, or are they added later as separate validation steps?
- When data quality issues are discovered, what approaches or strategies are used to address them?
- What measure could be adopted to automate the process of improving data quality?
- What risks would you have to be mindful of and how would they affect implementation?

## Roleplay/scenario

Scenario: **"The Data Audit That Stopped Everything"**

Setup: Your government is planning a major AI initiative to optimise emergency service response times across the country. Before beginning model development, a mandatory data quality audit was conducted on the emergency services database. The results are sobering: response time records are incomplete for 35 % of incidents, location data uses inconsistent formats across regions, incident categorisation varies wildly between urban and rural areas, and there is almost no linked data on outcomes. The project has secured EUR 2 million in funding and has ministerial backing, but the audit recommends a 12–18 month data remediation phase before any AI work begins. The project team now faces a choice: invest in systematic data quality improvements first, try to patch the data "good enough" to proceed, or fundamentally redesign the project around the data that actually exists.

Roles:

- **Ministry Project Manager:** Accountable for delivering results within the funding timeline; worried that a long data remediation phase will lose political momentum and budget
- **Data Engineer:** Clear that attempting AI without fixing foundational data issues will fail; proposes building cross-disciplinary teams and embedding quality workflows
- **Emergency Services Operational Lead:** Understands why the data is messy (frontline staff are overwhelmed, legacy systems do not talk to each other); wants solutions that do not add burden to responders
- **Innovation/Digital Transformation Lead:** Sees this as an opportunity to build systematic data stewardship capacity that will benefit future projects, not just this one
- **Challenge Question:** How do you transform this data quality challenge into an opportunity to build sustainable data stewardship capability rather than just a temporary fix? Discussion prompts:
- What would a 12–18-month data remediation programme actually involve? (cross-disciplinary teams, workflow redesign, training, incentives?)
- Could you redesign the project to deliver value during the data quality phase – for example, improving data systems in ways that help frontline staff immediately?
- How do you make the case to ministers and finance teams that investing in "boring" data work will deliver better long-term outcomes than rushing to AI development?
- What systematic changes (standards, governance, performance metrics, career paths) should be built alongside the technical data fixes?
- How can you ensure that data quality improvements are sustained after this project ends?

Extension: Develop three alternative approaches:
(1) **Quick fixes** – patch the data minimally and proceed with AI development (explore the risks and likely outcomes);
(2) **Parallel track** – begin data quality improvements while developing a simpler AI proof-of-concept with the best available data (explore the trade-offs)
(3) **Foundation-first** – invest the full 12-18 months in systematic data quality and stewardship infrastructure before any AI work (explore what this would include and how to maintain support).
Which approach is most sustainable? Which would you recommend and why?

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# Learning Pathway >
# Developing Internal Data and AI Strategies

## Reflection

- › What legacy systems or infrastructure constrain your ability to adopt new technologies?
- › What advantages might late adoption offer?
- › Where have you seen examples of leapfrogging in your context?
- › What made them succeed or fail?
- › How do you ensure that vulnerable groups benefit from, rather than being harmed by, AI adoption?
- › How strong is your organisation's ability to evaluate, adapt, and maintain technologies independently rather than relying on external consultants?
- › How can these processes be improved?

## Roleplay/scenario

Scenario: **"Two Paths to Digital Health"**

Setup: The Ministry of Health has secured significant funding to address growing healthcare workforce shortages and regional disparities in specialist access. Despite the country's advanced healthcare infrastructure, rural and underserved urban areas face increasing challenges: long wait times for specialist appointments, difficulty retaining healthcare professionals in remote regions, and growing pressure on emergency services. Two competing proposals have emerged for how to modernise the system:

**Proposal A – Leapfrogging**: Partner with leading tech companies to deploy cutting-edge AI-powered systems: advanced telemedicine platforms with real-time AI diagnostic support, predictive analytics for patient triage and resource allocation, and integration with existing digital health infrastructure. This could be operational within 18–24 months and would deliver immediate improvements in access and efficiency.

**Proposal B – Absorptive Capacity:** Invest in building internal capability over three to five years: upskill existing ministry and clinical staff in digital health systems, establish robust data governance frameworks compliant with GDPR and national health data regulations, develop in-house expertise to evaluate and maintain technologies independently, and gradually integrate new capabilities with legacy systems. This creates sustainable foundations but delivers results more slowly.

The Ministry of Health must choose how to allocate the funding – and the two approaches require fundamentally different partnerships, timelines, and institutional structures.

Roles (split into two groups):

### Group 1 – Leapfrogging Advocates:

- › Emphasise the urgent need to address workforce shortages and access disparities now
- › Highlight how your government could maintain its position as a healthcare leader through bold innovation
- › Point to successful examples from other countries
- › Argue that rapid deployment builds momentum for further digital transformation and demonstrates results to citizens

### Group 2 – Absorptive Capacity Advocates:

- › Emphasise risks of vendor dependency and losing strategic control over critical health infrastructure
- › Highlight the importance and tradition of data protection and the need for robust governance before scaling
- › Point to the complexity of integrating with existing systems
- › Argue that building internal expertise ensures long-term sustainability and public trust in a critical sector

Challenge Question: Which strategic pathway should the Ministry of Health prioritise, and is there a blended approach that captures the benefits of both whilst managing the risks?

## Discussion prompts:

- What are the real trade-offs between speed of impact and sustainability of solutions?
- How do you assess whether your institution has sufficient absorptive capacity to make leapfrogging work?
- Could you pursue leapfrogging in high-priority areas (remote diagnostics) whilst building absorptive capacity in foundational systems (data governance, interoperability)?
- What role should external partners play – and how do you structure partnerships to build local capability rather than create dependency?
- How do you ensure ethical principles and patient data protection are maintained regardless of which pathway you choose?

## Process:

1. **Initial advocacy:** Each group develops the strongest case for their approach

2. **Debate:** Groups present arguments and challenge each other's assumptions

3. **Consensus building:** The full group must reach agreement on a strategy—pure leapfrogging, pure absorptive capacity, or a blended approach with clear rationale for sector-by-sector decisions

Extension: Once consensus is reached, map out what the chosen strategy would require: What institutional structures? What partnerships? What timeline? What risks need mitigation? What would success look like in one year, three years, and five years?

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# Learning Pathway >
# Collaboration between Technical Units and Data and AI Policy Experts

## Reflection

- How often do technical and policy experts in your organisation work together? How is collaboration between the two structured?
- What are the most pressing gaps in policymaker's understanding of AI that are preventing effective evaluation of vendor proposals, risk assessments and their ability to provide oversight?
- Who in your organisation has the expertise to scrutinise AI systems and ensure they meet both technical and governance standards?
- When AI systems are being developed or procured, who gets a voice in shaping requirements and safeguards? Is this a standardised process, or does this depend on the project?
- What are some of the most effective knowledge-sharing initiatives you have participated in or witnessed? What made them successful?
- In what situations are multistakeholder approaches not suitable? How can this be firmly, yet diplomatically communicated?

## Roleplay / scenario

Scenario: **"Walking in Each Other's Shoes"**

Setup: The Ministry for Transport has been tasked with developing AI literacy training for all senior officials across ministries. A working group has been formed with both technical experts (e.g., data scientists, IT specialists) and policy experts. However, the two groups have fundamentally different views on what "AI literacy" should mean and how the training should be structured. To break the impasse, the working group decides to try a role reversal exercise where each side must argue from the other's perspective.

The Challenge: Design a six-month AI literacy programme that will help 500+ senior officials understand AI well enough to make informed decisions about procurement, oversight, and policy development.

Role Reversal Structure:

### Group A – Technical Experts Acting as Policy/Legal Officers

You must argue for what policy teams typically prioritise:

- Focus on governance frameworks, ethics, accountability, and legal compliance rather than technical details
- Emphasise that officials do not need to understand algorithms, they need to understand risks, rights, and democratic accountability
- Argue that technical jargon alienates busy officials who need practical guidance for oversight and procurement
- Point out that rushing into technical training without grounding in governance principles could lead to "innovation at all costs" thinking
- Highlight concerns about vendor management, avoiding lock-in, and maintaining government control

### Group B – Policy/Legal Experts Acting as Technical Specialists

You must argue for what technical teams typically prioritise:

- Emphasise that, without basic technical understanding, officials cannot effectively evaluate AI claims or identify unreliable vendors
- Argue that governance without technical literacy leads to either over-regulation (stifling innovation) or under-regulation (missing real risks)
- Point out that officials need to understand concepts like training data, bias, accuracy metrics, and model limitations to ask the right questions
- Highlight that purely policy-focused training creates dependency on external consultants who can mislead non-technical decision-makers
- Stress that procurement requires enough technical knowledge to write meaningful specifications

## Discussion Prompts (after initial arguments):

- What surprised you about arguing from the other perspective? What did you find most challenging?
- What legitimate concerns from the "other side" did you not fully appreciate before?
- Where do the perspectives actually align rather than conflict?
- What would a training programme look like that genuinely addressed both sets of concerns?

Reflection Phase: After the role reversal, participants return to their actual roles and discuss:

- What specific elements from both perspectives must be included in the literacy programme?
- How would you structure content to build both technical understanding AND governance capability?
- What assumptions did each side make about the other that turned out to be incomplete or wrong?

Extension: Now design the actual six-month programme together, drawing on insights from both perspectives. What does Week 1 look like? What is the balance between technical concepts and governance frameworks? How do you make it relevant to different ministerial contexts? What measures would indicate success?

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