European Commission

JRC TECHNICAL REPORT

AI Watch
Beyond pilots: sustainable implementation of AI in public services

Joint Research Centre

EUR 30868 EN

Contact information
Name: European Commission, Joint Research Centre (JRC), Digital Economy Unit
Address: Via Enrico Fermi 2749, 21027 Ispra (VA), Italy
Email: EC-AI-WATCH@ec.europe.eu

EU Science Hub
https://ec.europa.eu/jrc

JRC126665

EUR 30868 EN

PDF ISBN 978-92-76-42587-8 ISSN 1831-9424 doi:10.2760/440212

Luxembourg: Publications Office of the European Union, 2021

How to cite this report: Molinari F., van Noordt C., Vaccari L, Pignatelli F. and Tangi L., *AI Watch. Beyond pilots: sustainable implementation of AI in public services*, EUR 30868 EN, Publications Office of the European Union, Luxembourg, 2021, ISBN 978-92-76-42587-8, doi:10.2760/440212, JRC 126665.

Contents

Acknowledgements

Several people contributed to this report. The authors would like to thank the editor Francesco Pignatelli and the internal reviewers Montserrat Lopez Cobo, Marina Manzoni, Sven Schade and Peter Ulrich from the JRC as well as Dietmar Gattwinkel from DG CNECT, for reading earlier drafts and providing their comments and advice on both structure and contents. We are also grateful to the following colleagues and experts for their opinions and support: Dragan Cisic, Marco Combetto, Joe Cullen, Enrico Ferro, Sergio Gusmeroli, Rony Medaglia, and Francesco Niglia, who also provided an input on AI user centricity. All errors remain the sole responsibility of the authors.

Authors

Francesco Molinari - Independent Researcher

Colin van Noordt - Tallin University of Technology

Lorenzino Vaccari - Independent Researcher

Francesco Pignatelli - European Commission, Joint Research Centre

Luca Tangi - European Commission, Joint Research Centre

Abstract

Artificial Intelligence (AI) is a peculiar case of General Purpose Technology that differs from other examples in history because it embeds specific uncertainties or ambiguous character that may lead to a number of risks when used to support transformative solutions in the public sector. AI has extremely powerful and, in many cases, disruptive effects on the internal management, decision-making and service provision processes of public administration. Over the past few years, the European Union and its Member States have designed regulatory policies and initiatives to mitigate the AI risks and make its opportunities a reality for national, regional and local government institutions. 'AI Watch' is one of these initiatives which has, among its goals, the monitoring of European Union's industrial, technological, and research capacity in AI and the development of an analytical framework of the impact potential of AI in the public sector. This report, in particular, follows a previous landscaping study and collection of European cases, which was delivered in 2020.

This document first introduces the concept of AI appropriation in government, seen as a sequence of two logically distinct phases, respectively named adoption and implementation of related technologies in public services and processes. Then, it analyses the situation of AI governance in the US and China and contrasts it to an emerging, truly European model, rooted in a systemic vision and with an emphasis on the revitalised role of the member states in the EU integration process, Next, it points out some critical challenges to AI implementation in the EU public sector, including: the generation of a critical mass of public investments, the availability of widely shared and suitable datasets, the improvement of AI literacy and skills in the involved staff, and the threats associated with the legitimacy of decisions taken by AI algorithms alone. Finally, it draws a set of common actions for EU decision-makers willing to undertake the systemic approach to AI governance through a more advanced equilibrium between AI promotion and regulation.

The three main recommendations of this work include a more robust integration of AI with data policies, facing the issue of so-called "explainability of AI" (XAI), and broadening the current perspectives of both Pre-Commercial Procurement (PCP) and Public Procurement of Innovation (PPI) at the service of smart AI purchasing by the EU public administration. These recommendations will represent the baseline for a generic implementation roadmap for enhancing the use and impact of AI in the European public sector.

Foreword

This report is published in the context of AI Watch, the European Commission knowledge service to monitor the development, uptake and impact of Artificial Intelligence (AI) for Europe, launched in December 2018.

AI has become an area of strategic importance with the potential to be a key driver of economic development. AI also has a wide range of potential social implications. As part of its Digital Single Market Strategy, the European Commission put forward in April 2018 a European strategy on AI in its Communication "Artificial Intelligence for Europe". The aims of the European AI strategy announced in the communication are:

- To boost the EU's technological and industrial capacity and AI uptake across the economy, both by the private and public sectors
- To prepare for socio-economic changes brought about by AI
- To ensure an appropriate ethical and legal framework.

In December 2018, the European Commission and the Member States published a "Coordinated Plan on Artificial Intelligence", on the development of AI in the EU. The Coordinated Plan mentions the role of AI Watch to monitor its implementation.

Subsequently, in February 2020, the Commission unveiled its vision for a digital transformation that works for everyone. The Commission presented a White Paper proposing a framework for trustworthy AI based on excellence and trust.

Furthermore, in April 2021 the European Commission proposed a set of actions to boost excellence in AI, and rules to ensure that the technology is trustworthy. The proposed Regulation on a European Approach for Artificial Intelligence and the update of the Coordinated Plan on AI aim to guarantee the safety and fundamental rights of people and businesses, while strengthening investment and innovation across EU countries. The 2021 review of the Coordinated Plan on AI refers to AI Watch reports and confirms the role of AI Watch to support the implementation and monitoring of the Coordinated Plan.

AI Watch monitors the European Union's industrial, technological and research capacity in AI; AI-related policy initiatives in the Member States; uptake and technical developments of AI; and AI impact. AI Watch has a European focus within the global landscape. In the context of AI Watch, the Commission works in coordination with Member States. AI Watch results and analyses are published on the AI Watch Portal (https://ec.europa.eu/knowledge4policy/ai-watch_en).

From AI Watch in-depth analyses, we will be able to understand better the European Union's areas of strength and areas where investment is needed. AI Watch will provide an independent assessment of the impacts and benefits of AI on growth, jobs, education, and society.

AI Watch is developed by the Joint Research Centre (JRC) of the European Commission in collaboration with the Directorate-General for Communications Networks, Content and Technology (DG CONNECT).

This document specifically addresses the following objective of AI Watch:

"***To provide an overview and analysis of the use and impact of AI in public services***".

Particularly, it is a follow up to the first-year activities of AI Watch[1] towards the investigation of the effective uptake of AI in the public sector, that goes beyond the piloting phase. As such, it builds on the knowledge gained after the collection of 230 AI use cases from EU (Member States and Associated States) national, regional and local government officially presented in July 2020. This output has received extensive feedback from policy experts and practitioners, notably in the 2nd peer learning workshop with MS representatives held on September 29th, 2020 (van Noordt & Pignatelli, 2020).

While additional field research activities are now under way (including an EU wide survey and case specific interviews), in order to take full stock of that knowledge, this report elaborates on the evidence gathered so far and makes additional reflections on the common characteristics and the critical aspects observed in most real-life cases. In so doing, the concept of AI appropriation, i.e., the union of adoption and implementation phases, in government is introduced, defined as a sequence of two logically distinct (and sometimes recurring or

[1] https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/ai-watch-artificial-intelligence-public-services

alternating, rather than linearly consecutive) phases, respectively named **adoption** and **implementation** of related technologies.

Keeping the two phases separate surely holds heuristic value, confirmed from the preliminary outputs of field activities. Moreover, it provides support to drawing several policy relevant implications, touching on both strategic directions introduced by a previous Science for Policy report of the AI Watch series (Misuraca and van Noordt, 2020): "*governing with AI*" on the one hand, and "*governing AI*" on the other.

In the first direction, the key question is to determine whether and under which conditions AI appropriation can become supportive of a durable and positively impactful transformation of EU public processes and services, in line with the provisions of the Tallinn Ministerial Declaration on eGovernment. This requires a more advanced equilibrium between AI promotion and AI regulation going beyond the experimental nature of many observed cases. In the second direction, a number of challenges are associated with AI implementation and use in government, which have been outlined by several theoretical and empirical research studies and are summarised in this report. The comparison with the US and China leads to highlighting the basic and distinctive elements of a truly European governance model of AI. A governance model which could overcome the fragmentation of the EU GovTech market and set out the conditions for reconciling ethical values with technology adoption and implementation.

The latter reflections, among others, will be further extended and integrated with another forthcoming AI Watch publication, and will be shaped in the form of a proposed policy roadmap for securing the transition to an AI enabled and digitally transformed government in Europe.

Executive summary

The present document is structured in six Sections: here we summarize the main take-aways for the reader.

In **Section 1 (Background and vision)**, a brief overview is provided of the research and policy state of the art behind this report and the whole AI Watch initiative. The narrative starts by considering **AI as a General Purpose Technology**, due to its distinctive features of pervasiveness, fast pace of diffusion, and innovation-spawning tendency, which are also common to other examples of general purpose technologies in history. However, being a family of emergent, numerous and diversified technologies (not to speak about the proliferation of custom solutions) AI also holds traits of uncertainty and ambiguity, which require multiple rounds of experimentation before a solution is adopted and may generate issues or delays in the materialisation of expected impacts from its implementation and use. These traits make the adoption and implementation of AI more complex and different from the adoption and implementation of "conventional" Information and Communication Technology (ICT). In fact, in the EU public sector, despite the good number of early adopters from various national (and regional, and city) governments, AI-enabled public sector innovation – not to say, transformation – often appears as the result of several concurrent elements, which are barely technological in essence. These include legal, organisational, workforce-related, environmental, ethical or societal aspects that are often overlooked by a perspective embedded in technology determinism. The crucial relevance of most of those elements for the success or failure of AI solution implementation has started to be noted in the empirical search activities of AI Watch. To fit these considerations into a realistic representation of the Public Sector environment, **the proposed approach is systemic**: it takes into account the whole **multi-layered and networked operational scenario, exploring the complex interactions among actors, processes, decisions and behaviours**. This approach is necessary for research that goes beyond the analysis of some individual, pilot AI projects.

Section 2 (Definitions and concepts) introduces the notion of **AI appropriation** as one of the overarching contributions of this technical report towards developing an analytical framework of the potential impact of AI. Appropriation usually comes as the result of two consecutive (though often cyclically recurring) and conceptually distinct phases, which are named **adoption** and **implementation** of related technologies[2]. With some preliminary confirmation from the just started field study work at AI Watch, the existence of a gap is highlighted between the phase where AI is tested and evaluated for potential use in public service, and the phase where its injection and adaptation transforms the service (and its provider) more or less permanently. This gap is noteworthy for two reasons: **first**, qualitative analysis of a considerable number of known AI cases has shown that they successfully completed the phase of adoption but then found **a number of unexpected issues right in the phase of implementation**, which led to a total dismantling of the initial technology deployment. **Second**, any analytical framework for assessing the impact potential of AI in government would miss a crucial component if it only focuses on AI adoption rather than also on **implementation through service transformation and interoperability**. In the latter phase, which some authors also call technology "institutionalisation" or "instrumentalisation", the AI component is permanently embedded in the functioning model of the public sector organisation. This may have been done in ways that ultimately affect, and are affected by, the broader context the organisation belongs to: thereby including, but not being limited to, collaboration with other agencies and bodies and the generation of perceived value for public service beneficiaries. The main research question behind this report is how European public policy can and should contribute to a higher fraction of AI implementation efforts to go beyond technological and organisational pilots developed in very specific contexts.

Section 3 (Lessons from the US and China) makes some steps beyond the rhetorical argument that Europe is falling behind the US and China in a techno-economic "AI race", coming to the encouraging conclusion that under the perspective of AI governance, the EU gap does not seem to be as huge as shown by other metrics, such as number of companies or amounts of investment. Indeed, one of the main conclusions from this comparison with the US and China is the common lack of policy focus on the actual appropriation of AI

[2] (McKinsey, 2020b) defines adoption as the decision of an economic entity to invest in AI technology – as distinct from the decision to integrate it into the organizational processes, which is close to our understanding of AI implementation.

technologies in the practice of government. Europe might be in a favourable position to counteract earlier and more extensively. However, two main conditions need to be met:

- First, unlike several eGovernment benchmarking exercises of the past, the **demand side** – or the observed benefits of AI implementation to service beneficiaries, the EU citizens and businesses – should receive a similar (if not higher) level of attention than the supply side of AI. This is to avoid a mere count of AI solutions successfully trialled out, but never having become (permanently) used or still experiencing problems in terms of scalability or interoperability.
- Second, a **systemic approach** to facilitating AI in the eGovernment should be adopted; setting out an AI governance vision that can be shared by all EU Member States, but also Regional and (major) City governments. Defining a common strategic direction will facilitate reciprocal exchange and continuous learning from the best available experiences of AI take-up.

The section concludes with a slightly different declination of the known concept of European "exceptionalism", and by detecting the "weak signs" of **an emerging, truly European model of AI governance**. The model is rooted in EU intergovernmentalism, acknowledging the peculiarities of the "business of government"[3] and looking at the infrastructural elements of AI development and deployment in the public sector, not just as a collection of preconditions for implementation, but also as targets of an embryonic shared agenda for enabling "*governance of AI, with AI*".

Section 4 (Challenges to AI implementation in the EU public sector) follows the above line of reasoning and raises a number of relevant challenges to the attention of policy makers at EU, national, regional and local levels, willing to engage in and contribute to the proposed direction of AI governance:

- The first of these challenges is the **generation of a critical mass of public investments** in AI, nominally allowed by the endowments of the upcoming Digital Europe Programme. Two main risks might hamper this challenge: the dispersion of financial resources across multiple and heterogeneous projects (possibly also duplicating similar efforts in different countries) and the inadequate rooting, or embedment, of the newly developed solutions in the practice of EU public administration (possibly preventing the projects to go beyond adoption and into implementation).
- A second policy challenge is **making high quality datasets** available, interoperable, and continuously updated, maintained and published, that are required for the training and adaptation of all types of AI algorithms (supervised, unsupervised, reinforced) and more generally for the progress and sharing of benefits of government digitalisation in all EU countries. In doing so, the risk might be to have "wells of excellence" on case selected based on the data underlying AI-enabled solution, surrounded by "deserts of exclusion". In other words, the risk might be to qualify the AI solution and select the best ones based on the quality of underlying data excluding elements like the relevance and innovativeness of the technological innovation.
- A third has to do with **attracting young tech talents** in public administration and **widely improving the literacy and skills** of existing staff, particularly in the most "peripheral" public bodies and agencies with respect to the ongoing trends. This may sound paradoxical, as the challenge of making innovation happen by introducing a comparatively complex technology might itself be better suited to attract competent and smart staff." But, in fact, the reverse is also true, though probably more difficult to explain: without adequate digital capabilities available in-house, some governments may not even be able to replicate the most successful use cases they come to know about by adapting already developed AI solutions to their specific site requirements, since ensuring successful appropriation of AI requires digital skills as well. This can be particularly unfortunate given the technological and organisational singularity of solutions discussed before.
- A fourth group of challenges is associated with the **changing concept of legitimacy** for those governments making more decisive steps towards AI implementation. The design of AI systems may lead to developers taking political decisions with limited oversight from public managers and elected officials, not to mention the citizens or other stakeholders ("Input legitimacy challenge"). Especially in delicate or complex tasks, such as the award of competitions, some **controversial decisions taken by opaque**

[3] In the remainder of this report, we will consistently use the word "business" to make reference, without distinction, to the core activities of a private or Public Sector organisation. In the latter case, we will also speak of the "business of government", an expression that should be rather familiar to researchers in public administration: see e.g. the book by Kessler & Kelley (2000) or the homonymous research centre by IBM (http://www.businessofgovernment.org/).

machine algorithms in the place of human beings can be more difficult to justify, and even lead to prosecution and sanctions for law infringement ("Throughput legitimacy challenge").

- Moreover, and as shown by the field evidence gathered in the context of AI Watch so far, when moving from controlled to real life conditions of operation, **the use of some AI systems may induce unexpected and unwanted consequences to the internal equilibria of an organisation or the surrounding environment**, including some external stakeholders, while at the same time not significantly outperforming previous working methods or decision-making approaches ("Output legitimacy challenge").
- Finally, the diffused implementation of **user centric mechanisms** for service transformation, particularly at the local level, in line with the eight fundamental principles of the Tallinn Declaration on eGovernment, is posed as a complementary requirement to achieving a sustained organisational change in the public body or agency involved in AI implementation.

Section 5 (Policy implications) draws some lessons from the previous discussion and proposes a set of common actions for EU decision makers willing to undertake the systemic approach to AI governance towards a more advanced equilibrium between AI promotion and regulation in the public sector. The EU's AI strategy has at its heart the high level objective of balancing regulation and uptake, through the establishment of ecosystems of excellence and trust between parties, hence the correct balance shall be pursued. The underlying idea is that if AI innovation could generate common and shareable assets for many European (at least national and regional) public bodies and agencies, the formation and development of a new wave of AI start-ups participating in the GovTech arena would gain momentum, overcoming the fragmentation of the EU single market which is more prominent than in the US and China. We believe this argument should make an integral part of our analytical framework for impact assessment of AI implementation and use in the European public sector. Starting from these considerations, **three main suggestions or recommendations come to the forefront**[4]:

- Stronger integration of AI with data policies;
- Facing the issue of so-called "explainability of AI"; and
- Broadening the current perspectives of both Pre-Commercial Procurement (PCP) and Public Procurement of Innovation (PPI) at the service of smart AI purchasing by the EU public administration.

Section 6 (Conclusion and way forward) summarizes the key arguments made throughout the report and relates them to the upcoming work in AI Watch for the public sector during the year 2021. In particular, we highlight the **crucial importance of co-design, and therefore user and stakeholder engagement in public service transformation processes**, as an alternative way to negotiate the scope and purpose of AI enabled innovation and therefore achieve reconciliation between ethical values and technology shaping. In this perspective, **our proposed analytical framework for AI impact assessment** – apart from highlighting the need to reinforce four feedback loops (design, adoption, implementation and use) that materialise across its dynamic phases – paves the way for a sound integration of people, alongside algorithms, data and computing power, in the commonly accepted definition of AI: therefore, **its implementation may never be completely successful if it is only done "for" the people, but needs to be achieved together "with" them**.

[4] These recommendations will be the starting point for a more in depth analysis that will result in a roadmap and an extensive list of recommendations towards the adoption of AI in the Public Sector. Those results will be part of the next report within the AI Watch.

1 Background and vision

This introductory Section is structured in three parts. The first ("Research background") provides a brief overview of the global problem tackled, which is to explore the conditions for AI to produce durable transformative effects in the EU-27 public sector organisations adopting and implementing it. The second part ("Policy background") frames this technical report within the scope of the AI Watch for the public sector initiative of the European Commission and in continuity with its work schedule. The third and final part ("What this report is about") introduces the vision behind the proposed analytical framework for assessing the AI impact potential in EU government - which is to ignite and support a process of systemic learning among public sector experts and practitioners - and briefly outlines the contents of the following five Sections of this report.

1.1 Research background

AI is a portmanteau word standing for a collection of technologies that mimic or improve the capacities of the human brain – including **perception**, **reasoning**, and **action** (Misuraca and van Noordt, 2020). The term is not new, as it holds a long history, dating back to the post-WWII period. However, it gained popularity and widespread diffusion at the turn of the millennium, with the progress in the so-called **data economy**[5] (the real "fuel" of AI) and the exponential growth of **computing power** (the "engine" of AI) allowing the generation and validation of more and more complex algorithms and the emergence of promising applications in a variety of business domains.

For its positive impacts on total factor productivity at the firm and industry level, AI is more and more defined as the **General Purpose Technology** of the 21st century (Bassetti, Borbon Galvez, Del Sorbo, & Pavesi, 2020). According to the economic literature (Jovanovic & Rousseau, 2005), the three distinctive features of a General Purpose Technology, which are shared by e.g. the steam engine at the dawn of the industrial revolution and electricity at the beginning of the 20th century, are: **pervasiveness**, meaning that the technology is used in vast amounts of applications - as, for instance, electricity is used for heating and lighting, but also as a fuel for cars and trains (Korzinov & Savin, 2016); **fast pace of diffusion**, facilitated by its cross-sectoral nature, with various different industries at the same time taking benefit from productivity improvements as well as influencing technological adoption in other, related industries (Andergassen, Nardini, & Ricottilli, 2016); and finally an **innovation-spawning tendency** in terms of new products and services, which unfolds and gains momentum across time (Cantner & Vannuccini, 2012).

However, if we borrow part of the definition of emerging technology by Rotolo et al., (2015), "its most prominent *impact … lies in the future and so in the emergence phase [it] is still somewhat uncertain and ambiguous*". Such **uncertainty and ambiguity** are magnified by the fact that the specific AI technologies (not to speak about custom solutions) are so **numerous and diversified** that only by narrowing the focus on each of them it would be possible to assess their actual time to market (Girasa, 2020). Said differently, multiple rounds of experimentation are required before an AI solution is adopted and this may generate **issues or delays** in the materialisation of the expected impacts from its implementation and use.

While the potential of AI is great**, it is far from straightforward that this promising technology gets applied in the public sector**. Current examples of AI used in public services show that there are many different underlying factors and conditions to ensure the adoption of these technologies, starting from ensuring data access to develop AI models up to generating end-user acceptance (Desouza, Dawson, & Chenok, 2020). **AI-enabled public sector innovation is however the result of several concurrent elements, which are barely technological in essence** (van Noordt & Misuraca, 2020b). These include legal, organisational, workforce-related, environmental, ethical or societal aspects that are often overlooked by a perspective embedded in technology determinism. Public sector organisations must be ready or, at least, should strive to strongly advance in all such aspects before they can start developing or using AI to maximize its potential and minimize related risks. **Unfortunately, these other requirements are often overlooked**, with most resources going to technological development. This is not the best choice, as the state of digitalization in the public sector across the European Union, from the central administration down to the local administrations, still

[5] https://eur-lex.europa.eu/content/news/building_EU_data_economy.html

requires significant progress in all aspects, and not only technological, in order to benefit the most from the potential of AI.

Current trials and experiments involving AI in government now and soon are likely to determine to which extent they are going to drive the digital transformation of Europe's public administration. In fact, as also highlighted by recent publications of the JRC, there is still very little knowledge about the effects and consequences of the use of AI technologies within public administration (Barcevičius et al., 2019; Misuraca and van Noordt, 2020). **Empirical work is very scarce on how developed AI solutions work in practice and whether they are obtaining intended results successfully**, which is crucial for establishing a common knowledge base to share best practices among public administrations across borders. While there have been mentions of successful pilots with AI in the public sector, it remains challenging for public bodies to integrate these solutions into the day-to-day operations of the administration. If this remains difficult, it could be that successful pilots of AI halt after a time, due to the end of funding, lack of personnel to ensure continuity or other causes, thus wasting the opportunity to have a sustainable and positive impact on the business of government. The challenge of **overcoming 'ever-pilots'** or ensuring integration in regular work practices is not new in public sector innovation, but critical to harness the potential benefit of AI for the time being.

This challenge is not unrelated to the discourse on AI as General Purpose Technology, because the diffusion of AI technologies in the public sector can certainly contribute to the modernisation of European public administration, but also support the emergence of **industrial "champions" in this key technological domain**, potentially able to play the role of pan-European service providers.

In fact, compared with the US and China, the value of the European market for GovTech solutions – which AI empowered government applications are part of – is only a small fraction according to available estimates However investments are expected to grow in the next years.

Before the Covid19 crisis, a study from the Polish Economic Institute reports that the European expenditures on new technologies for public administration are in the range of €22 billion per year, about 6% of global demand, though expected to treble until 2025[6].

Moreover, a recent publication by the JRC (Dalla Benetta, Maciej, & Nepelski, 2021) reports that the AI investments for the European public sector account for 41% of total AI investments in 2019. This includes outlays on AI education as well as the adoption of AI technologies by the public sector. Compared to 2018, in 2019 AI investments in the EU grew by approximately €2.1-2.5 billion (39%). If growth will remain constant, by 2025 the AI investments will reach €22.4 billion. Hence it will surpass the target, set at €20 billion.

On the supply side, a very similar proportion was found in global GovTech deals (only 7% compared with 85% in the US) according to the Founders Intelligence think tank[7]. It is quite likely that this situation has remained unchanged during the pandemic, also in light of the low propensity to spend on ICT R&D of the EU public sector, which will be supported with evidence in Section 4 of this report.

1.2 Policy background

To gain better visibility of the above issues, in December 2018 the European Commission launched a dedicated initiative denominated "**AI Watch**". The initiative is a monitoring tool of the progress and achievements of the Coordinated Plan on the Development and Use of AI "Made in Europe" (European Commission, 2018a, 2018b, 2021b). A specific activity within AI Watch deals with AI in the public sector and, in a recently published study (Misuraca and van Noordt, 2020), presented the results of a first exploratory mapping of the use of AI in EU national, regional, and local government bodies and agencies. An inventory of 230 (and counting) interesting cases of AI adoption was built, covering all 27 EU Member States, as well as Norway, Switzerland, and the UK. Also, a narrow focus was set on eight illustrative examples, highlighting the problems and perils of AI implementation. In particular, the findings from case histories revealed that the **ethical, societal and organisational/HR implications of AI use in government** should be a matter of high concern for prospective adopters, notably because of the difficulty of predicting impacts in full when relevant decisions are taken. Another important piece of evidence was that **not only the technologies but also their uses were**

[6] Source: https://polandin.com/42532388/govtech-market-in-europe-to-treble-by-2025-polish-think-tank
[7] Source: https://medium.com/founders-intelligence/govtech-is-europe-missing-out-again-7815251e4617

rather diverse and the respective maturity levels quite heterogeneous. This result prevented the authors from drawing too general conclusions in terms of usefulness, sustainability, and cost-benefit comparison. Finally, the **geographical spread and thematic scope** of reported cases were often **wide**, but also unevenly distributed across Member States, government functions[8], and tiers of public administration. This was probably due to the use of secondary sources, of heterogeneous nature, for data collection, which hindered comparability to a great extent.

Additionally, the collection also included several **proofs of concept and temporary experimental trials**, not only permanent embeddings in the realm of public service (or policy), showing the importance of keeping up the distinction between "adoption" and "implementation" of AI. Moreover, a few specific cases, mentioned as running at the time of first gathering, were later found to have been **discontinued because of various reasons**, including significant criticism received from the general public, pressure from adversarial political forces or even executive orders from local courts of criminal justice.

Further, the AI Watch for the public sector study included a "deep dive" into eight **detailed case histories**, which confirmed that the ethical, privacy and social responsibility related concerns associated with the concept of "**trustworthy AI**", as first introduced by the High Level Expert Group on AI (HLEG) appointed by the European Commission[9] were fully grounded.

Even if **the evidence obtained in the study was an early exploration of the underlying (still largely unknown) universe of EU public sector organisations**, the study proposed **a taxonomy based on 10 "AI typologies"**, not with the ambition of systematizing a fast-evolving domain, but with the more practical intention of mapping the potential uses of this technology, as detected from the inside of the application cases.

Despite all the mentioned limitations, a number of findings are noteworthy from that study, which constitutes a sort of starting point for this follow-up publication. These include:

- A hands-on demonstration of the **increasing importance gained by AI in the EU-27 public sector**[10], both in support of existing processes and services – with an eye on efficiency, effectiveness and quality – and of their digital transformation into radically new ones;
- The **experimental nature of many**, potentially highly impactful, but still waiting to be validated or finalised, **thematic applications**;
- The **huge diversity of used technologies and related solutions**, still in search of a critical mass for permanent establishment at government site and of a credible scalability pathway for EU- (or national-) wide diffusion or replication[11];
- Widespread **awareness of the role of public policy** to promote and facilitate, but also regulate and manage AI implementation in the practice of government, as witnessed by the concurrent emergence of national strategies – though at different speeds – in almost all EU Member States; and
- The need was highlighted to **develop a socio-economic impact assessment framework**, looking beneath the surface of the supposedly unequivocal benefits of AI take-up in government.

1.3 What this report is about

In continuity with this work schedule, this publication aims to **develop an analytical framework of the impact potential of AI in government**. It does so by elaborating further reflections on available evidence –

[8] These were defined according to the COFOG functional classification of government originally developed by the OECD in 1999 and published by the United Nations, see: https://unstats.un.org/unsd/classifications/Family/Detail/4, which is well established in statistical research and practice. However, it should be borne in mind that such a "business oriented" definition of activities of public relevance leaves room for the inclusion (although only in few cases, such as in healthcare) of a number of entities that are not actually governed by public law.

[9] https://ec.europa.eu/digital-single-market/en/high-level-expert-group-artificial-intelligence

[10] The analysis and database of cases also included evidence from non-EU countries such as Norway, Switzerland and the UK.

[11] With all possible caveats related to the sampling mechanism, a relative prevalence was spotted in the observed cases of the following AI applications: Chatbots, Intelligent Digital Assistants, Virtual Agents and Recommendation Systems – followed at some distance by Predictive Analytics, Simulation and Data Visualisation.

also from third parties – as well as other noteworthy elements of the previous AI Watch for the public sector study. The latter also included a survey of national AI strategies and the inputs gathered from EU Member States at a first Peer Learning Workshop held in February 2020[12], which was followed by a second edition in September 2020, the results of which are separately reported by another JRC publication (van Noordt and Pignatelli, 2020)[13] and are taken into account as inputs for the reasoning attempted here.

Our starting assumption, better elaborated in Section 2 of this report, but still lacking firm empirical evidence in support, is that **a successful appropriation of AI brings with it a higher level of complexity than "conventional" ICT**. Said differently, the chances that (other things being equal) a private or even public sector organisation may plan and execute successfully and in a given time all the steps belonging to the adoption and implementation process are lower in the case of AI than ICT, with a greater likelihood of interrupting, stopping of reiterating some step.

In particular, for public administrations, the following key analytical, but also very pragmatic questions arise: what kind of evidence is available about the successful implementation of AI in public administrations? Which are the immediate results and longer-term outcomes/impacts? How long did it take to materialise that evidence? How many resources (financial, human, etc.) has been used? To fit this analysis into a realistic representation of the surrounding environment, **the proposed approach is systemic**: that is, it recognises that in order to understand the dynamics and potential impact of AI in such an important part of society as government, it will be necessary to go beyond the study of individual pilot site results and look at the broader interaction of actors, processes and decisions/behaviours as they occur in a multi-layered and networked operational scenario.

Learning must be systemic, because of the complexity of the European policy scenario, far higher than the corresponding US and Chinese systems analysed in Section 3, but also because of the need of singling out and widely sharing the most successful experiences of AI appropriation, in order to make them replicable and scalable in other EU public administration contexts.

To grasp these opportunities in full, the thesis of this report is that **the sustainable implementation of AI in public services is a key element for the uptake of AI in public services. In order to reach this sustainable use of AI, specific attention should be devoted to the appropriation process, defined in the report as the sum of adoption and implementation**. As the first step in that direction, Section 4 proposes a **reasoned list of the crucial challenges** that the EU public sector is facing at all levels on the way towards a diffused adoption and implementation of AI in its daily practice.

Section 5 – the last before the conclusions – proposes a set of common actions for EU decision-makers willing to undertake the systemic approach to AI governance towards a more advanced position between AI promotion and regulation in the public sector. Such a position is primarily suited at the level of coordination between the European Commission and the Member States.

The concluding Section 6 summarizes the key arguments made throughout the report and relates them to the upcoming work in AI Watch during the year 2021. It also presents the first version of the analytical framework for AI impact assessment in the public sector, which is associated with a number of testable implications for future field work, both within AI Watch and outside it.

In the coming months and years, adequate finance will be mobilised to support the experimental deployment of AI solutions in the EU public sector. This is encouraging, however, it remains of tantamount importance that these resources are finalised to a human-centric reshaping of government practice in Europe and that the introduction of AI enabled components in processes and services becomes pervasive at all administration levels, including across the country borders.

[12] https://knowledge4policy.ec.europa.eu/ai-watch/ai-watch-peer-learning-workshop-ai-use-impact-public-services_en

[13] For a full overview of the current situation at EU level the reader can consult the following URL: https://knowledge4policy.ec.europa.eu/ai-watch/national-strategies-artificial-intelligence_en

2 Definitions and concepts

This Section gathers most of the concepts acting as theoretical foundations of the proposed analytical framework of AI impact assessment in government. In particular, **three main messages are delivered to the attention of EU experts and practitioners**, to start materialising the "systemic way" of policy-oriented learning introduced in the first Section of this report:

- The analysis and evaluation of the impact potential of AI in government should not stop at the phase of adoption, but continue up to including the outputs and outcomes of the implementation phase. These two phases jointly constitute what we name technology appropriation in general, and AI appropriation specifically. See the following paragraph 2.1 for more details;
- For the success of AI appropriation, "context matters", in all its aspects, which are not necessarily only technical (e.g. they may be also legal, societal, or organisational) and add to the requirements of the expected users of the newly introduced solutions. See paragraph 2.2 for an in-depth discussion;
- While evidence is being gathered from individual AI case studies in terms of benefits and drawbacks, a systemic learning approach should be followed, enabling public policy, at EU and Member State levels, without forgetting the Regional and (at least the major) City governments[14], to build the conditions for AI take-up trials to be truly transformative for the public sector, leaving the status of technological and organisational singularities. How to achieve this goal is presented in the final paragraph 2.3 of this Section.

2.1 From adoption to implementation: the process of AI technology appropriation

Technology is broadly considered as a **social construct**, resulting from the convergence of the needs, tensions, ideas and actions (even contradictory sometimes) of human beings and social groups (Pinch & Bijker, 1984). However, technology is also known to **shape the course of societal life**, if not determining it, for the various aspects it touches and affects, which may well include cultural practices and interpersonal relations – as the examples of personal computing (Robinson, Barth, & Kohut, 1997), mobile phones (Ling, 2010) and social media networks (Simplilearn, 2016) convincingly demonstrate. These two opposite perspectives used to be contrasting each other, however, in the past few decades they have evolved into a unitary vision that speaks in terms of **co-construction of technology and society** (Feenberg, 2010).

Government – meant as a group of people with the authority to rule a community, depending on whether professionally or politically engaged – is also part of society. It can exercise power in various ways, as outlined above. Because of its large purchasing power (public procurement accounts for almost 25% of GDP in Europe), government can pull innovation to market and it can also be a prime mover, or a leader when it comes to technology change. In doing so, the fundamental act igniting the process is a public purchase, realised according to the rules of **public procurement**: "of innovation", if the case applies, or traditional procurement.

Put this way – i.e. with government seen as an integral part of society, and having the possibility of initiating or supporting the adoption and diffusion processes (Rogers, 2010) of novel technologies, particularly those with the stamina of positive and widespread impacts on the population – the vision of technology and society being reciprocally co-constructed gains two more analytical dimensions. On the one hand, government uncovers an additional policy instrument promptly available, that is public procurement, which can be used to accelerate or redirect technological change in the local or global environments; for example, towards sustainability (United Nations, 2017). On the other hand, by introducing more and more technologies in its own area of operation, government inevitably transforms itself and the way it delivers value to other societal actors – such as citizens and businesses, but also the policy makers and civil servants who work within it[15].

The theory (and practice) of **technology adoption in government** has a long history and plenty of evidence is now available, including controversial endeavours and unachieved goals. Quite interestingly, Vedung's original discourse on policy instruments was motivated by a perceived lack of understanding – more than twenty years

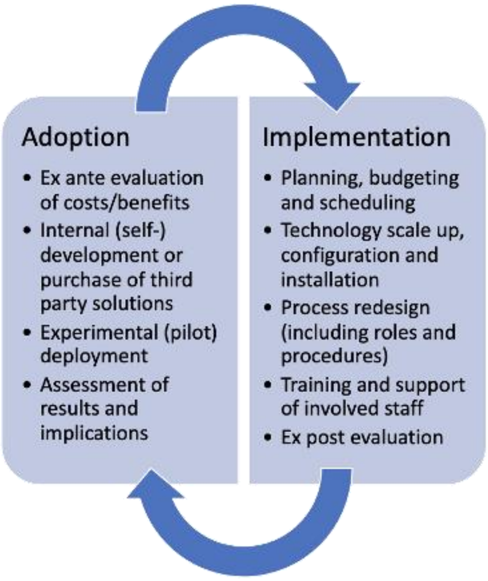
[14] In facts, several regions have their own AI strategy and some cities are in the forefront with respect to AI adoption. See for example the DT4REGIONS project: https://openlivinglabdays.com/enacting-digital-transformation/

[15] A specific field of research and practice is digital transformation of government (Hinings, Gegenhuber, & Greenwood, 2018), which has gained prominence in the recent academic debate. However, we prefer using the more generic concept of technology adoption and implementation, to align better with some of our reference sources (Jennie Carroll and Andrew Feenberg, above all) and also to include non-digital technologies (Barley, 1986; Delaney, Timbrell, & Chan, 2008) in the picture we are trying to draft herein.

ago – on the tools that could be used by public decision-makers willing to interfere with the course of societal actions (Vedung, 1998). Usually, such interference is referred to as **governance** (Hufty, 2011): a topic widely studied, and practised, over the past decades, in all its possible articulations (actors, stakeholders, territories, goals, needs, processes, even supportive technologies). There is one major exception: the problems and perils of **technology implementation**. Technology implementation comes right after the adoption phase and describes the transformative impacts of the permanence of that technology in the body of the organisation.

Keeping adoption and implementation conceptually distinct brings advantages[16]. The most important is to highlight the existence of a **gap** that is connatural to any process of **technology appropriation**[17]. This gap separates the phase where innovation is tested and evaluated for potential use from the phase where the underlying, technology enhanced product or service process is permanently affected and transformed into something different than what it used to look like before.

Figure 1. Technology appropriation disentangled.



Source: JRC, own elaboration.

The existence of this gap, which is made evident in Figure 1 by the fracture between the two halves of the rectangle, is even more clear if we read the (exemplary) list of tasks belonging to each of the two phases. There is little overlap if any at all. However, the most important thing is that **the global process of appropriation may well become cyclical** – that is, with its two phases of adoption and implementation alternating and repeating across time, in the framework of the same business application. This is because there is no guarantee that even a successful ending of a technology trial – particularly in, but not limited to, public sector organisations – will immediately and almost automatically yield the embedment of the corresponding technology, as it was trialled, in the daily operation of that organisation.

Echoes of this distinction between adoption and implementation can also be retrieved in the organisational literature stream initiated by James March (1991) when describing the fundamental tension – determined by the scarcity of available resources – between **exploration** "*captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation*" and **exploitation**, "*including such things as refinement, choice, production, efficiency, selection, implementation, execution*".

[16] Similar to the ones introduced by the taxonomy proposed by (Vedung, 1998).

[17] By this term, we roughly point at the union of adoption and implementation, also bearing in mind that individual and group users of a certain technology after it is embedded in an organisational setup make changes to both the technology and the environment, which inevitably feed back into both steps of the singled-out process (Barley, 1986; Carroll, 2004).

Whatever direction the organisation takes is unsatisfactory: exploration without exploitation may look like an unjustified investment of time and efforts in knowledge development or acquisition, while exploitation without exploration brings with it a number of risks related to a superficial appraisal of the convenience of that specific knowledge appropriation for the good functioning and long-term survival of the organisation[18]. The suggestion from Levinthal & March (1993) is therefore to find a proper balance between the two, a goal that is however far more easily stated than achieved.

Two major modes of balancing out have been highlighted in the literature, both termed **ambidexterity** to signify the capacity of an organisation, including a government body or agency (Choi & Chandler, 2015), to play on both fronts successfully. In particular, **structural ambidexterity** occurs when a private or public entity manages to create distinct subunits or working teams, each specialising in either exploration or exploitation activities (Gupta, Smith, & Shalley, 2006). We could think of something comparable in those public sector organisations having distinct offices for – say – IT support or procurement and service operations. On the other hand, **sequential ambidexterity** takes place when organisations alternate exploration with exploitation phases across time (Tushman & O'Reilly, 1996). This brings us back to the cyclical nature of technology appropriation outlined in Figure 1 above.

Reflecting on the conceptual distinction and actual gap between adoption and implementation is vital when it comes to new and innovative technologies – such as AI, the main subject of this report. In fact, innovative technologies have the potential to bear huge transformative implications, even though those implications remain largely unknown, due to conceptual confusion between the two phases and the presence of few, anecdotal information available on the implementation phase.

Unfortunately, and as witnessed by another JRC Technical Report (Bruno, Schiavone Panni, Marchetti, Molinari, & Valente Covino, 2020) analysing more than 150 pilot experiments of public service digitalisation: "*The propensity of pilot owners to share results and lessons learned in a structured manner is quite limited and this adds noise to the evaluation of scalability potentials, not to mention the difficulty of defining reliable reuse or transfer pathways involving other public sector organisations than those in the original pilots. This lack of information is particularly undesired in case of new and emerging technologies, such as blockchain or Artificial Intelligence, which naturally lend themselves to being trialled in very similar – yet never too much – pilot contexts, thus increasing the risk of 'reinventing the wheel' – i.e. of duplication, if not proliferation, of limited size experiments*".

In fact, even the analysis done within AI Watch over a meaningful number of AI cases known has shown that many projects successfully completed the adoption phase before finding some unexpected, yet critical, issues. This happened often in the phase of implementation and it led to a partial or total dismantling of the initial technology deployment. Typical issues were legal issues, biased recommendations, staff resistance and some others. The reasons for such a failure are certainly manifold, depending on the case specificities, but they can probably be reconnected to the observed gap between the first and the second phase of technology appropriation.

Indeed, paying utmost attention to adoption is well justified by **the predominantly experimental nature of current AI solutions**, which are hardly consolidated in standard products or services that can be purchased off-the-shelf and installed without further elaboration and adaptation. However, the need for experimentation, in our opinion, should also include the way public administration and its external environment are transformed after the implementation of AI, as well as the immediate and deferred (mostly non-technological) consequences of that transformation.

As a matter of fact, the **complexities and peculiarities of public service** requirements at all levels – local, regional, national – are so binding that each success story can be described with a complex appropriation process that goes far beyond a mere transfer of an AI solution already operational in the private sector. Although we are still missing supporting evidence, we hypothesize that the level of direct engagement of public buyers with private suppliers in the co-design, experimentation and refinement of AI prototypes was comparatively higher than the hypothetical benchmark of installing an IT solution already available off-the-shelf. On many occasions, the "power" of AI was not leveraged with a full-blown solution, but through the more nuanced and

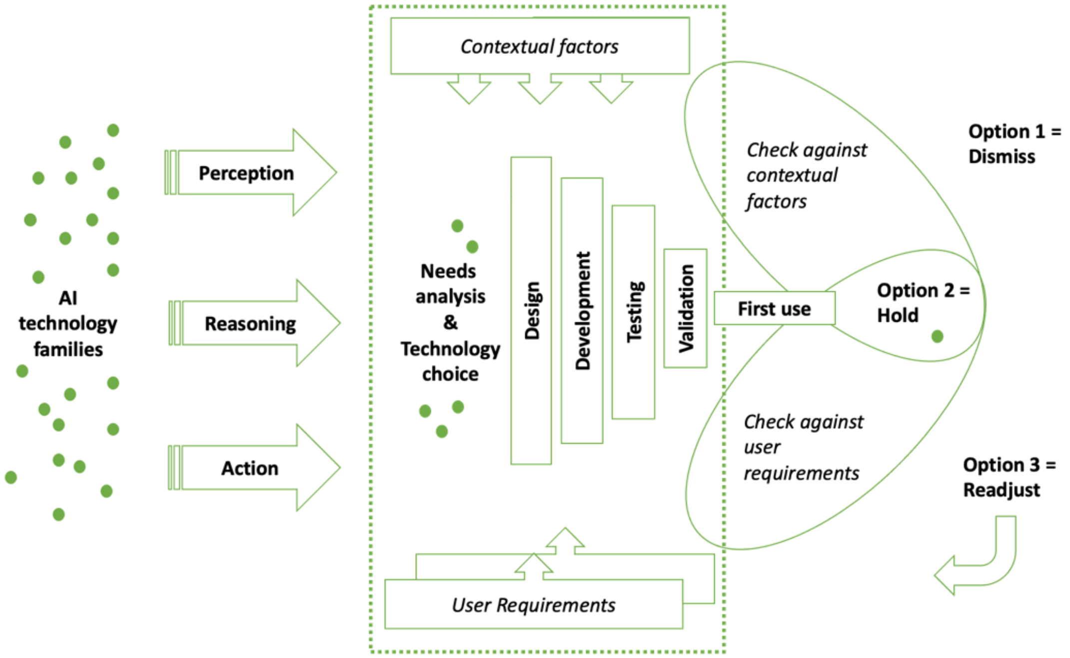
[18] An appraisal which usually consists in extrapolating from explorations undertaken elsewhere (in the case of public administration this is often the private sector).

subtle **insertion of AI technology elements** – such as the capacity to analyse data, to propose answers, or to interact with human beings – into a specific stage of the service delivery process. A considerable number of cases allegedly never went beyond the trial or piloting phase. In a few instances, the decision to "go live" was reverted because of unexpected complications or negative impacts on society, human rights etc. **This makes a "plug and play" AI solution difficult to be successfully implemented in a government context**: the best way to ensure success is the realisation of several rounds of multidisciplinary testing, refinement and validation prior to final technology embedment.

2.2 Putting AI innovation in context: the proposed analytical framework

Figure 2 is an idealistic representation of the scope of the evaluation. Given a certain collection of technologies, for instance, those globally termed "AI technology families" in the collection on the left-hand side; their appropriation inside an organisation usually starts with the creation of a subset of potentially suitable technologies.

Figure 2. The proposed analytical framework.



Source: JRC, own elaboration.

How technology choice is executed depends on several factors, the influence of which is highlighted by the use of arrows.

We know that the previous study (Misuraca and van Noordt, 2020) clustered AI technologies according to three main research and application strands, namely **Perception, Reasoning and Action**. "*Perception stands for the capacity of an intelligent machine, be it a piece of software or a robot, to understand (give meaning to) the signals coming from the external world - such as images, either still or in motion, and sound, e.g. music or speech. (…) Reasoning is … the goal to replicate/improve a human being's capacity to analyse and draw inferences from the data and information received from the external world*. (…) *Action [points at] a wide variety of application domains … both in software industry … and in hardware manufacturing*".

The technology chosen is expected to be a combination of technologies belonging to one or more strands that are suitable for the purpose. Hence, knowing which strand should be selected is the first move towards the choice.

The choice is expected to be subsequent to an analysis of **user requirements** (the elaborated needs of people inside and outside the organisation, who are going to be affected by or engaged in the future use of the AI solution):. It is extremely important to scrutinize the needs of the users to see where the automation of perception, reasoning or action (or a combination of the three) are desirable.

Finally, this exercise does not happen in a vacuum, but is or can be influenced by a number of **contextual factors**, i.e. crucial aspects of a public sector organisation's operational environment other than the specific needs and requirements that the chosen technology promises to fulfil. Contextual factors may include for instance: the nature of the service or process at hand, peer pressure from other organisations or a specific endorsement of technology change from key stakeholder groups. The following table provides a tentative list of such influential factors, the relevance of which is now being empirically assessed through direct interviews with AI Watch for public sector case owners.

Table 1. Tentative list of contextual factors.

CATEGORY	**EXAMPLES**
POLITICAL FACTORS	Elected officials endorsing the experimentation of that technology and/or its embedment in the administrative or policy processes
ORGANISATIONAL FACTORS	Support by the top and/or middle management and/or the frontline staff involved in the technology trial and/or the permanent implementation of its results inside the organisational structures
INFRASTRUCTURAL FACTORS	Availability of supporting datasets or IT equipment within the organisation adopting or implementing that technology innovation
DEMAND RELATED FACTORS	Needs expressed by third parties, i.e. other public organisations and/or their users interacting with the one engaged in technology acquisition
TECHNICAL FACTORS	Response to user needs offered by that technology and complementarity/interoperability with other IT solutions already in place of the same or similar kind
SUPPLY RELATED FACTORS	Integration of an external IT partner with functional expertise or specific capacity of the IT staff internal to the organisation
FINANCIAL FACTORS	Availability of adequate, "ad hoc" funding to the project and/or the embedment of its results in the current business practice
LEGAL FACTORS	A clear framework incentivising technology innovation, early resolution of data privacy and/or security aspects, other legal or regulatory requirements
ETHICAL FACTORS	Expected/actual and especially unwanted consequences of technology implementation to people, social groups, the environment etc.
DOMAIN FACTORS	In addition to the factors listed above, there could be various other factors, more fragmented and partially overlapping, which are dependent on the specific application domain (e.g. Health) and also on the specific geographic location (e.g. cultural factors)

Source: JRC, own elaboration.

During the adoption phase (see Figure 1) both the user requirements and (some or all of) the aforementioned contextual factors operate, and to a great extent interoperate with each other, along the familiar sequence of steps normally associated with new technology experimentation: solution design, technical development, testing and validation. These steps are visualised by a set of small vertical rectangles, of diminishing height because of the "narrowing down" process that usually starts from an initial range of options or alternative designs and prototypes to reach the final status of tested and validated technology deployment.

However, experience shows that any adopted technology rarely survives as such to the phase of implementation, as defined in the previous paragraph 2.1 – i.e. a situation that is no longer experimental, but close to permanent take-up of the newly developed solution in real use contexts. In fact, it is quite likely that during and because of usage, aspects related to human behaviour come to the surface, which were not planned by the developers (Bagozzi, 2007; Bailey & Barley, 2019). More generally, and as shown in the right part of the above picture, **the first use of a technology solution** inevitably leads to check its actual performance against the user requirements and the contextual factors considered as most influential on its choice and initial configuration. This **may lead to a variety of alternative outcomes, including dismissal** (Option 1), **confirmation without revisions** (Option 2), or a reiteration of the design-development-testing-validation process, to achieve **a different type of custom solution** (Option 3).

This variety of outcomes is mirrored by the evidence gathered in the AI Watch cases mentioned in (Misuraca and van Noordt, 2020) and probably also reflects the field experiences of most readers of this report. For the purposes of this report, which are related to the delivery of an analytical framework for assessing the impact potential of AI in government – indeed, one of the main expected outputs of the AI Watch for the public sector activity as a whole – the discussion should highlight three important implications:

1. **The first use of an AI solution is crucial** to refine or perfect its initial deployment. Probably more so because of the highly experimental nature of AI and the absence of suitable "plug and play" applications not needing further customisation. However, **it is not easy to achieve first use in controlled conditions** within real or realistic public sector environments, and this may be an obstacle for a more diffused take-up of AI in government;
1. **Relevant user requirements**, for shaping AI adoption, should not only reflect citizen and business needs in terms of service transformation but also extensively **include governmental actors**, from civil servants using the newly introduced solution in their daily work to managers responsible for service delivery and held accountable for its quality, transparency, etc.;
2. Alongside requirements, **contextual factors are also very important**. These are not only technical or infrastructural but legal, societal, organisational, ethical etc. Roles and accountability have to be assigned and defined appropriately. A tentative list is provided in Table 1 above and their consideration as potential drivers or barriers should accompany both phases of the AI appropriation process, i.e. not only adoption (or exploration) but also implementation (or exploitation).

When looking at context systematically, however, the first allowance to be made is its uncontrolled variability across time. This means that the same contextual factors may change, or act differently in relation to the same AI appropriation process, including because they are influenced by the appropriation process itself.

For example, in a related study, De Nigris et al., 2020 described the connection between AI take-up and Covid19 in terms that can be paraphrased as follows: in many EU countries, the curve of newly adopted AI solutions in healthcare has become almost as exponential as the contagion curve itself. Despite the absence of systematic field evidence, we can speculate that the unusual pressure (both in terms of time and scope) from the external and unforeseen circumstances related to the pandemic among other effects has forced many national authorities in charge of public healthcare to take a fresh look at the datasets they were already in possession of, as well as increasing the amount of funding available and allowed for more risk taking. For sure, the huge amount of potentially useful (if not vital) but till then unexploited information demanded a totally new approach to data handling and sharing, which was to be made compatible with the changing user requirements, as forced by the emergency situation.

Put in this way, fighting the **data overload issue** and increasing the **quality of intelligence** may have been the two most relevant needs fulfilled by choosing AI as a technological solution. Nevertheless, there is more: proceeding from adoption to implementation, healthcare users may have started to create new datasets or trial new uses of data that weren't considered relevant in the former, indubitably quieter and more predictable, scenario. On the one hand, this new data may have acted as a solid justification for continuing the use of that solution. On the other hand, it would require a supplement of reflection on the compliance with all the contextual aspects (above all ethical and legal factors).

Whether that could be the start of one of those massive imitation and emulation processes that are well known in the organisational learning literature (DiMaggio & Powell, 1983) through which innovation becomes widespread in the public sector it is too early to say. What can be anticipated is that its materialisation would most likely need a supplement of result analysis, strategic planning and maybe concerted action among the EU and Member States.

Also, in light of this example, however, it seems indispensable to include the implementation phase – which other authors call technology "**institutionalisation**" or "**instrumentalisation**" – into the scope of AI impact evaluation. During that phase, the use of an algorithm or any other developed component becomes permanently embedded in the functioning model of the public sector organisation, in ways that ultimately affect, and are affected by, the broader context the organisation belongs to. This can also include interoperability with existing datasets and services, creation of new AI-enables services, and collaboration with other agencies and bodies in the generation of perceived value for public service beneficiaries.

2.3 What can we learn? Towards a systemic view of AI appropriation in the public sector

The broadened analytical perspective proposed in this Section has two major implications in terms of the evaluation approach. The **first** is to transcend the consideration of AI as a **technological singularity**, i.e. something that came out of the blue and the organisational or societal impacts of which cannot be controlled for (Vinge, 1993). The second is to overcome the specular appraisal of AI as an **organisational or service singularity,** based on the assumption that success (or failure), of a certain AI technology appropriation, is irredeemably related to the specific conditions framing that process, and those conditions are unique and will never be replicable in different locations. Overcoming this aspect means going beyond the narrative of a single, unique case (Schon, 1983), looking at "*what works for whom and in what circumstances*" (Tilley, 2000). This implies starting the analysis and evaluation of a case with the goal to describe and generalise **the changes that occur in a public sector organisation – and in the broader context, it belongs to – as a result of AI appropriation.** Mapping these changes can help qualify the anecdotal evidence extracted from the cases analysed by the AI Watch for the public sector activity so far, in terms of lessons learned and suggestions for improvement, scalability potential or avoidance of duplicate efforts. Positioned as they are at the stage of implementation, rather than adoption, of AI technology in government, the cases mapped deep dive into the "black box" of public service redesign, reengineering, and restructuring – in one word, innovation. And any innovation is either pervasive, or ubiquitous, outside and inside an organisation, or cannot even be named as such (Bachman & Bozzone, 2011). This report goes exactly in this direction, and more research is still to come within the AI Watch.

Of course, some of the changes brought about may be negative, rather than positive. Just a mention of the known challenges, and often barriers and constraints, related to ICT (not only AI) take-up in government is enough to show that the devil is really in the details. Nevertheless, the learning aspect may concern which new **regulatory initiatives or investment programmes are most appropriate to enhance the positive and reduce the negative consequences** of transforming the business practice of the public bodies or agencies involved.

However, at this stage, the information already available from previous studies is too qualitative and anecdotal and it is mainly looking at specific case studies. Therefore, in the remainder of this report, we will focus on **what public policy should learn** from the available collection of cases (including failure stories) in such a way to **make learning as systemic as the nature of the cases themselves** seems to suggest.

In his seminal article, Evert Vedung (1998) introduced a popular taxonomy of policy instruments, suggesting that research on their functioning, effectiveness and impacts was still in its infancy at the time:

- **Regulation** ("*Sticks*"), which obliges people and organisations to a certain proactive behaviour against the threat of a penalty or punishment;
- **Incentives** ("*Carrots*"), mostly of economic or financial nature, although subsequent evidence has suggested that other influential 'nudges' should be considered, such as reputation and confidence/trust (Reisch et al., 2017);
- **Persuasion** ("*Sermons*"), the defining property of which is the use of rational arguments to motivate certain patterns of behavioural change.

According to Vedung, but also common sense, the "*degree of constraint intended by the policymakers*" declines from "Sticks" to "Carrots" and from "Nudges" to "Sermons". This leaves the issue partly unattended of which degrees of freedom societal actors are left with (or keep for themselves) by each instrument; including in, but not limited to, the exercise of innovation and use of technology in real life application domains. However, the role government can play is much broader, particularly in relation to diffusing digitalisation processes, which have influence not only on the technological change but also on the very evolution of society (of which, public sector transformation is a part).

Analysing the possible roles the Public Sector can play in the diffusion of AI, we can borrow from a taxonomy Borrás and Edler (2020) have suggested for the area of **Smart Cities**. In fact, research on smart cities is closely related to research on AI, above all because local government is one of the greatest producers of big data – the fuel of the AI engine – worldwide (Allam & Dhunny, 2019). Six of the 13 roles identified by Borrás and Edler (2020) are directly pertinent to an AI implementation process:

- **Facilitator** of some change dynamics autonomously initiated by the private sector (European Commission, 2011);
- **Lead user and co-designer** of particular solutions to public needs, technology supported;
- **Direct initiator of projects** for the transformation of the targeted (governed) community/constituency;
- **Promoter of third-party solutions** that need to be experimented in a real or realistic environment;
- **Enabler of societal engagement**, thus encouraging the participation of active stakeholders in defining the direction of change; and
- **Gatekeeper**, thus regulating access and fruition of public spaces, resting under its ownership, by other involved actors.

The existence of these roles acknowledges the existence of a broad network of actors that revolve around AI implementation. This network includes both governmental and non-governmental actors. The latter deserve specific attention. In fact, those are actors external to the governmental body but their collective and individual behaviours contribute to the achievement of the desired (or unexpected) outputs and outcomes. This element is often highlighted in the various cases of AI appropriation.

This is one of the possible meanings that can be attributed to the distinction introduced by the previous study (Misuraca and van Noordt, 2020) between "*governing with AI*" and "*governing AI*". In fact, these are not two separate and distinct policy lines, but simply two sides of the same coin, with the important, additional element constituted by the already highlighted importance of the **context** in which operations are taking place, described and generating their implications.

This vision is not new and has recently gained even more visibility and momentum. Two examples may suffice to demonstrate this.

First, the OECD Observatory of Public Sector Innovation, after reviewing national AI strategies, concluded that the most robust (and therefore useful) ones are those **holistic and systems focused** – i.e. that "*encompass all the various level of government and are attuned to structures and systems within the public sector that AI can influence or are trialled within. They are also considerate of the interactions of other sectors and stakeholders*" (Santos & Héang, 2019).

Second, in a recent JRC Technical Report on Projecting Opportunities for INdustrial Transitions (POINT), AI is considered an **industrial theme of growing global importance** for the EU Regions and Member States engaged in refining or extending the priorities of the respective Smart Specialisation Strategies (S3), in preparation for the next multi-annual financing period of the Structural Funds 2021-2027. In accordance with criterion No. 6 of the enabling condition of Good Governance, appropriate **actions to manage the industrial transition** are those "*that harness cross-portfolio complementarities (e.g. between ministries and between levels of governance) and cross-stakeholder coordination (e.g. between businesses and broad constituencies of consumers/users)*" (Pontikakis et al., 2020).

Already in 2018, however, **the EU as a whole**, rather than individual countries or regions, was identified as the **ideal dimension for coordination of AI adoption and implementation policies**, especially in, though not limited to, the public sector. This is one of the key commitments of the Declaration of Cooperation on Artificial Intelligence[19], signed by all Member States, which also embraced the sharing of best practice examples

[19] https://ec.europa.eu/digital-single-market/en/news/eu-member-states-sign-cooperate-artificial-intelligence

in procuring and using AI in government, as well as in open data development and deployment. The **connection between AI, Open Data and public sector digitalisation** is also documented in the White Paper on Artificial Intelligence[20] and the European Data Strategy[21] – both issued on the same day in February 2020 by the new Von der Leyen Commission.

As usual, a strategic direction is the first element of any viable policy. Now it certainly is the case that at a high political level the direction is very clear: quoting the **White Paper on Artificial Intelligence – A European approach to excellence and trust** (European Commission, 2020d), "*the Commission is committed to enabling scientific breakthrough, to preserving the EU's technological leadership and to ensuring that new technologies are at the service of all Europeans – improving their lives while respecting their rights*". This direction is also widely shared among the EU Member States, all of whom – including Norway, Switzerland and UK – are among the signatories of the Declaration of Cooperation on AI adopted on 10th April 2018 and reconfirmed with very few deviations within the National AI Strategies as also indicated by the Coordinated Plan on AI (European Commission, 2018b) and its recent review (European Commission, 2021a).

When it comes to AI in government, however, the picture becomes fuzzier. As Misuraca and van Noordt (2020) pointed out in their overview of state of the art, a "*sermon based*" approach seem to prevail in those EU countries that are taking action to stimulate the use of AI in public policies and services. Soft policy instruments abound, such as awareness raising campaigns, calls to improve data quality, and employee training initiatives. However, and with some exceptions, their inspiration does not seem to go beyond considering public administration's role as instrumental to (and maybe peripheral in) achieving the European goal of value laden and ethically responsible AI development and deployment.

As a matter of fact, **public administration is not identical to any other potential (corporate) adopter of AI** that is already active in this market. Hence AI appropriation should not be pursued, however, by the mechanical transposition of technologies that worked well (or at least seemed to work well) in the private sector, despite the fact that AI takes on the distinctive features of a General Purpose Technology: pervasive, fast-paced in its diffusion, and innovation spawning. In fact, **the distinctive traits of public administration in general, and the EU public sector specifically, are so peculiar and influential that the diffusion of AI technologies evidently follows alternative pathways**, which must be understood first, and then coherently acted upon.

[20] COM(2020) 65 final. Online: https://ec.europa.eu/info/publications/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en

[21] COM(2020) 66 final. Online: https://ec.europa.eu/info/sites/info/files/communication-european-strategy-data-19feb2020_en.pdf

3 Lessons from the US and China

In Section 2 we have made the argument that a systemic view is needed to overcome the singularities of AI take-up in the public sector. Here after a quick comparison with US and China, we highlight that a lack of policy focus on the actual level of appropriation of AI technologies in government is common to all, though the EU might be in a more favourable position to counteract this limitation earlier and more extensively. Specifically, paragraph 3.1 outlines, as a general and common issue to the three regions, that very little information is currently available on AI take-up and use in the respective Public Sector, and to a great extent also private sectors. Then, the next two paragraphs 3.2 and 3.3 briefly report about known initiatives – in the US and China, respectively – to stimulate the use of AI solutions in public administration. Finally, paragraph 3.4 wraps up the previous discussion and proposes to translate the systemic approach in terms of policy challenges and implications, thus introducing the reader to the contents of the following two Sections.

3.1 The terms of the techno-economic race

In the discourse about AI development, a global race between the US, China and the EU is often mentioned as ongoing (Craglia et al., 2018). International comparisons in terms of private investments, research and education projects, market applications and other metrics related to **AI development** are often mentioned within this discourse. Moreover, there is a great interest to identify the big players in the AI field, as it is believed that successful AI companies can bring substantial economic (and geopolitical) benefits. This is consequent to considering that AI business models tend to have a 'winner takes all-effect' (Makridakis, 2017): successful AI services tend to have more users involved in their use, which in return brings more data to the company owning the service, allowing for further optimisation of the initial AI system and gaining further advantage on the competition.

One of the most commonly mentioned metrics is the **size of private investments into AI** the three regions can record. McKinsey has estimated that the **US holds by far the lead in this ranking, with around 20 times higher value than Europe** between 2012 and 2018. In China, private investments have also increased rapidly in the last few years, leading to approach the US performance quite closely now (McKinsey, 2019). **Since 70% of global AI investment comes from private companies, this is a significant gap government funding is inadequate to cover**. In addition to having this large volume of investment, the US is also home to many of the largest technology companies who are also able to gather large quantities of data from people all over the world, which can be used for further developing their AI applications (Craglia et al., 2018). Europe, instead, has far less venture and public capital invested in GovTech solutions, which makes it **challenging for EU start-ups to access adequate resources and grow**. Some countries, indeed, have been allocating more finance recently, such as the UK, Germany and France, which has turned the UK already into one of the top five global markets for AI investments. However, in the Southern, Eastern and the smallest European countries far fewer investments in AI have materialised in general. This points at another anomaly in the comparison with the US and China, with the EU not only lagging behind significantly in terms of private sector investment but also suffering from an unequal distribution among its Member States. This could mean that, over time**, gaps between European countries might widen and lead to furthering the unequal distribution of potential benefits from AI uptake in their societies** (Shearer, Stirling, & Pasquarelli, 2020).

These findings are further supported by a related analysis of **techno-economic segments** conducted at AI Watch (De Prato et al., 2019). This showed that overall most AI players are located in the US with a high number of firms involved in AI development. According to this analysis, the US is strongly represented in all thematic areas of AI, such as Computer Vision, Robotics and Automation, Natural Language Processing and others. Additionally, the report shows that China closely follows the US in terms of a number of active AI players, with many specializing in Computer Vision, Machine Learning and Connected and Automated Vehicles, and has the highest number of governmental and research institutions involved in AI. The EU also takes a strong role worldwide, but mostly in research.

The analysis also shows that few AI companies in the EU file for patents and many of them are quite young compared to the US and China. Among the possible reasons for this performance, the principal seems (McKinsey, 2019) to point at the lack of human resources in the domain, low levels of employment in the ICT industry, a structural lack of innovation propensity in the private sector and the existence of only a limited number of tech hubs in Europe. Moreover, there are also some US-based companies entering the EU market where there is only a limited number of EU players. In particular, this phenomenon is observed at the local level o the take-up of local digital twins by cities.

While the EU lags behind in terms of private sector investment, **the European academic sector is much stronger**. For more than 20 years, the most influential academic papers on AI have come from European research institutions (McKinsey, 2020a). However, the AI Index 2019 reports that authors of AI publications from the US gain more citations than the EU's and China's academic publications (Perrault et al., 2019).

The reverse side of AI development is uptake. Here international comparisons are less easy because **very little information is available worldwide about the use of AI in companies and public sector organizations**. A few surveys have identified and measured the propensity to adopt AI in businesses, but especially China is not represented in them. Additionally, not all surveys use comparable methodologies or give general results for the entire region. Often the components of the technology families are not clearly described, there can be different understandings of what AI is or is not, the sophistication of used analytical techniques is varying and the purpose for which AI is adopted is vaguely defined. Thus, it **remains difficult to compare adoption rates, specialisations and purposes for adoption**.

As an example, a global study done by McKinsey in 2020 shows that 50% of respondents adopted AI in at least one business function (McKinsey Analytics, 2020). That ratio was in fact lower than the year before, with 58% of the respondents doing so in 2019. A closer look, however, shows that this difference is explained due to a slight change in the survey question. So, AI adoption was considered to be more or less equal to last year across the different regions, showing that there was not a large difference between the US, China and the EU. Similarly, a survey done by the firm Cognilytica in January 2020 reported that 40% of industry respondents were currently implementing at least one AI project or plan. Their findings highlighted that companies from the US were more actively engaged in the short term than in both the EU and China, which seem to have more propensity for the long term (Cognilytica, 2020).

The EC also carried out a survey among companies to assess their propensity to adopt AI technologies (European Commission, 2020c). This found out that **42% of EU-27 enterprises are using at least one AI technology.** However, a similarly sized group of 40% of respondents stated they did not use AI nor intended to do so in the following two years. Technology wise, no AI family has a particularly high uptake, as the Figure below shows.

Figure 3. Propensity to adopt AI across EU-27 enterprises.

AI technologies	Currently use it	Plan to use it
Process or equipment optimisation	13%	11%
Anomaly detection	13%	7%
Process automation	12%	11%
Forecasting, price optimization and decision-making	10%	10%
Natural language processing	10%	8%
Autonomous machines	9%	7%
Computer vision	9%	7%
Recommendation/personalisation engines		7%
Creative and experimentation activities	7%	4%
Sentiment analysis	3%	3%

Base question Q1: What is the current state of adoption in your firm for [AI technologies]?; Base size: EU27, N=8661. (Base size represents only EU27 Member States, excluding the UK, Iceland and Norway).

Source: (European Commission, 2020c).

Larger enterprises are more than two times more likely to become adopters of AI compared to smaller and medium sized enterprises, which shows that many smaller organizations do not have the current resources to exploit these technologies to achieve corporate value. Additionally, there is a big gap between the reported 42% of companies using AI technologies, and the fact that when asked about specific families, the adoption rates are much lower. For instance, only 3% of enterprises declared to be using sentiment analysis and 13% AI for anomaly detection and process optimization. One of the reasons may be **a different understanding of what AI is and is not**: the respondents may make another mental association when asked about AI rather than its specific applications, a difficulty already noted in empirical research on AI (Krafft, Young, Katell, Huang, & Bugingo, 2019). Finally, EU entrepreneurs report **significant obstacles limiting AI adoption, such as the lack of skills within existing staff and the costs of implementing AI** technologies from scratch within their organizations.

This lack of information concerning firm level adoption is similar, possibly even more scarce, in the case of government. Despite the fact that more information is available about the proposed governance strategies and initiatives with regards to AI, as documented in overviews such as (Cath et al., 2018; Craglia et al., 2018; van Noordt & Misuraca, 2020a), **very little information is available on the (current prospective) use of AI in EU public administration**. The same goes for US and China, not to mention that similar comparability problems would emerge in the case of survey data. In fact, most of the comparisons between the EU, China and the USA regarding the use of AI by governments seems solely based on strategic policy document analysis or intentions of use – rather than actual deployment.

In the following two paragraphs, a brief overview of initiatives undertaken by the US and Chinese governments to stimulate the use of AI in the public sector is provided.

3.2 Stimulating the use of AI in the US government

In the US, the Federal Government has been designing **initiatives to develop trustworthy AI for government services**, aligned with the constitution and the creation of national value. Several Federal agencies have already been using AI for various purposes, such as processing grant applications, checking for compliance, improving of nautical charts, predictive maintenance and more. Indeed, a **first mapping of the federal use of AI technologies showed 142 uses of AI in the most significant federal agencies** (Engstrom, Ho, Sharkey, & Cuéllar, 2020a). These solutions are reported to make the government more responsive, effective, and efficient. Thus, the US administration plans to continue expanding the use of AI in the public sector.

The Federal Administration also noted that there are talent and workforce challenges limiting the increased use of AI in government. Therefore, it is looking into **how to leverage expertise from the private sector to develop strategies to increase organizational trust in adopting AI.** In addition, some federal agencies are exploring new approaches to hire, train and retain existing workers with new skills to innovate government practice with AI technologies (The White House, 2020a).

Sharing expertise and best practice with AI is seen as an important mechanism to discover meaningful use cases and re-use existing applications. Thus, **several hubs have been established in a number of federal agencies.** In the General Services Administration, the AI Center of Excellence has been established to assist in developing AI solutions, but also help organizations in assessing their AI readiness (GSA Centers of Excellence, 2020). Similarly, the Department of Defence has established a Joint Artificial Intelligence Centre in order to execute the AI strategy of the institution. This acts as a central hub to accelerate organizational adoption of AI. Lastly, the Department of Energy has established an Artificial Intelligence and Technology Office to coordinate activities among various administrations (The White House Office of Science and Technology Policy, 2020a).

Naturally, it is essential to **improve building citizens' trust in the use of AI in government through a proper governance approach.** Thus, in an executive order signed in December 2020, the Federal Government has put forward a number of principles AI in the government should adhere by during design, development, acquisition and usage (The White House, 2020b). Similarly to the EU proposals on an ethical AI use, these principles include AI being:

- **Lawful and respectful** to the American values.
- **Purposeful** so that the benefits significantly outweigh the risks.
- **Accurate, reliable, and effective** in line with the purpose it was used for.
- **Safe, secure, and resilient** so that any malicious exploitation can be avoided.
- **Understandable**, so that its ways of operation and outcomes can be understood by experts in the same subject matter.
- **Responsible and traceable**, so that the roles and responsibilities of people are well assigned. The whole process of design, development, acquisition and use, its inputs and outputs, should be documented and made traceable.
- **Regularly tested** against these principles to ensure that performance and outcomes are consistent with their intended use.
- **Transparent**, so that agencies can disclose relevant information to stakeholders in accordance with the law.
- **Accountable**, so that agencies can be held accountable for implementing and enforcing safeguards of AI.

In 2021, a roadmap will be published with policy guidance to support the implementation of these principles across various agencies so that their AI use is consistent with the order. In addition, an **inventory will be prepared by each agency with their AI use cases** to improve interagency coordination and the implementation of the use and reuse of AI. It is planned to have this collection of inventories to be made public to the extent it is possible having in mind applicable law and policy constraints. Furthermore, the Presidential

Innovation Fellows program will establish an **AI track** with the aim to attract experts to help with the design, development, acquisition and use of AI in government, so as to increase the level of AI expertise in federal government (The White House Office of Science and Technology Policy, 2020b).

Under the new Presidency of Biden, the use of AI by the Federal Government remains one of the key strategic pillars in advancing on trustworthy AI in government. Work is ongoing to support and coordinate the use of AI in Federal administrations, mostly through the CSA AI Center of Excellence which has been introduced before. In January 2021 the National AI Initiative [22] has been launched, which aims to have the USA lead the world in the development and use of AI in the private, but also the public sector. Federal agencies seem to be tasked with a leading role in contributing to both facilitating AI development and uptake of AI across society. Application areas of importance in this initiative are agriculture, environment, financial services, healthcare, national security and defence, science, transportation, infrastructures, weather forecasting and the COVID-19 pandemic. The National AI Initiative is coordinated and supported by the National Artificial Intelligence Initiative Office, located in the White House Office of Science and Technology Policy. The **State or lower levels of public administration in the US seem to be investing far less** into the development and adoption of AI, although strong statements cannot be made, due to a lack of empirical research on the topic.

To support innovation at the local level, another important initiative under the Presidency of Biden focuses on local government: in the Infrastructure Plan proposed during his campaign, President Biden promised to launch a yearly USD 1 billion competitive grant programme to help five cities pilot new planning strategies and Smart City technologies that can serve as models for the country.

Some U.S. cities seem to be waking up to the technology. Despite that, surveys show that **many State administrations in the US do not seem to be ready for the next level of digital transformation**. A 2019 survey conducted among IT executives of the 45 State agencies showed that only **1% of them have achieved broad AI adoption.** Most AI adoption is merely in the Proof of Concept or Piloting phase. It is not yet being used in the core government processes (Center for Digital Government, IBM, & NASCIO, 2019).

One of the key reported challenges is that **core enablers of AI adoption, such as organisational readiness, have not made progress in recent years**. The aforementioned survey shows that the most significant barriers to AI adoption at the State level is an **outdated legacy IT infrastructure, poor organizational culture and lack of relevant skills.** In fact, two-thirds of the respondents to that survey respectively highlighted that **(72%) did not have any policy in place regarding the responsible use of AI and (60%) did not have an actionable framework to evaluate the risks of AI implementation**. While the survey was conducted before the announcement of the federal principles and actions described before, it shows the importance of diffusing governance principles for AI across multiple levels of public administration – including those who are less likely to have the needed resources to invest heavily into AI. What the current state of AI deployment is on the municipal level is currently not known, as no study or survey could be found which assesses the diffusion of AI at this level of government.

Finally, there is **mixed support in the US public opinion to the development of AI** according to a survey of Americans. Support for developing AI varies between different subgroups, with those who are male, with a higher income or a computer background being more likely than women and people with lower education or income. However, **Americans show little confidence in governmental organisations to manage the development and use of AI technologies**. Instead, they place greater trust in technology companies using AI for the best interest – although, there was not a majority of Americans placing a 'great deal' or 'fair amount' of trust in any kind of institution. Finally, this does show that many Americans may be apprehensive of the deployment of AI by government institutions, likely to cause some trust issues if the technology gets rushed or is deployed opaquely (Zhang & Dafoe, 2019). Trust in government heavily correlates with citizens approval of government use of AI, although it varies on a case by case basis (Carrasco, Mills, Whybrew, & Jura, 2019a).

[22] https://www.ai.gov/strategic-pillars/applications/#National-Security-and-Defense

3.3 Stimulating the use of AI in the Chinese government

Recently the Chinese government plans for AI use in government services included a number of **highly controversial initiatives, especially from a European perspective,** such as the Social Credit System (see below) or the setting up of invasive surveillance systems using AI technologies to monitor minority groups. These initiatives aside, **the Chinese AI strategy is also focused on improving public services and governance through the help of AI technologies**. Thus, public sector organisations are exploring actively AI projects to address real-life problems.

In 2017, the Chinese State Council released the New Generation Artificial Intelligence Development Plan which has been acting as a unifying document for China's various AI objectives. This document lays out the importance of developing AI in various Chinese sectors, including public administration. However, other central government policies also stimulate public sector digitalisation, providing a favourable environment for exploring the use of ICT and AI in many application domains (Chen, Ran, & Gao, 2019a).

A common misunderstanding is that the national AI strategy is pushed heavily from the top; in fact, the Plan is not a directive, but more a wish list, where the **lower levels of government are expected to play a vital role to take forward the actual transformation of society through AI** (Roberts et al., 2020a). The national strategy seems to focus more on technological development, whereas experimentation and pilots are expected to be stimulated at the local level. Some local governments indeed have taken the frontrunner role and implemented AI going far beyond the current national AI policy, but also sparking some controversies. For example, cities are starting to adopt smart city initiatives, creating digital twins[23]. There, tech giants are tasked with creating open innovation platforms to boost local innovation ecosystems. Partnerships with smaller companies or start-ups are argued to be less prevalent, which clearly differs from the European approach (Elliott, 2020a).

Although much more research is needed to understand how AI applications are deployed in the Chinese public sector, despite the great emphasis on developing AI for the provision of public services, **the applications used in China are not described as being cutting edge or highly sophisticated technology. Instead, their strength lies in the integration of various systems and capability to quickly scale up** – about the same as mentioned for the AI currently in use in the US administration (Engstrom, Ho, Sharkey, & Cuéllar, 2020b). Moreover, the actual delivery of AI-enabled public services seems to be mostly due to large technology companies favoured by the central government.

An overview of AI development in China cannot exclude one of the main flagship programmes of the Chinese government: **The Social Credit System**. This is an overarching policy initiative that aims to make individuals, businesses, legal institutions, and government more trustworthy by aggregating public data and improving Chinese law enforcement (Creemers, 2018a). Sharing of data across various public sector departments is used to evaluate how someone is likely to comply with legal and contractual obligations, so as to improve the civic virtue of the population. The programme, however, **has been perceived as an Orwellian government nightmare**, by the Western media in particular, as some local governments and private companies have been experimenting with the use of **social scoring based on the data collected in the city and other administrations**. However, some do highlight that the Western view on China is incomplete, as the Social Credit System faces many barriers in implementation, and the scoring still mostly relies on administrative documents, rather than including behavioural and third-party data – as these initiatives often fail to materialise (Drinhausen and Brussee, 2021).

However, in areas where (local initiatives of) the Social Credit System have been implemented a negative score can have significant consequences for citizens, such as limiting crediting, banning travels, or being excluded from using private services. Those with higher scores can for example gain discounts on public transport or priority access to government services. It is to be noted that according to some researchers, these initiatives are regarded as experimental and not directly related to the central government's strategic plans. In fact, most of the cases lack technical sophistication and are still based on pen and paper at the moment (Roberts et al., 2020b). Furthermore, **the opacity of AI affects the effectiveness of the Social Credit System as a**

[23] J.Watts KPMG https://www.amcouncil.com.au/membership/special-interest-group/data-in-asset-management/100001-shanghai-gets-a-digital-twin.html

whole, as citizens need to learn and understand how the decisions taken by the machine work so they can act accordingly. Without this extra transparency, social control may be strongly limited as it is not possible to define what the machines see as 'correct' behaviour (Creemers, 2018b). However, even recently, the Social Credit System is regarded as a disjointed mix of pilots, and large gaps remain in data completeness and data transfers across Chinese public administrations. Despite existing implementation gaps, recent initiatives placed forward by the Chinese government show to resolve data governance challenges, and in the roadmap for a 'rule of law society', the social credit system is a key instrument to do so (Reilly, Muyao Lyu, and Robertson, 2021).

The use of AI in China for security and policing purposes is advanced. There has been a lot of investments and government efforts to apply AI technologies for security or counterterrorism purposes, with especially widespread surveillance being put in place in the Xinjiang region to track the local Uyghur population (Roberts et al., 2020b).

As the **underlying ideology of social engineering and transformability of individuals through social control** is unlikely to change, it is likely that the Social Credit System will develop further and existing challenges related to data sharing will be resolved (Creemers, 2018b). **Citizens in China do indicate the highest level of support for government applications of AI** (Carrasco, Mills, Whybrew, & Jura, 2019b), but not much additional information exists with regards to their perspective on government's AI deployment to 'reward and punish' citizens based on actions taken.

Despite the fact that the Chinese government is exploring and deploying even more controversial surveillance technologies, **there are still legal and ethical challenges for the introduction of AI in the public sector**, just like in the EU and US. Concerns such as who is to be held accountable when governments base their decisions on AI or when something goes wrong are plaguing Chinese administrations just as much. Civil servants state their concerns on whether the AI systems can be regarded just as legitimate as human beings or lead to unfairness in public service delivery, especially to vulnerable groups (Chen, Ran, & Gao, 2019b).

In this respect, **China has also been working on the adoption of AI ethical principles and frameworks**, which seem to align with global discussions and principles (Elliott, 2020b). In 2019, a Chinese expert committee released 8 recommendations that should be adopted during AI development (Laskai & Webster, 2019):

- **Harmony and friendliness**: Enhancing the common well-being of humanity should be the objective of AI since the beginning and thus should conform to human values and morality. Adequate security safeguards should be put in place to avoid potential abuse.
- **Fairness and justice**: The development of AI should promote fairness and justice, the rights and interests of stakeholders and promote equality of opportunity. This should be done by raising the level of technology and eliminating bias and discrimination.
- **Inclusivity and sharing**: All AI should promote green development and be environmentally friendly, promote inclusive development by ensuring social divides should be removed and avoid data or platform monopolies.
- **Respect privacy**: Personal privacy and individual's rights should be respected and protected during AI development.
- **Secure/safe and controllable**: AI systems should improve their transparency, explainability, reliability and controllability continuously to make them more trustworthy. This includes that the safety and the security of AI systems are strong.
- **Shared responsibility**: Social responsibility among developers, users and other parties should be strong, and thus should follow relevant regulations, ethics, and norms closely. An AI accountability mechanism should be established to clarify the different stakeholder's responsibilities. People should have the right to know and comprehend potential risks and impacts.
- **Open collaboration**: Exchanges and cooperation across disciplines, regions, organizations, and others should be encouraged for the development and governance of AI. International dialogue should be followed to promote the formation of an international governance framework, standards and norms, with full respect of each country's principles and practices.

— **Agile governance**: The natural laws of AI development should be respected, but the search for new ways to develop AI and resolve risks should be encouraged. Potential future risks of AI should be anticipated to ensure that AI moves in a direction beneficial for society.

Despite the **similarities with the European and American ethical principles**, China is expected to place a stronger emphasis on social responsibility than individual rights in the interpretation of these principles. At the moment, most of these ethical norms and standards are limited to the statement of high-level principles, although there are emerging debates on how to raise data protection and privacy standards as well as ethical compliance, and a new regulation has recently been introduced in that sense, although with many exceptions for governments and state-endorsed companies (Roberts et al., 2020b).

How these ethical systems will be put into action, given the different interpretations in the EU, US and China, will help clarify where similarities and differences in governance approaches to AI in the public sector do exist (Elliott, 2020b).

3.4 Key take-aways

As mentioned before, only a few studies about the use of AI in government services in the US and in China have been conducted, which makes the lack of comparable field research even more evident than for the private sector (see e.g. Sousa et al. (2019). Apart from the controversial cases of adoption, AI applications already in use that are highly successful may neither be shared publicly nor have gained much research attention (Elliott, 2020b). This poses **limitations on the possibility of understanding where and how AI solutions are deployed for enhancing government capacity**, but also, what the practical effects are of their usage and reuse. Globally speaking, we can conclude that there **seems to be an enormous gap between used metrics to track and measure the comparative progress in AI investment and academic research, and the reality of AI deployment in public services and processes[24].**

With this caveat, **the gap in AI take-up in the public sector between the EU, US and China does not seem to be as great as shown by other metrics**, which focus on research and investments, although it is too early to make strong conclusions due to the severe lack of data on this topic. Federal or national administrations seem to be implemented far more policies and initiatives to make their organizations ready for AI, although more time is needed to assess if and how they will be successful in stimulating AI uptake. Conversely, **both local governments and SMEs seem to be plagued by similar implementation barriers, which limit the diffusion of AI where it may gain a significant impact**. As noted for the micro and small enterprises from the private sector, it looks like the limited size and quality of IT endowments and skills prevent public administration in all three regions from making significant steps towards digitalization in general and AI enabled service transformation in particular. This lack of expertise and hands-on experience in using AI in government is also likely to limit the public sector's ability to govern the development of AI in society with coherent public policies.

In this perspective, **there can be opportunities for the three regions to learn from their respective experiences with the promotion of AI** and decide if and how to replicate each other's success stories – while understanding that policy and cultural differences may limit the extent to which AI can be developed and/or adopted in the other regions. However, **this should not be meant as an invitation to start measuring which region uses more AI and which less, as this metric by itself would say very little about the impact and the public value gained from the use or reuse of this technology**. The deployment of AI per se should not be a target, but always take into consideration the needs of the citizens and the opportunities for better public service. The mere headcount of AI solutions successfully trialled out but never become permanently used or still experiencing problems in terms of scalability or interoperability should not be considered as a relevant success indicator. In other words, the risk should be avoided that too much policy and research attention is put on the supply side of AI-enabled innovation in public administration, without considering the demand side, a common tendency in eGovernment comparisons (Savoldelli, Codagnone, & Misuraca, 2012).

[24] In the forthcoming LORDI (Local and Regional Digital Indicator Framework) will provide further improved framework to measure take-up of digital technologies at sub-government level, see https://living-in.eu/

However, the key lesson learned from this comparison is that despite the rhetoric that Europe is falling behind the US and China in the "AI-race", **there is room for an EU initiative aimed at reinforcing appropriation of AI technologies in the practice of government**, which aligns with the "systemic way" of policy-oriented learning introduced in the previous Sections of this report and may substantially reverse the outcomes of benchmarking trends and developments in the public sector domain.

To grasp these opportunities in full, the thesis of this report is that **the sustainable implementation of AI in public services is a key element for the uptake of AI in public services. In order to reach this sustainable use of AI, specific attention should be devoted to the appropriation process, defined in the report as the sum of adoption and implementation.** This approach aims at preventing the appearance of unwanted and unforeseen effects. This thesis was probably implicit already in the suggestion made by Misuraca and Noord (2020) to take distance from the slippery narrative (or simply the trap) of **AI exceptionalism**, reconsidering it as a phenomenon that is not "*immune to existing governance structures, policies and laws*", and requires more than a mere extension of existing national rules and multilateral agreements to be successfully managed.

Along the same line of thought, we propose to re-elaborate the concept in a more positive (and encompassing) fashion, by reaffirming the primacy of a **European exceptionalism** – a controversial notion in the eyes of the constitutionalists (Bradford & Posner, 2011; Nolte & Aust, 2013), less so of the economists (Rifkin, 2004). In the domain at hand, this primacy should be broken down in (at least) three concurrent and qualifying directions, all of them pointing at a more advanced equilibrium between AI promotion and regulation in the EU public sector:

- Focusing on the fundamentally distinctive traits of the **functioning of government organizations** and acknowledging their peculiarities: transparency and accountability to the constituencies, efficiency and effectiveness in functioning, fairness and discretion in decision making, and focusing on creating public value – even when participatory or shared. This can also mark a difference, as this Section 3 has shown, between the European governance model and its global competitors such as the US and China;
- Aiming to devise and tackle the "**challenges**" of AI development and deployment in the public sector, as a collection of preconditions, in terms of methods and tools for nation- and EU-wide implementation, but also elements of a first embryo of a "governance of AI, with AI" shared agenda. Section 4 will analyse a considerable number of those challenges in some detail;
- Enhancing the goal of policy convergence among EU Member States on how to govern the contrasting forces behind the emergence and pervasiveness of the AI phenomenon, driving them to a synthesis in which the whole is more than the sum of its parts. In this endeavour, the most distinctive elements of the "**European intergovernmentalism**" (Moravcsik, 1993) might prove useful: a union of equals, united in diversity, a preference for non-binding policy rules and the allowance for different speeds of compliance, as epitomised by the Open Method of Coordination[25]. In Section 5 we will propose a set of policy actions that belong to this logic. Among them, as we will argue, **public procurement of innovative AI solutions would play a decisive role**, going even further beyond the known advantages – widely explored by both literature and practice – in terms of "smart purchasing" in and by government bodies and agencies.

[25] The open method of coordination may be described as a form of 'soft' law. It is a form of intergovernmental policy-making that does not result in binding EU legislative measures and it does not require Member States to introduce or amend their laws. https://eur-lex.europa.eu/summary/glossary/open_method_coordination.html#:~:text=The%20open%20method%20of%20coordination,introduce%20or%20amend%20their%20laws.

4 Challenges to AI implementation in the EU public sector

This Section overviews a number of systemic challenges which can be relevant for the attention of policy makers at EU, national, regional and local levels, willing to engage in and contribute to the proposed direction of AI governance, integrating promotion and regulation more effectively. Paragraph 4.1 points at the generation of adequate funding for the public sector organisations engaged in AI adoption. This funding should be nominally supplied by the upcoming Digital Europe Programme, but can also be hampered in practice by two main risks: dispersion of financial resources across multiple and heterogeneous projects (possibly duplicating similar efforts in different countries) and inadequate rooting, or embedment, of the newly developed solutions in the practice of public administration, possibly from different "tiers" and locations, including across national borders. Then paragraph 4.2 identifies a second policy challenge in making quality datasets and infrastructures diffusely available, interoperable, and continuously updated and maintained, for the needs of the novel AI algorithms and more generally for the progress and sharing of benefits of government digitalisation in all EU countries. In turn, paragraph 4.3 also taking stock of a discussion done in the previous Section 3 in comparison with US and China, outlines the third challenge of attracting young tech talents in public administration and widely improving the literacy and skills of existing staff, particularly in the most "peripheral" public bodies and agencies (from Southern and Eastern Europe as well as the smallest sized EU Countries). Then paragraph 4.4 associates a fourth group of challenges to an evolving concept of legitimacy for those governments making more decisive steps towards AI implementation. Finally, paragraph 4.5 focus on enabling user-centric services with and by AI and, to do so, describes how the goal of public service transformation, particularly at the local level, can and should be aligned with the eight fundamental principles of the Tallinn Declaration on eGovernment, to achieve sustained organisational change in the public body or agency involved in AI implementation.

4.1 Looking for a critical mass of AI investment

The Europe 2020 strategy adopted in 2010[26] set the long-standing objective to devote 3% of EU Gross Domestic Product (GDP) to Research and Development – the so-called R&D intensity. According to the latest evidence from Eurostat[27], Member States have increased their spending on R&D during the 2008-2018 decade by about 0.,3 GDP points, however without reaching the target. In fact, R&D intensity in the EU-27 stood at 2,18% in 2018, while it was 1,87% in 2008. Compared to other major economies, it is about the same ratio as in China (2,14%) but lower than the OECD average[28] (2,38%), the United States (2,82%), Japan (3,28%) and South Korea (4,53%). In nominal terms, the EU spending on R&D in 2018 – that is, what statisticians call Gross Domestic Expenditure on R&D (GERD) – was close to €294,5 billion, or about €660 per inhabitant. **Only 1/9 of that amount** – roughly 0,24% of EU-27 GDP – **can be attributed to the government sector**, a ratio that remained constant all along the decade, as the graph below shows.

During the same period, the R&D intensity of the higher education sector increased by 10% (corresponding to about 0,05% of GDP) but only during the first two years, then stagnated at a twice as high level as in government (0,48% of GDP). Taken together, **universities and public administration have not increased their annual R&D spend above €220 per inhabitant (at 2018 prices) over the past 10 years**. However, it is noteworthy that such level in proportion to GDP is comparatively higher in the EU than in the US, Japan and China, and only lower than in South Korea. In fact, **the 2018 public R&D intensity** (summing up government and university spending) **was 0,72% of EU-27 GDP, but only 0,66% in the US, 0,63% in Japan, 0,49% in China, while it was 0,83% in South Korea**[29].

Meanwhile, R&D expenditure of the private, non-profit sector has remained negligible (only 0,01% of GDP across the decade). Therefore, **almost the entire growth in the R&D intensity between 2008 and 2018 has stemmed from additional investments of the EU-27 business enterprise sector**, as Figure 4 clearly exhibits.

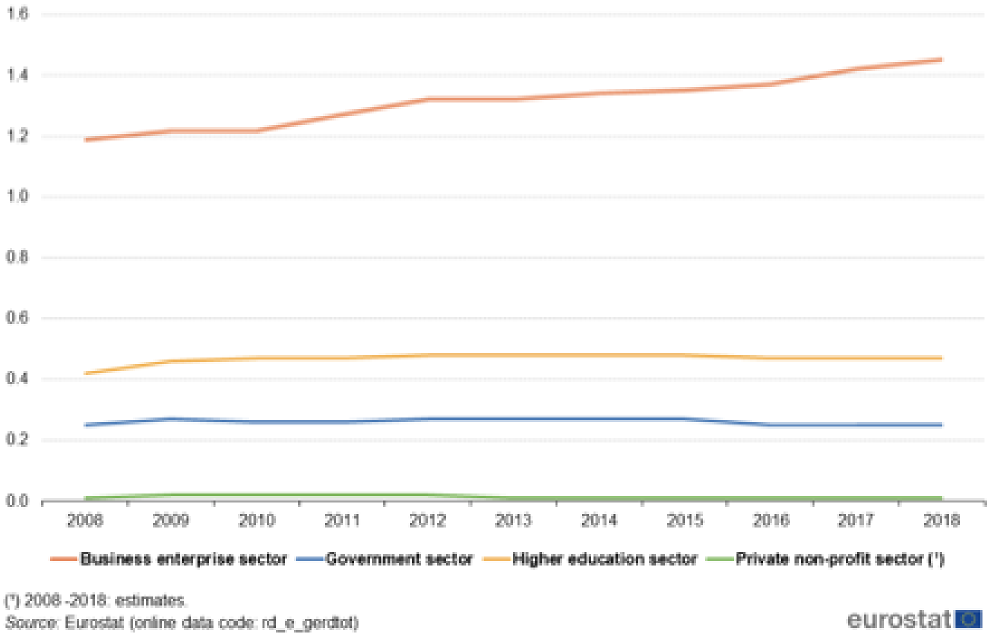
[26] http://ec.europa.eu/info/strategy/european-semester/framework/europe-2020-strategy_en

[27] Eurostat, Statistics Explained. R&D Expenditure. Latest data update: September 2020. Online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=R_%26_D_expenditure#R_.26_D_expenditure_by_sector_of_performance

[28] OECD, Main Science and Technology Indicators. Latest data update: August 2020. Online: http://www.oecd.org/sti/msti.htm

[29] European Commission, Science, Research and Innovation Performance of the EU 2020. A fair, green and digital Europe. Latest data update: May 2020. Online: https://ec.europa.eu/info/publications/science-research-and-innovation-performance-eu-2020_en

Figure 4. Gross Domestic Expenditure on R&D by sector of performance, EU-27, 2008-2018 (% relative to GDP).



However, according to the 2015 edition of the OECD Frascati Manual[30], the contribution of the public sector to national R&D can also be measured through **Government Budget Allocations to R&D (GBARD)** [31]in a given year. This alternative approach is still in its infancy but promises to be more informative than recording the intramural spending of government units, because it rules out what is reimbursed by a third party, such as a public grant, or repaid through a loan, which allows setting a specific focus on government's autonomous investment capacity (notably financed by taxation). On the other hand, there is a likely overestimate of yearly spending because both the capital and current costs are included therein, with multi-annual projects being attributed to the year(s) in which they are budgeted (Eurostat, 2020). This overestimate is partly or fully offset by the fact that local government funds and the budgets of public corporations are currently not included in the calculation.

Another aspect of interest of such an alternative approach is that data on **public funding of ICT R&D** is also made available as part of the global budget figure. This includes the support to all ICT-related R&D spending in every sector of the economy, including the NACE rev.2 industry entitled "84 Public Administration and Defence. Compulsory Social Security" – the closest proxy available to what we named the business of government. Roughly speaking, this is what the national government allocates for ICT research and development for its own purposes.

To get an impression of the size of this budget allocation, the following table compares EU-27 with the US across the same decade 2008-2018 as above. Figures are calculated in millions of current Euros PPS[32] and also shown in proportion to total GBARD for the same year. Comparable data for China, Japan and Korea are not available (Mas et al., 2020).

[30] http://www.oecd.org/innovation/inno/frascati-manual.htm

[31] National public funding to transnationally coordinated R&D is defined as the total budget funded by the government (central, regional, local), as measured by GBARD directed to transnational public R&D performers and transnational public R&D programmes

[32] PPS stands for Purchasing Power Standards. It is a sort of artificial currency used to make the US and EU GDP comparable in volume only, i.e. not considering the effect of price differences between countries. Euros are current for the year, i.e. the price differences due to the phenomenon of national inflation are still operating between years.

Table 2. EU-27 vs. US Public Budget Allocations to ICT R&D in Government (millions of current EUR PPS)

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
EU-27	**180,30**	**156,89**	**140,11**	**105,59**	**85,97**	**86,96**	**90,33**	**86,79**	**74,95**	**98,16**	**95,44**
%	3,6%	3,0%	2,6%	1,9%	1,6%	1,6%	1,6%	1,5%	1,3%	1,6%	1,5%
US	**1130,87**	**1253,94**	**1318,76**	**1223,21**	**1142,02**	**1014,11**	**1007,66**	**997,87**	**995,61**	**1011,12**	**1024,63**
%	15,1%	15,9%	18,5%	18,7%	16,4%	16,2%	15,7%	14,6%	13,9%	14,7%	14,0%

Source: PREDICT 2020 dataset (https://ec.europa.eu/jrc/sites/jrcsh/files/government_budget_allocations_for_ict_rd_predict2020.zip).

In every single year after 2010, the amounts budgeted for in-house ICT R&D investments by EU-27 (national and regional) governments have been less than one tenth of the corresponding ones in the US[33]. Summing up by row, **the cumulative contribution of the EU-27 public sector to its own ICT R&D has been €1,2 billion in 11 years, or about a quarter of Euro per inhabitant, per year compared with more than €12 billion in the US, almost 3,5 Euros per inhabitant**[34], so very low in comparison. Indeed, little can be said about the comparative quality of public spending or the return on the respective investments, but these figures reflect the reality we should be starting from in our discourse on the EU public sector's capacity to transform itself by the appropriation of innovative digital technologies, notably including AI amongst them.

Moreover, to ignite a true embedment process of novel ICT – hence also AI solutions - in the public administration in Europe, **making their initial adoption diffused and permanent**, beyond the mere and localised experimentation of promising (but sometimes also "fancy") innovations, **a dedicated injection of financial resources is indispensable**[35]. Just as an example, the proposed budget for the entire Digital Europe programme is in the range of €7,5 billion in 7 years, thus of comparable size to the gap outlined in Table 2 above. In particular, the estimated allocation for AI is about €2,2 billion in 2021-2027. Given the starting levels of R&D spend outlined above, **the expected impacts of those extra resources** – in terms of lever, if not also return on investment – **can be quite significant even in the short to medium term, especially when combined with additional investment.**

In this framework, the key question for the authors of this report is not whether adequate finance will support the experimental deployment of AI solutions in the European public sector for the years ahead. Evidently, this can be assumed as a matter of fact, including of an order of magnitude – right now, unpredictable in its future size – sufficient to generate transformative impacts. Instead, our matter of concern are **the infrastructural conditions and the systemic mechanisms** to be exploited by policy makers willing to make sure that **successful AI innovations introduced by early adopters** from specific EU countries (and regions, and cities) **become permanently embedded in the business of government and really pervasive at all administration levels** – according to the legal competences of public bodies and agencies and having in mind the political discretions of managers and elected officials – **within and particularly across the EU national country borders**.

We consider this question both timely and justified by evidence. Quite surprisingly, **research in this area is moving its first steps**, almost as if the evaluation of those enabling or preventing factors did not deserve a systematic (and most probably systemic) approach. The remainder of this Section constitutes a contribution in that direction.

4.2 Data quality, availability and interoperability

One of the most fundamental requirements of AI is data. By definition, AI relies on access being ensured to the "right" kind of data on which to perform its analyses, and which in most cases is augmented by the results of the analyses themselves. For many Public Sector organizations though, fulfilling this requirement is a challenge, due to **a variety of obstacles in obtaining data of the quality and format they require**.

[33] As it is known, EU-27 and the US (and China) are all about the same size in terms of GDP expressed in Purchasing Power Standards (PPS). In 2017 they were representing 16%, 16,3% and 16,4% of the world GDP, respectively. See Eurostat news release 84/2020, The 2017 results of the International Comparison Program. China, US and EU are the largest economies in the world. Latest data May 2020. https://ec.europa.eu/eurostat/documents/portlet_file_entry/2995521/2-19052020-BP-EN.pdf/bb14f7f9-fc26-8aa1-60d4-7c2b509dda8e
[34] These figures change little if we move to constant prices, using a deflator for the expenses reported in Table 2 for both EU-27 and US.
[35] These were also the conclusions of the 2nd peer review workshop of the AI Watch for the Public Sector initiative, held on 29th September 2020, with MS representatives. See van Noordt and Pignatelli (2020).

A key obstacle lies in **existing data infrastructure and organisational capabilities within the public sector**. As the strength of AI comes from the data it is "trained" on, the need for a resilient, high-quality and accessible data infrastructure is crucial (Harrison et al., 2019). However, not all government bodies or agencies have adequately digitalized their internal operations and services in the past decades, which leads to a **significant gap between the ambition of using novel AI technologies and the organizational readiness to do this** (European Commission, 2020b). Thus, while AI innovation may bring great benefits to public sector modernisation, the less prepared public organization and agencies may have the remarkable difficulties in achieving implementation.

Another related obstacle lies in the fact that sometimes no **data on service delivery can be combined with available external data**. Indeed, some of the successful experiments of AI in the public sector – such as the City of Helsinki's analysis of citizen feedback at its offices[36] - succeed in combining external with internal performance data in order to grasp new insights into how routine operations influence certain contextual factors. Naturally, if no or just too scanty internal evidence is available because of the digital immaturity of a public sector organization, most of those insights will be lost, as only external data will be available for analysis.

Thus, **public sector organizations that are genuinely interested in implementing AI in their operations must find ways to manage at the best their priorities, not leaving behind required improvement to the current level of digitization**, aiming to ensure that all evidence about service is digital by default. This should not be seen as a barrier to entry, though, but more as an opportunity to **fasten digital transformation of government finding AI adoption as an additional stimulus**. Of course, while AI's potential can accelerate the digital transformation efforts of public administration and ensure they include data governance as targets, it is likely that additional efforts are still required to ensure that the maximum for AI is gained from ongoing and past digitalization.

In fact, the digitalization of public processes requires good data governance, allowing the generation of reliable and useful sources for later analyses. Building a strong data governance system in public sector organizations has been highlighted as one of the most impactful elements on the development of trustworthy AI and consolidation of take-up by the end-users (Janssen, Brous, Estevez, Barbosa, & Janowski, 2020).

Fortunately, several EU governments have already transformed many of their services and digitized most of the previously analogue information reservoirs. **For a further advancement of AI in the Public Sector, it is now to be considered crucial to improve the quality and accessibility of their datasets**. As also highlighted in a previous study, Member State AI strategies normally dedicate attention to improving both the data quality as well as its accessibility (van Noordt, Medaglia, & Misuraca, 2020).

Despite these efforts, **there are still many barriers to opening, sharing, and reusing data belonging to different public sector organizations. This should probably be one of the next steps in the data curation process**.

Scholars have highlighted the barriers to making government data openly available to the general public – ranging from **poor interest or data literacy of civil servants, limited endorsement from middle or top managers, legal barriers, institutional constraints related to regulation or policy, or supply bottlenecks** such as lack of financial resources or of a technical infrastructure suitable to publish data on (Janssen, Charalabidis, & Zuiderwijk, 2012). Most of these barriers are also common to data sharing with other organisations.

But there is more: **data available in an open format may often be of poor quality or too heterogeneous**, which makes it difficult to extract the information embedded in it (Hellberg & Hedström, 2015). Alternatively, shared **data is often 'pre-processed', removing much of the information and limiting re-use by other actors** (Lämmerhirt, Rubinstein, & Montiel, 2017). Finally, evidence from the Global Open Data Index comparing the publications of government data worldwide shows that **it is often difficult to find the "right" data online**, due to the high number and variety of websites, platforms and protocols. As a consequence, while there is an ongoing trend to feed AI with big data by external sources, limited evidence is available on how open or

[36] See among others AI experiments (in Finnish), https://digi.hel.fi/projektit/helsinki-tekoaly-kokeilut/

shared data in public administration assist AI development and deployment (Janssen, Konopnicki, Snowdon, & Ojo, 2017). In that direction, the forthcoming Data Spaces Initiative[37] will enable new data sharing scenarios.

The need for interoperable data sources also applies to the deployment of the Internet of Things (IoT), which generates data that is often used in urban projects together with AI. Some large European cities have been frontrunners in deploying sensors and IoT devices to support public service delivery and gaining real-time insights into a variety of urban processes. However, the deployment of sensors is still far from mainstream (El-Haddadeh, Weerakkody, Osmani, Thakker, & Kapoor, 2019). Thus, **future developments in IoT should consider the analytical possibilities offered by a synergy with AI technologies**.

One of the best ways to **ensure compatibility between IoT sensor data and other sources** is through achieving full interoperability of government systems (Kankanhalli, Charalabidis, & Mellouli, 2019). **Thus, grasping the opportunities of AI and IoT together may be an accelerator for public administration as a whole to finalise its digital transformation**.

A recent phenomenon, noted by some researchers (Klievink, Van Der Voort, & Veeneman, 2018), is the creation of **ad-hoc, informal and small sized partnerships** where government actors work together with other public or private actors to exchange data related to solving a public challenge[38]. Such collaborations are regarded as promising examples of a new governance instrument, apt to generate value out of various datasets and to obtain new capabilities or create new public services. In that direction, it is worth mentioning the effort made by OASC (Open & Agile Smart City) through the definition of MIMs (Minimal Interoperability Mechanisms). MIMs' objective is to provide the technical foundation for procurement and deployment of urban data platforms and end-to-end solutions in cities and communities worldwide[39]

Despite the potential, however, research has highlighted that **extending such inter-organizational collaborations to AI development and adoption is not straightforward** due to the **need for interoperability** between different data sets to ensure data integration, but also to **organizational, legal, and political factors** restricting the scope of such partnerships. In a recent study, fears with regards to privacy and cybersecurity in data sharing are shown to lead to the risk that AI projects get halted. It is therefore crucial for public organizations to introduce ways to share data in a secure and trustworthy manner (Campion, Gasco-Hernandez, Jankin Mikhaylov, & Esteve, 2020).

Arguably, to ignite a diffused interest in collaborative data sharing among public and private actors, **new and well-functioning data ecosystems** need to be developed. As the value in many of these collaborations lies in the exchange and combination of several datasets (e.g. required to train AI models), which were previously not made available by public administration, there is a lot of potential in ensuring that digital technology take-up also occurs in local businesses and citizens[40].

The more digitalization occurs in the nearby ecosystem, the more data is likely to be available for potential AI projects involving the public sector. Naturally, these data ecosystems need to be developed in such a way as to protect citizens' rights and meet the public good (Calzada & Almirall, 2020). While some pilots of AI can take place in digitally immature environments, **data governance foundations should be established in all layers of government before AI is really scaled up across services and across borders**. Particularly, public bodies and agencies should **treat open data programmes according to an ecosystemic approach**: combining both policy initiatives for building reliable data infrastructures as well as the engagement of relevant stakeholders (Dawes, Vidiasova, & Parkhimovich, 2016). **Ensuring that different actors establish connections, relations and understand each other's needs is key to create a trustworthy and thriving local data ecosystem** prone to improve with time.

Initiatives such as the EU **Digital Innovation Hubs can reinforce and strengthen these ecosystems**, and most importantly, allow public sector organizations to harness the innovative spirits of businesses and citizens

[37] https://digital-strategy.ec.europa.eu/en/policies/strategy-data
[38] See the JRC DigiTranscope on B2G data sharing models, the B2G data sharing workshops and the forthcoming Data Act,
[39] https://mims.oascities.org/
[40] See forthcoming Data Space for Smart Communities, https://digital-strategy.ec.europa.eu/en/library/expert-workshop-common-european-smart-communities-data-space

to come up with promising solutions to pressing local issues[41]. Digital Innovation Hubs has played a key role in stimulating and implementing regional and local innovation strategies. Indeed, they can also be excellent training organizations for advancing the internal use of AI in the public sector (European Commission, 2021c). This requires their further establishment and diffusion across the EU and those already in place should be expanded with **additional resources to stimulate public sector innovation using AI as well**.

4.3 Talent attraction and skill improvement

The aim to develop and use AI in government organizations may, however, encounter issues if not accompanied by a similar interest in boosting the AI skills, literacy and awareness of civil servants. **Many public bodies and agencies have great difficulty in obtaining tech talents and governing and evaluating their internal ICT systems** (Mergel, 2019), though knowing that an adequate skillset is crucial for any digital transformation process (Mergel, Edelmann, & Haug, 2019).

For digital transformation projects involving AI, the lack of expertise is even more crucial. It is often mentioned that **capacities are missing within public sector organizations both for developing AI and for working with it, understanding its strengths and limitations**. As a result, most AI professionals tend to flock to the private sector where the benefits, also in terms of recognition, are significantly higher (Wirtz, Weyerer, & Sturm, 2020).

Therefore, investments in training and capacity building, but also talent attraction are required to ensure that every public sector organisation can have access to the right capabilities to develop and use AI, as well as young AI professionals seeing government as a concrete possibility of career advancement. However, **a vision** is also needed about which and how AI should be used so that the training can be developed accordingly.

As also highlighted in a recent AI Watch workshop (van Noordt & Pignatelli, 2020) actions are ongoing on the national administrative layer to raise awareness, train civil servants and establish knowledge hubs – such as data labs – where AI resources are shared across different departments of the administration. However, lower tiers of government may require ad hoc initiatives to ensure they too have access to relevant AI resources.

Without such interventions, **the public sector may become increasingly dependent on external AI consultants**, with evident risks of vendor lock-in and transparency threats due to the limited understanding of how AI affects the internal operations of government and perhaps to the additional inflexibility to change if something goes wrong (Andersen, Lee, & Henriksen, 2020).

It is also likely that, without adequate digital capabilities and skills within the public sector, **some bodies or agencies may face significant difficulties in adopting the AI solutions successfully deployed elsewhere or just replicating some case studies with the needed adaptations**. To build an effective governance framework, skills and competencies should extend as much to governance "with AI" as to governance "of AI" (Kuziemski & Misuraca, 2020).

Such lack of governance capacities does not only prevent or limit AI innovation in individual government bodies and agencies, but also at regional level, with the recurrent paradox that the lack of capacity is predominant in the regions that would need them most because they fail to catch up (Muscio, Reid, & Rivera Leon, 2015). In fact, the Covid19 crisis revealed that the geographical spread of online availability of public services, internet access and digital literacy in Europe is not as broad as imagined. Despite the improvements, even recently made, strong differences still exist between rich, poor, urban and rural areas (European Committee of the Regions, 2020).

While public administration has been to some extent forced to digitalise some processes and work practices due to Covid19, **it remains unclear whether these trends will lead to a more profound reform** and therefore require the attraction of further expertise and expertise on organisational and process reengineering. Indeed, working remotely and having gained an expanded network capacity cannot be considered a full digital transformation while many non-value-adding processes still remain the same without redesigning organisational activities and roles proactively (Gabryelczyk, 2020).

[41] For more information regarding the Digital Innovation Hubs part of the Digital Europe Programme, see also: https://ec.europa.eu/digital-single-market/en/digital-innovation-hubs

4.4 Input, throughput, and output legitimacy of AI use

There has been much research on identifying various ethical concerns related to deploying AI as there are indeed a number of issues potentially arising from the way AI operates (Dignum, 2018). For government deployment of AI, this brings specific risks, among which the following particularly stand out (Dwivedi et al., 2019; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016):

— **Producing unfair outcomes**, as AI algorithms can amplify some discriminatory biases already present in societies. This can result in AI basing decisions or recommendations on human factors, which is against the rule of law to consider, such as gender, race, or sexuality. Even when certain sensitive data is omitted from the learning process, AI can still amplify hidden biases in the data through proxies such as postal codes for marginal or troublesome urban neighbourhoods. The actions taken by AI systems are only as good as the data they are based on. . This requires a full awareness of the quality and possible limitations of the data used to feed the AI system. **Particularly when dealing with marginalized groups, public bodies and agencies using AI should always avoid having these systems worsen existing inequalities in society rather than helping resolve them.**

— **Increasing the opacity of decisions**, due to the "black box" nature of some AI algorithms. Despite some recent advancements in explainable or interpretable AI, most AI systems in certain cases remain inaccessible, overly complex, self organising, not sufficiently transparent, which makes it incomprehensible why AI suggested or took certain decisions. This also limits the ability of public administration to justify the decisions taken by the AI systems, monitor and correct them. This lack of transparency and accountability of AI-informed or enabled decisions brings not only ethical but also legal and political consequences, as **citizens may have difficulties in accepting and enforcing the decisions taken by their governments**. In that sense, the Amsterdam[42] and Helsinki[43] AI Registries for transparency purposes are good examples in the direction to explicit communicate and explain where AI is deployed and how automatic decisions are taken, describing clearly potential opacity when is the case.

— **Threatening the privacy of citizens unduly** is also a risk, as most AI systems require significant amounts of (personal) data to perform accurately. This introduces two types of issues, the **hiddenness of the real extent (and possible severity) of data collection practices and the unwanted knowledge gained from data analysis**. As the example, also highlighted as a risk in the GDPR, of merging public with restricted or even anonymised data shows, the knowledge produced through analysing various linked sources is at risk of revealing highly private or sensitive information which citizens arguably would not want to have disclosed (Janssen & van den Hoven, 2015). In addition, the continuous deployment of various AI systems that monitor and track people could establish some form of **Big Brother government**, reducing trust in public administration and the legitimacy of democratic power.

— **Promoting an "algocracy" scenario**, that is a subtle and extreme form of technocracy, whereby machine algorithms, rather than AI empowered people, collect information, take actions and administer the rules of a State. In that sense, further investigations are ongoing in order to explore in which cases there is a real need for such complex and self-organizing algorithms. Paradoxically, this potential algorithm-based governance system**, instead of amplifying and enabling human involvement in public processes**, tends to **restrict it**, inducing further limitations of citizen opportunities to participate in decision making (Danaher, 2016).

These risks may pose huge challenges to the legitimacy of public sector organizations. On the one hand, AI technologies are seen as improving the outcomes of policymaking and governmental operations by making them more effective and efficient. On the other hand, AI itself could severely undermine the legitimacy of governments in three distinct areas, namely Input gathering, Throughput generation, and Output delivery (Starke & Lünich, 2020).

[42] Amsterdam AI Registry: https://algoritmeregister.amsterdam.nl/en/ai-register/
[43] Helsinki AI Registry: https://ai.hel.fi/en/ai-register/

Figure 5. Key challenges to government legitimacy by AI adoption.

Challenges to input legitimacy	Opaque political decisons taken in development processes Weariness of unwarranted data usage for AI False citizen participation or representation through AI
Challenges to throughput legitimacy	Increased opacity of decisions taken by government Illegal practices due to the development and deployment of AI Reduced accountability and perception of fariness of AI-mediated decisions
Challenges to output legitimacy	Functioning of AI not as good as expected or marginally better Increased bias in decisions making and increased discrimination Overlooked costs and resources required for development and sustainable use

Source: JRC, own elaboration.

Firstly, the **input legitimacy** of government is challenged because the design of the **AI systems requires developers to make political decisions that may be difficult to detect or correct** at a later stage (Mulligan & Bamberger, 2019). There is often **limited political or citizen oversight in the design and deployment of "where, when, and how" AI systems get used in government services**. As also shown by the "DigiGov" study, citizens are watchful when their personal data is used – sometimes without their awareness or explicit approval – by private sector organizations asked to work with public administration in the development of AI systems (Barcevičius et al., 2019). Similarly, most marginalized groups risk being insufficiently involved or represented in digital transformation processes, leading to biases and false (e.g. using sentiment analysis in social media as a proxy for public support soft political decision making across society as a whole (Giest & Samuels, 2020). Not considering the political context and the wishes of some categories of citizens while using AI may thus severely reduce the input legitimacy of governments.

Secondly, the **throughput legitimacy** of government may be reduced when decisions become **increasingly more difficult to scrutinize or explain** (Burrell, 2016). The level of opacity with which some AI systems make certain decisions and the uncertainty on how their decisions are made could greatly diminish citizen trust in public administration. Civil servants themselves, when complex tasks get automated, may have the impression that the fairness of the procedure gets threatened[44]. Fully replacing people in tasks that used to rely on human skills may thus lead to a lack of perceived fairness. **Only for tasks that are regarded as simple and less complex, AI may be preferable**, although the outcomes of implementation should be examined on a case by case basis and require careful deliberation (Nagtegaal, 2020). In addition, it may always be possible that **during the development or the deployment of AI, some laws get broken** due to the data collection practices, unwarranted data sharing or the infringement of citizens' privacy rights (Meijer & Thaens, 2020). Although indispensable, **legal safeguards might be regarded as unwanted obstacles** during the development of AI systems, which would thus lead to unlawful use of AI. Consistently with this, the risk must be reduced as much as possible. Moreover, the level of risk is different with respect to the area of application for example areas like environmental monitoring and climate adaptation are expected to have fewer privacy-related issues.

Thirdly, the **output legitimacy** of government may be harmed when the **AI systems are not functioning as good as expected**. As mentioned before, the recommendations and decisions taken by AI may be heavily biased or flawed due to poor development or unproven performance in complex social settings. **Often, AI**

[44] Good practice may be the Amsterdam Fair AI contract clauses, where clauses are automated by the development of the so-called Fair AI MIM (Living-in.eu).

systems hardly work as well in real life conditions [45]as they do in controlled environments and make more errors than expected (Bailey & Barley, 2019; Coiera, 2019). Alternatively, the performance of using deep learning or other opaque machine learning methods in the development of AI systems may only have a **slightly better predictive accuracy** compared to less complex and more transparent techniques such as regression analysis using only a handful of variables (Dressel & Farid, 2018; Salganik et al., 2020). Furthermore, **the development and governance of AI systems may require significant organisational resources** which may be overlooked at first, thus ultimately limiting the cost reductions AI was supposed to bring to the organisation. Having many, expensive and opaque algorithmic systems the performance of which is unclear may in fact reduce the effectiveness of government dramatically (Andersen et al., 2020).

4.5 Enabling user-centric services with and by AI

AI is often used for increasing the quality of public service delivery and a large number of applications are under development in this area. Indeed, the main objectives of introducing the AI in governments' services relate to: a) improve internal processes; b) enhance and enabling faster policy-making mechanisms, and c) improve the participation and experience of citizens and business users when using public services (Misuraca and van Noordt, 2020).

This is a set of operational targets, which support the political commitment that the EC established at the EU level on significant priorities towards ensuring high quality, user-centric digital public services for citizens and seamless cross-border public services for businesses. This vision is reflected in **the eight fundamental user centricity principles** as defined by the Tallinn Declaration on Digital Government[46.]

User-centricity counts on new digital technologies, and therefore also on AI, for strengthening trust in governments. In particular, they focus on increasing transparency, responsiveness, reliability, and integrity of public governance.

A direct consequence of that is the need to embed the discussion on AI with the discussion on user-centric services: governments have to place citizens at the centre of public services and governance and AI can and should support this challenge.

For doing so, a stream of research on AI in the public sector should look at how to connect user centricity and service design principles with AI. This section is giving evidence to this stream and sets the ground for further research in the field.

As a brief background, user centricity challenge relates directly to tackling the issue of low satisfaction with public services and distrust in government and public administration. This may be because of delays in fully embracing digitalisation of public services, or surviving biases and discriminations in making them accessible, or lack of transparency, reliability or accountability during and after delivery. Moreover, with ICT skills becoming more widespread across generations, the global expectations in terms of technological performance and capacities may also increase, which is not always joined, however, by concurrent improvements in usability features, particularly to the benefit of the less expert groups. The reasons could be found also in the customisation phases that bring from the user-centric principles to the user-centric operative services. User engagement procedures must be contextualised in the territory on which the service will act and on the target users.

The first attempts of using new digital technologies for enhancing user-centric services may be found at the local level, thanks to the efforts made within the smart cities. The smart cities phenomenon is increasingly seen as far more than simply endowing an urban area with some technological infrastructure, rather as the creation

---

[45] There is a forthcoming AI Testing and Experimentation Facilities to further sustain the development and deployment of AI. https://digital-strategy.ec.europa.eu/en/activities/testing-and-experimentation-facilities

[46] The 2017 "Tallinn Declaration on Digital Government" provides eight clear principles Member States should commit to, with the purpose of redesigning public services around the user needs. These principles have been translated into a sort of additional "rights" for citizens, who should expect to: digitally interact with their administration; find accessible, secure and available services; experience a reduction of the administrative burden; receive services that are fully delivered online; being empowered and engaged in proposing new service ideas and suggestions for improvement; being removed of any barriers and incentivised to the use of digital services; protected in their personal privacy sphere and allowed control of their data; enabled to activate redress and complaint mechanisms.

of a place where citizens live in a smarter way and allocate their time and resources more efficiently and productively. This kind of lifestyle change alters citizens' perspective of the world and promote shifts in their behaviours and expectations, in particular, towards urban services. Moreover, with the level and intensity of demand becoming higher, service automation proves vital to alleviate pressure on government's delivery capacity and continue enhancing the quality of urban experience.

Many European cities have already realised the importance of user centricity. However, a systematic collection of success stories is still missing[47]. Cities have the ambition to support service (re)design with clear insights on the specific profiles of prospective beneficiaries and their aspirations in terms of quality and performance, up to the point of letting citizens and businesses participate in the development and validation of the new digital public services that are expressly tailored on their needs. Actors in these stories are, therefore: the general public, city networks (particularly for interoperability and scaling), regional and local government bodies and policymakers, innovation and technology hubs, living labs, science parks, university incubators, civil and social rights activists, not for profit associations etc.

Yet, it is still often difficult to reach various groups of citizens and businesses through digital public services only. And the relationship between empowerment and outreach is unavoidably two-way: while the removal of pre-emptive barriers and constraints to the use of electronic services does influence diffusion, their persistence as user centricity issues may negatively affect the digital transformation and therefore the trustworthiness and accountability of governments (European Commission, 2019c).

As a general remark, following the trend already ongoing on user centricity, it is important that **implementation of user centricity principles in AI appropriation starts at the local level**. As for general service redesign, cities should let the users participate in the appropriation of AI and, more generally, have always a careful eye on the eight fundamental user centricity principles when approaching the introduction of AI.

We can assume that AI solutions only designed and implemented following the user centricity principles can at full potential, for example, help reduce the administrative burden, support in resolving resource allocation problems, take up complex tasks, and deal with the heterogeneity and complexity of data sources. However, its inner nature and influential role in transforming government action and interaction with its stakeholders can also enable the enhancement of user centricity in the next generation of public services, (especially) at the local level.

Accordingly, authors such as (Barbero et al., 2016; Ferro, Loukis, Charalabidis, & Osella, 2013; Fredriksson, Mubarak, Tuohimaa, & Zhan, 2017) highlight that big data analytics, algorithms, and machine learning, provide a number of advantages to governments throughout the entire policy cycle. User centricity challenges and opportunities can be detected also by looking at the phases of the policy cycle.

Firstly, in the phase of agenda-setting, the implementation of AI may significantly increase the effectiveness of citizen participation through refined ways of annotating and grasping their feedback through sentiment analysis, crowdsourcing and physical or virtual (even including augmented reality or virtual reality) co-creation sessions.

Secondly, human-machine interaction has the potential to enhance efficiency, effectiveness and accuracy of policy making, also in the direction of better user centricity of the resulting services. For instance, predictive analytics may indicate the priority of focusing more on prevention, instead of just reacting, to crises and other societal problems. Or a more faithful handling and representation of service usage data may assist in developing more targeted, personalised interventions and even 'nudges' to beneficiaries. These approaches have been applied in healthcare, environmental and traffic management[48], education and other social services of general interest.

Thirdly, progress in user centricity requires a "sustained organisational change" in the involved public body or agency. This change has been defined as "altering existing organisational practices, changing organisational processes and/or tasks of government staff" (Misuraca, 2012). Such requirement is in line with the most accredited vision of **user centricity as a mindset**, rather than an organisational status to be reached; **an**

[47] Ongoing efforts funded by the EU include the Co-Val dashboard (https://www.co-val.eu/dashboard/municipalities) and the Designscapes geo database of urban innovation initiatives (http://designscapes.eu/funded-initiatives/)

[48] see DUET (digital twins) H2020 project or LEAD (H2020 project) on digital twins in urban mobility.

approach to be followed, for instance in service (re)design and delivery, rather than the specific methods and tools enabling it; and **a collection of moving targets**, depending on the interim progress made so far and also on the evolving expectations of citizens and businesses in terms of service quality, usability and trustworthiness.

Starting from the assumption described above, and taking Figure 2 (from Section 2) for approaching AI appropriation in the Public Sector, user centricity principles can be enabled in the process of AI appropriation at the governmental level through a variety of services co-design and participatory activities. It appears that the AI itself is an enabling technology for user centricity and it could be included in the cyclic process that brings to the AI appropriation maturity. Table 3 offers a bird's eye view of this conceptual scheme. In detail, column 1 refers to single phases of the process of AI appropriation, column 2 provides a list of activities paving the way to the implementation of user centricity processes and, finally, column 3 suggests the most relevant AI typologies supporting the mentioned activities.

Table 3. User centricity cultivation within the process of AI appropriation.

PHASES OF AI APPROPRIATION	ACTIVITIES FOR ENABLING USER CENTRICITY	SUPPORTIVE TYPES OF AI
USER REQUIREMENT ANALYSIS	Perform quantitative and qualitative studies, such as surveys and interviews to understand citizens' needs and identify which of those should be (re)addressed with the help of new or revised, AI-enabled public services	Natural Language Processing, Text Mining and Speech Analytics Tools
ANALYSIS OF CONTEXTUAL FACTORS	Complement available evidence with e.g. fresh environmental or perception data generated through interacting with the stakeholders who are to be served	Predictive Analytics, Simulation and Data Visualisation Applications
NEED ANALYSIS AND TECHNOLOGY CHOICE	Build rough prototypes to pre-test related ideas for sustainability and scalability, and iterate if needed	Chatbots, Intelligent Digital Assistants, Virtual Agents and Recommendation Systems
SERVICE (RE) DESIGN AND (RE) DEVELOPMENT	Generate insights and create new service concepts and processes based on the above findings	All of the above
SERVICE TESTING AND EVALUATION	Balance quantitative and qualitative measures to assess performance and impact on users	All of the above
CHECK AGAINST CONTEXTUAL FACTORS	Craft stories, share experiences, describe successful cases and lessons learned – also to inspire actions of other administrations in a logic of scalability and reuse	Predictive Analytics, Simulation and Data Visualisation Applications
CHECK AGAINST USER REQUIREMENTS	Refine ideas and gather feedback from stakeholders to deliver better services that will be adopted by citizens	Natural Language Processing, Text Mining and Speech Analytics Tools

Source: JRC, own elaboration.

All these activities belong to a **human-centred approach** that is transformative of the way governments engage with prospective beneficiaries to gather their pre-emptive insights and offer better responses to their needs and requirements. In so doing, people are positioned at the centre of public service transformation, across all steps from ideation to prototyping to validation. This can contribute to achieving user centricity in AI-enabled public services and also leads to increased citizens trust and an enhanced resilience of the social and economic systems (Alzahrani, Al-Karaghouli, & Weerakkody, 2017).

Finally, and by no means surprisingly, user centricity principles can be more effectively guaranteed if sound achievements are also ensured for the previously outlined challenges in terms of e.g. skills improvement, data availability and accuracy, interoperability of datasets and processes as well as, more generally, increased sharing and collaboration propensity among administrations.

5 Policy implications

This Section draws some overall suggestions that set the ground for identifying a list of policy implications from the previous discussion. With a high-level approach, we made the first attempt to support EU decision makers that are willing to undertake the systemic approach to AI governance towards a more advanced equilibrium between AI promotion and regulation in the public sector. This equilibrium should be redefined at the predominant space of high-level coordination between the European Commission and the Member States, that is the macro level.

Accordingly, the next three paragraphs formulate as suggestions or recommendations:

1. a stronger integration of AI with data policies, to face the issue of the so-called "explainability of AI" (Arrieta et al., 2019; Vilone & Longo, 2020)
2. to broaden the current perspectives of both Pre-Commercial Procurement (PCP) and Public Procurement of Innovation (PPI) at the service of smart AI purchasing by the EU public administration[49].

As reported at the beginning, the main goal of the entire report was to set the theoretical ground on which future research can build a precise and detailed list of recommendations. For this reason in this Section will contain only, some bounded high-level suggestions that shall and will be detailed in further researches that are conducted within the AI Watch. Hence, the three policy implications reported are the direct result of the analysis reported in the previous chapter and aim at being neither exhaustive nor extremely detailed or refined.

5.1 In search of a critical mass for the "champions" of AI for government

In Section 3 of this report, an attempt at benchmarking EU with US and China was made in terms of the respective performances of their governance systems in framing, promoting, and regulating the use of AI solutions within the public sector. While the scarcity of comparable data, other than merely anecdotal or qualitative evidence, impedes any definite judgment on the real degree of AI take-up at the different tiers of administration, it seems quite reasonable to affirm that **this is a key dimension of the global techno-economic race too**.

In fact, the economic implications of a growing demand for AI solutions in any sector and country – above and beyond the gains in productivity and efficiency of the appropriation "pioneers" – include the formation and growth of a wave of specialised technology providers or the consolidation of the existing or emerging national industry players in that domain. Making a comparison of the demand side of the three markets is made – as far as government is concerned, but more generally in all sectors where digital solutions can be successfully deployed – it is necessary to concede that Europe is at disadvantage, compared to the US and China, because of the relative fragmentation of the European GovTech market, and the need to adjust solutions based on the national contexts. (Probst, Pedersen, Lefebvre, & Dakkak-Arnoux, 2018).

However, if one looks at the supply side of the AI industry, assuming that the trends of globalisation of the pre-Covid19 era will be to a great extent resumed in the coming years, it would seem quite logical for European firms born after the successful deployment of some technologies in Europe to become more competitive and start serving US or China based clients with their original and innovative products and services. Indeed, there is already a wide set of AI solutions experimented in many domains that could be rather easily scaled from a single/local experimentation site to multiple/global business locations. Of course, various aspects of market segmentation would still be operational, including language barriers: it may be the case that automatic speech to text services in Croatian language underperform those working in English, or that analysing the sentiment of social media posts may not be as great as a business in Maltese as in French or Spanish. Even so – as highlighted by a quick look into the growth pathways of IT "giants" such as Facebook, Google or Twitter – a number of technological, as well as commercial synergies, could be exploited irrespective of the language spoken in the countries these AI innovators are operating in.

Discussing the most appropriate policy measures to promote the growth in market size and internationalisation of European AI industry would obviously exceed the scope of this report. However, the important point here is that there may be another way of tackling the same issue, particularly for government-oriented AI solutions.

[49] the forthcoming EU Adopt AI programme is expected to offer a support to this

This is to **promote the reuse and transfer of AI implementation best practice examples**, starting from those within the same EU country, then analysing the conditions for their replication in other EU countries, up to the possibility of identifying a new generation of cross-border or pan-European public services that leverage AI as a common enabler.

In fact, while a number of value-adding AI solutions successfully trialled so far seem to refer to specific digital infrastructures, datasets and service delivery environments, others are **agnostic with respect to the domain of application**. This is the case of AI tools such as automatic translators or transcribers which, once developed and tested, can be effectively re-used in different situations without the need for further adaptation. For example, the European Commission recently launched an online machine translation service called eTranslation[50], which is available to registered EU users free of charge. **Other AI prototypes that have proven useful in specific contexts may require little effort to be extended to similar or related ones**. Another example is a solution recently developed in the Netherlands to interpret handwritten documents, such as those stored in historical archives, and convert them into a digital format. Such use of AI could also prove helpful for government bodies and agencies still relying on paper exchange with some service beneficiaries, rather than adopting a "natively digital" approach, which the organisation might not yet be ready. After digitising and analysing the files through AI, new applications could become viable, leading to further insights to act upon.

While such examples look reasonable to follow and expand further, for many reasons they are not representative of the current scenario in the EU public administration. In fact, with all the caveats suggested by all-too-scanty empirical evidence, the following two (clusters of) barriers seems to prevail at the moment:

— **The "AI for government" supply side seems comparatively less market-ready than the broader GovTech industry it belongs to**. This may not necessarily be due to a lack of technology maturity (low TRL), although this could be perceived to some extent if we tried to disentangle the generic categorisation of AI typologies – such as Machine Learning or Robotic Process Automation – into their individual components showing high grades of heterogeneity in terms of time to market. Our impression is that such heterogeneity hides a more general issue, which is related to a comparatively higher difficulty in gaining a critical mass of commercial applications of a certain AI technology, which is a prerequisite to turn the latter into a commercially viable and attractive product or service.

— While several collections of developer tools exist indeed, such as Google's AI Hub[51], Amazon's AWS[52], Microsoft's AzureML[53], Cognitive Services[54], and ML.Net Model Builder[55], or IBM Developer[56] and Watson[57], it is rather unusual that a "plug and play" solution can be immediately adopted as it is taken from off-the-shelf. Instead, in order to achieve a satisfactory degree of AI appropriation in a public service environment, a supplement of local configuration and custom installation is usually needed, which leads to additional "pains and perils" during onsite experimentation. The latter is witnessed by the significant number of case histories gathered in the AI Watch collection, which does not seem to have ever left the "ongoing project" status, due to unexpected problems that emerged during the transition from adoption to implementation. Conversely, from an overview of the various GovTech startup and business listings that are published from time to time in the US[58], in Europe[59], and worldwide[60], the reality emerges of **many "champions" of AI for government** – i.e. bearers or inventors of a cutting-edge technology, which is now available to the public buyer – **not selling the AI application as such**, but only as a component of a broader solution, which is supposed to fulfil the domain- and context- related requirements of the business case(s) it addresses. Moreover, the ERASMUS Data Analytics Centre's study identified that one of the main obstacles to scaling up smart city digital solutions was - and still is - the lack of interoperable, standards-based platforms[61] that would allow public administrations to manage large amounts of data from heterogeneous

[50] https://ec.europa.eu/info/resources-partners/machine-translation-public-administrations-etranslation_en
[51] https://aihub.cloud.google.com/
[52] https://aws.amazon.com/free/machine-learning/?nc1=h_ls
[53] https://azure.microsoft.com/en-us/services/machine-learning/#product-overview
[54] https://azure.microsoft.com/en-us/services/cognitive-services/
[55] https://dotnet.microsoft.com/apps/machinelearning-ai/ml-dotnet/model-builder
[56] https://developer.ibm.com/technologies/artificial-intelligence/
[57] https://www.ibm.com/watson
[58] Such as https://www.govtech.com/100/2021
[59] Such as https://view.publitas.com/public-1/the-european-govtech-150-the-startups-driving-europes-govtech-revolution/
[60] Such as https://aithority.com/ait-featured-posts/100-emerging-govtech-startups-you-should-know-about/
[61] See: https://www.rsm.nl/about-rsm/news/detail/14476-smart-cities-need-to-trust-technology-and-data-quality/

data sources. Compared with the private sector, **government has a more heterogenous range of business needs to fulfil**, which are inextricably related to the contextual factors presented in Paragraph 2.2. Additionally, even within the same country or region, therefore under a common legal system, **the organisational, process- and service- level peculiarities** outnumber the commonalities **among public bodies and agencies**, which makes every AI appropriation quite often a single case. This is witnessed by a number of global surveys of the "AI maturity" of (usually large sized) organisations from various industries, including the public sector. With this term, which is broken down in different ways depending on who has carried out the survey, the implication is made that every organisation follows a sort of learning and capacity building process, which will ultimately lead it to make strategic use of AI in its processes and therefore to grasp all the benefits and impacts from implementation. For example, according to a 2021 survey of the Boston Consulting Group[62], **the Public Sector has the second highest share of organisations that are not AI mature (only the Consumer industry fares worse)**. Quite reasonably, this is explained by the prevalence of AI applications that interface human beings, as users or beneficiaries, rather than fabrication processes or B2B transactions. A previous research by Capgemini, released in mid-2020[63], showed that only 9% of surveyed government bodies and agencies had been successful in going beyond the stage of pilot or small-scale deployment of AI, compared to 27% in life sciences and – surprisingly enough – 21% in retail and 17% in consumer products.

I**t remains very difficult (and mission critical) to define a prompt and clear scalability pathway for the "average" AI for government applications**. According to the Boston Consulting Group, this pathway should consist of 10% introduction of algorithms, 20% of new technologies and 70% of embedment of AI into the existing business processes and ways of working[64]. In practice, it is not very frequent that public sector organizations invest twice as much in people and processes as they do in AI algorithms and technologies.

We add to this that **current best practice examples of AI implementation and use in the EU public sector are not easily retrievable or accessible**[65]. While many government organizations are indeed conducting experiments, **there is no clear stocktaking of the different initiatives, also to avoid the replica of similar or identical failure stories**. Therefore, it proves difficult to know which AI works, which does not, which contributes to societal goals and which threatens public confidence (AlgorithmWatch, 2020a). More proactive sharing of results, both good and bad, from the use of AI in public services or policies, should be encouraged, such as the establishment of AI repositories as initiated by the Cities of Amsterdam, Helsinki and Nantes, which are already sharing which AI they are using and for which purposes (Floridi, 2020). Expanding this initiative could help both citizens, as well as other city governments, see what AI really is about and what value it can bring to them. This calls for the creation of a (probably federated) repository of good practice examples, widely accessible to potential adopters, less focused on the AI tools having the potential of being implemented locally[66], and more on the characteristics of the public sector environments that would be surrounding them.

Further to the above, **even the AI innovation projects, which were not successful, should be openly shared outside the organizational borders. Often, such projects are not made public– unless they had been negatively covered in the press, see for example** (AIAAIC, 2021) - which limits peer learning across other organizations, increasing the odds of the same mistakes occurring again in another project. This goal should be part of a broader cultural transformation of the EU public sector, in the direction of considering failure as an integral component of any systematic approach to innovation, and even more than so, a precondition for success (Stamm, 2018). One important reason for failure is that **AI should not be deployed just because it is possible to use it**. While experimentation on proofs of concept should be encouraged, **active deployment of AI should always be aimed at solving a relevant service requirement and creating public value[67].** ICT-enabled innovation in the public sector cannot be disconnected from end user

[62] https://www.bcg.com/publications/2021/the-four-stages-of-responsible-ai-maturity
[63] https://www.capgemini.com/research/the-ai-powered-enterprise/
[64] See https://www.bcg.com/capabilities/digital-technology-data/artificial-intelligence
[65] See DT4REGIONS project
The DEP will also call for the creation of AI catalogues in cities (AI catalogues of AI-enabled solutions).
[66] For example, in a collection like https://www.thedevmasters.com/ai-tools
[67] See AI4CITIES pre-commercial procurement of AI-enabled solutions by 6 cities for reducing GHG emissions (https://ai4cities.eu/)

needs and expectations, which might lead to unintended and negative consequences (Benbunan-Fich, Desouza, & Andersen, 2020). If too little consideration is given to this aspect during AI implementation, this could lead to a significant backlash by citizens, reducing trust in the administration as well as future AI projects. Given the tendency of many AI systems to make (significant) errors, and the opacity of AI's decision support mechanisms, **the opportunity of AI to achieve efficiency gains should be measured against other public values such as accountability, resilience and inclusiveness.**

More generally, **a culture of innovation within EU public administration should be encouraged**. While there are still many unknowns with regard to the effects and potential of AI in government contexts, this should not be a barrier to trying out (small) experiments and seeing what benefit they could provide to the administration. **Staff who work with policy issues daily are likely to have innovative ideas on how to improve public services, but often do not have the opportunity to work on these ideas**. A risk- and innovation- adverse culture, limiting public management support or funding, may be one of the root causes why innovation in the public sector does not occur. However, for stimulating the use of AI in the public sector, such a culture should be widely diffused (in the sense of Everett Rogers, 2010).

In this respect, initiatives such as the Experimentation Accelerator in Helsinki could be replicated in other administrations. This is a new programme where **internal civil staff are encouraged to come up with innovations utilizing AI, which can be experimented in a relatively short time** with limited funding.[68] Naturally, this goes hand in hand with **improving the digital skills and literacy of civil staff**. Therefore, internal training programmes on using data, both generalist as well as specialist, should be encouraged and introduced to ensure that all public bodies and agencies have access to the capabilities needed for adopting AI and using AI in their organizations.

To conclude, apart from any further opportunity offered to EU service providers by the ongoing or upcoming AI governance initiatives in the US and China, **only scalability of the most successful applications delivered by the European GovTech "champions" can lead Europe to fully grasp the benefits of AI implementation**. Scaling AI is a complex task though, requiring far more than a one-off experimentation in real or realistic environments.

In the following three sections, we highlight a set of policy initiatives, some of which have already been initiated, that we see as particularly apt to counteracting the two clusters of barriers introduced above. Quite interestingly, most of them would not duplicate, but simply add to or qualify the contents of the national AI strategies monitored by AI Watch and overviewed in a previous JRC Science for Policy report (Misuraca and van Noordt, 2020). What would make a real difference is the systemic approach, already introduced in Section 3 as part of a truly European AI governance model, based on a tight collaboration between the European Commission and Member States (possibly also including Regional and large sized City governments).

Should this collaboration not materialise in full, **the EU might be exposed to the risk of proceeding with AI innovation in the public sector in an uncoordinated manner**[69], as the experience of Covid19 tracing apps during the pandemic crisis has shown. According to a recent study by IFRI, the French Institute of International Relations (Tonon, 2020), the persistent lack of an effective European strategy for the GovTech industry in general, and for AI in government specifically, might result in a permanent advantage to Chinese and American actors, which benefit from governmental support both at home and abroad. On this aspect, leverage towards a more coordinated approach to the definition of AI-related standards at the EU level can support European growth.

However, and despite the lack of comparable empirical evidence in the US and China, our qualitative view is that the peculiarities and heterogeneities of the public sector are recurrent phenomena also in those countries, which are therefore experiencing similar difficulties to the EU in making AI scalable therein. Therefore, our tentative conclusion – much in the same way as we put it in Section 3 with regard to AI governance in general

[68] This is an initiative by the city to encourage employees to come up with experiments using AI and scale workable solutions, see also: https://www.hel.fi/uutiset/en/kaupunginkanslia/helsinki-develops-experiment-activities-with-artificial-intelligence

[69] EC DG CONNECT has recently formally relaunched a Member States 'Expert group on Artificial Intelligence and Digitalisation of Businesses'. This expert group will specifically focus on AI.One of the main tasks of the group will be to follow-up and implementation of the actions proposed in the Coordinated Plan (including for the public sector), https://ec.europa.eu/transparency/expert-groups-register/screen/expert-groups/consult?lang=en&groupID=3795

– is that **the gap between Europe, the US and China, in terms of critical mass for active national "AI for government champions"**, potentially able to play as global service providers, **has chances to be filled in**, **provided the negative influence of market fragmentation and lack of policy coordination is neutralised**.

5.2 Tackling data availability and quality as an example of market failure

As discussed in Section 4, it seems rather uncontroversial that most AI technologies – including those developed for and/or deployed in the public sector – find their rationale and justification in the need to handle large volumes of data, of various nature and sources, with a speed or sophistication or simply coverage it would be impossible to reach when only using human reasoning and computing capacity. Indeed, one of the key drivers of "**next generation AI**" (aka Artificial Superintelligence see Bostrom (2014) and Yampolskiy (2015) is exactly the expectation that the growing proliferation of data generated on the fly in all sectors of individual and community life could not be successfully managed, interpreted and turned to the common good without the use of powerful AI algorithms and other computing, sensing and visualisation techniques that outperform the sheer possibilities offered by our brain and senses.

In this context, it seems more than a bit of a paradox that the top EU industry players, gathered under the umbrella of the so-called Big Data Value Association (BDVA), presenting itself as "*the private counterpart to the European Commission to implement the Big Data Value PPP program*", point at the fundamental lack of "*cross-sectoral, unbiased, high-quality and trustworthy data*" to unleash the potential of AI innovation in Europe and beyond (BDVA, 2019).

If such a lack is evident in industry, one could easily imagine an even worse situation in the public sector. Despite some 20 years of open data policies, initiatives and examples of good practice in Public Sector Information (PSI) disclosure, there remains room for improvement of open government data sets. The situation can well be summarized in the following quote from the 2017 edition of the Open Data Barometer: "*Government data is usually incomplete, out of date, of low quality, and fragmented. In most cases, open data catalogues or portals are **manually** fed as the result of informal data management approaches. Procedures, timelines, and responsibilities are frequently unclear among government institutions tasked with this work. This makes the overall open data management and publication approach weak and prone to multiple errors*" (World Wide Web Foundation, 2017).

In a recent paper, (Concilio & Molinari, 2021) propose to look at this situation as a textbook example of **market failure** – a concept borrowed from the economy – as **the existing framework of incentives to PSI disclosure is evidently not compelling enough to accompany public bodies and agencies across the whole lifecycle of data publication, maintenance, continuous update, and quality assurance, improving the data sharing paradigm**. The implications of such lack of incentives are even more substantive if one considers the case of an AI solution that uses, but also adds new data to the original set by a continuous machine intelligence and decision-making process. Knowing how sensitive the decisions of an algorithm can be to changes of the underlying PSI structure, we can probably realise how seriously the concerns of BDVA should be taken – before it gets too late.

As a matter of fact, the February 2020 Communication on "A European strategy for data" (European Commission, 2020a) proposed a roadmap of investments and policy measures aimed at the creation of a **European-governed data sharing space**: a sort of "single market for data", open to the integration of sources from all over the world, but complying with the European principles and rules of privacy, security, safety and ethics. The Communication was followed by a public consultation, which highlighted the importance of making every PSI that possibly holds commercial value available free of charge, without restrictions and accessible via Application Programming Interfaces (APIs)[70].

Then in November 2020, the Commission adopted a proposal for Regulation on data governance[71] (the so-called Data Governance Act), which is now under discussion at the European Parliament. The proposal built on

[70] See https://data.europa.eu/en/highlights/data-governance-act-open-data-directive
[71] https://ec.europa.eu/digital-single-market/en/news/proposal-regulation-european-data-governance-data-governance-act

an Impact Assessment exercise, stating that the limited amount of data sharing may be caused by insufficient trust and culture, by a lack of structures and processes conducive to the collection and reuse of PSI, or by technical obstacles to the reuse of data for the common good. Feedback on the Data Governance Act was received until early February 2021, with the participation of 149 EU organisations[72].

The vision of both policy documents – the Communication and the Regulation proposal – is to intervene with concrete actions at the EU level, without interfering with, and possibly building on or facilitating the concurrent development of sectorial strategies carried out by the Member States.

Using the taxonomy of policy instruments from Vedung (1998) recalled in Section 2, we can suggest two distinct approaches to inspire those actions, one more based on "sticks", the other on "carrots":

- The opportunity of the Data Governance Act might be grasped to **impose – rather than simply recommend – the refinement and update of existing data ecosystems as well as their federation** as proposed by the GAIA-X project and AISBL[73]. Particular attention should be paid to predefining and implementing the rules of interoperability (in the broadest sense, thus including the cultural, the semantic as well as the legal and organisational dimensions, alongside the technical one, as per the European Interoperability Framework – EIF (European Commission, 2017b)[74].
- As proposed by Concilio and Molinari (2021), forthcoming, a simpler intervention – to be coordinated at the European level, but not necessarily ruled centrally[75] – might take the form of **providing direct subsidies to regional and local governments** engaged in disclosing and maintaining their own datasets clean, updated and accessible over time. Moreover to push the supply (PS) to meet demand (businesses), focusing the effort on opening and maintaining the most useful and high value PS datasets. In so doing, the negative externalities of the aforementioned market failure could at least be reduced, if not fully compensated for.

It seems quite obvious that the two options are neither fully new nor incompatible with one another. Particularly the former proposal echoes the European Commission's view to create common data spaces differentiated by domain, such as for the EU Green Deal supported by the Digital Europe Programme, granting a pivotal role to climate-neutral and smart cities and communities (European Commission, 2019b, 2020a). Another similar initiative is the Covid19 Data Portal[76], which was launched in April 2020 to bring together and share relevant datasets to accelerate coronavirus research. In a similar vein, we might think of **building a federation of local government datasets** with a specific orientation to promoting AI enabled services according to a reuse logic.

Federations of datasets can be for example obtained by reinforcing the use of web standards (W3C, 2009) and by the permanency of both data sources and technical enablers such as APIs (Grzenda & Legierski, 2019). The latter one, in particular, is expected by both data providers and application developers, also and primarily to develop AI applications that need to access big volumes of data in a fast, updated and reliable way. API-based access becomes the only choice for some AI applications when near-real-time data streams are exposed. In particular, high volume, variety and velocity data, requires API-based exposition rather than a file download. Indeed, the ability to use and design APIs is one of the key competencies identified in a study on open data value capability architecture (Zeleti & Ojo, 2017), rewarded by the Open Government Data Portal Index (OGDPI) proposed by (Thorsby, Stowers, Wolslegel, & Tumbuan, 2017) and recently recognised as one of the key enablers of digital government (Boyd, Vaccari, Posada, & Gattwinkel, 2020). The research work made at the JRC has also emphasized the potential of API's for digital government and includes additional recommendations on how to improve the use of APIs across Europe.

[72] For more information see https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/12491-Data-sharing-in-the-EU-common-European-data-spaces-new-rules- and https://data.europa.eu/en/highlights/high-value-datasets

[73] https://www.data-infrastructure.eu/GAIAX/Navigation/EN/Home/home.html

[74] This was also recognised as a priority in the Coordinated Plan on Artificial Intelligence (European Commission, 2018) which required actions to make datasets more easily accessible in practice and facilitate aggregation by adopting the "design and implementation of interoperable data and meta-data formats as well as the deployment of standardised Application Programming Interfaces (APIs)".

[75] For instance, one of the pillars of the EU Recovery and Resilience Facility (RRF) is about digitalisation of public administration. See https://ec.europa.eu/info/business-economy-euro/recovery-coronavirus/recovery-and-resilience-facility_en. In turn, the AI White Paper (European Commission, 2020d) predicts that "*to stimulate private and public investment, the EU will make available resources from the Digital Europe Programme, Horizon Europe as well as from the European Structural and Investment Funds to address the needs of less-developed regions as well as rural areas*".

[76] https://www.covid19dataportal.org/

A feasibility study of either intervention exceeds the scope of this report but could be easily drafted and made accessible to all EU stakeholders for consultation and contributions in the very short term. As both options are not necessarily linked to AI requirements, so that released datasets may prove to serve broader scopes, an idea might be to "start small" and **make an inventory of the kinds of dataset reused in AI in some active locations** (or specifically indicated in existing data catalogues such as the European Data Portal[77]) **and suggest them for publication in others**. On this direction is moving the Data Space for Smart Communities initiative, with the objective of setting up a governance structure for data sharing, with a focus on the most useful data.

Whatever the direction is taken, we would like to stress here **the vital need for integrating the EU level agenda for AI development and deployment with a firmer consideration of data policies and their implementation prospects**, having in mind that for many reasons, the Member State level may not be the most appropriate one to promote data sharing in a harmonious and effective manner. This would be the first in a row of three proposed instantiations of our concept of "**European AI policy exceptionalism**".

5.3 Emphasising AI explainability as another key facet of accountability

The idea of explaining to lay people – be they the purchasers or the end users of an AI solution – the inner logic of its learning or inferential algorithms has always been around as a parallel research thread to the mainstream thinking and is normally referred to as **eXplainable Artificial Intelligence (XAI)**. This is not a marketing or trust building feature, however. Scholars engaged in XAI research have highlighted a number of crucial dilemmas, which might be more easily solved by opening up the "black box" of machine reasoning and making it fully transparent and interpretable in its design and ways of operation. Such dilemmas include the trade-off between accuracy and simplicity of the functional descriptions of an AI system (Bernease, 2019), the so-called "infobesity" (information overload) versus selective use of information according to the interests or preferences of target stakeholders (Przegalinska, 2019), and the reasonableness of an AI model's predictions contrasted with the effective power of disruption of the underlying patterns of logic (Gilpin et al., 2018).

As far as Europe is concerned, the principle of AI explainability has gained recognition after the entry into force of the GDPR – the EU/EEA General Data Protection Regulation, No. 2016/679 – in May 2018. Articles 13(2)(f), 14(2)(g), and 15(1)(h) of the GDPR requires data controllers to provide data subjects with "*confirmation as to whether or not personal data concerning him or her are being processed, and, where that is the case, access to the personal data*" as well as to specific information about "*the existence of automated decision-making, including profiling, referred to in Article 22(1) and (4) and, at least in those cases, meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for the data subject*". In brief, this set of articles imposes notification duties on data controllers "*to ensure fair and transparent processing*" whenever AI solutions are in use that have fully or partly automated decision-making or user profiling. Moreover, the data subjects enjoy a right to access, not only the personal data created throughout AI processing, as long as it pertains (although as a derivative) to their own profiles, but also a supplement of technical information concerning the purpose, nature and modalities of this innovative way of data elaboration.

Whether these legal provisions should be considered as the introduction of a new "**right to explanation**" or the recognition of a pre-existing right has been widely debated among jurists and philosophers (see e.g. Selbst and Powles, 2017 for a discussion). Whatever the opinion one may want to express, the substance of the problem is clear: not only are data subjects entitled to receive that supplement of information, but its contents must be "**meaningful**" – i.e. sufficiently detailed and specific to motivate an action, or reaction, from their side. And the nature of such possible (re)action is well described in Article 22(3) of the GDPR providing that when automated decision-making is contractually necessary or consensual, certain safeguards for data subjects must apply, including "*at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision*". This is because according to Article 22(1) data subjects "*have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her*". Article 22(2)–(4) specifies the limited circumstances whereby automated decision-making is permitted, and caters for different safeguards

[77] https://data.europa.eu/en

so that data subjects can effectively exercise their own "*rights and freedoms and legitimate interests*". Finally, the non-binding Recital 71 reaffirms that safeguards for data subjects "*should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, [and] to obtain an explanation of the decision reached after such assessment and to challenge the decision*".

To summarise, **the emphasis given by the GDPR to safeguard the "*rights and freedoms and legitimate interests*" of data subjects when AI solutions are in place has certainly contributed to supporting the case of AI explainability**. However, this is only part of the story. Indeed, depending on the complexity as well as the novelty of the AI solution compared with the state of the art, **the data controller itself is likely to suffer from the same lack of "*meaningful information about the logic involved*" as its data subjects**. This would inevitably impact the users of the solution, be they employees at the same organisation that delivers an AI enabled public service or direct beneficiaries of that service or simply external stakeholders to the service environment, thus formally deprived of the safeguards introduced by Article 22 of the GDPR[78].

Omitting to consider this broader set of stakeholders is a severe limitation because they belong to the target community of **administrative accountability** - the ability of government to give a satisfactory account of the use of power and resources, including, and though not being limited to, AI in public service. If no proper account can be given of the way certain decisions are taken by AI - because some of the dilemmas the XAI literature has singled out are actually in operation – how can the legal obligations to accountability be properly addressed? More generally speaking, if some of the obstacles to making machine reasoning fully transparent and interpretable materialise at the stage of solution development, what are the implications for the purchasing process itself? Should it be stopped or complemented by an extra round of reflection and evaluation, before – rather than after – the final solution has gone into operation?

We conclude this subsection by stressing that despite some recent attempts at systematising the XAI research domain, "*there are still important scientific issues that must be tackled. Firstly, there is no agreement among scholars on what an explanation exactly is and which are the salient properties that should be considered to make it effective and understandable for end-users, in particular non-experts. Secondly, the construct of explainability is a concept borrowed from Psychology, since it is strictly connected to humans, and it is also linked to other constructs such as trust, transparency and privacy. Thirdly, this concept has been invoked in several fields, such as Physics, Mathematics, Social Sciences and Medicine. All this make its formalisation and operationalisation a non-trivial research task*" (Vilone & Longo, 2020).

D**irect financial support** from the EU to a dedicated, inevitably multi-disciplinary, research agenda on such topics, would give a tremendous impulse to a **knowledge-based approach** to AI implementation that we recognize and refer to as the second core instantiation of our proposed concept of "**European AI policy exceptionalism**".

Such support would be fully in line with the provisions of the 2019 Communication on 'Building Trust in Human-Centric Artificial Intelligence', setting out as principles that "*processes and data sets used must be tested and documented at each step such as planning, training, testing and deployment. This should also apply to AI systems that were not developed in-house but acquired elsewhere*" and that "*it is important to log and document both the decisions made by the systems, as well as the entire process (including a description of data gathering and labelling, and a description of the algorithm used) that yielded the decisions. Linked to this, explainability of the algorithmic decision-making process, adapted to the persons involved, should be provided to the extent possible. Ongoing research to develop explainability mechanisms should be pursued. In addition, explanations of the degree to which an AI system influences and shapes the organisational decision-making process, design choices of the system, as well as the rationale for deploying it, should be available (hence ensuring not just data and system transparency, but also business model transparency)*".(European Commission, 2019a)

5.4 Fully exploiting the degrees of freedom allowed by Innovative Public Procurement

According to a DG GROW study (European Commission, 2017a) only 1,7% of the contract awards in EU28 dated between 2009 and 2015 saw the involvement of a successful bidder that was not located in the same country

[78] See also forthcoming EU Digital Principles (DG CNECT D2)

as the contracting authority and was not domestically owned. In terms of value, the figure was 3% of all contracts between €1.000 and €200 million documented on the Tenders Electronic Daily (TED) database. However, the same percentages increased considerably, up to 21,9% and 20,4% respectively, when the successful bidder was based in the same country as the contracting authority but was a subsidiary of a foreign company.

Compared with the private sector, import penetration, or the share of goods and services purchased from other countries than where the buyer resides, was estimated to be 10% lower in the EU public sector. That was only an average, however. In fact, the study showed that at the product level, import penetration was actually more often higher in the public than in the private sector, while the opposite was true for services, and especially for crucial government functions like security, public administration and defence, social security, education and health. These five functions alone represented over 58% of public sector purchasing at the time and were all heavily tilted towards domestic purchasing. To some extent, this result was unsurprising as the provision of services is more likely to be dependent on geographical proximity and language barriers. Besides this, there are maybe also security and privacy concerns about the subject involved that holds/stores the data and about where the data are stored (especially if it involves personal data)

For instance, 75% of contracts awarded in the Republic of Ireland to non-Irish companies were won by UK bidders and 69% of the Slovakian ones by Czech firms. Furthermore, certain services are inherently non-tradable since they cannot be produced and delivered in separate locations. The conclusion was therefore that in the aggregate, the nature of what is purchased prevails on any other source of domestic bias on the part of contracting authorities.

The implications of AI take-up for the practice of procurement – especially in the private sector – have already been noted and commented on by many observers before.

Based on a quick survey of the grey literature worldwide, the most prominent impacts and benefits are those shown in Table 4. With the needed adjustments, it is possible to argue that they also apply to the corresponding phases of a public procurement process.

Table 4. AI-supported public procurement. Overview of potential benefits[79].

PROCUREMENT PHASE	***DESCRIPTION OF POTENTIAL IMPACTS AND BENEFITS***	***(A)***	***(B)***	***(C)***	***(D)***	***(E)***	***(F)***
INTERNAL NEEDS RECOGNITION	Supplier market innovation scouting based on big data and advanced analytics to detect new technologies, product substitutes, new suppliers and start-ups.					√	
PLANNING AND BUDGETING	Linking the R&D strategy with the procurement strategy and the project portfolio, supported through digital dashboards/ KPIs, jour fixes, etc.					√	
PREPARATION OF THE CALL FOR TENDER	Virtual Personal Assistants guiding the procurers to select the most appropriate purchasing tools. AI algorithms to find hidden opportunities across multiple levers.		√		√		√
CALL PUBLICATION AND HANDLING OF RFI/Q&A	Use of chatbots and virtual assistants as user friendly interfaces to the prospective bidders. Enhancement of the strategic leadership skills of the procurement staff.	√	√	√			
RECEPTION OF PROPOSALS	Accelerated execution of procurement activities.				√		
EVALUATION OF RECEIVED PROPOSALS	Improved profiling of bidders through refined analyses of their track records. Better capacity to analyse and compare received bids.	√					
CONTRACT NEGOTIATION AND SIGNATURE	Advanced contract analytics. Improved management of risks and contingencies. Cognitive procurement advisors providing summaries, recommendations and advice	√					√
MONITORING OF CONTRACT EXECUTION	Gathering field information and processing it automatically to generate performance alerts. Predictive supplier risk management to detect supplier failures or frauds early on.	√		√		√	
PAYMENTS AND DISPUTE SETTLEMENTS	Digital procure-to-pay solutions. Automated tracking of target achievements and bonus/malus payments.	√				√	√
CUSTOMER FEEDBACK AND RECORD KEEPING	Digital claim management system with integrated automatic warning systems. Availability of real time spend data.	√				√	
OTHER ORGANISATIONAL BENEFITS	Improved communication and information exchange between the procurement office and other critical business functions/departments. Greater automation of menial tasks.		√	√	√		

Key: (a) = Biedron (2020), (b) = Malone (2019), (c) = McCrea (2018), (d) = Prakash (2018), (e) = Schreiber et al. (2016), (f) Meulen (2017).

Source: JRC, own elaboration.

In this scenario, **the instrumental relations between AI and procurement can become relevant in two distinct directions**:

1. To support the execution of public tender procedures on the one hand, by using AI technologies within the procurement process.

With such terms as “cognitive procurement” or “procurement 4.0”, the ongoing trend is highlighted towards an increasing availability of AI resources in support of the purchasing process. However, and to paraphrase the conclusions of a comprehensive study by (Meulen, 2017), it is not advisable that all procurement phases embrace AI immediately and at the same time. Despite the plethora of success stories one can hear about, a feeling to be resisted is the “fear of missing out, causing a ‘big bang’ adoption approach”. In fact, not all technologies have the same level of maturity, and several organisational factors may condition implementation, including the skills and experiences of procurement staff. Therefore, a time frame of 6 to 12 months should be allowed for even the simplest solutions to generate their positive impacts. More complex technology investments such as AI supported market intelligence, contract drafting and authoring, and bid evaluation, among others, should be prioritized in an arc of 12 to 18 months.

2. To promote or accelerate the penetration of AI in government, by using innovative procurement methods as a way to facilitate the introduction of AI within governments

Some of the documents or reports monitored by AI Watch do include invitations to contracting authorities to adopt AI solutions to improve the efficiency, timeliness and transparency of tender procedures. In France, the report entitled “For a meaningful Artificial Intelligence: Towards a French and European strategy” by the

[79] See upcoming Adopt AI programme that will consider increasing take up of AI in the Public Sector and in the procurement process itself

Parliament Member and mathematician Cédric Villani[80] analysed how AI could support public procurement in enhancing its existing workflows. In the UK, the House of Lords Select Committee on Artificial Intelligence report entitled "AI in the UK: ready, willing and able?" estimated savings of £4bn a year by the extended use of AI across government departments[81]. In Belgium, the AI4Belgium program paving the way for a concerted national strategy highlighted the need for SMEs and contracting authorities to closely collaborate on projects related to the redesign of public procurement processes[82]. Also, the Norwegian government representatives who responded in early 2020 to an AI Watch survey did mention the scenario of enhancing procurement processes using AI technologies, making them more inclusive, accessible, fast and robust. Finally, Malta was developing at that time a template for the procurement of emerging technologies (including AI) and would enact a training and awareness programme for civil servants in order to equip them with the required AI related skills (Misuraca and van Noordt, 2020). Does this mean that until we reach a standard way of offering AI services to public administration (e.g. in the cloud – one of the additional priorities of the European Data Strategy Communication) there will be no future for AI beyond time limited and resource constrained experimentation? Not necessarily, in our opinion. The reason for this is that apart from the occasional participation in R&D and innovation projects, **government bodies and agencies do not have a single way to purchase AI**, but at least two:

- What we can name "**Traditional Procurement**" – i.e. oriented to products and services that are well established on their market of reference, the technical specifications of which can be clearly and fully described in the public tender documentation, and the competition for which can be based on the best price quality ratio, also referred to as MEAT (Most Economically Advantageous Offer). In case the product, service or process bought is simply new to the public procurer, we can say innovation is not even purchased per se – as we can assume that someone else has already implemented it before – but for the positive outcomes it brings to the organisation, for instance, because it enables similar or even better services delivered to the general public at reduced unit costs;
- And "**Innovation Procurement**", or "**Procurement of Innovation**" – where the above characteristics can be relaxed to some extent. According to an acknowledged definition (European Commission, 2018), this term refers to any purchasing process that targets one or both of the following aspects: the **process** of innovation (such as research and development of products, services or processes, which do not exist yet on the market) and/or the **outcomes** of innovation (a product, service or process that is new to the market or simply new to the public procurer). In the first instance, the public sector organisation acts as a **buyer** of R&D services. In the second instance, as an **early adopter** of third party's R&D results.

Involving small sized enterprises that can work agile on new AI solutions certainly requires the use of innovative procurement schemes. **Such use should be encouraged to facilitate more start-ups and smaller businesses to work together with public administration at all levels**. Around this topic, the EC has recently published a study [83]on the uptake of emerging technologies in public procurement, which presented potential use-cases for AI in public procurement, set up an online repository of projects and gave recommendations for the next steps.

A major impulse to Innovation procurement was given by the modernised EU framework (based on the Directives 2014/23/EU, 2014/24/EU and 2014/25/EU), which introduced or reinforced the possibility of using a **negotiated procedure** for the adaptation of existing or readily available solutions of particularly complex nature, and/or the technical specifications of which cannot be established with sufficient precision. In these circumstances, the **competitive procedure with negotiation** or the **competitive dialogue** can be used. Alternatively, if the market does not offer a satisfactory solution or an adaptation of existing solutions is unlikely to meet the needs of the public buyer, R&D services can be procured to develop a tailor-made innovative solution and/or a set of detailed technical specifications to enable traditional procurement of the respective products, services or processes. That is the case where an **innovation partnership** or a **pre-commercial procurement** procedure [84]can be initiated.

[80] Available at https://www.aiforhumanity.fr/pdfs/MissionVillani_Report_ENG-VF.pdf
[81] See https://publications.parliament.uk/pa/ld201719/ldselect/ldai/100/100.pdf
[82] See https://www.ai4belgium.be/wp-content/uploads/2019/04/report_en.pdf
[83] See https://ec.europa.eu/growth/single-market/public-procurement/digital/emerging-technologies_en
[84] See project example AI4CITIES pre-commercial procurement of 6 cities (https://ai4cities.eu/)

Whatever the approach chosen, the essence of Innovation procurement is to introduce **elements of formal negotiation** between the buyer and the supplier(s), **before, rather than after, the materialisation of an offer and the award of the same** (usually according to the MEAT principle). This together with the fact that obviously a solution being purchased in this way is relatively far from the market and/or generically or partially described by the available technical specifications, makes **Innovation Procurement the preferred or recommended way of purchasing AI in government**.

Thanks to such negotiation, the public buyer can, to a great extent, **transfer most of the AI implementation risks from the delivery (or contractual) to the bidding (or pre-contractual) phase.** In other words, rather than first selecting the supplier and the solution based on precarious elements of evaluation, and then jointly undertaking the definition of the technological, organisational, and service level configuration of the post-implementation scenario, multiple solution options and the respective suppliers can be made to compete with one another, based on their capacity to fulfil the stated objectives for the AI initiative in full.

There are of course **differences** between the various Innovation procurement procedures in terms of scope and purpose of the negotiation(s) they admit. For example, in the competitive procedure with negotiation, the public buyer has a more precise idea than in the competitive dialogue of the nature and characteristics of the solution envisaged. Or in the innovation partnership the negotiation is made before making a price for the entire set of R&D activities and the delivery of a full blown solution, while in pre-commercial procurement a stepwise process is followed, never ending with a final purchase of a commercial result but anyway leading to the definition of multiple viable configurations of the same target product or service.

In any case, the conclusion is that all these Innovation procurement procedures, if properly carried out, go well beyond the known advantages – widely explored by both literature and practice – in terms of "smart purchasing" in and by government bodies and agencies. With specific reference to AI, they can **enable a more prudent and reflective approach to implementation, which promises to overcome or at least reduce the likelihood of some of the challenges outlined in Section 4** in relation to the experimental nature of those solutions.

Unfortunately, and with a bit of paradox, not the same attention has been spent so far on the way governments might allocate their financial resources to buy AI solutions according to Innovative Procurement rules – in the EU countries, the 2014 procurement directives and the national legislation transposing them – than on the likely impacts of AI on the public procurement processes.

Two partial exceptions are:

- The UK Cabinet Office's **Guidelines for AI Procurement**[85], issued on 8 June 2020, and
- City of Amsterdam's contract clauses for procuring Trustworthy AI, and
- The WEF - World Economic Forum's - **AI Procurement in a Box** toolset, also released in the same month[86].

Furthermore, the reference to public procurement (of innovative, but also traditional goods and services) as a valuable engine for AI to become more widespread is present the White Paper on Artificial Intelligence with the action 6 about the "**Adopt AI Programme**" (European Commission, 2020e) and in most policy orientation papers, including from the OECD (Berryhill, Heang, Clogher, & McBride, 2019), the World Economic Forum, CEPS (Renda, 2019), and PWC for the European Commission (forthcoming)[87].

However, if we look at the issue in perspective, it would be highly beneficial for a variety of reasons to pursue a **joint promotion initiative at EU level** of both Innovation Procurement and AI in the Public Sector, highlighting the reciprocal benefits and particularly the extra degrees of freedom allowed by a correct use of the former in a view to appropriately implementing the latter.

Part of this initiative should certainly be the **sharing of existing good practices on AI purchasing** from e.g. the already identified (from the AI Watch team) case studies, if not **a wide capacity building programme** –

[85] https://www.gov.uk/government/publications/guidelines-for-ai-procurement/guidelines-for-ai-procurement
[86] https://www.weforum.org/reports/ai-procurement-in-a-box
[87] Source: https://ec.europa.eu/digital-single-market/en/news/benchmarking-national-innovation-procurement-investments-and-policy-frameworks-across-europe

concerted with the Member States – to increase and diffuse the competencies and capacities of “smart AI purchasing” within the EU national, regional and local public sector bodies and agencies.

Finally, and as a derivative, we might envisage the creation of **a freely available collection of technical tools and maybe templates of tender and negotiation documents,** as for example of Amsterdam, turned into a guidance document (re-usable) has been already being standardised across the Netherlands, to facilitate the implementation of AI solutions under controlled conditions. However, a similar booklet to the UK and WEF examples provided above would already be a (non-minimalistic) start of the process.

With the above, we have exhausted our proposed shortlist of three instantiations of the concept of “**European AI policy exceptionalism**”. Now the time to move to the end of this short journey.

6 Conclusion and way forward

This Section is composed of three conceptual blocks. Paragraph 6.1 proposes to create the conditions for establishing a more advanced equilibrium between AI promotion and regulation, to go beyond the predominantly experimental nature of many observed cases, which can only be considered technological and organisational singularities. Paragraph 6.2 focuses on the ethical dimension of AI and the possibility for government bodies and agencies to conceive and become "first testers" of trustworthy AI principles. Paragraph 6.3 concludes with a summary of the key arguments made throughout the report and relates them to the upcoming work in AI Watch for the Public Sector activities during the year 2021.

6.1 Governing with AI in the Public Sector

During the Covid19 pandemic, interest in AI has not lessened. In particular, as shown in a recent JRC publication (De Nigris et al., 2020) its great potential was acknowledged to assist clinical research, ensure better compliance with quarantine obligations and contact tracing requirements, measure and predict mobility behaviours and virus diffusion trends. Moreover, due to the restrictions accompanying the lockdown, **AI has been regarded as a key technology to tackle and cope with the associated changes in work, study and life practices** (Naudé, 2020) as well as to tackle environmental challenges (monitor, react, predict) The enthusiasm on harnessing the benefits provided by a responsible and trustworthy use of AI has therefore stayed very high on the policy and media agenda. Some countries, like Estonia, had committed to introducing at least 50 working AI applications in the Public Sector by the end of 2020 (Government of the Republic of Estonia, 2019), which has been successfully achieved.

First, **AI repositories** have been introduced in some EU cities. This highlight the extremely important role of transparency when approaching AI. The obscurity of algorithms is something that public administrations have to take into account, not only for their internal ethical judgments but also for clarifying to citizens and firms how the algorithm is used and why and to what extend the algorithm is trustable. For this, publicly available repositories, inventories or registers of AI in use at public administrations is a necessary starting point for providing transparency, explanations and trust in the use of AI in government.

Second, the possible role of **Digital Innovation Hubs** has been considered to bring together various actors, share knowledge and best practices. This is fostering the systemic approach on AI where different competences should be brought together for the appropriation of an AI solution by public administrations, by bringing the local AI ecosystem together and sharing best practices in both developing and applying AI within the organisation.

Covid19 has also interfered – negatively this time – with the pace of development of some of the cases from EU (MS and AS) national, regional and local government presented in July 2020 by the AI Watch for the Public Sector initiative (Misuraca and van Noordt, 2020). With the focus now being narrowed down on the most inspiring ones, which are further explored through an online survey[88] and specific interviews with the case owners, a preliminary conclusion is that not only the AI technologies, but also their uses are rather diverse and the respective maturity levels, geographic quite heterogeneous. Finally, the geographical spread and thematic scope of reported cases were indeed wide, but also unevenly distributed across Member States, government functions, and tiers of public administration.

Apart from the obvious limits of representation of this quantitative analysis, **a comparison with the US and China points at a lower level of integration of the various systems and applications, and therefore a less pronounced capability to quickly scale up**. However, the situation in terms of AI take-up rates and diffusion of consolidated technologies doesn't seem much different from Europe, particularly looking at local public administration and the smallest sized bodies and agencies. What is really worrisome is the fragmentation of the EU single market for GovTech solutions in general and AI-enabled specifically, which is more prominent than in the other countries and should be overcome by **a supplement of policy coordination among the key European stakeholders**.

[88] https://ec.europa.eu/eusurvey/runner/IA-of-AI-public-sector

Such coordination should operate at three distinct, "ecosystemic" levels: European, national/regional and organisational.

- At the **European level** (i.e. the predominant space of coordination between the European Commission and the Member States) the aggregation of existing experiences and good practice examples should be oriented at creating the **next generation of AI enabled public services and processes** - inspired by value creation and human centricity principles - the technological roots of which could be made common, and the respective instantiations interoperable by default; thus, turning the limited technology maturity of AI and the correlated need for experimentation, from a barrier into an opportunity for the accelerated digital transformation of the entire EU government.
- At the **national/regional level** (i.e. the Member State area of legal and jurisdictional competence, but also recommended cooperation between Member and Associated States, as stipulated by the Coordinated Plan on AI) **shared resources and collaboration spaces should be established**- including e.g. legal and administrative sandboxes, data repositories, etc. - to promote the instantiation of processes of reuse and scaling (up/out/deep) of individual take-up cases recognised as excellent or simply replicable with the needed adjustments, in other national or multi-national Public Sector environments.
- At the **organisational level** i.e. (where punctual or singular AI solutions are adopted and implemented in the specific Public Sector environments) **the generation of new success stories in digital transformation** of existing public services or processes should be enhanced by appropriate public procurement guidelines, capacity building and training initiatives[89] of Public Sector staff, data literacy programmes for adults and students, reforms of administrative and legal instruments, etc.

With more and more government bodies and agencies utilising AI, or planning to do so, the issue of financially supporting Public Sector demand is also very relevant. Compared with the EU with the US government budget allocations to ICT R&D – which AI experimentation or innovation is part of – **Europe needs to regain order of magnitude in terms of PPS (Purchasing Power Standard[90]) expenditure**.

Just to give three examples:

- The European Commission's reported investment on AI in the (still ongoing, in terms of funded projects) **Horizon 2020 programme** for R&D and innovation has been in the range of €1,5 billion having the entire economy as the target[91], thus including, though not being limited to, public administration as an application field.
- Further to that, the new **Digital Europe Programme (DEP)** which aims to build a diffused infrastructural and knowledge capacity for AI in Europe, complementing other EU programmes such as Horizon Europe for research and innovation and the Connecting Europe Facility for digital infrastructure, originally proposed a budget of €2,2 billion[92] – still waiting for a final definition in the approved Multiannual Financial Framework 2021-2027 – for opening up the use of AI in both the private and the public sectors.
- Finally, Artificial Intelligence and Human Machine Interfaces are already in the scope of a **Thematic Smart Specialisation Platform** co-led by the Emilia-Romagna Region and the National government of Slovenia since May 2018[93]. Although the scope of the S3 Platform seems currently limited to promoting the deployment of a few demonstrative cases in the AI field, it seems reasonable to predict that such partnership will grow up and consolidate even further in the new programming period 2021-2027, including a possible extension to government case studies[94].

[89] DT4REGIONS will develop training material and MOOC to help regions implement AI.
[90] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Purchasing_power_standard_(PPS)
[91] https://ec.europa.eu/info/research-and-innovation/research-area/industrial-research-and-innovation/key-enabling-technologies/artificial-intelligence-ai_en
[92] https://ec.europa.eu/digital-single-market/en/europe-investing-digital-digital-europe-programme
[93] https://s3platform.jrc.ec.europa.eu/en-US/w/interregional-partnership-for-smart-specialisation-on-artificial-intelligence-and-human-machine-interface
[94] Currently it includes 2 Member States and 10 NUTS-2 Regions, namely: Emilia-Romagna and Autonomous Province of Trento (IT), Slovenia (SI), Baden-Württemberg (DE), Navarra (ES), North-Brabant and East Netherlands (NL), Salzburg (AT), Hungary (HU), Provence-Alpes-Cote d'Azur and Auvergne-Rhone-Alpes (FR), Örebro-lan (SE).

Thus, in their multiple roles of early adopters, promoters and facilitators, not only rule setters and supervisors, EU governments at all levels and in all Member States, regions and cities can do a lot to **make AI Innovation far more widely impactful than a technological or organisational singularity**.

Having in mind the conspicuous heterogeneity of the EU national strategies for AI established until now, it is probably important to reach a broader consensus on a set of common actions that could be conferred to the EU regulatory or soft coordinating level, in order to promote a more harmonised approach to AI implementation in public administration, cutting across the country differences and valorising the peculiar aspects of the Public Sector as a whole.

Conversely, innovation policies of Member States and Regions should not stay focused on stimulating the deployment of AI *per se*, without considering that such technologies may not be the answer for each and every issue related to service improvement or transformation. However, there have been important achievements that could be regarded as crucial to ensure that the challenges of Public Sector digitalization are being overcome, and that could serve as inspiration to use AI sustainably and durably.

To help systematize the current scenario analysis and point at credible directions for improvement, another, ongoing activity of AI Watch will be a collection of policy recommendations taking the shape of an EU-wide roadmap for securing the transition to AI enabled and digitally transformed government.

6.2 On governing AI in the Public Sector

Governing AI is as relevant as a policy issue as using it for government or governance related purposes. Especially in the EU, this issue has been answered in terms of an ethical approach to the development and deployment of such technologies in operating environments.

The High-Level Expert Group on AI published a set of **7 key requirements in order to ensure that AI is trustworthy** (High-Level Expert Group on Artificial Intelligence (HLEG), 2019). Through the Assessment List for Trustworthy AI (ALTAI)[95], developers and deployers of AI can **assess by themselves whether their solutions are in line with these principles** (High-Level Expert Group on AI (HLEG), 2020). The assessment list is intended for use by a multidisciplinary team of people, each having specific competencies on the various requirements. It is expected that by following the Assessment List, organizations implementing new AI systems or applications can identify associated risks and consequently act to minimize or even avoid them. The Assessment List is made with flexibility in mind and encourages organizations to further develop the guidelines to fit into their specific sector as well. Such guidelines and requirements are also key to include within AI Procurement procedures, as key risks of AI could be mitigated already at the start, during and following the completion of procurement processes.

A related, though not completely clear concept is Ethical AI. Great progress has been recently made in igniting a worldwide debate on this topic, although the various stakeholders have slightly different interpretations of it. AlgorithmWatch keeps an inventory of all published AI ethical guidelines, which is currently including more than **160 different publications from all over the world** (AlgorithmWatch, 2020b). Previous research had analysed 84 ethical AI documents published by various businesses, NGOs and (international) governmental organizations, highlighting that some principles such as transparency, fairness, justice, and responsibility were quite common in all. However, not a single one of those principles was found in all of the scrutinised documents (Jobin, Ienca, & Vayena, 2019). Despite this, **many governments worldwide have issued policy documents highlighting the need for ethical AI** (European Parliamentary Research Service (EPRS), Scientific Foresight Unit (STOA), 2020). This is also the case of most national strategies of EU countries monitored by the AI Watch initiative and has been highlighted by the recent "Proposal for a Regulation laying down harmonised rules on artificial intelligence (**Artificial Intelligence Act**)"[96].

The development and deployment of ethical AI applications could involve governance challenges in the Public Sector. These are made more serious by the **commitment of public administration to be accountable**, not only for its decisions and decision-making mechanisms but also for the – anticipated or unwanted – societal implications of moving from the realm of AI experimentation to the permanent embedment of AI solutions in

[95] https://futurium.ec.europa.eu/en/european-ai-alliance/pages/altai-assessment-list-trustworthy-artificial-intelligence
[96] https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-european-approach-artificial-intelligence

processes and services. This poses the question of whether **more concrete and operationalised ethical AI guidelines could be proposed and tested first within a public administration environment,** for example within "regulatory sandboxes"[97] and with AI Testing and Experimentation Facilities.

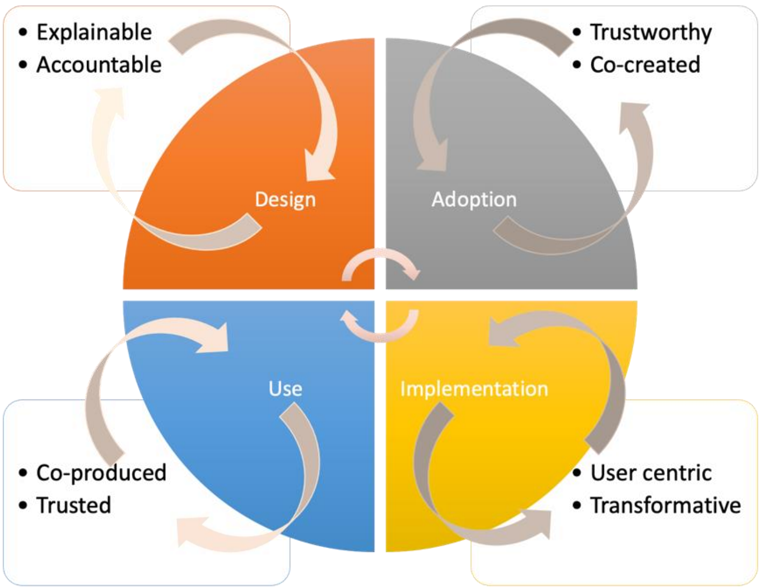
Such a question is not easy to answer. For example, self-attributed guidelines could possibly be designed by an external panel of experts (such as the HLEG on AI) and then be used by government bodies and agencies in relation to the service to be delivered. An alternative option would be to rely on some of the (even too many) templates and blueprints that can be retrieved in the state of the art. There are also ongoing standard setting efforts, for example at IEEE, which are reported about by (European Parliamentary Research Service (EPRS), Scientific Foresight Unit (STOA), 2020). However, we think it is more likely that in different countries and layers of public administration (e.g. cities or regions) the preference would go towards developing their own guidelines rather than using those made available by other Public Sector organisations. In which case, apart from the issue of finding adequate resources to support the activity, the **risk of proliferation of approaches and interpretations** would still become apparent.

Moreover, this does not assure that involved staff would understand and operationalize these guidelines in an intended way. Therefore, **it is crucial for governments to anticipate how guidelines will be worked with and whether the users of those guidelines have the appropriate expertise and capacity to apply them**. For example, Digital Innovation Hubs should be able to support public administrations with procurement and be multipliers of useful templates and processes. This echoes the discourse made in this report on the crucial importance of specific training and cultural transformation of civil servants involved in AI development and deployment.

6.3 Main insights from the report towards an analytical framework for evaluating AI impact in government

To conclude, Figure 6 summarizes and offers a visual representation of the key arguments made throughout this report. Those arguments can be considered as the first attempt at an analytical framework for evaluating AI impact in government.

Figure 6. Analytical framework for AI impact assessment.



Source: JRC, own elaboration.

[97] https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-european-approach-artificial-intelligence

The four analytical dimensions of the framework include: **design, adoption, implementation** and **use of AI solutions in the Public Sector**. Let's now comment on them in turn:

- During the **design** phase, a key contextual element to borrow is the need for *explainable* AI. This has been already discussed in Paragraph 5.3 as well as in the previous one. The main potential benefit, also self-reinforcing in case the feedback loop acts in the right direction, can be grasped in terms of *accountability* for the government body or agency engaged in this exercise. There can be other relevant aspects of course, but the idea is to focus on the most important ones. Note that the discourse previously made on AI can be fully recovered here. Finally, a testable implication is that whenever explainable AI is given emphasis to, the level of accountability (however measured) increases, both within the same and between different public sector organisations.
- During the **adoption** phase, the principles of *trustworthy AI* find appropriate room. Indeed, this is the locus of experimentation, where technology is tested and evaluated for potential use. Again, some of the arguments made in paragraph 6.3 – especially on the importance of co-design together with end users and stakeholders – can and should be referred to here. A testable implication can be that the more services are *co-created*, the better their "smart" alignment with Assessment List for Trustworthy Artificial Intelligence (ALTAI)[98] requirements – where smart means that the benefits would largely outnumber the critical aspects of ethical compliance.
- During the **implementation** phase, as it is known from the definition and analysis provided in Section 2, the main expectation is to permanently embed the AI innovation into the involved government body's or agency's business practice. Therefore, a strong recommendation coming from the external context is to make this innovation *user centric*, as far as the associated digital public services are concerned. In so doing, the chances of transforming the "business of government" in a visibly durable and sustainable fashion should probably be enhanced. This can also be the testable implication of this feedback loop: the more user centric is the AI enabled services while in operation, the more pervasive and radical will be the *transformation* of government practice.
- During the **use** phase, citizens and businesses enjoy the benefits and suffer from the criticalities of AI enabled public processes and services. Here the known concept of *co-production* should be made applicable so that beneficiaries are actively and seamlessly engaged in co-delivering (and perhaps, also co-evaluating) the promise of government transformation. This is expected to contribute to legitimising public administration in the eyes of its reference stakeholders and therefore enhance the levels of *confidence and trust* within the constituency. Based on the currently too immature stage of most AI applications in the state of the art, it is doubtful that sufficient empirical evidence exists to support this testable implication. However, this stream of field research would also contribute to answering the broader question of whether AI innovation improves or undermines government's democratic legitimacy.

How the future of AI-enabled innovation in government is going to look like depends in our opinion largely on the four analytical dimensions outlined above, and if the related feedback loops are reinforced and in which direction (i.e. as "virtuous" or "vicious" cycles) in the coming years. In fact, history tells us that the Public Sector's digital transformation has not proceeded as linearly or predictably as it is often mentioned, but in a more complex and full of ups and downs way, depending on a variety of contingent factors (Barcevičius et al., 2019).

In this situation, what we propose to do in the future analysis is to start with this analytical framework and to integrate it with the known definition of AI, which also the White Paper has made its own (see European Commission, 2020e, p. 2), with the following simple, yet clear-cut statement: **AI is not only about algorithms, data and computing power, but also about people**. Therefore, **its implementation may never be completely successful is only done "for" the people, but needs to be done together "with" them**.

This attitude will probably help break the ultimate barrier preventing the inclusion of government in the range of the downstream industries affected by the concurrent adoption and widespread implementation of AI as a General Purpose Technology, driven by the convergent attitude of multiple actors – both public and private – who use it as an input to enhance the performance (however defined, but without excluding ethical and societal compliance) of the respective application environments.

[98] https://digital-strategy.ec.europa.eu/en/library/assessment-list-trustworthy-artificial-intelligence-altai-self-assessment

Based on the results illustrated in this report, future work will be dedicated to use the analytical framework conclusions in the development of a generic implementation Roadmap for the use of AI in the Public Sector and to increase a diffused human-centric and value-creation oriented AI deployment in the European Public Sector and may possibly serve as a concrete input to the Better Regulation package[99].

[99] https://ec.europa.eu/info/law/law-making-process/planning-and-proposing-law/better-regulation-why-and-how_en

List of abbreviations

AI	Artificial Intelligence
AIA	Algorithmic Impact Assessment
API	Application Programming Interface
AS	Associated State(s)
BDVA	Big Data Value Association
COFOG	Classification Of the Functions Of Government
EEA	European Economic Area
EU	European Union
GBARD	Government Budget Allocation for R&D
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GovTech	Government Technology
GSA	General Services Administration
HLEG	High Level Expert Group
ICT	Information and Communication Technology
IoT	Internet of Things
JRC	Joint Research Centre
MEAT	Most Economically Advantageous Tender
MS	Member State(s)
NACE	Nomenclature statistique des Activités économiques dans la Communauté Européenne
OECD	Organisation for Economic Cooperation and Development
OGDPI	Open Government Data Portal Index
PCP	Pre-Commercial Procurement
POINT	Projecting Opportunities for INdustrial Transitions
PPI	Public Procurement of Innovation
PPS	Purchasing Power Standard(s)
PSI	Public Sector Information

Q&A	Questions and Answers
R&D	Research and Development
RFI	Request For Information
RRF	Recovery and Resilience Facility
S3	Smart Specialisation Strategy
SDGs	Sustainable Development Goals
TED	Tenders Electronic Daily
TRL	Technology Readiness Level
UN	United Nations
WEF	World Economic Forum
XAI	eXplainable Artificial Intelligence

List of figures

List of tables

References

AIAAIC. (2021). AI, algorithmic and automation incident and controversy repository (AIAAIC) repository. Retrieved May 4, 2021, from https://www.aiaaic.org/aiaaic-repository

AlgorithmWatch. (2020a). *Automating society report 2020*. Retrieved from https://automatingsociety.algorithmwatch.org/wp-content/uploads/2020/12/Automating-Society-Report-2020.pdf

AlgorithmWatch. (2020b, April). AI Ethics Guidelines Global Inventory. Retrieved December 15, 2020, from https://inventory.algorithmwatch.org/

Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities*, *89*, 80–91. https://doi.org/10.1016/j.cities.2019.01.032

Alzahrani, L., Al-Karaghouli, W., & Weerakkody, V. (2017). *Analysing the critical factors influencing trust in e-government adoption from citizens' perspective: A systematic review and a conceptual framework*. Retrieved from https://bradscholars.brad.ac.uk/handle/10454/11683

Andergassen, R., Nardini, F., & Ricottilli, M. (2016). Innovation diffusion, general purpose technologies and economic growth. *Structural Change and Economic Dynamics*, *40*. https://doi.org/10.1016/j.strueco.2016.12.003

Andersen, K. N., Lee, J., & Henriksen, H. Z. (2020). Digital sclerosis? Wind of change for government and the employees. *Digit. Gov.: Res. Pract.*, *1*(1), 1–14. https://doi.org/10.1145/3360000

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., … Herrera, F. (2019). Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI. *ArXiv:1910.10045 [Cs]*. Retrieved from http://arxiv.org/abs/1910.10045

Bachman, B., & Bozzone, S. (2011). Pervasive innovation: Taking innovation throughout the organization. *Business and Information Technology Faculty Research & Creative Works*. Retrieved from https://scholarsmine.mst.edu/bio_inftec_facwork/132

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems*, *8*(4). https://doi.org/10.17705/1jais.00122

Bailey, D. E., & Barley, S. R. (2019). Beyond design and use: How scholars should study intelligent technologies. *Information and Organization*, *30*(2), 100286. https://doi.org/10.1016/j.infoandorg.2019.100286

Barbero, M., Coutuer, J., Jackers, R., Moueddene, K., Renders, E., Stevens, W., … Versteele, D. (2016). *Big data analytics for policy making*. Retrieved from Deloitte website: https://joinup.ec.europa.eu/sites/default/files/document/2016-07/dg_digit_study_big_data_analytics_for_policy_making.pdf

Barcevičius, A. E., Cibaitė, G., Gineikytė, V., Klimavičiūtė, L., Matulevič, L., Misuraca, G., & Vanini, I. (2019). *Exploring digital government transformation in the EU* (No. EUR 29987). https://doi.org/10.2760/17207

Barley, S. R. (1986). Technology as an occasion for structuring: Evidence from observations of CT scanners and the social order of radiology departments. *Administrative Science Quarterly*. https://doi.org/10.1017/CBO9780511618925.007

Bassetti, T., Borbon Galvez, Y., Del Sorbo, M., & Pavesi, F. (2020). *Artificial Intelligence – impact on total factor productivity, e-commerce & fintech* (JRC No. EUR 30428). Retrieved from Publications Office of the European Union website: https://publications.jrc.ec.europa.eu/repository/handle/111111111/61622

BDVA. (2019). *Towards a European data sharing space—Enabling data exchange and unlocking AI potential*. Retrieved from https://www.bdva.eu/sites/default/files/BDVA%20DataSharingSpace%20PositionPaper_April2019_V1.pdf

Benbunan-Fich, R., Desouza, K. C., & Andersen, K. N. (2020). IT-enabled innovation in the public sector: Introduction to the special issue. *European Journal of Information Systems*, *29*(4), 323–328. https://doi.org/10.1080/0960085X.2020.1814989

Bernease, H. (2019). The promise and peril of human evaluation for model interpretability. *ArXiv:1711.07414 [Cs, Stat]*. Retrieved from http://arxiv.org/abs/1711.07414

Berryhill, J., Heang, K. K., Clogher, R., & McBride, K. (2019). *Hello, World: Artificial intelligence and its use in the public sector*. Retrieved from OECD website: https://www.oecd-ilibrary.org/governance/hello-world_726fd39d-en

Biedron, R. (2020, June 17). Artificial Intelligence in procurement. Retrieved May 3, 2021, from PLANERGY Software website: https://planergy.com/blog/ai-in-procurement/

Borrás, S., & Edler, J. (2020). The roles of the state in the governance of socio-technical systems' transformation. *Research Policy*, *49*, 103971. https://doi.org/10.1016/j.respol.2020.103971

Bostrom, N. (2014). *Superintelligence: Paths, dangers, strategies* (Reprint edition). OUP Oxford.

Boyd, M., Vaccari, L., Posada, M., & Gattwinkel, D. (2020). *An Application Programming Interfaces (APIs) framework for digital government.* Retrieved from Publications Office website: https://data.europa.eu/doi/10.2760/772503

Bradford, A., & Posner, E. A. (2011). *Universal exceptionalism in international law* (SSRN Scholarly Paper No. ID 2770597). Retrieved from Social Science Research Network website: https://papers.ssrn.com/abstract=2770597

Bruno, I., Schiavone Panni, A., Marchetti, V., Molinari, F., & Valente Covino, B. (2020). *A multi-dimensional framework to evaluate the innovation potential of digital public services: A step towards building an Innovative Public Services Observatory in the EU* [EUR - Scientific and Technical Research Reports]. https://doi.org/10.2760/09628

Burrell, J. (2016). How the Machine "Thinks:" Understanding Opacity in Machine Learning Algorithms. *Big Data & Society*, *January-*, 1–12. https://doi.org/10.2139/ssrn.2660674

Calzada, I., & Almirall, E. (2020). Data ecosystems for protecting European citizens' digital rights. *Transforming Government: People, Process and Policy*, *14*(2), 133–147. https://doi.org/10.1108/TG-03-2020-0047

Campion, A., Gasco-Hernandez, M., Jankin Mikhaylov, S., & Esteve, M. (2020). Overcoming the challenges of collaboratively adopting Artificial Intelligence in the public sector. *Social Science Computer Review*, 0894439320979953. https://doi.org/10.1177/0894439320979953

Cantner, U., & Vannuccini, S. (2012). *A new view of general purpose technologies* (No. 2012–054). Retrieved from Friedrich-Schiller-University Jena website: https://ideas.repec.org/p/jrp/jrpwrp/2012-054.html

Carrasco, M., Mills, S., Whybrew, A., & Jura, A. (2019a). *The Citizens Perspective on the Use of AI in Government*. Retrieved from https://www.bcg.com/publications/2019/citizen-perspective-use-artificial-intelligence-government-digital-benchmarking

Carrasco, M., Mills, S., Whybrew, A., & Jura, A. (2019b). The Citizens Perspective on the Use of AI in Government. In *Boston Consulting Group*.

Carroll, J. (2004). *Completing design in use: Closing the appropriation cycle*. 337–347.

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., Floridi, L., Wachter, S., … Cath, C. (2018). Artificial Intelligence and the 'Good Society': The US, EU, and UK approach. *Science and Engineering Ethics*, *24*(2), 505–528. https://doi.org/10.1007/s11948-017-9901-7

Center for Digital Government, IBM, & NASCIO. (2019). *Delivering on Digital Government: Achieving the Promise of Artificial Intelligence*. Retrieved from https://iapp.org/media/pdf/digital_government_artificial_intelligence.pdf

Chen, T., Ran, L., & Gao, X. (2019a). AI innovation for advancing public service. *Proceedings of the 20th Annual International Conference on Digital Government Research*, 100–108. https://doi.org/10.1145/3325112.3325243

Chen, T., Ran, L., & Gao, X. (2019b). AI innovation for advancing public service. *Proceedings of the 20th Annual International Conference on Digital Government Research*, 100–108. https://doi.org/10.1145/3325112.3325243

Choi, T., & Chandler, S. M. (2015). Exploration, Exploitation, and Public Sector Innovation: An Organizational Learning Perspective for the Public Sector. *Human Service Organizations: Management, Leadership & Governance*, *39*(2), 139–151. https://doi.org/10.1080/23303131.2015.1011762

Cognilytica. (2020). *Global AI Adoption Trends & Forecast 2020*. Retrieved from https://www.cognilytica.com/2020/01/22/global-ai-adoption-trends-forecast-2020/

Coiera, E. (2019). The last mile: Where Artificial Intelligence meets reality. *Journal of Medical Internet Research*, *21*(11), e16323. https://doi.org/10.2196/16323

Concilio, G., & Molinari, F. (2021). The un-exploitable smartness of open data. *Sustainability*. Retrieved from Forthcoming

Craglia, M., Annoni, A., Benzcur, P., Bertoldi, P., Delipetrev, B., De Prato, G., … Vesnic Alujevic, L. (2018). *Artificial intelligence: A European perspective* (JRC No. EUR 29425 EN). Retrieved from Publications Office of the European Union website: https://ec.europa.eu/jrc/en/publication/artificial-intelligence-european-perspective

Creemers, R. (2018a). China's social credit system: An evolving practice of control. *SSRN Electronic Journal*, *222*(2015), 59–71. https://doi.org/10.2139/ssrn.3175792

Creemers, R. (2018b). China's Social Credit System: An Evolving Practice of Control. *SSRN Electronic Journal*, *222*(2015), 59–71. https://doi.org/10.2139/ssrn.3175792

Dalla Benetta, A., Maciej, S., & Nepelski, D. (2021). *AI watch: 2020 EU AI investments*. https://doi.org/10.2760/0175141

Danaher, J. (2016). The threat of algocracy: Reality, resistance and accommodation. *Philosophy and Technology*, *29*(3), 245–268. https://doi.org/10.1007/s13347-015-0211-1

Dawes, S. S., Vidiasova, L., & Parkhimovich, O. (2016). Planning and designing open government data programs: An ecosystem approach. *Government Information Quarterly*. https://doi.org/10.1016/j.giq.2016.01.003

De Nigris, S., Gómez-González, E., Gómez Gutierrez, E., Martens, B., Iglesias Portela, M., Vespe, M., … Junklewitz, H. (2020). *Artificial Intelligence and Digital Transformation: Early lessons from the COVID-19 crisis, Craglia, M. editor(s)* (JRC No. EUR 30306 EN). https://doi.org/10.2760/166278

De Prato, G., López Cobo, M., Samoili, S., Righi, R., Vázquez-Prada Baillet, M., & Cardona, M. (2019). *The AI techno-economic segment analysis* (JRC No. EUR 29952). Retrieved from Publications Office of the European Union website: http://op.europa.eu/en/publication-detail/-/publication/d4893b4e-0f38-11ea-8c1f-01aa75ed71a1/language-en

Delaney, P., Timbrell, G., & Chan, T. (2008). A marxian model of technology appropriation. *Proceedings of the JAIS Theory Development Workshop. Sprouts: Working Papers on Information Systems*, *8*(1), 1–37.

Desouza, K. C., Dawson, G. S., & Chenok, D. (2020). Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. *Business Horizons*, *63*(2), 205–213. https://doi.org/10.1016/j.bushor.2019.11.004

Dignum, V. (2018). Ethics in artificial intelligence: Introduction to the special issue. *Ethics and Information Technology*, *20*(1), 1–3. https://doi.org/10.1007/s10676-018-9450-z

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*(2), 147–160. https://doi.org/10.2307/2095101

Dressel, J., & Farid, H. (2018). The accuracy, fairness, and limits of predicting recidivism. *Science Advances*, *4*(1), eaao5580. https://doi.org/10.1126/sciadv.aao5580

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … al, et. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, (August), 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Edquist, C. (2001). *The systems of innovation approach and innovation policy: An account of the state of the art*.

El-Haddadeh, R., Weerakkody, V., Osmani, M., Thakker, D., & Kapoor, K. K. (2019). Examining citizens' perceived value of internet of things technologies in facilitating public sector services engagement. *Government Information Quarterly*, *36*(2), 310–320. https://doi.org/10.1016/j.giq.2018.09.009

Elliott, H. (2020a). The AI powered State: China's approach to public sector innovation. Retrieved May 1, 2021, from https://www.nesta.org.uk/feature/ai-powered-state/

Elliott, H. (2020b). *The AI Powered State: China's approach to public sector innovation*.

Elzen, B., Geels, F. W., & Green, K. (2004). *System innovation and the transition to sustainability: Theory, evidence and policy*. Edward Elgar Publishing.

Engstrom, D. F., Ho, D. E., Sharkey, C. M., & Cuéllar, M.-F. (2020a). *Government by Algorithm: Artificial Intelligence in federal administrative agencies*. Retrieved from https://www.ssrn.com/abstract=3551505

Engstrom, D. F., Ho, D. E., Sharkey, C. M., & Cuéllar, M.-F. (2020b). Government by Algorithm: Artificial Intelligence in Federal Administrative Agencies. In *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3551505

European Commission. (2011). *Social experimentation: A methodological guide for policy makers*. Retrieved from https://ec.europa.eu/social/BlobServlet?docId=7102&langId=en

European Commission. (2017a). *Measurement of impact of cross-border penetration in public procurement, Final report.* Retrieved from Publications Office of the European Union website: http://op.europa.eu/en/publication-detail/-/publication/5c148423-39e2-11e7-a08e-01aa75ed71a1

European Commission. (2017b). The new European interoperability framework (EIF) [Text]. Retrieved March 12, 2019, from ISA^2—European Commission website: https://ec.europa.eu/isa2/eif_en

European Commission. *Communication on Artificial Intelligence for Europe*. , Pub. L. No. COM/2018/237 (2018).

European Commission. *Communication on the Coordinated Plan on Artificial Intelligence*. , Pub. L. No. COM/2018/795 (2018).

European Commission. *Communication on Building Trust in Human-Centric Artificial Intelligence*. , Pub. L. No. COM/2019/168 (2019).

European Commission. *Communication on the European Green Deal*. , Pub. L. No. COM/2019/640 (2019).

European Commission. (2019c). *eGovernment benchmark 2019: Empowering Europeans through trusted digital public services. Insight report.* Retrieved from Publications Office of the European Union website: http://op.europa.eu/en/publication-detail/-/publication/c896937b-f554-11e9-8c1f-01aa75ed71a1/language-en

European Commission. *A European strategy for data COM/2020/66*. , Pub. L. No. COM/2020/66 (2020).

European Commission. (2020b). *eGovernment benchmark 2020: EGovernment that works for the people*. Retrieved from https://digital-strategy.ec.europa.eu/en/library/egovernment-benchmark-2020-egovernment-works-people

European Commission. (2020c). *European enterprise survey on the use of technologies based on artificial intelligence*. https://doi.org/10.2759/759368

European Commission. *White Paper on Artificial Intelligence – A European approach to excellence and trust*. , Pub. L. No. COM/2020/65 (2020).

European Commission. (2020e). *White paper on Artificial Intelligence: A European approach to excellence and trust*. Retrieved from https://ec.europa.eu/info/files/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en

European Commission. (2021a). Coordinated Plan on Artificial Intelligence 2021 Review. Retrieved May 7, 2021, from https://digital-strategy.ec.europa.eu/en/library/coordinated-plan-artificial-intelligence-2021-review

European Commission. *Coordinated plan on Artificial Intelligence 2021 review (ANNEXES to the Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions Fostering a European approach to Artificial Intelligence)*. , COM/2021/205 § (2021).

European Commission. (2021c). Digital Innovation Hubs: Helping companies and public administrations make the most of digital opportunities. Retrieved May 6, 2021, from https://digital-strategy.ec.europa.eu/en/library/digital-innovation-hubs-helping-companies-and-public-administrations-make-most-digital

European Committee of the Regions. (2020). *2020 barometer of regions and cities*. Retrieved from https://cor.europa.eu/en/our-work/Pages/EURegionalBarometer-2020.aspx

European Parliamentary Research Service (EPRS), Scientific Foresight Unit (STOA). (2020). The ethics of artificial intelligence: Issues and initiatives. Retrieved May 3, 2021, from https://www.europarl.europa.eu/thinktank/en/document.html?reference=EPRS_STU(2020)634452

Eurostat. (2020). Government budget allocations for R&D (GBARD) (gba). Retrieved May 4, 2021, from https://ec.europa.eu/eurostat/cache/metadata/en/gba_esms.htm

Feenberg, A. (2010). *Between reason and experience: Essays in technology and modernity* (Illustrated edition). Retrieved from https://mitpress.mit.edu/books/between-reason-and-experience

Ferro, E., Loukis, E. N., Charalabidis, Y., & Osella, M. (2013). Policy making 2.0: From theory to practice. *Government Information Quarterly*, *4*(30), 359–368. https://doi.org/10.1016/j.giq.2013.05.018

Floridi, L. (2020). *Artificial Intelligence as a public service: Learning from Amsterdam and Helsinki*. 3–8.

Fredriksson, C., Mubarak, F., Tuohimaa, M., & Zhan, M. (2017). Big data in the public sector: A systematic literature review. *Scandinavian Journal of Public Administration*, *21*(3), 39–62.

Gabryelczyk, R. (2020). Has COVID-19 accelerated digital transformation? Initial lessons learned for public administrations. *Information Systems Management*, *37*(4), 303–309. https://doi.org/10.1080/10580530.2020.1820633

GEP. (2018). *Artificial intelligence and its impact on procurement and supply chain*. Retrieved from https://sig.org/system/tdf/srcDocs/Artificial_Intelligence_and_Its_Impact_on_Procurement_and_Supply_Chain_White_Paper_2019.pdf?file=1&type=node&id=14913&

Giest, S., & Samuels, A. (2020). 'For good measure': Data gaps in a big data world. *Policy Sciences*, (0123456789). https://doi.org/10.1007/s11077-020-09384-1

Gilpin, L. H., Bau, D., Yuan, B. Z., Bajwa, A., Specter, M., & Kagal, L. (2018). Explaining explanations: An overview of interpretability of machine learning. *2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA)*, 80–89. https://doi.org/10.1109/DSAA.2018.00018

Girasa, R. (2020). AI as a disruptive technology. In *Artificial Intelligence as a Disruptive Technology: Economic Transformation and Government Regulation* (pp. 3–21). https://doi.org/10.1007/978-3-030-35975-1_1

Government of the Republic of Estonia. (2019). *Estonia's national artificial intelligence strategy 2019-2021*. Retrieved from https://e-estonia.com/nationa-ai-strategy/

Grillitsch, M., & Asheim, B. (2018). Place-based innovation policy for industrial diversification in regions. *European Planning Studies*. https://doi.org/10.1080/09654313.2018.1484892

Grzenda, M., & Legierski, J. (2019). Towards increased understanding of open data use for software development. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-019-09954-6

GSA Centers of Excellence. (2020). *Accelerate adoption of Artificial Intelligence to discover insights at machine speed*. Retrieved from https://coe.gsa.gov/docs/2019/AIServiceCatalogNov19.pdf

Gupta, A., Smith, K., & Shalley, C. (2006). The interplay between exploration and exploitation. *Academy of Management Journal*, *49*. https://doi.org/10.5465/AMJ.2006.22083026

Harrison, T., F. Luna-Reyes, L., Pardo, T., De Paula, N., Najafabadi, M., & Palmer, J. (2019). *The data firehose and AI in Government*. 171–176. https://doi.org/10.1145/3325112.3325245

Hellberg, A. S., & Hedström, K. (2015). The story of the sixth myth of open data and open government. *Transforming Government: People, Process and Policy*, *9*(1), 35–51. https://doi.org/10.1108/TG-04-2014-0013

High-Level Expert Group on AI (HLEG). (2020). *The assessment list for trustworthy Artificial Intelligence (ALTAI)*. https://doi.org/10.2759/002360

High-Level Expert Group on Artificial Intelligence (HLEG). (2019). *Ethics guidelines for trustworthy AI*. Retrieved from https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, *28*(1), 52–61. https://doi.org/10.1016/j.infoandorg.2018.02.004

Hufty, M. (2011). Investigating policy processes: The Governance Analytical Framework (GAF). In *Research for Sustainable Development: Foundations, Experiences, and Perspectives* (pp. 403–424).

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. *Government Information Quarterly*, *37*(3), 101493. https://doi.org/10.1016/j.giq.2020.101493

Janssen, M., Charalabidis, Y., & Zuiderwijk, A. (2012). Benefits, adoption barriers and myths of Open Data and Open Government. *Information Systems Management*, *29*(4), 258–268. https://doi.org/10.1080/10580530.2012.716740

Janssen, M., Konopnicki, D., Snowdon, J. L., & Ojo, A. (2017). Driving public sector innovation using big and open linked data (BOLD). *Information Systems Frontiers*, *19*(2), 189–195. https://doi.org/10.1007/s10796-017-9746-2

Janssen, M., & van den Hoven, J. (2015). Big and Open Linked Data (BOLD) in government: A challenge to transparency and privacy? *Government Information Quarterly*, *32*(4), 363–368. https://doi.org/10.1016/j.giq.2015.11.007

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Jovanovic, B., & Rousseau, P. L. (2005). *General purpose technologies* (No. w11093). https://doi.org/10.3386/w11093

Kankanhalli, A., Charalabidis, Y., & Mellouli, S. (2019). IoT and AI for smart government: A research agenda. *Government Information Quarterly*, *36*(2), 304–309. https://doi.org/10.1016/j.giq.2019.02.003

Kelemen, A. (2020). *Supporting sustainability transitions under the European Green Deal with cohesion policy. Toolkit for national and regional decision-makers*. Retrieved from European Commission Directorate-General for Regional and Urban Policy website: https://ec.europa.eu/regional_policy/en/information/publications/guidelines/2020/supporting-sustainability-transitions-under-the-european-green-deal-with-cohesion-policy-toolkit-for-national-and-regional-decision-makers

Kessler, T. G., & Kelley, P. A. (2000). *The business of government*. Vienna, Va: Berrett-Koehler Publishers.

Klievink, B., Van Der Voort, H., & Veeneman, W. (2018). Creating value through data collaboratives: Balancing innovation and control. *Information Polity*, *23*(4), 379–397. https://doi.org/10.3233/IP-180070

Korzinov, V., & Savin, I. (2016). *Pervasive enough? General purpose technologies as an emergent property*. https://doi.org/10.13140/RG.2.2.15495.39848

Krafft, P. M., Young, M., Katell, M., Huang, K., & Bugingo, G. (2019). *Defining AI in policy versus practice*. Retrieved from http://arxiv.org/abs/1912.11095

Kuziemski, M., & Misuraca, G. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, *44*(6), 101976. https://doi.org/10.1016/j.telpol.2020.101976

Lämmerhirt, D., Rubinstein, M., & Montiel, O. (2017). *The state of Open Governement data in 2017*. Retrieved from https://blog.okfn.org/files/2017/06/FinalreportTheStateofOpenGovernmentDatain2017.pdf

Laskai, L., & Webster, G. (2019, June 17). Translation: Chinese Expert Group Offers "Governance Principles" for "Responsible AI." Retrieved December 17, 2020, from New America website: https://www.newamerica.org/cybersecurity-initiative/digichina/blog/translation-chinese-expert-group-offers-governance-principles-responsible-ai/

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic Management Journal*, *14*(S2), 95–112. https://doi.org/10.1002/smj.4250141009

Ling, R. (2010). *New tech, new ties: How mobile communication is reshaping social cohesion*. Cambridge, Mass: The MIT Press.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, Vol. 90, pp. 46–60. https://doi.org/10.1016/j.futures.2017.03.006

Malone, S. (2019). How will machine learning affect public procurement? Retrieved May 3, 2021, from Supply Management website: https://www.cips.org/supply-management/opinion/2018/november/how-to-survive-the-public-sector-shift-to-ai/

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, *2*(1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Mas, M., Fernandez de Guevara Radoselovics, J., Robledo, J. C., Cardona, M., Righi, R., Samoili, S., & Vazquez-Prada Baillet, M. (2020). *The 2020 PREDICT: Key facts report: An analysis of ICT R&D in the EU and beyond* (JRC No. EUR 30305). Retrieved from Publications Office of the European Union website: https://data.europa.eu/doi/10.2760/291872

McCrea, B. (2018). 4 Ways Artificial Intelligence impacts procurement. Retrieved May 3, 2021, from https://www.sourcetoday.com/supply-chain/article/21867095/4-ways-artificial-intelligence-impacts-procurement

McKinsey. (2019). Cutting through the noise: How banks can unlock the potential of APIs. Retrieved February 7, 2020, from https://www.mckinsey.com/industries/financial-services/our-insights/banking-matters/cutting-through-the-noise-how-banks-can-unlock-the-potential-of-apis

McKinsey. (2020a). *Global survey: The state of AI in 2020*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020

McKinsey. (2020b). *How nine digital frontrunners can lead on AI in Europe*. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/how-nine-digital-front-runners-can-lead-on-ai-in-europe

McKinsey Analytics. (2020). *Global survey: The state of AI in 2020*.

Meijer, A., & Thaens, M. (2020). The dark side of public innovation. *Public Performance & Management Review*, *0*(0), 1–19. https://doi.org/10.1080/15309576.2020.1782954

Mergel, I. (2019). Digital service teams in government. *Government Information Quarterly*, *36*(4), 101389. https://doi.org/10.1016/j.giq.2019.07.001

Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, *36*(4), 101385. https://doi.org/10.1016/j.giq.2019.06.002

Meulen, R. van der. (2017). Prepare for the impact of AI on procurement. Retrieved May 3, 2021, from https://www.gartner.com/smarterwithgartner/prepare-for-the-impact-of-ai-on-procurement/

Misuraca, G. C. (2012). *Assessing ICT-enabled Innovation for Governance and Policy Making* (École polytechnique fédérale de Lausanne). https://doi.org/10.5075/epfl-thesis-5497

Misuraca, G., & van Noordt, C. (2020). *Overview of the use and impact of AI in public services in the EU* (JRC No. EUR 30255). Retrieved from Publications Office of the European Union website: https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/ai-watch-artificial-intelligence-public-services

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, *3*(2). https://doi.org/10.1177/2053951716679679

Moravcsik, A. (1993). Preferences and Power in the European Community: A Liberal Intergovernmentalist Approach. *JCMS: Journal of Common Market Studies*, *31*(4), 473–524. https://doi.org/10.1111/j.1468-5965.1993.tb00477.x

Mulligan, D. K., & Bamberger, K. A. (2019). Procurement as policy: Administrative process for machine learning. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3464203

Muscio, A., Reid, A., & Rivera Leon, L. (2015). An empirical test of the regional innovation paradox: Can smart specialisation overcome the paradox in Central and Eastern Europe? *Journal of Economic Policy Reform*, *18*(2), 153–171. https://doi.org/10.1080/17487870.2015.1013545

Nagtegaal, R. (2020). The impact of using algorithms for managerial decisions on public employees' procedural justice. *Government Information Quarterly*, (January), 101536. https://doi.org/10.1016/j.giq.2020.101536

Naudé, W. (2020). Artificial intelligence vs COVID-19: Limitations, constraints and pitfalls. *AI & SOCIETY*, (0123456789). https://doi.org/10.1007/s00146-020-00978-0

Nolte, G., & Aust, H. P. (2013). European exceptionalism? *Global Constitutionalism*, *2*(3), 407–436. https://doi.org/10.1017/S2045381713000038

North, D. C. (1990). *Institutions, institutional change and economic performance* (59262nd edition). Cambridge ; New York: Cambridge University Press.

Perrault, R., Shoham, Y., Brynjolfsson, E., Clark, J., Etchemendy, J., Grosz Harvard, B., … Mishra, S. (2019). *Artificial Intelligence index 2019 annual report*. Retrieved from https://hai.stanford.edu/sites/g/files/sbiybj10986/f/ai_index_2019_report.pdf

Pinch, T. J., & Bijker, W. E. (1984). The social construction of facts and artefacts: Or how the sociology of science and the sociology of technology might benefit each other. *Social Studies of Science*, *14*(3), 399–441.

Pontikakis, D., Fernández Sirera, T., Janssen, M., Guy, K., Marques Santos, A., Boden John, M., & Moncada Paterno' Castello, P. (2020). *Projecting Opportunities for INdustrial Transitions (POINT): Concepts, rationales and methodological guidelines for territorial reviews of industrial transition* (JRC No. EUR 30375). Retrieved from Publications Office of the European Union website: https://publications.jrc.ec.europa.eu/repository/handle/111111111/60962

Prakash, S. (2018, May 23). The profound benefits of AI a doption in procurement. Retrieved May 3, 2021, from Medium website: https://towardsdatascience.com/the-profound-benefits-of-ai-adoption-in-procurement-7f1e90dcdfc6

Probst, L., Pedersen, B., Lefebvre, V., & Dakkak-Arnoux, L. (2018). *Digital transformation monitor. USA-China-EU plans for AI: Where do we stand?* Retrieved from https://ati.ec.europa.eu/sites/default/files/2020-07/USA-China-EU%20plans%20for%20AI%20-%20where%20do%20we%20stand%20%28v5%29.pdf

Przegalinska, A. (2019). *State of the art and future of artificial intelligence*. Retrieved from https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/631051/IPOL_BRI(2019)631051_EN.pdf

Renda, A. (2019). *Artificial Intelligence*. Retrieved from https://www.ceps.eu/ceps-publications/artificial-intelligence-ethics-governance-and-policy-challenges/

Rifkin, J. (2004). The European dream: How Europe's vision of the future Is quietly eclipsing the American dream. *Foreign Affairs*, *83*. https://doi.org/10.2307/20034170

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2020a). The Chinese approach to artificial intelligence: An analysis of policy, ethics, and regulation. *AI & Society*, *4*(1), 64–75. https://doi.org/10.1007/s00146-020-00992-2

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2020b). The Chinese approach to artificial intelligence: An analysis of policy, ethics, and regulation. *AI & SOCIETY*, *4*(1), 64–75. https://doi.org/10.1007/s00146-020-00992-2

Robinson, J. P., Barth, K., & Kohut, A. (1997). Social impact research: Personal computers, mass media, and use of time. *Social Science Computer Review*, *15*(1), 65–82. https://doi.org/10.1177/089443939701500107

Rogers, E. M. (2010). *Diffusion of innovations, 4th Edition*. Retrieved from https://books.google.it/books?id=v1ii4QsB7jIC

Rotolo, D., Hicks, D., & Martin, B. (2015). What is an emerging technology? *Research Policy*, *44*, 1827–1843. https://doi.org/10.1016/j.respol.2015.06.006

Salganik, M. J., Lundberg, I., Kindel, A. T., Ahearn, C. E., Al-Ghoneim, K., Almaatouq, A., … al, et. (2020). Measuring the predictability of life outcomes with a scientific mass collaboration. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(15), 8398–8403. https://doi.org/10.1073/pnas.1915006117

Santos, R., & Héang, K. K. (2019, September 5). How public sector AI is going from hype to reality. Retrieved January 10, 2021, from https://apolitical.co/en/solution_article/how-public-sector-ai-is-going-from-hype-to-reality

Savoldelli, A., Codagnone, C., & Misuraca, G. (2012). Explaining the eGovernment paradox: An analysis of two decades of evidence from scientific literature and practice on barriers to eGovernment. *ACM International Conference Proceeding Series*, 287–296. https://doi.org/10.1145/2463728.2463784

Schon, D. A. (1983). *The reflective practitioner: How professionals think in action* (1st edition). Retrieved from https://www.amazon.com/Reflective-Practitioner-Professionals-Think-Action/dp/0465068782

Schreiber, B., Janssen, R., Weaver, S., & Peintner, S. (2016, October 25). Procurement 4.0 in the digital world. Retrieved May 3, 2021, from Arthur D Little website: https://www.adlittle.com/en/insights/viewpoints/procurement-40-digital-world

Selbst, A. D., & Powles, J. (2017). Meaningful information and the right to explanation. *International Data Privacy Law*, *7*(4), 233–242. https://doi.org/10.1093/idpl/ipx022

Shearer, E., Stirling, R., & Pasquarelli, W. (2020). Government AI Readiness Index. *Oxford Insights*, 4–143.

Simplilearn. (2016, March 14). What is the real impact of social media? Retrieved January 8, 2021, from Medium website: https://medium.com/@Simplilearn/what-is-the-real-impact-of-social-media-2afd57cfd538

Sousa, W. G. de, Melo, E. R. P. de, Bermejo, P. H. D. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. *Government Information Quarterly*, (July). https://doi.org/10.1016/j.giq.2019.07.004

Stamm, B. von. (2018). Failure in innovation: Is there such a thing? In *Management for Professionals*. *Strategies in failure management* (Kunert S. (eds), pp. 27–45). https://doi.org/10.1007/978-3-319-72757-8_3

Starke, C., & Lünich, M. (2020). Artificial intelligence for political decision-making in the European Union: Effects on citizens' perceptions of input, throughput, and output legitimacy. *Data & Policy*, *2*. https://doi.org/10.1017/dap.2020.19

The White House. (2020a). Executive order on promoting the use of trustworthy Artificial Intelligence in the Federal Government. Retrieved December 18, 2020, from The White House website: https://www.whitehouse.gov/presidential-actions/executive-order-promoting-use-trustworthy-artificial-intelligence-federal-government/

The White House. (2020b, December 3). Executive Order on Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government | The White House. Retrieved December 15, 2020, from Whitehouse.gov website: https://www.whitehouse.gov/presidential-actions/executive-order-promoting-use-trustworthy-artificial-intelligence-federal-government/

The White House Office of Science and Technology Policy. (2020a). *American Artificial Intelligence Initiative: Year One Annual Report*.

The White House Office of Science and Technology Policy. (2020b, December 3). Promoting the Use of Trustworthy Artificial Intelligence in Government | The White House. Retrieved December 15, 2020, from Whitehouse.gov website: https://www.whitehouse.gov/articles/promoting-use-trustworthy-artificial-intelligence-government/

Thorsby, J., Stowers, G. N. L., Wolslegel, K., & Tumbuan, E. (2017). Understanding the content and features of open data portals in American cities. *Government Information Quarterly*, *34*(1), 53–61. https://doi.org/10.1016/j.giq.2016.07.001

Tilley, N. (2000). Realistic evaluation: An overview. *Founding Conference of the Danish Evaluation Society*, *8*. Citeseer.

Tonon, C. (2020). *La GovTech, nouvelle frontière de la souveraineté numérique*. Retrieved from Ifri website: https://www.ifri.org/fr/publications/etudes-de-lifri/govtech-nouvelle-frontiere-de-souverainete-numerique

Tushman, M. L., & O'Reilly, C. A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review*, *38*(4), 8–29. https://doi.org/10.2307/41165852

United Nations. (2017, September 27). Global review of sustainable public procurement. Retrieved January 10, 2021, from UNEP - UN Environment Programme website: http://www.unenvironment.org/resources/report/2017-global-review-sustainable-public-procurement

van Noordt, C., Medaglia, R., & Misuraca, G. (2020). Stimulating the uptake of AI in public administrations: Overview and comparison of AI strategies of European Member States. In S. Virkar, M. Janssen, I. Lindgren, U. Melin, F. Mureddu, P. Parycek, … H. J. Scholl (Eds.), *EGOV-CeDEM-ePart 2020: Proceedings of Ongoing Research, Practitioners, Workshops, Posters and Projects of the International Conference EGOV-CeDEM-ePart 2020* (pp. 269–278). CEUR.

van Noordt, C., & Misuraca, G. (2020a). Evaluating the impact of artificial intelligence technologies in public services: Towards an assessment framework. In *Proceedings of the 13th International Conference on Theory and Practice of Electronic Governance* (pp. 8–16). Retrieved from https://doi.org/10.1145/3428502.3428504

van Noordt, C., & Misuraca, G. (2020b). Exploratory insights on Artificial Intelligence for government in Europe. *Social Science Computer Review*, 089443932098044. https://doi.org/10.1177/0894439320980449

van Noordt, C., & Pignatelli, F. (2020). *2nd peer learning workshop on the use and impact of AI in public services*. Retrieved from https://joinup.ec.europa.eu/collection/elise-european-location-interoperability-solutions-e-government/document/report-2nd-peer-learning-workshop-use-and-impact-ai-public-services

Vedung, E. (1998). Policy Instruments: Typologies and Theories. *Carrots, Sticks and Sermons: Policy Instruments & Their Evaluation. Rist, Ray C; Bemelmans-Videc, Marie-Louise; Vedung, Evert, Eds.,*. Retrieved from https://www.academia.edu/42748022/Policy_Instruments_Typologies_and_Theories

Veldhuizen, C. (2020). Smart Specialisation as a transition management framework: Driving sustainability-focused regional innovation policy? *Research Policy*, *49*(6), 103982. https://doi.org/10.1016/j.respol.2020.103982

Vilone, G., & Longo, L. (2020). Explainable Artificial Intelligence: A systematic review. *ArXiv:2006.00093 [Cs]*. Retrieved from http://arxiv.org/abs/2006.00093

Vinge, V. (1993). *Technological singularity*. Retrieved from https://frc.ri.cmu.edu/~hpm/book98/com.ch1/vinge.singularity.html

W3C. (2009, December 5). *Improving access to government through better use of the web—W3C note*. Retrieved from https://d1wqtxts1xzle7.cloudfront.net/4177376/improving_access_to_government_through_the_better_use_of_the_web.pdf

Wirtz, B. W., Weyerer, J. C., & Sturm, B. J. (2020). The dark sides of Artificial Intelligence: An integrated AI governance framework for public administration. *International Journal of Public Administration*, *43*(9), 818–829. https://doi.org/10.1080/01900692.2020.1749851

World Wide Web foundation. (2017). *Open data barometer global report, 4th edition*. Retrieved from https://idl-bnc-idrc.dspacedirect.org/bitstream/handle/10625/57676/57620.pdf

Yampolskiy, R. V. (2015). *Artificial Superintelligence: A futuristic approach* (1° edizione). Retrieved from https://www.amazon.it/Artificial-Superintelligence-Futuristic-Roman-Yampolskiy/dp/1482234432

Zeleti, F. A., & Ojo, A. (2017). Open data value capability architecture. *Information Systems Frontiers*, *19*(2), 337–360. https://doi.org/10.1007/s10796-016-9711-5

Zhang, B., & Dafoe, A. (2019). *Artificial Intelligence: American attitudes and trends* (SSRN Scholarly Paper No. ID 3312874). https://doi.org/10.2139/ssrn.3312874

Glossary

Accountability	The ability of government to give a satisfactory account of the use of power and resources.
Adoption	The phase of technology appropriation where an innovation is tested and evaluated for potential use. Aka Exploration.
AI appropriation	The union of adoption and implementation phases – more cyclically recurrent than linearly consecutive.
Algocracy	A form of technocracy, whereby machine algorithms, rather than people, collect information, take actions and administer the rules of a State.
Algorithm	A set of instructions designed to perform a specific task.
Cocreation	Collaborative development of new and innovative products, services, solutions by a number of users and stakeholders.
Codesign	Collaborative design.
Concretisation	The process of combining multiple functions within fewer structures.
Coproduction	Collaborative implementation of existing services by beneficiaries and providers.
Design	The thoughtful activity of delivering information on business requirements, technical specifications and development procedures related to new technologies, products or services.
Deployment	Embedment of a new technology in business operations.
Development	Prototyping, testing and validation of a new technology in controlled environments.
Explainability	The possibility to explain the functioning of something in full.
Exploitation	See Implementation.
Exploration	See Adoption.
Implementation	The phase of technology appropriation where the underlying product or service delivery process is permanently affected and transformed. Aka Exploitation (see).
Instrumentalisation	The activity of sense making of a certain technology. Can be analytically separated into Primary and Secondary instrumentalisation.
Interpretability	The possibility to describe a cause and effect relationship in full.
Primary Instrumentalisation	The activity of decontextualising technical artefacts to reduce them to their useful aspects
Secondary Instrumentalisation	The activity of integrating the simplified technical artefacts into the natural and social environments.
Technical Code	A criterion that selects between alternative feasible Technical Designs in terms of a social goal.

Use	The action of using something for a purpose.
User Centricity	The ability of putting the person or customer at the heart of the process of service.

KJ-NA-30868-EN-N

The European Commission's science and knowledge service

Joint Research Centre

JRC Mission

As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

EU Science, Research and Innovation

EU Science Hub

Publications Office
of the European Union

doi:10.2760/440212

ISBN 978-92-76-42587-8