# Artificial Intelligence in the Public Sector – An Agenda for Responsible Innovation through Learning

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## ABSTRACT

The optimism about the benefits of using artificial intelligence to innovate public services is tempered by concerns about its risks, limitations, and disbenefits. Given the rapid changes in the technology itself, the opportunities and needs for cross-sectional solutions, and the nascency of the field of AI-based innovation, we contend that policy, strategy, and implementation must include feedback loops that enable institutional learning for the entire public sector. The scope of challenges creates and imperative to facilitate learning must transcend functional, organizational, geographic, and national boundaries. We propose a learning agenda that includes 1) alignment of strategy and policy; 2) initial understanding of goals, benefits, disbenefits, limitations, and risks; 3) data sharing across jurisdictions; 4) technical robustness and societal alignment in governmental oversight; 5) convergence of architecture for AI support; and 6) a portfolio approach to selecting and learning from enabling service innovation with AI.

## CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; • **General and reference** → Design; • **Software and its engineering** → *Designing software*; • **Security and privacy** → **Privacy protections**; *Social aspects of security and privacy*; • **Applied computing** → **E-government**; • **Social and professional topics** → **Governmental regulations**.

## KEYWORDS

Artificial intelligence, Public Sector, Feedback cycles, Governance, Technology Strategy, Privacy

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## 1 INTRODUCTION

The rapidly advancing state of artificial intelligence (AI) in general and generative AI in particular places public sector institutions in a difficult situation. On the one hand, there is an ongoing and increasing need for significant productivity gains that ensure the quality and cost-effectiveness of public services. On the other, aspects of AI threaten critical requirements from public services, including privacy, accountability, and equality. The literature on public sector AI is characterized by calls for a systematic, structured, and realistic approach that balances these conflicting demands [1, 2].

The European Union has been actively developing policies and regulations related to AI over the past few years. This includes the EU AI Strategy launched in 2018, the European AI Alliance for stakeholders to collaborate, and most notably, the proposed AI Act which the European Parliament approved in 2023.[1] The AI Act aims to regulate high-risk AI systems to ensure that they are trustworthy and human-centric, and also to support innovation in the field. Other countries are also developing their own approaches – the UK is working towards decentralized, principle-based governance,[2] while the US and China are enacting some regulations around privacy, ethics, and transparency, e.g., Biden's presidential executive order [3].

In addition to regulations, the EU and many other countries have implemented policies and programs to spur AI research and adoption across sectors such as healthcare, transport, manufacturing and energy. The EU's Coordinated Plan on AI brings together member states to align strategies to avoid fragmentation, and similar multi-stakeholder efforts are underway globally. [4]. The Group of Seven (G7) has also published a common code of conduct for governing AI known as the *Hiroshima Process* [5]

[1]https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence
[2]https://www.mwe.com/insights/the-eu-artificial-intelligence-act-whats-the-impact/
[3]https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/
[4]https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence
[5]https://www.mofa.go.jp/files/100573473.pdf

As it is, the preponderance of literature on the subject proposes many benefits, limitations, and risks in implementing AI for public services, highlighting the need for trading off and balancing these in the years ahead. Given the lack of experience in actually doing this, there is relatively little that suggests how this should be accomplished.

The goal with this work is to contribute to the ongoing discourse on AI in the public sector by offering a structured agenda based on insights that can guide public sector organizations in their journey to harness AI's potential while ensuring responsible and effective implementation.

## 2 BACKGROUND

As an example to illustrate the matter at hand, the Norwegian public sector provides a wide array of services essential to the functioning of Norway's evolving welfare state. These services employ a significant share of the Norwegian labor pool and consume much of Norway's gross domestic product. With the aging population, there is an apparent need to improve the productivity of these services to reduce the economic burden for future generations and to reallocate resources to meet the increasing demand for inherently labor-intensive services [6].

A recent survey among IT practitioners in the Norwegian public sector suggests a deep ambivalence about artificial intelligence. While there is optimism about its potential for improving public service performance, there is an equivalent level of pessimism about limitations, risks, and the public sector's ability to implement AI-based capabilities responsibly [3].

The possibility of artificial intelligence has been discussed for several years, and efforts are underway in Norway to assess the viability of artificial intelligence through initial projects and pilots. The Norwegian government has published a national strategy for artificial intelligence [4] calling for principle-driven, responsible implementation of artificial intelligence. The amount of attention, scope and magnitude of expected benefits, and the societal risks associated with AI suggests to us that this class of technology may be a category of its own, as suggested by Yuval Harari [5] and others [6].

Consequently several calls have been made for Norway and the public sector in all countries for better coordination that addresses and resolves issues more systematically [7]. The results of these initial efforts should include products and policies for future use. As the field changes so quickly, the Norwegian public sector must establish ways to rapidly learn and adjust from its own and others' experiences.

## 3 THE NEED FOR AN EVIDENCE- AND EXPERIENCE-BASED LEARNING

Management research suggests that organizations exhibit certain behaviors in collecting, interpreting, and acting on performance feedback under conditions of uncertainty, depending on whether they act on aspirations or beliefs [8]. Some prominent sources of uncertainty for AI in the public sector are:

- The technology itself is evolving rapidly [9]
- Implementing the technology responsibly and effectively is highly complex [10]
- There is lacking competence in virtually all aspects that drive the complexity [11]
- Benefits, disbenefits, and risks are as yet unclear [12]
- The effects are potentially substantial, even disruptive [13], while evaluation and ethics and alignment checks are not in place or often even topics of discussion.
- Requirements for accessing and sharing data are under development [14]

[6]https://www.digdir.no/digitaliseringskonferansen/riksrevisorens-innlegg-pa-digitaliseringskonferansen-2023/4631

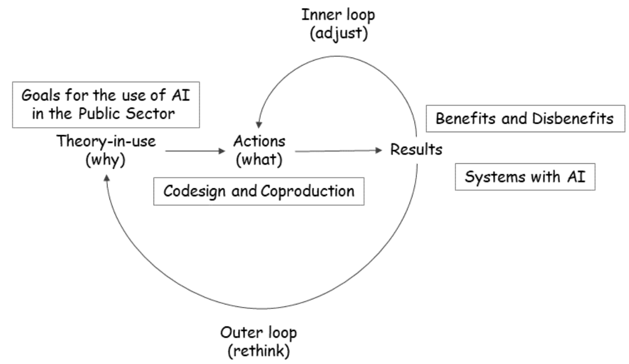


**Figure 1: Double-loop learning model for adaptive public-sector AI strategy generation**

To ensure progress under continuous change, iterative learning is necessary and may be facilitated by approaches variously called "evidence-based roadmaps" [15], or "learning agendas," defined as "a set of processes and questions that guide the prioritisation of activities to facilitate learning and information sharing, including findings. A learning agenda can help fill gaps in knowledge and make the associated work more efficient and effective by supporting informed decisions. It can also facilitate collaboration with peers and colleagues, generating new evidence..." [16] This constitutes a purposeful learning process based on *adaptive thinking* [17, 18] that capitalizes better on emergent effects rather than when planned, orchestrated, and directed by senior management [19].

Figure 1 sets these ideas in a double-loop learning model [20, 21], in which systems with AI are codesigned and coproduced [22] by relevant stakeholders of public service provision and consumption where effects of the resulting systems are experienced, observed, captured, and interpreted. In addition to informing codesign and coproduction processes, the inner loop learning and adjustment will eventually initiate the need to adjust these goals as the efforts deal with the complications and effects mentioned in Section 3. The outer-loop learning, whereby the rationale and strategic goals for AI in the public sector are deliberately rethought, is the core of the adaptive planning that we are proposing. The term *Theory-in-use* alludes to the explicit and implicit (tacit) mental models upheld among stakeholders that guide actions [20], and we posit that this theory-in-use must be stated as explicitly as possible for AI in the public sector and that the process of updating, refining and changing that theory-in-use is also made explicit and legitimate.

We also assert that the pursuit of this learning agenda is best organized as a collaborative, interagency (and possibly international) effort, given the increasing interest in and experience with such efforts to solve complex, even "wicked" problems [23]. To be effective, however, such collaboration programs need support at all management levels [24].

While the learning process is adaptive, this process must be initiated by a set of commonly held and understood goals that serve as hypotheses for the learning process. In the following, we to propose an agenda that we elaborate and explain with literature to date. It should be viewed as a starting point, because we assume this agenda will change as the field unfolds. These goals are to:

(1) Continuously Align Policy and Strategy Through an Explicit Learning Process
(2) Gain an initial understanding of goals, benefits, disbenefits, limitations, and risks
(3) Enable data sharing across jurisdictions
(4) Ensure technical robustness and societal alignment in governmental oversight
(5) Converge architecture to support strategy and policy
(6) Devise portfolio approach for AI-enabled public services

Each of these elements is outlined in the following subsections.

## 3.1 Continuously Align Policy and Strategy Through an Explicit Learning Process

Since artificial intelligence is a rapidly evolving field most likely still in its nascence, it is difficult to formulate a strategy incorporating all its potential and limitations. By the same token, public policy toward its use suffers from a lack of insight into pitfalls and perils.

While it is clear that national governments and international organizations actively pursue policies for AI, the strategies for realizing those policies are less clear. While a deliberative, holistic approach to artificial intelligence can be seen as positive, concerns are raised that the traditional staged policy and strategy development model is insufficient for successful AI implementation [25]. Policies, however well conceived, require strategies to be implemented [26] and belong to the "executive function" of the public sector [27]. Given the imperative for systematic learning, policy evolution must be included in the learning agenda described above. This will enable policy to drive strategy development at the organizational level but also that policy be informed by the outcomes of these strategies as they are implemented and evaluated [28].

This means including policymakers and strategy developers in the learning agenda and integrating the scope of their work in the feedback loops. Based on insights from research on benefits management [29], we propose these loops be tied to an explicit understanding of expected positive and negative effects on public services and administration while fully recognizing that these will likely change due to the experiences gained. This adaptability in strategic thinking requires a mindset that demands explicit attention [20, 30] in ordinary settings and all the more so for understanding and dealing with the emergent effects of AI.

## 3.2 Gain an Initial Understanding of Goals, Benefits, Disbenefits, Limitations, and Risks

To kickstart the learning process, revisiting the objectives set for an AI initiative is essential. For example, in the realm of public healthcare, the overarching goal revolves around improving patient care, optimizing resource allocation, and cutting possible waiting times. These objectives are not set in stone; they are often subject to refinement, adjustment, or even a complete overhaul as our understanding deepens through double-loop learning.

Equally important is grasping the potential benefits. Picture improved diagnostic precision, resource allocation efficiency, tailor-made treatment plans, reduced administrative hassles, and an accelerated pace of medical research. On the flip side, there are possible negative aspects to consider, like concerns regarding bias, data privacy, overreliance on technology, and the financial implications of implementation.

In addition, one also needs to take into account possible limitations, encompassing challenges linked to accuracy, the enigma of interpretability, data quality assurance, bias and cultural values of models, data and society, and navigating the labyrinth of regulatory compliance. While these facets may seem daunting, they are often unavoidable for risk mitigation. Possible risks involved, such as misdiagnosis, data breaches, technical glitches, and the ethical quandaries arising from AI's role in public healthcare need to incorporated in decision-making.

A holistic understanding of these dimensions lays the groundwork for a judicious and responsible integration of AI, all while staying agile in response to the ever-evolving landscape of implementation.

Among expected benefits cited from the use of artificial intelligence are:

- More efficient case processing regarding speed and accuracy - AI can automate certain determinations to make decisions or aid decision-making among experts. The requirement for explainability can also increase accountability and transparency compared to discretionary decision-making [31].
- Higher quality decisions because larger and more diverse data is available for advanced analysis and interpretation [32]
- Aid in learning processes, both in schools and workplaces [33, 34]
- Better coordination of services that enable seamless end-user experiences [35]
- Automation of routine tasks, such as archiving and indexing [36]
- More personalized user experiences and dialogue, typically with advanced bots [37]
- Monitoring to enable earlier detection of changes, ranging from physical maintenance (through Internet of Things) to sentiment analysis in social media [38]

Expected disbenefits are likely to include but may not be limited to [3]:

- Overreliance on the merits of artificial intelligence
- Inaccurate or false determinations by AI
- Neglect of empathy and other distinctly human capabilities
- Lack of interpretability of results

- Amplification of existing biases
- Emergent ethical dilemmas that AI is not equipped to handle
- Violations of privacy

The realization of both benefits and disbenefits hinges on fortunate conditions for either. Indeed, enablers may coincide for benefits and disbenefits alike. In any event, limitations and risks that can hamper the use of AI in public-sector systems include (but are not limited to) [39]:

- Accountability and explainability in judgments and decisions that are necessary for the rule of law and civil liberties
- Legal and regulatory constraints on the capture, use, and sharing of data to prevent misuse and abuse
- Overconfidence in the technology itself, leading us to negligent use

When benefits and disbenefits such as those mentioned above are experienced and observed, in the context of relevant limitations, the inner-loop adjustments can take place. Eventually, this should trigger the rethinking of goals so that policies and strategies can be rewritten.

## 3.3 Enable Data Sharing across Jurisdictions

AI depends on large quantities of data for learning and testing. The Norwegian public sector has built and maintains many registers about its population, property rights, enterprises, health, etc., which are essential for delivering public services and helping generate artificial intelligence. However, there is a growing need for sharing data among public institutions to ensure quality service provision and privacy rights protection. Technical and legal barriers inhibit such sharing and require dedicated effort on several levels to resolve [40]. These include the resolution of semantics to ensure consistent use and understanding of data, unambiguous legal foundations for exchanging data, protocols for sharing data that ensure integrity, quality, and confidentiality, technical solutions for timely and reliable data exchange, and others. Reflecting the difficulties of doing this, a report on data sharing from the auditor general of Norway in late 2023 provided an overall assessment of "unsatisfactory", highlighting legal obstacles, lack of capacity, lack of funding and other resources, and technological barriers [41].

Issues identified both in our survey and the auditor general's report need, in large part, to be resolved through inter-organizational (and in some cases international) collaboration rather than top-down mandates.

## 3.4 Ensure Technical Robustness and Societal Alignment in Governmental Oversight

Integrating AI in the public sector necessitates a nuanced approach to government oversight, emphasizing technical robustness and alignment with societal values. This oversight requires the establishment of comprehensive metrics and evaluation methods tailored to assess AI systems' performance, fairness, and ethical alignment.

*3.4.1 Technical metrics for AI system evaluation.* A critical aspect of evaluating AI in public services lies in applying technical metrics that measure performance and reliability [42]. Key areas of focus include precision and recall, particularly in high-stakes sectors like healthcare and criminal justice, where accuracy is critical. Equally important is assessing fairness and bias, where tools like AI Fairness 360[7] play a crucial role in identifying and mitigating algorithmic biases. Robustness and generalizability are also vital, ensuring AI systems can handle a variety of inputs and scenarios, maintaining their functionality and reliability.

*3.4.2 Aligning AI with societal values.* Beyond technical performance, aligning AI with societal values is a complex yet essential task. This involves conducting ethical impact assessments that mirror environmental impact assessments in their thoroughness and scope. These assessments should be complemented by stakeholder engagement, involving public, private, and civil society actors to gauge societal implications and expectations. Transparency and explainability are also key, with frameworks like Google's AI principles[8] ensuring that AI decisions are accessible and understandable to non-experts.

*3.4.3 Incorporating current scientific insights.* Recent academic contributions provide valuable insights into this field. For example Selbst et al.[43] examine the challenges in designing fair AI systems, advocating for a socio technical perspective in AI evaluation. Corbett-Davies and Goel's[44] critically review fairness metrics in AI, underlining the complexity of fairness in algorithmic contexts. Arrieta et al.[45] offer a comprehensive overview of explainable AI, underscoring its importance in aligning AI systems with societal expectations. The integration of these technical metrics, methodologies, and current scientific knowledge is essential for effective government oversight of AI systems, ensuring not only their technical efficacy but also their adherence to societal values and ethical norms.

## 3.5 Converge Architecture that Supports Strategy and Policy

As the above discussion suggests, AI is likely a concern that typically cuts across public institutions and requires interagency collaboration on several levels. Trusted data exchange requires identification and authentication, and responsible use of data also requires harmonized security policies [46]. To ensure correct use of the data, semantics for data elements and structures must be shared and understood [14]. Common standards for explainability, transparency, and accountability of AI solutions dictate shared learning and common approaches [45].

All these concerns are manifest in structural arrangements that amount to strategies and AI-amenable architecture, which is to say a series of well-considered design principles that enable use of AI to meet stated benefits, reduce the risk of abuse or adverse results, comply with laws and regulations, and set the stage for learning [47].

## 3.6 Devise a Portfolio Approach for AI-enabled Public Services

One of the key governance tools is an analytical framework that maps opportunities to improve individual public service against a range of salient factors, including the services' characteristics relevant to AI, target benefits, likely disbenefits and risks. We offer

[7] ai-fairness-360.org
[8] https://ai.google/responsibility/principles/

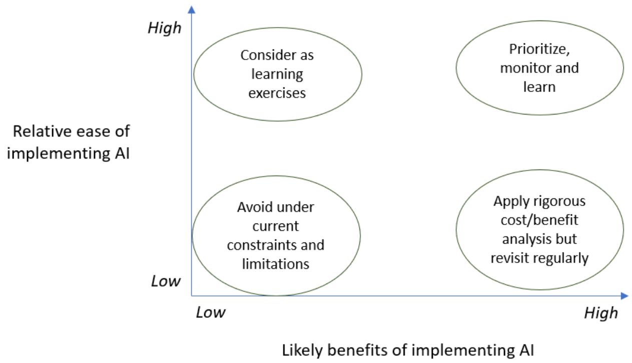


**Figure 2: Proposed portfolio framework for AI initiatives**

a matrix allowing public institutions to jointly and transparently prioritize and sequence AI initiatives, illustrated in Figure 2.

Both axes in this framework require consideration of several factors, including:

- Likely benefits of implementing AI
  - Analytic approach to identifying and evaluating potential benefits as described above
  - A shared understanding across public institutions about the meaning of these benefits and how to compare them and weigh them against other considerations
  - Shared models for benefit measurement and realization
- Relative ease of implementing AI
  - Legal complexity, especially the legal basis for using and protecting the data
  - Semantic consistency to ensure that data is used and understood correctly
  - Technical compatibility that allows for secure and reliable use and exchange of data

This matrix provides a simple decision-making framework to trade off difficulty and benefits of AI-enabled public services in a way that ensures efficient learning, similar to a portfolio model [48], but with the key emphasis on learning rather than building market position.

## 4 DISCUSSION

We contend that the challenges in implementing AI are too large and complex for any one public institution to manage effectively and responsibly. It is incumbent on the public sector to develop and pursue the proposed learning agenda in a coordinated fashion across organizational or even national borders. The combination of complexity, rapid change, and cross-organizational imperatives creates the need for an innovative governance approach in which participating public institutions voluntarily accept common standards and solutions. These are subject to continuous change based on systematic learning processes. This learning is inherently interdisciplinary, as many of the issues often lie far outside the expertise of those who develop or implement AI-based solutions.

The proposed approach builds on and emphasizes calls for agile development and collaboration across organizations and countries, breaking with deterministic and formal approaches common in the public sector [49, 50].

Inherent challenges of building cross-organizational cooperative structures, as well as the inertia of established practices, are likely to make our approach difficult, but the challenges posed by AI-based innovation likely necessitate it. We hope that this paper informs fruitful efforts to make this happen.

Further research is needed on the described elements as distinct issues, mainly as they apply to inter-organizational and international efforts. Coordination, collaboration, and shared learning is already evident in international organizations (particularly the EU), federal forms of government, regional governments, and public institutions. Whether AI accelerates these approaches remains to be seen.

For practitioners, this paper provides an overview of essential elements and the principles for the learning approach we advocate. We hope that coordinating agencies find it useful for their discussions.

## 5 CONCLUSION

Politicians, researchers, executives and practitioners alike see AI to be both of great promise and of great hazard to society in general and public services in particular. Resolving this dilemma is not just a matter of finding and maintaining a balance between competing interests but of institutionalizing learning across functions, organizations, and countries so that the dilemmas are resolved in creative, productive ways that support responsible diffusion of AI-based innovations in public services. We present an initial agenda and a framework for decisions and feedback to facilitate this.

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