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Public Value Creation with Artificial Intelligence Technologies in Public Administration

Colin van Noordt

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Colin van Noordt

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signature

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COLIN VAN NOORDT

TALTECH KIRJASTUS

Contents

List of Publications

The list of author's publications, on the basis of which the thesis has been prepared:

Core articles:

I **van Noordt, C.**, & Misuraca, G. (2020). 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). ETIS 3.1

II **van Noordt, C.** (2022). Conceptual challenges of researching Artificial Intelligence in public administrations. In DG. O 2022: The 23rd Annual International Conference on Digital Government Research (pp. 183–190). ETIS 3.1

III **van Noordt, C.**, & Misuraca, G. (2022). Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union. Government Information Quarterly, 39(3), 101714. ETIS 1.1

IV **van Noordt, C.**, Medaglia, R., & Tangi, L. (2023), Policy initiatives for Artificial Intelligence-enabled government: An analysis of national strategies in Europe, Public Policy and Administration. ETIS 1.1

V **van Noordt, C.**, & Tangi, L., (2023) The Dynamics of AI Capability and its influence on Public Value creation of AI within public administrations, Government Information Quarterly, 101860, ETIS 1.1

VI **Van Noordt, C.**, & Misuraca, G. (2022). Exploratory insights on artificial intelligence for government in Europe. Social Science Computer Review, 40(2), 426–444. ETIS 1.1

Supplementary:

VII **Van Noordt, C.**, & Misuraca, G. (2019). New Wine in Old Bottles: Chatbots in Government: Exploring the Transformative Impact of Chatbots in Public Service Delivery. In Electronic Participation: 11th IFIP WG 8.5 International Conference, ePart 2019, San Benedetto Del Tronto, Italy, September 2–4, 2019, Proceedings 11 (pp. 49–59). Springer International Publishing. ETIS 3.1

VIII Misuraca, G., **van Noordt, C.**, & Boukli, A. (2020). The use of AI in public services: results from a preliminary mapping across the EU. In Proceedings of the 13th international conference on theory and practice of electronic governance (pp. 90–99). ETIS 3.1

IX **van Noordt, C.**, & Misuraca, G. & Mergel, I., (2024, Forthcoming). Driving public values of Artificial Intelligence in government Analysis of driving public values of AI initiatives in government in Europe. In Y. Charalabidis, M. Rony, & C. van Noordt (Eds.), Research Handbook on Public Management and Artificial Intelligence. Edward Elgar Publishing. ETIS 3.1.

X McBride, K., **van Noordt, C.**, Misuraca, G., & Hammerschmid, G. (Forthcoming, 2024). Towards a systematic understanding on the challenges of procuring artificial intelligence in the public sector. In Y. Charalabidis, M. Rony, & C. van Noordt (Eds.), Research Handbook on Public Management and Artificial Intelligence. Edward Elgar Publishing. ETIS 3.1

XI Tangi L., **van Noordt, C.** & Paula Rodriguez Müller A.P, 2023. The challenges of AI implementation in the public sector. An in-depth case studies analysis. Proceedings of the 24th Annual International Conference on Digital Government Research, 414–422. ETIS 3.1

Author’s Contribution to the Publications

Contribution to the papers in this thesis are:

I First author. The author of the doctoral thesis was the lead author of this paper, responsible for the writing up of most of the content of the paper, including the literature review, the overall framework and the writing up of the article. The author also presented the work and was the corresponding author with the conference outlet.

II First author. The author of the doctoral thesis was the sole author of this paper, responsible for all parts of the paper. The author also presented the work and was the corresponding author with the conference outlet.

III First author. The author of the doctoral thesis was the lead author of this paper, responsible for the writing up of most of the content of the paper, including the literature, research design, coding, analysis and writing of the article. The data collection was done in-part with the second author. The author was the corresponding author with the journal and was responsible for the revisions of the article.

IV First author. The author of the doctoral thesis was the lead author of this paper, responsible for the writing up of most of the content of the paper, including the literature, research design, coding, analysis and writing of the article. The data collection was done in-part with the second author. The article follows a work-in-progress conference article that was done together with the third author. The author was the corresponding author with the journal and was responsible for the revisions of the article.

V First author. The author of the doctoral thesis was the lead author of this paper, responsible for the writing up of most of the content of the paper, including the literature, research design, coding, analysis and writing of the article. The data collection through interviews was done together with the second author. The author was the corresponding author with the journal and was responsible for the revisions of the article.

VI First author. The author of the doctoral thesis was the lead author of this paper, responsible for the writing up of most of the content of the paper, including the literature, research design, data collection, coding, and writing of the article. This article is based upon the author’s Master Thesis, which was supervised by Anu Masso, as well. The author was the corresponding author with the journal and was responsible for the revisions of the article.

VII First author. The author of the doctoral thesis was the lead author of this paper, responsible for the writing up of most of the content of the paper, including the research design, literature review, data collection and writing up of the results. The author also presented the work and was the corresponding author with the conference outlet.

VIII Second author. The author of the doctoral thesis is not the lead author of this paper yet was still heavily involved in the writing up of most of the content of the paper, including the research design, literature review, data collection and writing up of the results.

IX First author. The author of the doctoral thesis was the lead author of this paper, responsible for the writing up of most of the content of the paper, including the literature, research design, coding, analysis and writing of the article. The data collection was done in part with the second author, although the lead author was responsible for gathering more information. The literature review was in support of the third author. The author was the corresponding author with the journal and was responsible for the revisions of the article.

X Second author. The author of the doctoral thesis played a supportive role in assisting the lead author of the article. In particular, support in the literature review, the conduction of the interviews and the analysis.

XI Second author. The author of the doctoral thesis played a supportive role in assisting the lead author of the article. In particular, the author was responsible for the data collection of which the authors based the article on.

1 Introduction

"*Is artificial intelligence in human society a utopian dream or a Faustian nightmare? If future generations are to have reason to thank us rather than to curse us, it's important that the public (and politicians) of today should know as much as possible about the potential effects—for good or ill—of artificial intelligence.*" (Boden, 1990, p.450)

Artificial Intelligence (AI) is often regarded as the key technology to drive economic flourishing and societal change in the coming decades (Katz, 2017). Such narratives of the impending "AI revolution" (Makridakis, 2017) have captured the attention of countries worldwide and spurred them to access this momentum and the associated economic opportunities by establishing themselves as leaders in the field. As a result, they are spending significant amounts of money on AI technology (Dwivedi et al., 2019). Governmental organisations are often considered key players in this narrative and are expected to play several roles (Criado & Gil-Garcia, 2019; Valle-Cruz et al., 2020). For instance, Guenduez and Mettler (2022) note that by reducing any potential barriers and restrictions that businesses may face in developing and using AI technologies, governments are crucial enablers and facilitate the use of AI. By promoting the appropriate infrastructure, adjusting legislation, and investing in the private sector, governments aim to strengthen their AI industry to achieve economic growth. Moreover, governments must regulate AI by establishing new rules to minimise the potential risks of developing, diffusing, and using this technology in their countries (Guenduez & Mettler, 2022).

The last role that governments play in this general development of AI is the user role, where governmental organisations themselves use AI technologies instead of encouraging others to develop and use them. AI promises to enhance the quality and effectiveness of public administration (Mehr, 2017) by improving policymaking (Valle-Cruz et al., 2019), automating routine processes (Lindgren et al., 2021), and augmenting civil service with insights from AI technologies (Veale & Brass, 2019), among other things. Despite the potential benefits that AI technologies could bring to both public administrations and citizens, the role of governments as users of these technologies is often overlooked, as highlighted in academic publications (Medaglia, Gil-Garcia, et al., 2021), and, although limited, in grey and policy documents (Berryhill et al., 2019; Mehr, 2017; van Wynsberghe, 2020). For instance, European countries in particular, do not often discuss AI's potential to improve the operations of their public administrations; instead, they are more concerned with either maximising the opportunities for their industries or ensuring that the negative consequences of AI are minimised in their societies (Guenduez & Mettler, 2022).

This makes the distinction between public administrations' governance *of* AI technologies and their governance *with* AI technologies crucial in researching the public value of AI. Through their activities in governing AI, governmental organisations play an essential role in mitigating the negative consequences of AI that arise in their societies. They do so by introducing new legislation, enforcing existing laws, and implementing other nonbinding initiatives. However, such activities are distinct from having governments deploy these technologies to ensure that their organisational goals and objectives can be achieved (Guenduez & Mettler, 2022; Misuraca, 2021).

Since governmental organisations' use of AI is also subject to governance, this thesis focuses on governance *with* AI rather than the governance *of* AI, which is the focus of other research on governing the rise of AI in society (Djeffal et al., 2022; Sigfrids et al., 2022).

The examination of the user role of governments links well with the research field of e-government, which focuses on public administrations' use of digital technologies (Andersen et al., 2010). Similar to the discussion of AI, there has long been enthusiasm about introducing new digital technologies to public administrations to enhance their effectiveness, efficiency, and citizen-centricity, as well as other forms of public value, despite questionable results thus far (Bekkers & Homburg, 2007). Adopting innovations in public administrations is not straightforward, and the expectation is that the adoption of AI technologies in this arena will likely face similar challenges to those encountered in previous technological waves (Gil-García et al., 2014; Kankanhalli et al., 2019).

Therefore, learning from the lessons from previous research on the impact and effects of ICT in government, it is much more likely that the effects of AI will not be as deterministic as many may suggest. At the moment, if public administrations were to use AI technologies, it remains largely unknown which factors influence this, for what purpose, and, most notably, what the effects will be (de Sousa et al., 2019). The available studies lack empirical validation of the positive and/or negative consequences of the use of AI in public administration (Medaglia, Gil-Garcia, et al., 2021; Mergel et al., 2023; Sun & Medaglia, 2019; Wirtz et al., 2019). As such, many elements concerning the creation of public value within public administrations remain relatively unknown. This thesis, therefore, consists of exploratory research to uncover various aspects of the creation of public value by AI technologies. Public value is regarded here as the positive effects that follow the implementation of AI technologies in public administrations, which should be aligned with citizens' expectations (Alford & O'Flynn, 2009).

Research objectives and goals

In doing so, the thesis provides the first empirical evidence of using AI in public administrations, examines how public administrations adopt the technology beyond widespread expectations, and explores the myths of how AI changes governments. To a certain extent, this research is a "journey in an unchartered territory" (Misuraca & van Noordt, 2020, p.11) and regards the use of AI as a form of public sector innovation (De Vries et al., 2016), requiring transformation in governmental practices obtain effective results (Nograšek & Vintar, 2014; Tangi et al., 2021). Such a transformation is challenging due to the interplay between technology and socioeconomic factors that limit the uptake, scope, and effects of the transformation (Kempeneer & Heylen, 2023). In order to provide a better understanding of how AI technologies are used in public administrations, the thesis is underpinned by the aim of answering three main research questions, which act as crucial pieces of the puzzle of creating public value through AI.

Despite significant interest in AI technology, it is poorly defined, with various actors using the term differently and referring to multiple technologies – even those that do not yet exist. Therefore, to understand the public value of AI, it is crucial to be more precise about what it entails. Therefore, the first research question is the following: *How is AI in public administrations understood by civil servants, considering AI's varying definitions and interpretations?*

By examining the various definitions and understandings of AI in relevant literature and surveying the perceptions of AI among Belgian civil servants, **I** provides an overview of the different ways in which AI has been understood and researched, which has implications for studying its adoption in public administrations. Different interpretations and taxonomies of AI used in public administration are also discussed in **III and VIII**.

In addition to the challenges with defining AI in order to research its adoption in public administrations, there is also a lack of clarity about which drivers and barriers influence the adoption of AI in public administration. As such, the second research question this thesis aims to address is the following: *What are the drivers and barriers to the adoption of AI in public administrations?*

These different factors are examined in various research articles throughout the thesis. In **IV**, the AI strategies of EU Member States are analysed to understand which actions governments plan to take to stimulate the adoption of AI in governments. Exploring the use of AI in public administrations more closely, **VI** examines the adoption of AI with existing theories on public sector innovation and provides an overview of environmental, organisational, innovation-related, and individual factors that assist in the adoption of AI. **XI** examines how public administrations overcome AI-related challenges in the implementation phase, while one of these observed factors, using public procurement for AI, is examined more closely in **X.**

Furthermore, there is seemingly great uncertainty about whether AI could or could not contribute to public value due to limited empirical evidence, which mainly leaves scholars to speculate about its potential positive and negative impacts. Therefore, the third research question is as follows: *What is the expected public value creation of AI in public administrations?*

To answer this research question, **V** examines the AI capabilities of public administrations to ensure that they develop and deploy AI effectively in their organisations and create public value. In addition, an analysis of existing use cases of AI implementation in public administration gathered in **VIII** provides a first glimpse into the potential value that AI could create, which was examined more in-depth in **III** to analyse how AI contributes to several governance functions and in **IX** to better understand which public value the AI initiatives aimed to create.

The primary research approach and logic of this thesis are discussed in the conceptual framework in **I**. This framework was the basis for connecting the different research articles and attempting to understand the various components of how AI technologies may create public value. In doing so, the framework, as seen in Figure 1, is derived from several elements, which have been further explored in subsequent research articles, such as the enablers of AI in government, the various forms of AI technologies and their usage in government, organisational change, and public value.

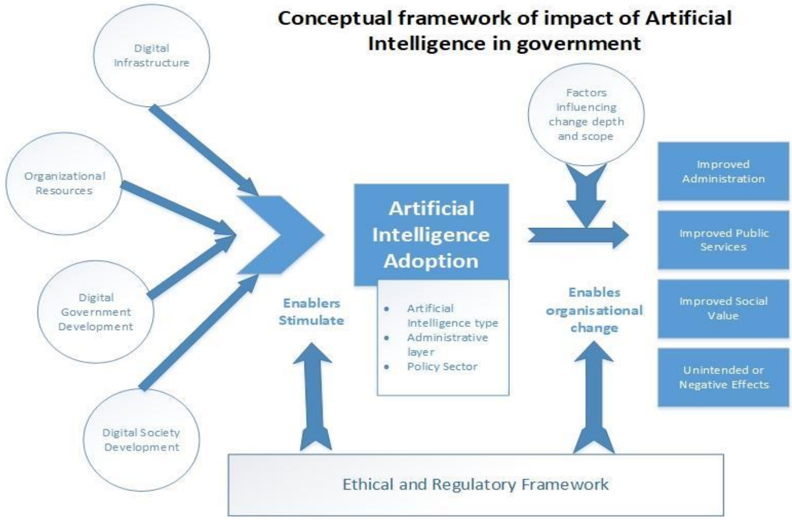

*Figure 1 Conceptual framework for examining the impact of AI in government (in **I**, p.3)*

One of the main contributions of this thesis is that it provides empirical evidence of the type of AI used in public administrations as part of the landscaping exercises done in collaboration with the European Commission's AI Watch (European Commission, 2018a), which was thoroughly lacking in research on AI in government (Medaglia, Gil-Garcia, et al., 2021; de Sousa et al., 2019). In doing so, the research findings highlight the importance of the (internal) factors that public administrations require to use AI technologies effectively and consequently derive value from them, rather than assuming that the technology alone will do so.

The introduction chapter of the thesis includes the following sections:

Section 2.1 discusses the theoretical background of public value creation within the digital government research domain as one of the main theoretical foundations underpinning the research. In Section 2.2, the early phase of the research on AI in the digital government research domain is illustrated by a brief introduction to the main research topics through a short review of the articles on AI within the Digital Government Reference Library (DGRL). This introduction discusses several issues with AI that have been examined in this developing research field.

The overall methodological approach of this thesis and the data collection methods applied within the individual articles are described in Section 3 – as are the implications and limitations of the methodological approach of this study.

In Section 4, an exploration of the various definitions and understandings of AI in digital government research and policy documents are discussed, providing crucial implications for the study of the use of AI within the public administration context.

Section 5 presents the main findings on creating public value through the use of AI in public administrations by examining the factors of implementing AI in government in Section 5.1, followed by the drivers and barriers influencing the adoption of AI in Section 5.2, and the factors related to implementing AI in public administrations in Section 5.3. In Section 5.4, the expected public value creation of AI technologies is described, as are some of the potential negative consequences and difficulties of creating this value.

Lastly, in Section 6, the introductory chapter of the thesis concludes with concluding remarks and recommendations for future research on this emerging research topic.

2 Background

2.1 Using technology to create public value

There has been considerable interest in using digital technologies to improve the functioning of public administration for several decades. In the early 2000s, there was a rising interest in the topic of e-government and the use of Information and Communication Technologies (ICT) within governmental organisations due to the developments in digital technologies and the increasing adoption thereof within both the private and public sector (Dunleavy et al., 2006; Savoldelli et al., 2014). Already in the 1990s, the transformative consequences of ICT were often widely narrated, with digital technologies being capable of creating positive change, such as increasing the efficiency and effectiveness of government services and improving information provision to citizens (Andersen et al., 2010). In this digital era of governance (Dunleavy et al., 2006), digital technologies are often heralded as a key innovation in improving government functions, reducing bureaucracy, and improving public services, making the state more accessible and available to citizens (Norris, 2010).

For over two decades, there has been an interest in using digital technologies as the primary way to make the government more effective and efficient (Andersen & Henriksen, 2006). Many early and recent publications illustrate that the use of ICT could improve governmental efficiency, effectiveness, and responsiveness and reduce corruption (Bekkers & Homburg, 2007; Criado & Gil-Garcia, 2019; Panagiotopoulos et al., 2019). While many different names exist for e-government practices and are used interchangeably – such as e-government (Andersen & Henriksen, 2006), e-governance (Bannister & Connolly, 2012), digital government (Janowski, 2015), and smart government (Kankanhalli et al., 2019) – despite some differences, all of them point towards governmental organisations using more ICT (Andersen et al., 2010).

Key concepts in e-government research

Despite the importance of research and policy in stimulating innovation in government, the concept of innovation is not always well defined, if at all (De Vries et al., 2016). In general, innovation is regarded as a perceived new idea, practice, or product that is used for the first time in a new organisation (Rogers, 2010). This often implies that the new idea, practice, or product is regarded as such a novelty for it to be considered an innovation, for instance, a new digital technology. Alternatively, innovation may mean that the resulting change in the organisation is so radical that it is considered innovation, despite the fact that the idea, service, or product is not necessarily new (Bloch & Bugge, 2013). Nevertheless, a crucial component of innovation is that it requires adoption in an organisation. More popular depictions of innovation might focus on exploring new ideas, yet this is better understood as creativity, which is a prerequisite for innovation (Houtgraaf, 2022). Actual adoption thus requires not only developing new potential innovations but also using them, which is often more challenging (Real & Poole, 2004; Schedler et al., 2019).

The adoption of innovation thus relates to incorporating it within an organisation, which is distinct from its development. Adoption of innovations in public administrations may, on the one hand, refer to the organisational decision to adopt a specific technology within the organisation (Kamal, 2006), whereas others focus more on the inclusion of certain individuals, such as civil servants, in the organisation (Nagtegaal, 2021).

The adoption of ICT-based innovation has been described as progressing through various stages, and while different researchers use different phases to explain this process, it generally consists of three distinct stages: the initiation phase, where the pressure to innovate begins; the adoption phase, where the organisation decides to commit resources to the adoption of the innovation; and the implementation phase, which refers to the stage where the benefits of the innovation are realised (Kamal, 2006). This thesis follows these three distinct phases with consideration of the difference between the adoption and implementation phases, which are often excluded from adoption studies (Kamal, 2006).

Despite the similarities to the use of technology in the private sector, public sector innovation scholars emphasise how innovation and digital transformation are distinct from the private sector. For instance, public administrations are more strictly bound by regulations that govern their activities (Kraemer & King, 2006), face additional media scrutiny for failures hindering experimentation, and have different reward structures for successfully innovating compared to the private sector (Potts & Kastelle, 2010). A more cynical take on innovation in the public sector highlights the lack of incentives to adopt innovation reactively rather than proactively (Kamal, 2006), as there is no competition like in the private sector. As a result, a lack of innovation only leads to public administrations having to do more work or having a smaller budget (Kraemer & King, 2006; Potts & Kastelle, 2010).

As a result, even when similar technologies are discussed, public sector innovation is considered distinct from the private sector, which warrants its own theory-building. In the case of AI, a similar narrative is emerging. While some mention that AI in the public sector does not differ from AI in the private sector (Criado & de Zarate-Alcarazo, 2022), other authors highlight the distinction between the public and private sectors. For instance, public administrations face specific barriers (Cinar et al., 2018; Sun & Medaglia, 2019; Wirtz et al., 2019) as well as higher expectations from citizens (Gaozhao et al., 2023; Gesk & Leyer, 2022) and transparency, and explainability requirements (de Bruijn et al., 2022; Janssen, Hartog, et al., 2020), among other things (Zuiderwijk et al., 2021). As such, practices on how to adopt AI from the private sector cannot be directly translated to the public sector without adjusting to the context in which public administrations operate.

One of the critical challenges in this dynamic, complex, and changing research field is the theoretical foundations, as is evident in the various interpretations of the main concepts previously discussed. The e-government research field has been criticised for a lack of scientific rigour and theoretical underpinnings. A great deal of research in this domain tends to be highly descriptive because of its managerial and project-related nature(Meijer & Bekkers, 2015). Another tendency in the field is to draw theoretical frameworks from other disciplines, such as information science, public administration, economics, managerial science, and social science, among others.

While, on the one hand, this interdisciplinary focus allows for the examination of these various topics in the research domain through several analytical lenses (Gil-Garcia et al., 2018), it also hinders providing the research domain with a set of core theories upon which to build, or it may cause culture clashes between those from computer science and public administration research domains (Bannister & Connolly, 2015). Various theoretical frameworks from different disciplines may focus on different methodologies and perspectives. Alternatively, it may cause challenges in building upon previous studies as many of the theoretical frameworks could be seemingly developed on an ad hoc basis compared to other research fields. This has led to widespread theoretical fragmentation in the area, leading to confusion and limiting theory-building (Meijer & Bekkers, 2015).

The theoretical fragmentation is additionally supported by rapid technological developments, with new technologies quickly becoming the focus of the research field. As there is a tendency in the field to focus on the latest technological developments, it is common that previous insights from past e-government research are not immediately included in the examination of new technologies. Alternatively, it could be argued that the technology differs significantly from prior technologies and thus warrants the development of new theories, occasionally from square one, to tailor specifically to this technology, despite the fact that the focus of the research topics remains somewhat similar (Yildiz, 2007). The risks of reinventing the wheel by examining similar challenges faced by the new technology further add to the plethora of different models and theories that are present in the domain (Heeks & Bailur, 2007), which often do not perform very well (Bannister & Connolly, 2015).

Another common challenge within the research field is over-optimism about digital technologies without empirical evidence. As a result, there is criticism in the field that research could be a de facto advertisement for some of the technologies, which are occasionally even developed by some authors (Heeks & Bailur, 2007). As such, there has been an increased focus in the field on the value of digital technologies, given the challenges in deriving such value from the technology. What is noteworthy from the research field is that, despite the positive rhetoric on technology-driven improvements in public administrations, which is supported by the significant investments made by governmental organisations in ICT, there is limited empirical evidence of these positive effects (Andersen et al., 2010).

Studies further focus heavily, often exclusively, on the supply side of digital technologies by examining the technology itself without considering how the demand side, such as citizens, contributes to a lack of public value (Savoldelli et al., 2014). Indeed, it has proven somewhat challenging for e-government to create public value as many of its initiatives fail to achieve their intended goals (Kempeneer & Heylen, 2023; Twizeyimana & Andersson, 2019). This lack of empirical validation of the positive effects of digital technologies is further hindered by the lack of studies evaluating the impact of ICT within the e-government domain. Thus, it remains unclear whether they achieve their intended goals (Choi & Chandler, 2020; Savoldelli et al., 2012, 2014). Public administrations often lack competencies in developing or deploying the technologies effectively, leading to a significant implementation gap between the technological developments on the one hand and the use of the technologies by public administrations on the other (Zhang & Kimathi, 2022).

Importance of public value creation

Avoiding failure and achieving success has strengthened academic interest in acquiring public value within the e-government research domain. This often implies that public value is created through the success of a digital government initiative (Twizeyimana & Andersson, 2019). These studies borrow the theory of public value from the public administration research domain, defining public value as meeting the expectations of citizens with government services and policies (Jørgensen & Bozeman, 2007; Moore, 1995). Public value theory has been introduced as an alternative to the often highly economical view of how public administration reforms as part of the narratives of New Public Management (Panagiotopoulos et al., 2019) with a focus on efficiency and market values. What exactly accounts for public value, however, is not always clear.

Many different definitions and taxonomies have been proposed to assess the public value of digital government initiatives (Savoldelli et al., 2013) – often without any form of empirical assessment of the framework in practice (Twizeyimana & Andersson, 2019).

The e-government research field can also be overly focused on efficiency-related goals (Rose et al., 2015), which often leads to digital government initiatives not aligning with the expectations of citizens (Kempeneer & Heylen, 2023; Panagiotopoulos et al., 2019). The theory of public value has quickly become one of the main theories in the field for studying the effects and transformation of public administration after the introduction of new technologies (Bannister & Connolly, 2014; Criado & Gil-Garcia, 2019; MacLean & Titah, 2022). In particular, public value theory not only allows for an analytical perspective for the design of public service but also determines to what extent it aligns with citizen expectations and the goals of the transformation (Twizeyimana & Andersson, 2019). Furthermore, it provides a normative analytical framework to assess digital government initiatives from a value perspective (Panagiotopoulos et al., 2019), allowing for a better understanding of the sociopolitical impacts of the use of ICT in the public sector beyond merely assessing efficiency to include other values, such as fairness, trust, and any other expectations citizens have regarding the functioning of their government (Cordella & Bonina, 2012).

Furthermore, some authors emphasise the distinction between public *value* and public *values*, where the former is the assessment of the value that is created by the government on behalf of the public, and the latter is the norms and principles guiding the activities of public administration (MacLean & Titah, 2022). Because there is particular interest in understanding the effects created by the introduction of AI within public administration, there is a considerable connection to the public values that guide these initiatives. Arguably, they are interconnected because AI systems designed to enhance efficiency-related public values are also likely to aim to achieve efficiency-related goals. As such, both perspectives are included in the thesis despite the main intention to examine the created public value.

One of the most comprehensive collections of what can be considered public value comes from Jørgensen and Bozeman (2007). These authors identified 72 different forms of public value, ranging from the public's contribution to society, the transformation of interests into decisions, the relationship between public administrators and politicians, the relationship between public administrators and their environment, the interorganisational aspects of public administration, the behaviour of public employees, and the relationship between public administration and citizens.

While comprehensive, using such an extensive list of public values has been argued to be quite problematic in practice because the definitions of these values are often vague, overlapping, and challenging to operationalise.

Building on this work, Bannister and Connolly (2014) thus propose another typology of public values that is more applicable to analysing the impact of ICT in government. In doing so, they categorise public values into three categories. First, there are duty-oriented public values, such as a responsibility to citizens and using public funds efficiently and in compliance with the law. Second, there are service-oriented public values, such as the responsibility to provide a high level of service to citizens, respecting individual needs, and being responsive and transparent. Third, these authors describe socially oriented public values, which include broader social goals such as inclusiveness, fairness, equality, accountability to the public, and protecting citizens from exploitation (Bannister & Connolly, 2014).

More recently, following a literature review of the existing literature on public value in e-government research, Twizeyimana and Andersson (2019) provided a rather practical classification of how e-government may contribute to public value through six somewhat overlapping categories. These include improving public services, administrative efficiency, open government capabilities, ethical behaviour and professionalism, trust and confidence in government, and social value and well-being. Due to its practical use and potential applicability to a more pragmatic assessment of public value (O'Flynn, 2007), this framework has been at the basis of understanding the more tangible and practical benefits of using AI and has thus been integrated into the conceptual model of the thesis in **I**.

Public value theory has also been used in research to examine the intrinsic value of coproduction within digital government (Luna-Reyes & Zhang, 2023). From this perspective, researchers examine how public value is created due to coproduction with citizens, noting that coproduction brings value in itself through collaboration with citizens rather than focusing on the output of such activities (Capolupo et al., 2020). However, this perspective is not followed within the thesis, as the focus is on the public value created as a result of these activities.

Despite the conceptual unclarity of what constitutes public value, there is agreement that public value should be the primary outcome of digital government initiatives. As such, digital government initiatives should encompass a broader range of strategic goals. Not only to reach beyond mere efficiency goals but also to achieve other objectives such as enhancing equality, social inclusion, openness, well-being, accountability, democracy, transparency, and citizen participation, among many others (Twizeyimana & Andersson, 2019). Doing so, however, is not a straightforward task, and it requires consideration of both organisational and institutional factors (Panagiotopoulos et al., 2019), capabilities, and resources (Pang et al., 2014) that consequently allow the organisation to create public value by improving its public services, resources, innovation, coproduction, or engagement with citizens (MacLean & Titah, 2022).

Failure to acquire these required capabilities and resources often results in a failure to meet the expectations of digital government initiatives. This occurs when the administration either does not fully take into consideration the opportunities provided by the technology or does not adequately redesign processes and organisations to obtain value from the technology (Chen & Xie, 2015; Kempeneer & Heylen, 2023; Nograšek & Vintar, 2014).

As such, organisational performance is often one of the main factors that lead to increasing public value (Mellouli et al., 2020), yet considering these capabilities to develop, support, and sustain digital innovations in public administrations in order to create public value is often overlooked (Panagiotopoulos et al., 2019).

With interest in emerging technologies such as blockchain, AI, and big data, which are argued to provide significant benefits to society, it becomes even more crucial to study these through the lens of public value theory. This allows for a better understanding of whether these technologies actually create public value, including new forms thereof (Panagiotopoulos et al., 2019). Therefore, examining and understanding the consequences of deploying these new technologies by public administrations is argued to be best explored through public value theory (MacLean & Titah, 2022). Noting the importance of organisational capabilities in ensuring public value through these technologies (Panagiotopoulos et al., 2019), this thesis thus focuses on the resources, capabilities, and other factors that are required to achieve public value through AI rather than assuming the public value deriving from the technology itself.

2.2 AI in digital government research

The wider field of AI and the interest therein have not necessarily translated into increased research on AI within the context of the public sector. A noteworthy gap between the number of research articles on AI within both the public and private sectors was highlighted in 2019 by de Sousa et al. (2019). This study identified that, from a screening of 1,438 articles on AI published since 2000, almost all of the articles either focused on the private sector (1,251 articles) or only on the technical aspects of AI (969), leaving only 59 articles that discussed AI or AI-related terms within the public sector. Since 2019, research on the use of AI within the public sector has grown considerably. Yet, it arguably remains in an early and fragmented state, and it is minor compared to the broader research trends on AI. The research tends to focus only on the technological aspects of AI without considering its implications for public administrations or its application in various policy domains (Sharma et al., 2020). The research on the challenges of implementing AI in public administrations remains lacking (Mergel et al., 2023).

Comparative overviews tracking the progress of AI, such as the AI Index, highlight that the number of AI publications has doubled since 2010, from 200,000 in 2010 to nearly 500,000 worldwide in 2021 (Stanford University, 2023). The tracking of such publications is often done within the context of illustrating the AI race between China, the United States, and the European Union by comparing the amount (and impact) of AI publications in these regions and illustrating the overall growth of academic research interest in AI in general. Despite the massive volume of publications on AI-related topics, studies within the digital government research field constitute only a small fraction of this. However, there has been an increase in studies on developing, using, and researching AI within government, such as Madan and Ashok (2022), Medaglia, Gil-Garcia, et al. (2021), Wirtz et al. (2021), and Zuiderwijk et al. (2021).

This discrepancy is likely caused by the different definitions and research objectives in AI, as the broader AI research trends may be too focused on the technical development and application of AI learning techniques. In contrast, the e-government and public administration research fields are more concerned with understanding the drivers, barriers, effects, and perceptions of the developed AI system.

To illustrate the limitations and growth of the literature on AI, a brief overview of the publications on AI within the DGRL v18.5 (February 2023) is shown in this chapter. This library of academic research from the digital government field is a well-known reference for acquiring articles on digital government or reviewing how the research field has progressed on specific topics (Scholl, 2021). While the DGRL is limited in scope due to the requirement that articles be translated into English, prefiltered on key terms in academic databases and from preselected journals and conferences (Scholl, 2021), it remains a core research inventory that is dedicated to the study of digital government.

As such, to discuss the recent growth of AI, a keyword search on AI and other related terms shows an illustrative example. As there were only a handful of articles published at the start of the thesis in 2019, as indicated in Figure 2, the number of research articles on AI within the digital government research domain had been limited until 2019, with a significant increase between 2019 and 2022, peaking at 77 research articles in 2022.

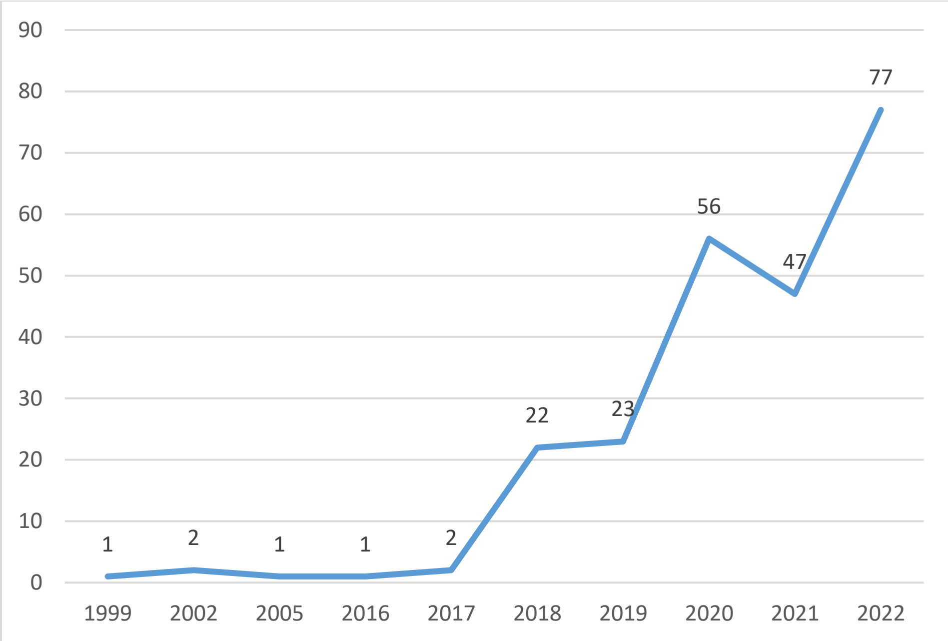

*Figure 2 Digital government research on AI**

**Records mentioning Artificial Intelligence, machine learning, automation, and/or automated decision-making in the DGRL v18.5 (February 2023)*

When examining only published journal articles within the DGRL, the number of publications shrinks further, with eight articles published before 2019, as illustrated in Figure 3. There are only 105 journal articles in the DGRL as of February 2023, of which 81% have been published since 2020. This low volume of publications confirms that the amount of research on AI that focuses specifically on the public sector, compared to the private sector, remains relatively small. It also shows the rapid growth over the past few years and the course of this doctoral research. At the start of the research process in 2019, the amount of literature on this topic was minimal, thus encouraging the exploratory nature of this thesis.

The field will likely grow in the coming years, allowing for more theories on AI in government, systematic literature reviews, hypothesis testing, and more rigorous and generalisable research findings. Some of the findings from the thesis have been examined in-depth in other publications as the field has progressed significantly in the last few years. Nevertheless, the scant literature on AI is remarkable and limits much of the understanding of what is meant by AI, the various drivers and barriers facilitating or hindering its use, and the current perceptions, effects, implications, and future perspectives thereof (Criado et al., 2020; Medaglia, Gil-Garcia, et al., 2021; de Sousa et al., 2019).

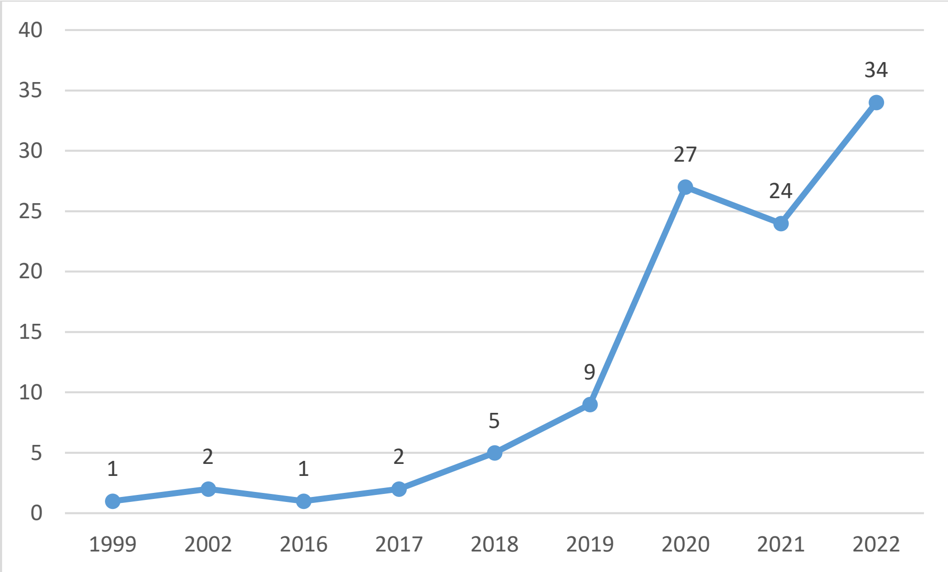

Figure 3 Journal articles on AI in digital government research*

**Articles mentioning Artificial Intelligence, machine learning, automation, and/or automated decision-making in the DGRL v18.5 (February 2023)*

This sudden, increasing interest in AI within the digital government research domain between 2018 and 2020 is also somewhat reflected in government policy documents on AI. In Europe, policy documents on AI emerged in 2018 with the European Commission's release of the Communiqué "Artificial Intelligence for Europe" and the Coordinated Action Plan on the Development and Use of Artificial Intelligence Made in Europe, which launched the first set of activities on AI within Europe. Except for one of the first policy reports released by the Organisation for Economic Co-operation and Development (OECD) in 2019 (Berryhill et al., 2019), there has been a limited focus on the opportunities that AI could provide public administrations in this period.

For instance, in the above-mentioned communiqué, public administrations' use of AI was only sparsely mentioned, and it was simply stated that the European Commission would facilitate access to AI for all potential users through an AI-on-demand platform and AI-focused digital innovation hubs.

However, in the Coordinated Action Plan (European Commission, 2018b), AI is regarded as crucial for the future work of public administrations, and actions to make European public administrations the frontrunners in the use of AI are more outlined.

Yet, detailed activities to support public administrations are lacking. The long-awaited White Paper on Artificial Intelligence (AI) by the European Commission, published in 2020, does include a section on promoting the adoption of AI by the public sector but focuses primarily on healthcare and transport services (European Commission, 2020). A dedicated focus on AI within public administrations was thus not a clear priority for the European Commission and arguably neither for many of the national governments at that time (Guenduez & Mettler, 2022), which is examined more in-depth in **IV**.

Instead, similar to the academic field, the policy community also started to focus more on the opportunities, barriers, and risks of using AI in public administrations after 2020. The updated Coordinated Action Plan, with the accompanying "Communication on Fostering a European Approach", further noted that stimulating the adoption of AI within the public sector is a critical element in building strategic leadership in AI (European Commission, 2021). These placed renewed importance on ensuring how the public sector could be a trailblazer in using AI and included more concrete actions, such as funding opportunities, and focused specifically on using public procurement to improve the adoption of AI in public administrations. This included the emergence of the Adopt AI programme, aiming to support public administrations to overcome common challenges in the public procurement of AI systems, exchanging best practices on the use of AI in the public sector across the European Union, and designing a public procurement data space, among other things. In June 2022, the European Commission also organised a High-Level Policy roundtable with Commissioner Gabriel and Commissioner Hahn that was dedicated to the challenges and opportunities of using AI in the public sector. The rising interest and political importance of AI are notable, as it evolved from the sparse mentioning of AI in government in 2018 to dedicated roundtable meetings in 2022.

Journal publications on AI in government prior to 2020

When examining only the journal publications, early works on AI within the field of digital government use similar keywords but do not necessarily refer to AI in the same manner as recent works. For instance, Bellamy (2002) outlines how the British government often takes the benefits of e-government for service delivery for granted. The work on desktop automation by Rossi et al. (2005) explores how open-source software can assist with some tasks in public administration without hindering productivity, but it focuses on replacing Microsoft Office, which is hardly considered AI.

The sole article mentioning AI, published in 1999, describes the potential benefits and dangers of using AI in public administration. What is noteworthy in this article is that it discusses the implications of the "third level of computing", such as the development of fuzzy systems that allow AI to adjust to changing conditions.

These authors point out that the potential benefits of AI systems include examining underlying assumptions and values within public administrations, helping society understand how public administrators justify their decisions, and, regarded as a most significant benefit, providing citizens with the necessary information to understand various public policy debates through reinforced citizen participation (Barth & Arnold, 1999). Moreover, AI could cause accountability issues when making decisions, as well as a less representative bureaucracy, because elitist programmers will dominate how AI will work. There are further risks that people will increasingly rely on AI systems to the extent that it erodes their responsibility for decision-making (Barth & Arnold, 1999).

It is insightful that, even though these authors do not necessarily focus on machine learning but on "the pursuit of machine or computer intelligence that approximates the capabilities of the human brain", the implications and discussions raised are similar to some of the more recent articles, such as Zuiderwijk et al. (2021), suggesting that there are challenges associated with AI's use in public administrations that are not necessarily connected to the underlying learning technique, such as machine learning, alone.

Journal articles published between 2016 and 2020 discuss various topics related to AI in government. Several papers described specific applications of machine learning in government, such as predicting participation in open government data (Piscopo et al., 2017), in citizen participation tools (Fernández-Martínez et al., 2018), analysing public comments for policymaking purposes (Clark & Brudney, 2018), or predicting the outcome of the UK referendum by combining e-petition data and machine learning (Clark et al., 2018). Other publications indicate how AI could be used to predict infant mortality (e Silva et al., 2020), economic crises (Loukis et al., 2020) and COVID-19 outbreaks (Gupta et al., 2020) and reduce corruption (Lima & Delen, 2020). These works often describe the application of the AI learning algorithms within this domain, focusing more on the development and piloting phases than the adoption and results of the systems development. Other articles describe a general overview of what machine learning could mean for public administration scholars and practitioners (Anastasopoulos & Whitford, 2019) or what it could mean for various phases of the public policy cycle (Valle-Cruz et al., 2020).

Other scholars focused on the governance of AI in society by public authorities, including how the different governance models of digital platforms and AI differ (Schneider, 2020) and how government regulation on data sharing can influence the impact of personal data on potential human rights abuses (Chatterjee & Sreenivasulu, 2019). The Estonian AI strategy (Kerikmae & Parn-Lee, 2020) highlights how various legal challenges, a division between the public and private sector's capability to use AI, and an unclear strategic vision challenges Estonia's aspirations for AI.

Whereas AI was previously associated with improving citizens' opportunities for democratic participation (Barth & Arnold, 1999), it is also possible that the increasing adoption and use of AI technologies in society changes the functioning of liberal democracies more widely. By examining how the capabilities of AI affect the information requirements of processes in a democracy, König and Wenzelburger (2020) note that, depending on the input, throughput, and output levels of the political system, AI could either increase or reduce the information deficits of citizens and policymakers. Potential or adverse effects of AI on democracy, therefore, do not depend on the technology per se but are the result of social and political consequences that cannot be mitigated through the careful design of AI systems (König & Wenzelburger, 2020).

Others highlight the legal differences in personhood in terms of computer automation between the United States and the European Union (Jones, 2017). The European Union views automation as dehumanising individuals, whereas in the United States, this is regarded as more neutral or fair due to the objectivity of computers. Consequently, this influences how and when AI technologies will be deployed in these different cultures.

Taking note of the increased interest in and use of AI technologies, researchers started highlighting the negative consequences of the deployment of these technologies by governmental organisations.

For instance, the adoption of smart technologies, in particular AI, suggests that bureaucracies are changing to a new form of bureaucratic organisation that, instead of following procedures, solves social challenges by means of adaptive algorithmic models, potentially moving towards a state of algorithmic bureaucracy due to the complex imbrication of technology with traditional bureaucracy (Vogl et al., 2020). AI technologies may influence public organisations' discretion and bureaucratic form (Bullock et al., 2020), but the identified effect is unclear and circumstantial.

Diving more deeply into the controversies surrounding increased automated decision-making with AI, Liu et al. (2019) demonstrate how outsourcing decision-making to machines challenges human rights and the rule of law due to the uncertainty and complexity involved. Public administrations may find themselves in a challenging position as they are tasked with protecting citizens from harm from AI technologies, yet temptations of efficiency gains could lead to institutions themselves becoming a leading cause of such harm (Kuziemski & Misuraca, 2020). An adequate governance framework for using AI in public administration might help mitigate some of these negative consequences, as highlighted in Wirtz et al. (2020).

Moreover, the literature highlights public administrations' difficulties in adopting these technologies. Thus, aiming to become a more intelligent public administration comes with different challenges (Corvalan, 2018). In both Sun and Medaglia (2019) and Wirtz et al. (2019), various multidisciplinary barriers to the use of AI technologies in the public sector have been highlighted that limit the use of these technologies and, consequently, any potential positive or negative effects derived from their usage. These two works have been the foundation of most of the research throughout the doctoral thesis, laying the foundation to further examine these adoption barriers and how they influence the creation of public value for AI technologies. Examining the data-related factors more specifically, Janssen et al. (2020) emphasise the importance of having data governance practices for AI and describe challenges and approaches to data governance for AI systems, proposing 13 "simple" data governance principles that are difficult to achieve in practice.

Other works from this period aim to analyse some of the then-published AI strategies to better understand the values and perceptions of AI held by these governments. For instance, Ossewaarde and Gulenc (2020) examine political discourses on AI and highlight how AI strategies often include mythical discourse about AI in Western Europe. Political discourse primarily views AI as an ideological force that will create a better future by overcoming many political, social, and ecological problems while ignoring most of its potential disadvantages. Moreover, AI is not regarded as a potential tool for strengthening democracy but rather as a way to reinforce existing power structures. Existing cultural values that shape public policy on AI in Nordic countries are characterised by a lack of citizen involvement policies (Robinson, 2020).

When more broadly examining which values drive AI strategies, Viscusi et al. (2020) highlight an emergent tension between instrumental and administrative matters and societal issues, with some countries focusing more on the risks and challenges of AI technologies than others. Diving more concretely into one specific example, Ranerup and Henriksen (2019) examine the use of automated decision-making in Trelleborg through a public value perspective to understand the intentions behind the use of technology, following the framework by Rose et al. (2015), which has also been utilised in analysing 549 use cases of AI in public administration in **IX**.

Journal publications on AI in government after 2020

Articles published after 2020, up to the analysed version of the DGRL, follow similar research areas. Various works aim to examine the use of AI in various application domains, such as critical infrastructure (Laplante & Amaba, 2021), a warning system for fire hazards (Zhang et al., 2021), the analysis of social media data to understand public concerns about COVID-19 (Alomari et al., 2021; Zheng et al., 2021), the perception of contact-tracing apps (Cresswell et al., 2021), budgeting and expenses (Valle-Cruz et al., 2022; Wu, 2022), cyberattack motivations (Banerjee et al., 2022), and citizen participation (Arana-Catania et al., 2021). What emerged more during this period were case studies on AI applications being implemented in public administrations, such as the examination of Robotic Process Automation (RPA) (Sobczak & Ziora, 2021) or the use of AI in the Brazilian Supreme Court (de Sousa et al., 2022), which not only focus on the (potential) use of machine learning algorithms but also describe how these systems are already in use. A new area of research interest emerged in understanding the opportunities in using AI for sustainability purposes, such as pollution threats (Liu et al., 2021), energy efficiency (Zekić-Sušac et al., 2021), urban sustainability (Zhang et al., 2022) as well as how AI itself could be more sustainable and efficient for public organisations (Chao & Fuhai, 2022; Yigitcanlar et al., 2021).

Furthermore, rather than examining the political discourse on AI, these more recent publications focus on the public's perceptions of various opportunities and risks of AI. For instance, research has emerged regarding citizens' attitudes towards the use of automated decision-making (Denk et al., 2022) and the use of AI in the public sector (Gesk & Leyer, 2022). The research revealed that citizens' awareness of automated decision-making positively affects their belief that decisions are more legally secure and impartial yet less transparent and personalised (Denk et al., 2022). Furthermore, there is a greater acceptance of AI when it is used in general public services, but the service of a person is preferred in specific public services (Gesk & Leyer, 2022). Other research examining the perceptions of AI includes those from Chief Information Officers (CIO) in public administration (Criado & de Zarate-Alcarazo, 2022) as well as what different stakeholders think about the meaning and implications of automated decision-making (Kaun, 2022).

Previous studies have also examined the various challenges that public administrations face when using AI technologies. These include more general assessments of the use of machine learning (Pi, 2021) as well as various risks and challenges in the Spanish public administration (Sobrino-Garcia, 2021), the challenges of integrating AI in the public sector (Ishengoma et al., 2022), organising collaboration between several stakeholders (Campion et al., 2022) and, more specifically, maintaining public trust when AI technologies are being deployed in governmental organisations (Harrison & Luna-Reyes, 2022). Additional articles highlight different challenges pertaining to equality and inclusion (Goggin & Soldatic, 2022; Larsson, 2021), privacy concerns due to surveillance (Clarke, 2022; Saura et al., 2022), biases that occur from systematic societal challenges (Fountain, 2022), human rights violations (Nalbandian, 2022), and various limitations of using data and AI technologies for policymaking purposes (Gerrits, 2021).

Further articles that emerged recently include several discussions on legal elements, such as the European Commission's Artificial Intelligence Act (Barkane, 2022) and the creation of a legal framework for AI use in the South African government (Brand, 2022). Examining how AI technologies could provide positive value has also emerged, such as Chohan and Akhter's (2021) research on the value creation of AI-based e-government services in Pakistan. However, as highlighted (Andersson et al., 2021), the automation process is the result of the affordances of technology, materials, roles, and existing power structures. Lastly, several literature reviews have also emerged that assess the current research on AI in the public sector, resulting in a research agenda (Wirtz et al., 2021), an overview of AI and public policy (Paul, 2022), AI in smart cities (Harnal et al., 2022), and the known implications of AI for public governance (Zuiderwijk et al., 2021).

This brief overview of publications on AI in the DGRL shows that the current research on AI in the digital government field touches upon a wide variety of different issues that do not necessarily concern themselves with developments in the technical field of AI. Instead, the area is more concerned with specific application examples, case studies, governance challenges of AI, driving values in AI, challenges of using AI in government, challenges that stem from governments' use of AI, perceptions, and legal frameworks, among other things. During the initial stage of this study in late 2019, the literature on AI in the digital government research field was in an early phase, with a limited understanding of what AI is, what it could mean for public administrations, how it could be adopted, which consequences would emerge, and what public value governments will aim to achieve with the deployment of such technologies.

3 Methodology

Due to the scarcity of research on the use of AI in government, this thesis has been exploratory in its research design and approach. In doing so, the research articles follow the research philosophy of interpretivism, considering the understanding of complex phenomena rather than predicting and establishing causal relations (Chowdhury, 2014). Interpretivist research is often concerned with interpreting and understanding the beliefs, viewpoints, and values of people (Chowdhury, 2014), and it is commonly deployed in digital government research to better understand the experiences of those involved with the implementation of technologies (Kamal, 2006; McBride et al., 2022; Mergel, 2019). As one of the main research gaps in the field is a limited understanding of the value created by AI, an interpretivist approach is well suited to understanding various factors that influence the deployment of AI technologies within public administration (Mikalef et al., 2021). As such, many of the research articles examined in this thesis follow qualitative research methodologies that are in line with the interpretivist approach.

Research design of the articles in the thesis

Multiple case studies, often with an exploratory case-study research design (Yin, 2018), have been the primary research methodology in most articles. These exploratory case studies (**V, VII, VI, X**, and **XI**) allowed for a better understanding of how AI technologies are developed, adopted, and used in public administrations when there was still a scarcity of such empirical research in the digital government research domain. Multiple exploratory case studies are well suited to exploring new social phenomena while allowing for varied outcomes, especially when illustrative results are the main goal (Stewart, 2012). Furthermore, these case studies allowed for a first exploration of the experiences of public administrations and provided insights into the extent to which these new technologies have contributed to the creation of public value as well as the challenges that public administrations have encountered. Such an exploratory case study research approach is well suited to examining the adoption of new innovations, especially when there is a need to gain a more broad and holistic understanding thereof (Meijer, 2015). Multiple case studies allow for a better experience of key differences and similarities between the cases (Baxter & Jack, 2008) in different situations and organisations to clarify whether the findings are valuable and sound (Yin, 2018).

While it is suitable for exploring this new research domain, one of the main limitations of such exploratory work is that the findings may be limited in generalisability as they only focus on a small number of cases (Yin, 2018). Thus, to complement the exploratory nature of these qualitative case studies that have been conducted, the thesis also includes quantitative studies (**III**, **IX**, and **VIII**) due to the landscaping exercises conducted as part of the AI Watch's research activities. By examining large volumes of use cases in a qualitative way, the aggregation thereof has assisted in providing more generalisable research findings despite not having a quantitative or positivistic research approach.

Similarly, a systematic content analysis (**IV)** of the AI strategies was conducted, which, despite the qualitative examination of the strategy and the coding approach, resulted in a large volume of text segments. Lastly, a survey (**II**) was conducted among employees of the Belgian public administration to support the literature review's findings and better understand the various interpretations that civil servants have of AI.

As such, despite the exploratory nature of the thesis, the mixture of research methods provides many findings and insights into the emerging use of AI within public administrations. Varying types of data were collected in support of these findings. Therefore, while several of the publications conducted were strongly exploratory, especially in the early phases of the research – such as **III**, **VII**, **VIII**, **VI**, **X**, and **XI** – the latter publications included more explanatory elements that are derived from recent theoretical insights, as the field of AI in government grew within the research design, such as **V** and **IX.**

The practical component of the study further supports the thesis. Much of the research has been conducted in collaboration with the European Commission's AI Watch as part of the institution's attempt to better understand the impact of the use of AI in public services. The AI Watch is an initiative of the European Commission's Joint Research Centre and DG CONNECT that is tasked with monitoring the technological progress of AI, policy developments, research, and the uptake of AI in both industry and the public sector. As part of the research activities and gathering of use cases, four different peer-learning workshops were organised to gain insights into the experiences of European Member States concerning their intended activities to stimulate the use of AI in government, the existing use of AI, and the challenges they have encountered (Manzoni, Medaglia, et al., 2021; van Noordt et al., 2021, 2020; van Noordt & Pignatelli, 2020).

Furthermore, this collaboration – as the AI Watch was one, if not the only, research unit focusing on the use of AI within public administrations at that time – facilitated access to information about AI use cases from the EU Member States. It provided support for the interviews conducted with relevant stakeholders from public administrations as part of the case study research. Most of the findings conducted as part of the AI Watch research are included in policy-oriented reports as part of these research activities, addressing a wider audience than the academic community alone, such as the landscape reports (Misuraca & van Noordt, 2020; Tangi et al., 2022), the theoretical backgrounds (Molinari et al., 2021), and a policy recommendation roadmap (Manzoni, Rony, et al., 2021). These contributions have had a noticeable impact on the developments in the use of AI in government, as these works have been included in several publications of the OECD, the Council of Europe, the European Parliament, other works of the European Commission, including the AI Act, and activities from various governments, which include some of the AI strategies that were published.

Data collection and analysis

Despite the qualitative nature of the research, various data collection methods have been included in the thesis to support the findings. All of the articles featured some form of document analysis within their data collection procedures, although the scope varies per article. For instance, in some of the research articles, document analysis was used as part of the data collection methods for the use cases, such as in **III**, **IX**, and **VIII**, as the use cases were often gathered from various documents available online. In other publications, document analysis was more integral to the research scope, such as supporting the case studies to gain complementary or additional information regarding the examined AI use cases in **V**, **VII**, **VI**, and **XI**. In **X**, the procurement guidelines and strategies discussed in this work also followed a document analysis. Document analysis was the most prominent data collection method in **IV**, examining the in-depth AI strategies published within the European Union.

Semi-structured interviews were conducted in the case studies of **V**, **VI**, **X**, and **XI**. These interviews were conducted with various stakeholders responsible for the development or implementation of AI systems in their public administrations or to gain a better understanding of the AI procurement guidelines that these organisations have published. Typically, the interviewees were selected pragmatically by contacting individuals involved with the selected use cases. For **III**, 15 interviews with 19 informants were conducted to gain insights on the various aspects of AI capability in their organisation, four interviews were conducted as part of **VII,** and nine interviews were conducted as part of the research done in **X.** The findings in **XI** were derived from the same interview data collected in **III**, which resulted in 28 interviews.

The four workshops conducted as part of the AI Watch research were not the main data collection method in any of the articles but have played an important role in gathering and validating the AI use cases as part of the landscaping exercises. They often allowed the EU Member States to present new AI use cases to be included in the landscaping activities, share their own inventories, or act as a catalyst for future research activities, such as sharing additional insights through email or providing the contact information of the stakeholders for the semi-structured interviews. As intermediate and final findings were presented in the workshops, they further facilitated the validation of the research findings and suggestions for follow-up research.

These AI Watch workshops played a crucial role in creating the AI use case inventory, which has been the basis of several research articles in this thesis. This inventory of use cases has evolved in terms of the quality, quantity, and depth of the identified use of AI within public administrations, from **VIII**, to **III**, and later **IX** through the accumulation of various data collection methods from 2019 to 2022, starting with document analysis of news articles and policy documents, submissions from EU country representatives, and the workshops and surveys done as part of the AI Watch research. The inventory has gone through a process of validation within the European Commission and EU Member States to ensure the highest possible quality of information, even though limitations remain due to the self-reporting nature of the cases, the challenge of reliable public information of the use of AI, language barriers, and challenges of the definition of AI. It is available as open data on the JRC Open Data Catalogue,[1] inviting additional research on the full dataset or focusing on a subset of the inventory data. The complete inventory of use cases has been subjected to further secondary data analysis, focusing on the governance functions (policymaking, service delivery, or internal management) in **III** and the public value drivers in **IX**.

Three surveys were conducted as part of the research. The first survey was done in early 2020 to gain additional information about the current activities on AI from European Member States as well as information about the current use of AI within their public administrations in preparation for the first workshop of the AI Watch (van Noordt et al., 2020). The second survey was held as part of the AI Watch research on barriers to AI adoption (Medaglia & Tangi, 2022), which allowed for an additional collection of use cases but was not the leading methodology in any of the research articles. In **II**, however, a survey was conducted within the AI4Belgium community to better understand how civil servants understood the use of AI.

[1] European Commission, Joint Research Centre (JRC) (2021): Selected AI cases in the public sector. European Commission, Joint Research Centre (JRC) [Dataset] PID: http://data.europa.eu/89h/7342ea15-fd4f-4184-9603-98bd87d8239a

While the survey had more objectives, such as examining barriers and collecting examples of AI used in the Belgian public administration, the data on perceptions of what AI is has been the primary data for this research article. In each piece, a literature review has been conducted to gain insights from the academic literature to complement the empirical material and include new relevant publications as the field progresses. Being conceptual in nature, and as the basis of the overall approach to public value creation, this thesis does not provide any empirical data and is fully based on academic and policy literature.

An overview of the main research methodology and data collection for each article can be found in Table 1 below.

Table 1 Overview of main research methodology and data collection per article

		Data Collection					
Article	Main methodology	Document analysis	Interviews	Workshops	Survey	Secondary data analysis	Literature review
I	Literature review	X					X
II	Survey	X			X		X
III	Secondary data analysis	X		X	X	X	X
IV	Content analysis	X					X
V	Multiple case study	X	X				X
IX	Secondary data analysis	X		X	X	X	X
VII	Multiple case study	X					X
VIII	Secondary data analysis	X				X	X
IX	Multiple case study	X	X				X
X	Multiple case study	X	X				X
XI	Multiple case study	X	X				X

To analyse the collected data, several data analysis approaches were employed. These include various deductive coding approaches to analyse the responses on the perceptions of AI in **II**, the policy initiatives in **IV**, and the public value of AI use cases in **IX.** The coding process was supported by the MAXQDA software. In **III**, the coding was done by analysing the descriptions of the gathered use cases for each governance function. Other coding approaches in the thesis include a thematic coding approach from the collected data from interviews in **V** and a cross-case analysis based on a coding scheme of AI challenges in **XI**.

Limitations

The research design comes with some limitations as well. For instance, the scope of the research is rather broad, as there is limited understanding and literature. Most of the study examines various aspects of the adoption and implementation of AI in public administrations holistically, which, while providing several insights, limits the analysis to specific elements that are relevant to utilising AI in government and creating public value. Furthermore, as AI remains in a nascent phase in public administrations, the findings might have limited generalisability and transferability to other public administrations – especially those still in an early stage of digitalisation, as they have not been examined in the case studies. This is especially relevant for the applicability of the findings in regions beyond Europe, as the results yield a geographical bias towards countries within the European Union. All the publications focus on using AI within the European Union, which could potentially overlook unique challenges in other regions.

Defining what AI is and is not also introduces difficulties in the research design, as examined more deeply in the following section. As long as there is no agreed-upon definition of AI or its scope, different interpretations create difficulties for the theoretical underpinnings of the research, case selection, and analysis of the findings. The user-reported nature of the data collection for the thesis, relying strongly on the public administration's own perceptions and understandings of AI, might thus introduce potential subjectivity and misunderstandings of how AI is presented in public administrations and how it could create public value.

4 Understanding of the concept of AI in public administration

Despite the significant interest in AI by society, policymakers, and academia, influenced further by the narratives of the "AI race" taking place, there is still no universally accepted definition of AI (Medaglia, Gil-Garcia, et al., 2021). Furthermore, any classification of what is and is not considered AI is bound to be incorrect after a while due to the so-called "AI effect", which means that, due to a lack of a clear definition, AI is often discussed as the most cutting-edge technology at any given time. Once this technology becomes more widely available and diffuses into society, it will no longer be described as AI, and a new cutting-edge technology will take its place (Wang, 2019).

As also highlighted in **II,** various challenges and inconsistencies contribute to the conceptual challenges of AI. While no universally accepted definition of AI exists, this does not mean that there are none. Instead, there are 28 definitions in the information science research domain alone (Collins et al., 2021), which are not all alike and refer to different elements. Moreover, despite the variety of definitions, many academic articles do not define AI (Collins et al., 2021) or discuss AI in general without further specification (Rjab et al., 2023). As examined more in **II**, these definitions often follow several approaches and depictions of researching AI, which are not necessarily alike, as seen in a selection of definitions in Table 2.

Table 2 Overview of a selection of definitions of AI

Source	Definition
(McCarthy, 1959)	"The science and engineering of making intelligent machines."
(Minsky, 1967)	"The science of making machines do things that would require intelligence if done by men."
(Russel et al., 2016)	"AI to describe systems that mimic cognitive functions generally associated with human attributes such as learning, speech and problem solving."
(Ballester, 2021)	"An AI system is a machine-based system capable of influencing an interlocutor in a particular task by making recommendations, predictions or decisions for a given set of objectives. It uses machine and/or human-based inputs/data to: i) perceive a context; ii) generalize, learn and abstract perceptions into replicable models with or without human guidance; and iii) interpret the models to posit a humanly interpretable outcome."
(Wirtz et al., 2021)	"The capability of a computer system to show human-like intelligent behaviour characterised by certain core competencies, including perception, understanding, action, and learning, which includes concepts such as machine learning, speech recognition, and natural language processing."
(Zuiderwijk et al., 2021)	"Systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals."
(Mikalef & Gupta, 2021)	"An AI application is that of any form of manufactured system that can autonomously generate insights and/or take action based on these, to reach a set of objectives. These objectives are narrowed to those that are directly or indirectly relevant to the directions set out by organizations and societies."

Futuristic AI technology

For instance, some works focus primarily on futuristic AI technologies, which will arise when the field of AI advances too far. Such forms of superintelligent AI are discussed to identify potential or catastrophic concerns when the research field of AI develops too far, and machines surpass human intelligence (Kaplan & Haenlein, 2019; Müller & Bostrom, 2014). These studies are fruitful in highlighting the dilemmas of technical progress in society or the AI field to raise concerns about or focus attention on the advancements of technology in society, such as the frequent warnings about godlike AI which could enslave or kill humanity or that in the words of Stephen Hawking, "the development of full artificial intelligence could spell the end of the human race"(Cellan-Jones, 2014). Others yield a much more utopian vision of what such a futuristic AI could mean for human flourishing and view it as a technological redemption for many of the problems of modern-day society (Sheikh et al., 2023), even leading some to wonder what it would mean if our governance systems were handed over to an "all-knowing" AI system (Sætra, 2020).

Others associate AI more with creating human-like intelligence, also regarded as Artificial General Intelligence (AGI) (Makridakis, 2017; Sun & Medaglia, 2019). Such human-like robots would be highly similar to human intelligence and understand language, feel emotions, and be capable of learning in similar ways. The creation of such AGI is often regarded as one of the main aspirations of the AI research domain, and despite regular claims to the contrary, the creation of human-like intelligence is close. For instance, while such claims were present in the 1970s (Katz, 2017), even more recent headlines mention that society is close to achieving human-level AI (Cuthbertson, 2022), despite the fact that no such form of AI has been developed or may be developed soon. While thought-provoking, these futuristic and human-like AI systems are not of concern within the current research domain on AI in modern society, nor are these kinds of AI systems the focus of the central policy debates. Instead, the academic and policy focus is on narrow AI applications, which are regarded as those that are equal or slightly superior to human intelligence, yet only in a specific task, and not similar to the full capacity of human intelligence (Collins et al., 2021).

Technical AI classifications

Consequently, there have not only been many different definitions of AI over time but also many different practices for categorising AI. As argued in **II**, there can be a focus on AI learning techniques to determine if AI is utilised and which type. In doing so, authors often highlight the distinctions in various approaches within the machine learning methodologies and aim to categorise AI based on the machine learning approach followed (Samolili et al., 2020).

The techniques argued to be AI are, for instance, the use of artificial neural networks, case-based reasoning (CBR), natural language processing, multi-agent systems, and machine reasoning, among many others (Medaglia, Gil-Garcia, et al., 2021), yet a definitive overview of which techniques are or are not AI does not exist, with different articles including different techniques as AI, which further change over time. While AI is commonly regarded as the use of machine learning, there are many other techniques and algorithms that fall under these analytical techniques and are regarded as machine learning (Ray, 2019; Shrestha & Mahmood, 2019).

With this understanding, AI can be based on supervised machine learning approaches in which labelled training data is used to draw patterns and predict new cases. Supervised machine learning is arguably more labour-intensive as the data must be labelled adequately (Liu et al., 2019). As a result, it is possible to determine the classification of new data (Burrell, 2016). While simple statistical techniques such as linear regression may also be regarded as supervised machine learning, complex approaches utilising neural networks are at the basis of what AI systems are capable of, such as identifying different objects on digital media (Kaplan & Haenlein, 2019).

Instead, unsupervised learning approaches use unlabelled data to measure the similarity of data (Coglianese & Lehr, 2017) and create a structure within the data itself (Kaplan & Haenlein, 2019). This allows for the detection of hidden patterns in data that would not have been detected otherwise (Pugliese et al., 2021), yet it simultaneously creates difficulties in assessing its accuracy or validity. Such unsupervised learning approaches can be deployed to detect fraud, yet it still requires follow-up to determine if there is actual fraud (Simonofski et al., 2022). It requires domain expertise to interpret the created correlations in the data and, perhaps more importantly, its usefulness (Pugliese et al., 2021). Patterns identified could be useless for civil servants as they do not align with known expertise in the field or may just be patterns by chance (Smith, 2020). In reinforcement machine learning approaches, AI systems learn over time through serious rewards or punishments upon completion or failure of the task (Kaplan & Haenlein, 2019). Such methods are often used in AI learning how to play games in a simulated environment (Pugliese et al., 2021) and have been the basis of AlphaGo Zero's victory over the GO champion (Wirtz et al., 2019).

Classifications of AI as artefacts

However, such classifications are often technical and do not necessarily reflect how public administrations regard AI or whether specific individual applications are regarded as AI. Alternatively, several classifications of AI focus more on the types of artefacts or applications considered to be AI. These are often more tangible technologies, as they are the result of the development processes derived from AI learning techniques. Whereas there is no clear overview of which applications are or are not AI, various categories have been developed, including voice assistants, image recognition software, facial recognition software, recommendation software, prevention systems, audio detection applications, chatbots, RPA, autonomous vehicles, robots, and Internet-of-Things (IoT) applications, among many others (Cabrera-Sánchez et al., 2021; Medaglia, Gil-Garcia, et al., 2021; Wirtz et al., 2019). The variety and diversity of such software and hardware applications are noteworthy, which poses challenges in comparing the different applications and their developments, capabilities, risks, and benefits for public administrations.

However, these are the applications with which the final users, whether they are civil servants or civilians, interact and create a positive contribution through such interactions.

It is not just the research community which has disagreements and different approaches to what AI is, how to define it and which forms of applications fall under the definitions (Ruschemeier, 2023). There is no agreement within the policy community on how to define AI best, nor which applications would fall under this definition. With the increased demand for regulation, public administrations themselves are defining AI in similar yet occasionally crucially different approaches. In the Recommendation on the Ethics of Artificial Intelligence, adopted by UNESCO's 193 Member States, there is neither a single definition of AI nor a willingness to establish a definition (UNESCO, 2022).

Instead, UNESCO approaches AI systems as “systems which have the capability to process data and information in a way that resembles intelligent behaviour, and typically includes aspects of reasoning, learning, perception, prediction or control.” As such, UNESCO regards AI as ICT technologies that integrate models and algorithms, such as those based on machine learning, and include the IoT, robotic systems, and human–computer interfaces, among other cyber-physical systems.

In the Recommendation of the Council on Artificial Intelligence, the OECD regards AI systems as “a machine-based system that can, for given a set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy”, thus omitting machine learning (OECD, 2022b). However, the OECD also notes that there is a need for classifying AI systems to determine the types of AI and their impact. In doing so, the OECD Framework for the Classification of AI systems helps to categorise AI based on the data and input of the AI, the AI model, the tasks and output, the economic context, and the people and planet,although not necessarily providing clarity on which specific applications could or should be classified (OECD, 2022a).

The United States has no specific AI legislation, and no definition has been put forward in the Blueprint for an AI Bill of Rights, which aims to address key concerns regarding the application of AI technologies (The White House, 2022). The scope of this document applies to “automated systems that have the potential to meaningfully impact the American public’s rights, opportunities, or access to critical resources or services” and, thus, does not necessarily focus on the technological approaches concerned with the development of AI but instead on systems which act automated and have a potential impact – thus focusing more on the elements of automation. For instance, the European Commission defines AI as “software that is developed with one or more of the techniques approaches listed in Annex 1 and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations or decisions influencing the environment they interact with”. Consequently, Annex 1 is of great importance to determine which applications fall under this definition. In the current draft,[2] this includes machine learning, logic- and knowledge-based, and statistical approaches.

However, this may account for almost all modern software as they have one or more of these approaches, leading some to argue that the scope of the legislation is unnecessarily broad (Edwards, 2022). There is no consensus on what is to be under the scope of the definition of AI.

[2] As of February 2023 – and is likely to change due to amendments in the European Parliament and future negotiations between the European Parliament and the Council of the European Union

*Table 3 Varying perspectives of AI (in **III**)*

Understanding of AI	Explanation
AI as superintelligence	A futuristic machine or computer which (far) surpasses human intelligence
AI as general intelligence	A futuristic machine or computer which displays equal human-like intelligence in a variety of domains
AI as narrow intelligence	Current AI in which systems display human-like intelligence in one specific function
AI methods/techniques	Techniques and methods that allow the analysis of large volumes of data to develop AI such as case-based reasoning, cognitive mapping, fuzzy logic, machine learning, multi-agent systems, and rule-based systems, among many others. These may fall under supervised, unsupervised, or reinforcement learning methods
AI as human-like cognitive capability	Ability of machines to carry out tasks which require human capabilities, by displaying human-like behaviour, to behave rationally, the ability to solve hard problems
AI as applications	A special form of IT systems, applications, or software that is capable of performing tasks that normally require human intelligence
AI as a science	The general study and science behind the pursuit of making machines or computers intelligent

Given this broad diversity of various understandings of AI, as seen in Table 3, it is crucial to understand how civil servants themselves perceive AI. Therefore, in **II,** a web survey was conducted among Belgian civil servants (*N* = 116) to analyse their understanding and perception of AI. What emerged from this research is that AI is neither associated with superintelligent robots (1 coded answer) nor related to the overall branch of the science of AI (four coded answers). Furthermore, rather than the learning techniques (29 coded answers), AI is more often perceived as an ability (59 coded answers) or as an application (53 coded answers). As such, a key finding in **II** is that civil servants do not necessarily associate AI with these various learning methods. Instead, they focus more on the capacities, capabilities, and types of AI applications. AI is thus associated with being able to perform tasks previously done by humans, being capable of learning new things, conducting tasks autonomously, automating repetitive tasks, and finding connections in the data, among other things. As emphasised in **II,** it is insufficient to categorise AI purely based on the learning techniques used, as others may only consider AI to be systems that have certain capabilities and can perform specific tasks.

However, as noted in **II**, what is to be considered is that, despite the interplay between AI learning techniques and applications, some applications may be regarded as AI even when not based on, or only sparsely, AI learning methods. Others, such as chatbots, may be based on AI learning techniques, traditional programming, or a combination thereof, making it difficult to determine which application is AI.

Alternatively, public organisations may use AI learning techniques, such as deploying statistical methods on datasets, without the intention or development of a final artefact or application embedded in the organisation. This limits the researching of AI as a tangible technology and understanding how it is utilised in work processes (Bailey & Barley, 2019).

Flexible approach to defining AI technologies

Due to the complexity of placing clear boundaries on what is or is not AI, researchers have stated a preference for understanding AI as an umbrella of technologies and methodologies requiring computers to conduct human-like intelligent tasks (Chen et al., 2023). These suggest adopting a more flexible approach to defining AI, which depends on the context and discipline of the field of research and often relates to a "cluster of digital technologies that enable machines to learn and solve cognitive problems autonomously without human intervention" (Madan & Ashok, 2022). These studies do mention machine learning algorithms or applications based on machine learning, yet they view AI as broader and not solely based on machine learning, such as "advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions and take actions" (Neumann et al., 2022).

This thesis follows the flexible approach to defining AI, preferring not to view AI as a goal-oriented tool aiming to create a new system (Scherer, 2016) but instead as a tangible technology (Chen et al., 2023) that could be examined as an innovative tool in the public sector. In doing so, this thesis is not necessarily concerned with the sole development of new models through the use of the various AI learning methods (Desouza et al., 2020), as described in **II**, nor is it concerned with the design of such systems, but instead examines the ICT systems that have been developed as a result of these and are regarded as AI due to their capabilities (Wirtz et al., 2019). As such, the work aims to avoid a precise definition of AI by, on the one hand, examining them as a "special form of ICTs, capable of displaying intelligent behaviour and completing tasks normally said to require human intelligence" (**III,** p.2) or as an "umbrella technology, referring to a wide range of different technologies and applications that display intelligent behaviour by analysing their environment" (**V,** p.5).

In this thesis, AI applications that have been examined, particularly in **III**, **V**, **IX**, **VI**, and **XI**, include those AI technologies that do not always, nor fully, depend on machine learning. Others note that while there are several ways to further classify the technical specifics of AI technologies as examined earlier, for some research purposes, such as understanding the (citizen) acceptance of AI technologies or other perceptions of the technology, these deeper classifications are not required (Gesk & Leyer, 2022). More importantly, public administrations may refer to some of the technologies they are using as AI technologies, regardless of whether this label of AI is universally accepted. This already emerged when chatbots (Aoki, 2020), or some form of RPA, were the focus of the study (Harrison & Luna-Reyes, 2022). While this is understandable because promoting deployed technologies as a form of AI may indicate innovation and prestige, it hinders research on the use of this technology in government.

As such, while adopting a flexible approach to defining AI has merits, this flexibility also comes with the critical remarks that the label of AI is placed on too many applications and technologies, making it an unclear “suitcase word” that has no inherent meaning and is accepted by researchers as long as research results are viable (Wang, 2019). Consequently, it also causes challenges in understanding which kinds of AI systems are to be desired, which are regulated, and which are to be avoided entirely (Collins et al., 2021). As pointed out throughout the thesis and more in-depth in **II**, the different definitions, technologies, and methodologies challenge assessing the type of AI used in government. As a result, this creates difficulties in determining how different types of AI provide impact while ensuring generalisability. Despite best efforts, the findings and contributions of the thesis do not provide a noteworthy solution to this challenge, yet further research is advised to take close notice of these interpretations and, in doing so, ensure a more holistic approach to studying AI, taking into account the data, capabilities, and application type to avoid some of these generalisation difficulties.

The challenge of defining and researching AI is further complicated by studies investigating similar challenges of AI in government that do not utilise the concept of AI in their research. Instead, they include concepts such as predictive algorithms, automated decision systems, or automated decision-making, for instance: “predictive algorithms that aim to automate, aid or replace decision-making by government officials” (Schiff et al., 2021, p.4). Potential benefits and challenges thus appear from eliminating human discretion or agency and the role ICT plays, whether this is AI or not, rather than the type of technology necessarily (Bullock et al., 2020; Newman & Mintrom, 2023). At times, while the term AI is not used, the cases examined in these works are occasionally also considered AI in other research publications, such as the Dutch system SyRI, described as an algorithm in some research works (Dekker et al., 2022) yet described as a form of AI in other publications (Ballester, 2021; de Bruijn et al., 2022; Newman & Mintrom, 2023). These works often discuss similar challenges regarding the deployment of these systems, such as accuracy, bias, transparency, and fairness, which are the focus of analysis (Busuioc, 2021). The system might also be described as an algorithm or AI (Giest & Klievink, 2022), further adding to its complexity.

Moreover, several arguments are made in the literature about why AI technologies are distinct from other types of digital technologies and thus require separate conceptualisation and theory-building. For instance, AI is regarded as additionally complex compared to normal ICT, as the technology is perceived to be more challenging to understand and use (Rjab et al., 2023). Compared to other technologies, there is a closer interconnectedness with data than other ICTs, which brings additional challenges regarding data access and ownership (Neumann et al., 2022). A key characteristic of AI compared to “regular” ICT is that AI-based software holds a notion of self-learning, which is often made possible by retrieving important information derived from large datasets, such as patterns that are not easily detectable by humans (Gesk & Leyer, 2022). However, in doing so, these applications are often black boxes that bring more transparency and explainability challenges than other ICTs (Sun & Medaglia, 2019). It is argued that it differs further from traditional technologies or automation as it does not follow preprogrammed if–then logic (Medaglia, Misuraca, et al., 2021).

However, following the research findings in this thesis, it is unclear to what extent AI technologies differ from other digital technologies deployed in public administrations and whether these distinctions are present with all AI technologies used in public administrations. For instance, while AI technologies may be regarded as more complex to understand and use, as chatbots and RPA technologies are seemingly more straightforward and easier to comprehend, this is not always the case. The interconnectedness of data is also a crucial element of AI identified in the research findings.

However, the extent thereof varies per AI examined, with some use cases requiring less data than others. Especially in AI, which remains strongly rule-based, the interconnectedness of data is less present. Therefore, the extent to which these distinctive characteristics of AI are current depends strongly on the type of AI used in public administration, emphasising the need for additional conceptual clarity and possible classifications to allow for such distinctions in future research.

5 Public value creation through the use of AI in public administrations

One of the main findings and contributions of this thesis is that creating public value through the use of AI technologies in public administrations is not straightforward, despite the transformative narratives often associated with the technology (Ossewaarde & Gulenc, 2020). Public value creation results from the interplay between various factors, processes, and requirements. Despite the association with AI replacing jobs and making people redundant, the research findings show that the important criteria for creating value with AI technologies lie with the people working within the government. AI requires a significantly educated and skilled workforce within the public administration to initiate, manage, and use AI technologies effectively. Such a workforce is too often lacking within public administrations (Wirtz et al., 2019), and it is also one of the main factors that currently limit the broader adoption of AI within public administrations (Sienkiewicz-Małyjurek, 2023). In that sense, and as anticipated from the earlier research on public value creation in digital government research, creating and realising public value through AI technologies is far from automatic and requires significant work and sufficient capabilities, competencies, and resources.

Developments in AI in a technical sense, such as accuracy rates through advancements in research on AI, do not necessarily translate into the use of AI within governmental organisations. The availability of technology does not necessarily mean that it is adopted by governmental organisations (Zheng et al., 2013), or if it is, whether it is providing the effects it is supposed to (Pang et al., 2014). This noteworthy gap between technological and societal developments and the use of technology by governmental organisations has been well established in the e-government literature (Choi & Chandler, 2020). This thesis emphasises that a similar gap is present regarding the adoption of AI technologies by public administrations, as the availability of AI technologies does not automatically lead to their adoption by governmental organisations (Madan & Ashok, 2022) nor to public value creation if they are adopted, as emphasised in **IV**, **VII**, **VI**, and **XI**.

This gap, as well as the factors limiting the adoption of AI, creates an entirely different, yet more nuanced, picture of how emerging technologies, such as AI in particular, could generate value in society, business, and public institutions. A complex interplay between technological, social, institutional, environmental, and historical factors determines the decision to use AI technologies and to what extent the administration reorganises organisational practices to gain the most value from the adopted technology (Ahn & Chen, 2022; Rinta-Kahila et al., 2021; Sanina et al., 2021).

These factors, as well as the interplay between them, are examined in several of the research articles in this thesis, highlighting that the use of AI technologies in public administrations requires effort to establish the right conditions to start with developing and using AI systems, the right conditions to adopt the technology, and the additional need to introduce organisational changes to achieve this. Public value creation with AI technologies thus requires public administrations to go through several barriers in overlapping phases – the initiation, adoption, and implementation phases – as highlighted in the literature on the innovation process (Kamal, 2006). An overview of the various elements and considerations in these phases can be found in Figure 4, which highlights the key differences between the pre- and postadoption phases that are also present in AI adoption (Madan & Ashok, 2022).

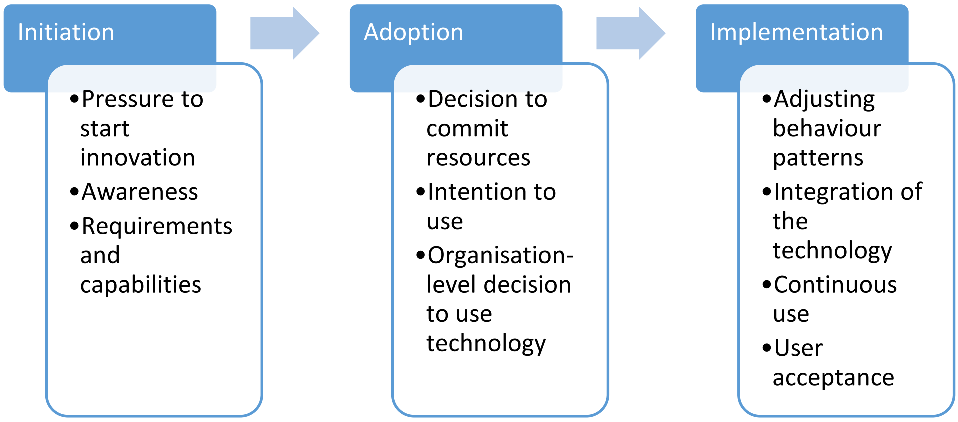

Figure 4 IT Innovation adoption phases, based on Kamal (2006)

5.1 Initiation of AI technology in public administration

The first set of barriers that public administrations face in gaining value from AI technologies relates to starting innovation with AI in these organisations. This crucial first phase occurs before any adoption or implementation takes place. However, these challenges are not necessarily unique to AI, as other public sector innovations face similar difficulties (De Vries et al., 2016; Schedler et al., 2019). It is crucial that public administrations are aware of what AI technologies could provide for them and are willing to initiate the innovation process. Such a willingness to innovate with AI is the result of a partnership between an innovator and the broader organisational culture, as this individual needs to be given the room and opportunity to initiate an AI-innovation process (Kamal, 2006). Without such support, the innovation process could be halted from the beginning if management or the broader organisational culture is too risk-averse. However, the entire organisation does not need to immediately support the use of AI, as the willingness to trial, use, and implement AI is a longer, more exhaustive process that plays a more substantial role in the latter phases of the innovation process.

The willingness to trial AI technologies follows from awareness of the latest technological developments, often passed through the networks in which the administration is active. This allows public administrations to remain up to date on private sector offers or innovations that are used in other organisations. However, more crucially, the organisation must be aware of a problem that requires solving and was previously not solvable through other methods (Neumann et al., 2022). Awareness of AI's possibilities thus requires identifying a problem relevant to the organisation that could potentially be solved through AI technology. These elements were also identified in **VI,** highlighting that the local networks in which the administrations operate are vital to developing and adopting AI innovations.

It is, however, possible that the organisational environment is too risk-averse to initiate any AI-related innovation, thus limiting future potential AI adoption. This may be because of the perceived risks of using AI, the challenges of linking organisational goals and processes with AI's opportunities, or simply a lack of understanding of what AI is and could mean. There is a general lack of understanding of what AI is, could do, or could not do due to the various myths surrounding the technology and claims from technology vendors. A severe lack of AI-related skills within the public sector, which do not only need to be technological, as also emphasised in Mikalef et al. (2021) and Wirtz et al. (2019) and explored in **V**, further limits the initiation of AI technologies in public administrations. For instance, in this work, one of the respondents highlighted how only a handful of data scientists are available in the country, with fewer being able and willing to work for the public sector, which significantly limits their AI activities.

The environmental conditions in which public administrations operate play an important role as well. These relate to, for instance, external pressures to initiate AI innovation from citizens or policymakers (Altayar, 2018; Fan et al., 2022) that also result from the wider AI uptake and digitalisation in society. The environmental conditions cannot be regarded as disconnected from broader digital government activities. This was argued in **I** and further highlighted in **V**, stating that using AI technologies in government falls on a continuum that includes previous digitalisation. Without such historical digitalisation efforts, it is highly challenging – for technological, cultural, and societal reasons – to start any innovation process with AI technologies; however, some exceptions exist.

Some AI innovations have been used within public administrations to assist them in digitalisation and ensure that the data quality within public administrations is higher, potentially providing the right conditions for future AI innovations. Such examples can be seen in **IX** and **VI**, where some of these cases are described.

Strategies to support AI in government

AI strategies have been researched in **IV** to identify which policy instruments are described to overcome various barriers to developing and using AI technologies in public administrations and how strategies are used to provide the foundational conditions to create and use AI in public administrations. More often than not, the focus of AI strategies lies on governing AI technologies in society through governmental organisations rather than using these technologies themselves to support their activities (Guenduez & Mettler, 2022). Despite this limitation, several key policy instruments have been identified that could assist in overcoming these initiation barriers and provide the right foundations for public administrations to start, adopt, and use AI, as seen in Figure 5.

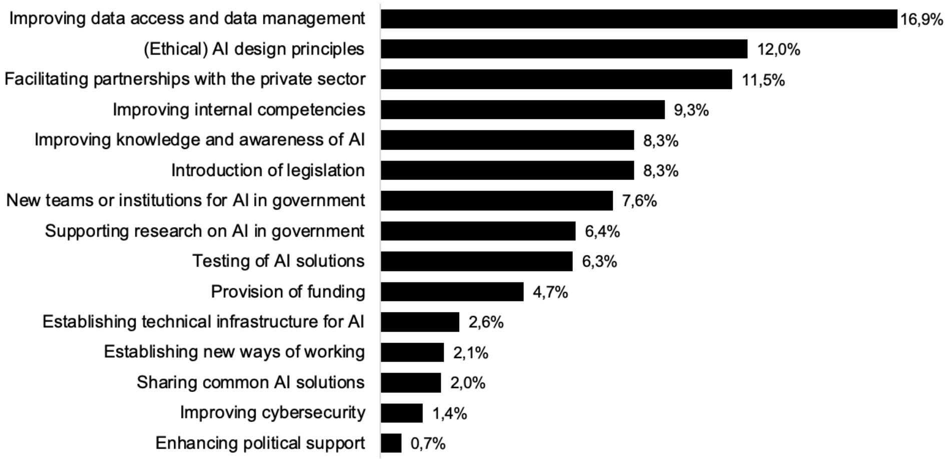

*Figure 5 as percentages of coded policy initiatives, in **IV** (N = 1050)*

The analysis highlights how strategies describe activities tasked with improving the general knowledge and awareness of AI through international collaboration, the sharing of best practices through awareness campaigns, and new government platforms dedicated to AI in their administration. These activities are meant to spark interest and promote the understanding that AI could also be applied within the public sector. Other initiatives aim to include improving the public sector's data ecosystem to strengthen the quality and availability of data, the development of ethical guidelines, design principles, and other guidance documents, improving possibilities for partnerships with the private sector, legislation, and supporting internal competencies and skillsets, among others, to overcome precisely some of the key technological, societal, legal, and ethical challenges public administrations face in initiating and adopting AI (Wirtz et al., 2019).

However, despite the variety of initiatives proposed in the AI strategies, a key finding of this research is that there is a generally strong emphasis on overcoming data-related barriers to AI development and adoption. In some AI strategies, initiatives almost exclusively focus on the data-related aspects, which run the risk that other implementation barriers, such as a lack of skills or funding, are overlooked. In this respect, the analysis shows that AI strategies often do not discuss improving the internal capability of AI within public administrations, and there is a lack of reference to funding programmes to do so effectively. Instead, there seems to be a strong focus on relying on the private sector to assist the public administration in developing and implementing AI technologies.

Therefore, the pre-adoption phase remains crucial for any adoption process with AI technologies in public administrations. There first needs to be some awareness about the possibilities of AI for the administration and a willingness to explore what AI could mean for the institution. Strategic activities through AI strategies aim to provide the foundational conditions for public administrations to kickstart these innovations – although they currently focus too strongly on the data-related barriers rather than all the barriers that public administrations face during the adoption process, which are discussed in the next section.

5.2 Drivers and barriers to the adoption of AI

When public administrations pass the initiation phase and find themselves interested in experimenting, testing, and adopting AI technologies, several interdisciplinary barriers limit this. For instance, as described in **VI,** many factors enable or hinder AI adoption in government: environmental, organisational, individual, and technological, rather than only the technical drivers of AI, such as data, computing power, and machine learning algorithms. Even a single motivated civil servant within the organisation often plays a deciding role throughout the innovation process (Kamal, 2006) out of personal interest or motivation, whether they have developed AI skills or not.

As identified in **VI**, the perceived value, ease of use, security, privacy concerns, and compatibility of AI systems with organisational values are vital factors in either adopting or not adopting AI technology. These antecedents play a more prominent role in the perceived attributes of AI technologies, which are dynamic and can change over time rather than having a fixed set of characteristics. As noted in **II**, civil servants have widely different interpretations of what is or is not AI, with various perceived risks, benefits, and values that can change over time, depending on their (lack of) experiences with the technology, as seen in **III** and **V.**

The increased potential risks of AI technologies, which are widely discussed (Bannister & Connolly, 2020; Dwivedi et al., 2019; Sigfrids et al., 2022), are legitimate, yet the perception of these risks plays a more significant role than the actual realisation of these benefits or risks (Kuziemski & Misuraca, 2020). This may make some public administrations, by default, more hesitant to adopt AI technologies as they perceive that the risks outweigh the benefits, whereas others regard the potential benefits of increased efficiency and effectiveness as worth exploring (Ahn & Chen, 2022; Guenduez et al., 2020).

As emphasised in **VI** and subsequent sections in this thesis, AI can be considered a form of public sector innovation when deployed in public administrations. This research identified that building on the antecedents of public sector innovation identified by De Vries et al. (2016), there is a high overlap between the antecedents of public sector innovation and the adoption of AI technologies in public administrations. As shown in Figure 6 below, the same environmental, organisational, innovation-related, and individual factors all play a role during the process of adopting AI in public administrations. As such, considerable theoretical overlap exists between AI-based innovations and other public sector innovations. However, the complexities and characteristics of AI technologies may indirectly influence these antecedents. For instance, if AI is more complex than other types of digital innovations, this may require additional demand for organisational resources, which would limit its adoption if not present.

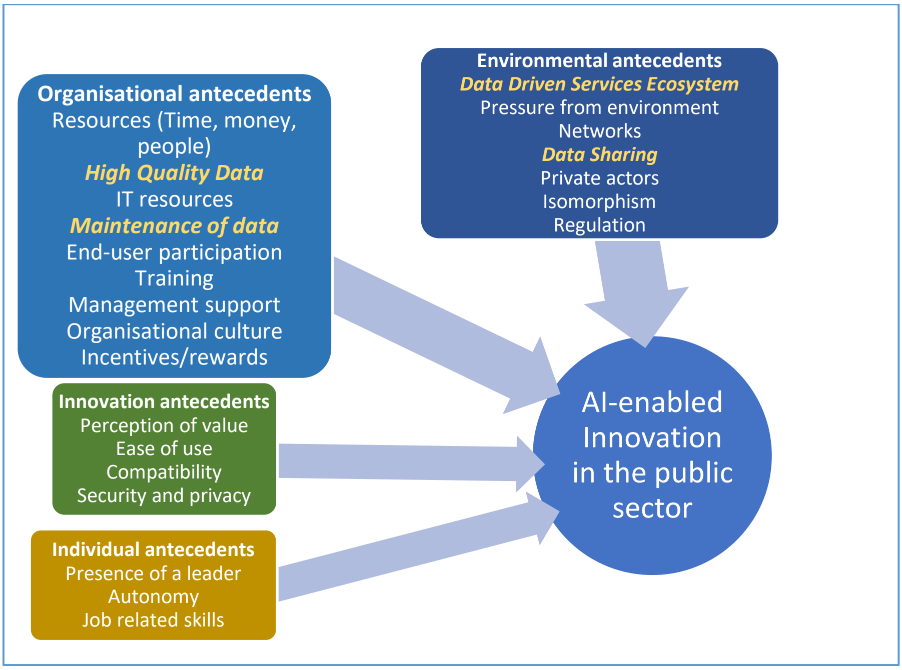

*Figure 6 Antecedents to AI-enabled innovation in the public sector, based on de Vries et al. (2016; in **VI**)*

AI-related innovation antecedents

In this regard, the research did identify specific AI-related antecedents that are considered crucial for adopting AI in public administrations. AI technologies come with additional adoption challenges compared to other public sector innovations, mainly related to data-related factors. AI technologies do require the presence of adequate, high-quality data sources, which require that the administration have sufficient data management processes internally, the maintenance of said data, and the possibilities and willingness to share inter- and intra-organisational data.

As such, these technical resources often follow historical e-government growth, as anticipated in **I** and found in **V** and **VI**. Nonetheless, the technical resources are inadequate by themselves to ensure the adoption of AI.

In addition, specific to AI, there is a need to better understand how public procurement processes influence the adoption of AI in public administration, as it is regarded as a critical strategy for implementing AI in government (Madan & Ashok, 2022). As highlighted in the review of strategies in **IV**, many governments perceive the current public procurement processes as hindering the adoption of AI, which is why administrations are exploring changing procurement processes or strengthening the use of innovative public rocurement processes. Public procurement rules have been mentioned in **V** as a limiting factor for rivate sector involvement in AI. A dedicated focus on the challenges of public procurement of AI in the public sector in **X** does show that, despite the interest and potential for utilising public procurement, there are procurement, data-related, and AI-model challenges, which limit the potential for using procurement for AI. However, other cases researched in the research articles show that public–private sector collaboration is present, despite these hurdles. More research on understanding how to organise public procurement to facilitate AI adoption in government is a topic of growing academic and policy interest, yet empirical research is scarce (Medaglia, Gil-Garcia, et al., 2021; Wirtz et al., 2021).

Other authors built upon the antecedents of AI-related public sector innovation by researching the factors of AI adoption in governmental organisations, utilising different frameworks, and doing so more in-depth, primarily based on the Technology–Organisational–Environment (TOE) framework. For instance, Madan and Ashok (2022) conducted a literature review of publications on AI in government to develop an overview of AI adoption and diffusion challenges based on the TOE framework, identifying environmental, organisational, technological, and absorptive capability factors that play a role in doing so, relating to the identified elements in **VI**. This review noted the importance of AI strategies, policies, directives, and mandates encouraging AI in the public sector as a vertical environmental pressure yet reported the uncertainty regarding to which extent these factors affect AI adoption, similar to what has been identified in **IV.** According to Neumann et al. (2022), the factors hindering or facilitating AI adoption in government further depend on the organisation's level of AI maturity, with initial resources to launch an AI project becoming more critical at low maturity levels and strategic management support with additional resources and organisational diffusion becoming more crucial in later phases.

Despite the general awareness of the various barriers limiting the use of AI, as identified in the studies below, it remains somewhat unclear which barriers play a more substantive role in adopting AI and which challenges could be overcome. A survey among 414 Polish cities found that public organisations face many challenges when adopting AI technologies (Sienkiewicz-Małyjurek, 2023). Public managers highlight the lack of an AI strategy or plan in their organisation, difficulties in ensuring that AI is aligned with human values, insufficient knowledge of staff members on how to use AI, limited policies and regulations on AI, and the wide range of expectations about what AI can and will do. Researching the perceptions of public managers, such as in Criado et al. (2020), found that CIOs in Spain and Mexico mainly have positive outcomes from AI for public management operations.

Yet, the digital divide, inadequate technological infrastructure, legislation, and administrations with limited budgets will likely hinder implementation. A literature review of 18 different adoption barriers (Rjab et al., 2023) found that the primary technological obstacles to AI adoption are privacy, cyber-security, and the lack of explainability. The main organisational barrier is the lack of financial resources in public administrations, while the risk of mass unemployment and lack of public trust are the leading environmental barriers.

Barriers to specific AI technologies

The diversity of AI technologies and application areas suggests that there can be additional barriers depending on the type of AI as well as the context of the application. For instance, Neumann et al. (2022) propose that there are differences in the complexity of AI applications that influence the adoption process. Specific applications of AI that are less complex, such as conversational agents, are possible to adopt in public organisations even with limited maturity in AI adoption. These AI applications may thus be relatively simple and independent, and they may require fewer internal resources. The seemingly vast preference for adopting chatbots and other virtual assistants in public administrations, as seen in **VII** and **III**, may support this statement. What exactly is meant by the complexity of AI applications is unclear, as it could relate to the level of complexity of the AI applications themselves, such as their limited explainability (Busuioc, 2021; de Bruijn et al., 2022) or the type of complexity of the tasks they are automating or augmenting (Young et al., 2019), such as the number of rules and exceptions surrounding the provision of a service (Janssen, Hartog, et al., 2020). Complexity may also mean the transparency standards society has for specific use cases compared to others (Kuguoglu et al., 2021).

Indeed, even chatbots may vary significantly in complexity, as highlighted in **VII** and **III**, with some chatbots being relatively simple sources of information requiring relatively little preparation. In contrast, others are much more substantial in capabilities, personalisation, and scope of information provision. As argued in **I**, **II**, and **VI**, there are various types of AI that are not necessarily alike and operate differently. Some studies focus, for instance, on the drivers and barriers of chatbot technology (Aoki, 2020), emphasising the importance of citizens' trust in its usage. In contrast, Maragno et al. (2022) note that organisational resources and the redesign of work processes and tasks ensure that chatbot technology is effectively adopted and used.

Another specific type of AI that has been examined more is RPA. In Lindgren (2020) and Lindgren et al. (2022), barriers such as a lack of value for the organisation, the unsuitability of processes for automation, IT policies, and legacy systems, as well as varying perspectives from stakeholders in the adoption process, play an essential role in the decision to adopt or not adopt RPA technology. Insights from the private sector identify 32 different criteria that organisations should consider before deciding which processes they could automate using RPA technology, namely the feasibility, process description, and availability of input and output data (Farinha et al., 2023). Likely, other types of AI applications, such as those focused on image recognition, computer vision, robotics, recommendation systems, and other pattern recognition systems as found in **I** and **III** may thus have more specific requirements for their adoption within the public sector.

Thus, adopting AI technologies in public administrations is not straightforward, resulting from many interdisciplinary barriers. Despite what may be expected, the adoption of AI does not solely depend on technological factors, in particular data and technical infrastructure, but is affected by a multitude of environmental, organisational, innovation, and individual antecedents. AI can be considered a form of public sector innovation, as there is a substantial overlap between the antecedents of public sector innovation and AI-enabled public sector innovation. Nevertheless, there are some AI-specific factors that make the adoption of AI even more complex than other digital innovations. In particular, specific AI challenges (**XI**) build on these existing challenges and are amplified when adopting AI. Additionally, AI-enabled public sector innovation requires various data-related antecedents not commonly found in other digital innovations. These include having a developed data ecosystem where the administration operates, with possibilities for data sharing across stakeholders. The administration should also have high-quality data available for AI, which requires adequate data management and governance processes. It remains unclear whether different types of AI are affected by all these antecedents to the same degree and which antecedents play a more profound role in adopting AI.

5.3 Barriers to implementing AI technology

The findings and academic works highlight that the first adoption of AI technology within public administrations requires overcoming some of these barriers. However, for the creation of public value, even AI adoption alone is insufficient. As mentioned in **I**, adopting AI technology does not necessarily create any public value for the public administration. At worst, the decision to adopt the technology by the organisation or a subset of the organisation may not translate into effective use of the technology, a wider uptake of the technology, or integration of the technology within existing work practices. As such, the implementation of AI technologies follows the adoption phase, focuses on the organisational acceptance of the innovation by the users, and becomes routine in the organisation's operations (Madan & Ashok, 2022).

What emerged as the research field progressed is that, despite achieving a test or trial of AI in public administration, sustained and integrated use of AI technologies did not follow (Aaen & Nielsen, 2021; Kuguoglu et al., 2021; Meijer & Grimmelikhuijsen, 2020). As a result, many of the small-scale pilots end up failing due to challenges in scaling out the AI solutions wider in the organisation (Neumann et al., 2022), thus failing to continue AI use after a smaller deployment (Sienkiewicz-Małyjurek, 2023). While adequate testing and experimentation are crucial for advancing AI in public organisations (Madan & Ashok, 2022), there are severe difficulties in moving beyond the pilot phase. Similar findings occurred as a result of the landscaping exercise, where several use cases of AI were, upon closer inspection, no longer in use or never used beyond a first trial, as mentioned in **III**.

There is an overemphasis on the practice of developing innovations, such as the development and (small-scale) testing of AI applications in the public sector, rather than on the actual use and integration of these technologies (Real & Poole, 2004; Schedler et al., 2019). Commonly, public administrations highlight these cases as examples of successful innovation (Kuguoglu et al., 2021), arguably because they were capable of overcoming some of the initiation and first adoption barriers.

Being extremely keen on testing new pilots occurs as it may enhance organisational prestige, is the core task of the innovation department, or because innovation funding only funds this, increasing the risk of focusing only on pilots with limited implementation activities, as noted in **V** as well.

However, what is not shown is how these innovations are integrated into the organisation and their value to the organisation after a more extended period. Adoption alone does not necessarily reflect if and how the innovation is deployed in a public organisation (Real & Poole, 2004), as mentioned in **VII** and **I**. Most of the adoption studies seem to focus only on a snapshot of AI adoption in public administrations, yet it is much more crucial to examine a longer, sustained focus on how the technology truly embeds in the organisation in order to understand how these technologies are utilised in public administrations and, more importantly, what consequences they bring later on (Bailey & Barley, 2019).

Organisational AI capability

Beyond a first adoption and test, this integration requires additional organisational resources (Neumann et al., 2022). Several organisational factors play a more crucial role in the latter phases of the innovation process but are overlooked in the first phases of AI development and piloting. Later, these factors may lead to a failure to integrate AI into organisational work practices (Kuguoglu et al., 2021). In addition, the factors that initiate and adopt AI innovations are distinct from those that determine performance and results (Wang et al., 2022). For example, governmental policies, such as strategies or competitive pressure between organisations, support the initiation of chatbots. However, based on the policy, organisational, economic, or technological context, organisational readiness plays a much more influential role in the performance of the chatbots (Wang et al., 2022).

With many identified use cases in **VIII** and **III** seemingly being at risk of solely being at the Proof of Concept (PoC) or piloting phase, there is a lack of examination of how public administrations can ensure that explorations of the use of AI could be integrated within their organisation to obtain public value.

Building on the work on AI capability (Mikalef & Gupta, 2021; Mikalef et al., 2021), and following research on the innovation capability of public organisations (Bekkers et al., 2011; Lewis et al., 2015, 2018), the research findings of **V** indicate that organisational AI capability is crucial to ensure that AI technology is incorporated into public administrations effectively. One noteworthy result of this research is the apparent distinction between the capability to develop AI technologies and the capability to implement them. The researched public administrations in this thesis were more often capable of the former but faced difficulties in the latter. In **V**, some factors described that lead to difficulties in implementation include the lack of technical expertise to maintain and update the AI systems after development. A lack of strategic alignment between the possibilities of the system and the organisational goals results in the AI initiatives being developed in an ad hoc manner and for innovation purposes only. Legal difficulties may become more prominent and noticeable during the implementation phase than anticipated during the development phase. Inadequate possibilities for introducing organisational changes, as well as the challenges of having civil servants actively use AI systems in their work, are also factors that limit the implementation of AI.

As a result, **V** proposes several propositions to provide additional insights into this emerging research field, which can be seen in Table 4 below.

*Table 4 Propositions on AI capability (in **V**)*

Tangible resources *A sporadic continuation of past e-government legacy*	***Proposition 1.*** Digitalisation is crucial for developing AI capability in public administrations. These resources emerge from a past e-government legacy, although new data for AI are often still required as well as ensuring legal/ethical controls***.***
	Proposition 2. AI requires a powerful infrastructure, both for the development and the continuous training of AI systems. This can be acquired either through internal infrastructure, or through an external partner– with different effects on their AI capability.
	Proposition 3. Financial resources affect the capability of AI greatly. Ad hoc and sporadic funding creates challenges in maintaining and scaling up AI systems, whereas stable resources allow a structural and sustainable use of AI inside the organisation.
Human resources *Balancing between internal and external expertise*	***Proposition 4.*** A functional arrangement is to have a core AI team to develop, implement, and maintain AI solutions while being responsible for working with externals. Full reliance on third parties, given the difficulties in hiring people with the right profile, affects the AI capability of public administrations greatly.
	Proposition 5. Nontechnical employees, both civil servants and managers, play a crucial role in AI capability. They require understanding and knowledge of the features of AI technology, bridging the technology to organisational tasks and the responsible use thereof.
Intangible resources *The invisible link between initiation and implementation*	***Proposition 6.*** Being capable of managing co-creation and collaboration is a strong component of AI capability. Internal collaboration between IT and business departments is needed to ensure the quality of AI in the organisation, while external collaboration allows for data sharing and summing computational resources. Collaboration with citizens, however, remains uncommon.
	Proposition 7. The ability to conduct complementary changes often determines the success of AI and is thus a leading component in AI capability. A co-evolution of AI technology, personnel, leadership, work processes, and organisational structures is difficult to achieve yet crucial for positive results.

Organisational capability to develop and implement AI technologies requires tangible, intangible, and human resources, similar to the antecedents of public sector innovation. As the findings from **V** show, acquiring these various resources is cumbersome for public administrations. As anticipated in **I**, many of the tangible resources required, such as the data and infrastructure, are the results of years, if not decades, of previous digitalisation efforts.

However, even then, AI initiatives often require the additional collection of other data, which is restrictive, or the data quality is not as high as initially expected, leading to their discontinuation. Continued use of AI systems may require stricter data governance practices after AI has been introduced to avoid misuse of the system.

Not acquiring the resources needed for AI capability limits the possibilities for public administrations to use AI beyond a small-scale AI pilot. For instance, the more AI becomes integrated within the organisation, the more resources are required internally within the organisation rather than relying on external partners (Neumann et al., 2022). Many digital government transformation initiatives have already failed to achieve their expected results (Kempeneer & Heylen, 2023). The higher complexity of AI technologies could make it even more challenging to effectively accomplish a digital government transformation with AI technologies. For instance, public administrations often lack the financial resources to implement and maintain the developed systems, thus requiring other funding sources (Neumann et al., 2022). As mentioned in **V**, there may be a disconnect between the funding for the development and the implementation phases. It may be the case that the budget for the development does not include funding for the implementation phase, requiring different sources of funding that might not be available. Often, it is not considered whether the developed AI is a worthwhile investment, considering the costs of deploying and maintaining the system and the required changes in the organisation (Kuguoglu et al., 2021). Furthermore, AI systems are not separate from existing information systems. While it is possible to develop or test AI systems in isolation, during implementation, existing systems and the developed AI have to operate together and may face interoperability challenges, limiting their usage (Kuguoglu et al., 2021).

To roll out AI solutions more widely throughout public administrations, acquiring adequate human skills and resources becomes more prominent, making investments in upskilling their staff more important (Kuguoglu et al., 2021). However, many administrations face difficulties in doing so as the organisational costs for developing qualifications in AI are too high (Sienkiewicz-Małyjurek, 2023). As a result, the administration remains reliant on external actors, as seen in **V**, which may often be even more expensive in the longer term. As such, some form of co-evolution in the data and technical infrastructure, human resources and organisational culture has to occur as AI takes a more prominent role in the public organisation. Public administrations often lack a strategy or plan for continued usage of AI (Kuguoglu et al., 2021; Sienkiewicz-Małyjurek, 2023). While some governments have drafted national AI strategies as examined in **IV**, individual public administrations have not developed AI strategies that are more applicable to their organisational, rather than national, context. Apart from several municipalities worldwide[3] and one organisation studied in **V**, a tailored organisational AI strategy is missing.

[3] For instance Amsterdam, Barcelona, Buenos Aires, London and New York are among the few with a local AI strategy.

From **V**, it also emerged that public administrations underestimate the challenges of diffusing AI technologies across their organisations. Yet, such diffusion is crucial to gaining value from AI technologies. Resistance to the adoption of AI internally may occur because of a lack of understanding of AI and a lack of essential AI competencies (Neumann et al., 2022). The inherent lack of explainability of AI technologies (Janssen, Hartog, et al., 2020) further limits diffusion, as users typically require an understanding of how AI makes decisions (Rjab et al., 2023).

The general perspective of AI replacing jobs (Ahn & Chen, 2022) may create fear among civil servants for their job positions or future careers, making them resistant to changing the organisation by implementing AI technologies beyond a relatively isolated pilot (Sienkiewicz-Małyjurek, 2023).

As such, it is recommended that the end user be brought on board throughout the design and development of AI systems in the organisation, overcoming organisational silos as much as possible. Co-creation and collaboration between developers and civil servants, among public organisations, and between the organisation and citizens are vital to understanding varying perspectives on the AI to be created and implemented (Madan & Ashok, 2022). A lack of doing so may lead to an isolated development process, creating AI systems with poor usability as end users' perspectives are not considered (Aaen & Nielsen, 2021).

One might argue that there is a certain level of waste of public resources when such significant sums of money are being spent on AI innovations that fail to be developed, adopted, or implemented in such a manner as to provide benefits (Meijer & Thaens, 2020). Indeed, it is regrettable that seemingly successful AI innovations, either through experiences in one setting or following an early trial, fail to scale up within public organisations due to these factors, which can simply be the result of bureaucratic inertia or a lack of willingness to change (Madan & Ashok, 2022). However, it should also be noted that AI innovations do not only fail to be implemented in public organisations because of these factors. AI remains an emerging technology, and many private vendors' claims about their AI systems are over-inflated. Most AI systems are not evaluated in real-life settings and thus are not mature enough in implementing contexts (Aaen & Nielsen, 2021), which could lead to an unrealistic assessment of what AI can do or which problems AI can solve, as highlighted in **IX**. Many social challenges are complex, and AI may only attempt to address an isolated issue without taking note of the broader, systematic factors that underlie it (Aaen & Nielsen, 2021). With a wider tendency to find problems AI could solve, it should be the other way around: "AI is a means to solve previously unsolved problems, not for solving problems you first have to create" (Neumann et al., 2022, p.21).

Alternatively, several AI systems have been used in governments are illegal due to their data-gathering practices, discriminatory predictions, infringements of human rights, and various other ethical concerns (Giest & Klievink, 2022; Rinta-Kahila et al., 2021; Schiff et al., 2021). These risks are substantial and should not be overlooked in the push to increase AI technologies just for the sake of doing so. As such, it is regrettable if the implementation of perceivably successful AI technologies fails due to limited organisational capability or bureaucratic inertia, unless these systems are discontinued due to ethical or legal concerns. Additional research in these suspended cases would be required to better understand the factors and reasons for the discontinuity of AI technologies in public administrations.

5.4 Expected public value creation

Thus, the main lingering question is what the effects are when AI technologies successfully overcome these different barriers and finally reach the point of providing positive results for citizens and administrations, as argued in **I**. Indeed, a vast body of literature has discussed the potential public value that AI technologies may either provide or harm (Schiff et al., 2021).

The most commonly mentioned public benefits of AI technologies are efficiency and performance-related benefits. This is acquired through the automation of processes, relieving staff members from mundane tasks and reducing administrative burdens for both citizens and civil servants (Zuiderwijk et al., 2021), reducing the number of civil servants needed to free up resources (Kuziemski & Misuraca, 2020) and making existing systems and services more cost-effective. In addition, several authors note that the increased use of AI technologies also makes services and operations more effective, as the decisions taken by public administrations will be more based on data rather than driven by political reasons or assumptions from decision-makers (Valle-Cruz et al., 2020; Vydra & Klievink, 2019).

Furthermore, the use of AI in government may support the professionalism values of government by having more accurate identification of citizens, data security, and more accountability through the recording of government actions and records, strengthening the traditional bureaucratic values by ensuring that government actions are more closely followed by (AI-supported) rules and formalised procedures, often through automation (Newman et al., 2022). Biassed, corrupt, or discriminating civil servants or street-level bureaucrats may be mitigated through AI technologies, thus improving the state's equity and fairness values (Miller & Keiser, 2020). Audits, either done internally or by external actors, may be further strengthened by AI technologies as more possibilities for analysing public administrations become possible (Bullock et al., 2020).

Others note that, regarding service-related public values, AI can improve the accessibility, availability, and usability of public services in line with previous technologies. Faster public services, delivered in a more targeted and personal manner, could make public services more efficient, effective and in line with the expectations of citizens (Bryson et al., 2014; Zuiderwijk et al., 2021). In particular, providing information from government authorities to citizens could become more accurate, relevant, personal, and less complicated. AI could further facilitate proactive public service delivery models, significantly reducing the burden of receiving public services from citizens as these services would be granted to them "automatically" (Bharosa et al., 2021; Kuziemski & Misuraca, 2020). AI could also allow for increased opportunities for citizen and government collaborations in ways that would not have been possible with previous technologies or resources (Zuiderwijk et al., 2021). Government employees and managers often see great potential in creating public value due to AI in governmental organisations; however, more often so for the potential to improve efficiency and effectiveness than accountability (Chen et al., 2023).

Potential negative consequences of AI

However, research also highlights the negative consequences for public value that could occur from using AI technologies (Zuiderwijk et al., 2021). These challenges and conflicts result from a conflict between the prioritised efficiency values and other public values, which are either ignored or seen as subpar, such as fairness, transparency, and responsiveness (Schiff et al., 2021). An excessive focus on efficiency may thus come at the cost of other public values, most commonly maximising data analysis effectiveness at the expense of privacy, opacity, and accountability (de Bruijn et al., 2022).

Other scholars, such as Chen et al. (2023), utilising the public value taxonomy of Bannister and Connolly (2014), highlight that using AI may threaten several public values.

In their literature review, the challenge to public value mentioned most often is AI systems' lack of transparency and accountability. It is usually difficult for citizens to understand, monitor, and know when and how AI technologies are involved in the delivery of public services. As also argued in **VI**, the increasing use of untransparent and unexplainable AI systems in public administrations may further limit the effectiveness and legitimacy of public institutions rather than enhance them. A lack of a responsible actor behind decisions taken by AI is often a leading cause of this challenge (Sun & Medaglia, 2019).

It is noted throughout the research that there is an overall lack of transparency regarding the use of AI systems by public administrations, limiting research on them and information on whether these systems have a positive impact. As such, it is not only the black box nature of AI technologies that accounts for transparency issues but also the general lack of transparency about when, why, and by whom AI technologies are deployed in public administrations (Liu et al., 2019). While work is progressing on the introduction of AI transparency registers, this is in such an early phase that many administrations do not have such a register, and if they do, they do not provide all the information that might be needed to address such challenges (Cath & Jansen, 2022).

Another key challenge of the use of AI relates to the public value of privacy, as the sharing of datasets across public administrations, from business to government and government to businesses, with increasing granularity risks the creation of a surveillance state that has often been stressed (Chen et al., 2023; Saura et al., 2022; Veale et al., 2018). It is highlighted that public administrations should be careful to adhere to relevant privacy legislation, ensuring that the use of data analytics does not infringe on the privacy of citizens, despite having the best interest of citizens at heart in offering them higher quality services and information (Sigfrids et al., 2022).

In some of the use cases examined in the thesis, such as those in **VI**, privacy concerns were not obvious and thus did not limit the adoption of AI in organisations. In other cases, however, there was a consideration, such as in cases **V** or **IX,** where administrations took deliberate action to limit the amount of data used to develop the AI system. However, privacy challenges might be regarded as primarily legalistic, such as compliance with the General Data Protection Regulation (GDPR) as identified in **XI**. Yet, it might also mean accommodating citizens' concerns about using their data despite being legally allowed to do so.

A key challenge of using AI systems is that, despite the intention to improve the equity of public administration's activities through the neutrality of machines and computers, they contribute to the inequity thereof (Chen et al., 2023). During the development of AI systems, historical biases in the data will reflect themselves in the recommendations and actions of AI systems (Giest & Samuels, 2020; Janssen & Kuk, 2016), and, if not noticed attentively, could lead to discriminatory results for a subset of the population. These risks are particularly relevant for public administrations, as they are usually concerned with assisting the marginalised and vulnerable groups in society yet are most likely the least often involved when and why AI systems are deployed (Liva et al., 2020). Through the biases in the development of AI systems, the risk of discrimination against these marginalised individuals is thus considered of increased importance, mainly when it involves critical areas of service delivery with potential life-changing outcomes (Schiff et al., 2021).

In particular, fairness, transparency, and responsiveness are the central public values at risk.

These values may be compromised to enhance efficiency and effectiveness. Responsiveness is closely linked to having public administrations convey empathy and trust towards citizens; yet, the increased use of AI and other technologies within service delivery may limit this responsiveness towards citizens (Schiff et al., 2021). Indeed, while one of the main potential benefits of AI is to limit contact with human individuals in the provision of services to citizens, there are likely to be citizens who prefer to have the opportunity to talk to a person. The inability to do so, and being obligated to communicate with various AI systems may thus limit the creation of public value. In situations where the AI system may make mistakes, this lack of responsiveness to citizens' needs due to increased reliance on AI systems and the inability to override the computer's decisions may lead to a lack of resilience and failure to tailor the service to the citizen's needs (Andersen et al., 2020).

While these are some of the main risks to public value, AI is argued to bring many other dangers. These may include the increased lack of responsibility by public administrations due to the delegation of decision-making authority to machines, safety concerns, the lack of safeguards against malicious use of AI technologies by administrations or civil servants, cybersecurity concerns, and others (Chen et al., 2023). Furthermore, these considerations do not even include the broader societal consequences that may arise from the increased digitalisation of societies or other governance challenges that could arise due to the actualisation of data among larger technology companies, geopolitical challenges, or environmental damages, which are beyond the scope of this work.

As a result of these concerns, there has been a focus on constraining these risks through the development of ethical guidelines, impact assessments, and other frameworks. These are designed to mitigate conflicts of public values within the design of AI systems (Bostrom & Yudkowsky, 2021; Dignum, 2018; Floridi et al., 2020; Mikalef et al., 2022). These guidelines assist in determining which public values may be overlooked in the early phases of the development of AI systems or how specific public values may be threatened due to the development and deployment of AI systems. This perspective, however, often excludes the deployment phase of the AI artefacts into specific contexts and organisations that are more difficult to predict ex-ante (Bailey & Barley, 2019).

Despite the interest in creating ethical guidelines and frameworks, there remains a very limited understanding of how these ethical frameworks translate into AI development and deployment within public administrations. This seems more difficult or less common, as the plethora of AI ethics publications and guidelines seem to suggest. In examining the Estonian public sector, Hinton (2023) highlights that ethical principles are only indirectly considered during the design and development of AI, depending on the maturity of the AI system as well as the knowledge and competence of the public administration. Rather than ethical concerns, practical considerations such as data restraints are more critical during development.

Intended public value created by AI

The thesis provides an empirical body through an ongoing collection of AI use cases in the public sector. This started with a preliminary collection in 2019, described in **VIII**, in which 85 cases of AI were identified, and consequently, a first exploration was conducted of the type, application area, value drivers, and expected effects of AI.

In this early work, it was already identified that 70% of the initiatives aimed to achieve efficiency or other performance-related goals, with 27% related to inclusion and only 3% to openness-related barriers.

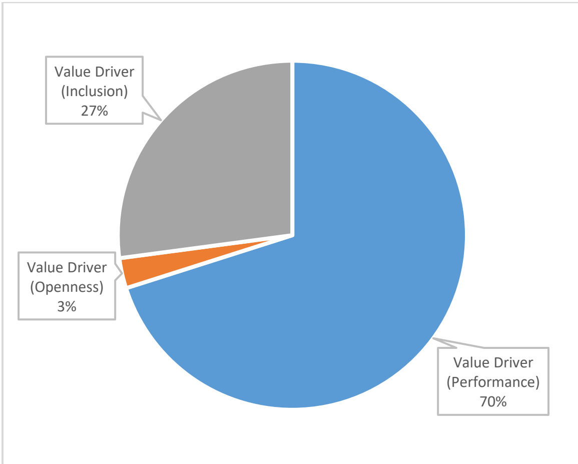

*Figure 7 Public value drivers of AI initiatives (N = 85) (in **VIII**)*

This activity continued in **III,** with the collection of 250 use cases, and in **IX,** with an inventory of 686 gathered use cases, of which 549 were included for the analysis of which public values they aim to achieve. Adopting the public value framework of Rose et al. (2015), this study discovered, in line with the early exploration done in **VIII**, that the results of **IX** showed how efficiency-related public values drove 78,5% of the gathered use cases. Only 24% of the use cases drive service-related values, 12,8% drive professional-related public values, and/or only 3.5% of the initiatives drive engagement-related values. This shows the predominant tendency for public administration to apply AI to achieve economic-related values, in line with the historical narratives of digital government applications (Schiff et al., 2021; Wilson, 2021).

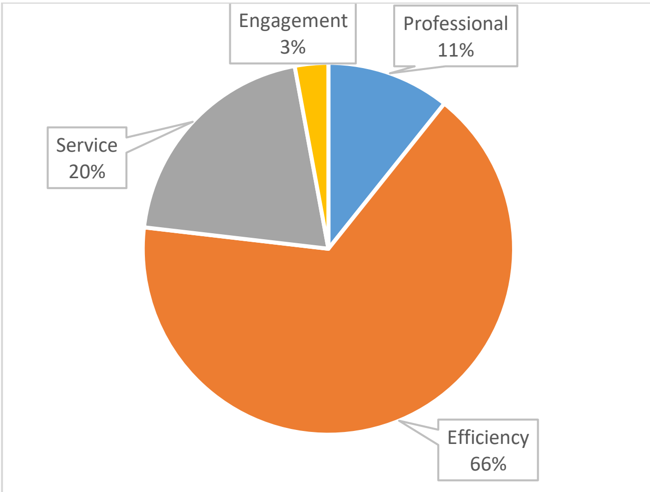

*Figure 8 Driving public values in AI use cases (N = 549) (in **IX**)*

This lack of support for transparency with AI technologies may be there because of resistance to increased transparency. If civil servants perceive AI as contributing to government transparency, it is more likely that they are less willing to adopt AI (Ahn & Chen, 2022). As illustrated earlier, this does come with the risk of harming other public values at the cost of those efficiency-related goals, which emerge from the conflict between reducing costs through AI at the expense of illegal data gathering practices, being irresponsive to citizen needs, or failing to have the AI systems work as intended due to the assumptions that they will work well without maintenance, as also argued in **IX.** In particular, the tensions between efficiency-related values and professional values, such as the interest in strengthening the record-keeping of public administrations with more checks and more data – often for fraud prevention purposes – may come at the cost of accountability, privacy, and nondiscrimination (Giest & Klievink, 2022; Simonofski et al., 2022).

As such, an emerging body of knowledge aims to look at these public values and how AI use in public organisations could contribute to or limit these values as a result. However, most of these values are arguably rather abstract, making them challenging to assess. Adopting a more practical lens to public value (O'Flynn, 2007; Twizeyimana & Andersson, 2019), proposed in **I** and focusing more on concrete values such as improving public administrations, improving public services, and improving social value. This was first explored in **VIII** with 85 use cases, showing that most use cases focused on enhancing the operations of the internal public administration.

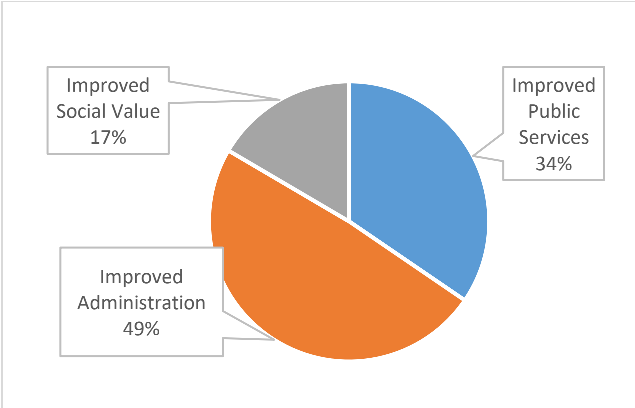

Figure 9 Expected effects of AI initiatives (N= 85) (in ***VIII****)*

With a more comprehensive dataset of 250 use cases in **III**, this study examines more closely how AI in the public sector of the European Union focuses on improving core governance functions, thus creating public value in doing so. These core governance functions were based on **I** and classified the use cases in improving policymaking, public services, or internal management functions. As the analysis is limited in scope, depth, and granularity, it remains unclear if they do so effectively. Nevertheless, the landscaping activities and the research done in **VIII**, **III**, and **IX** provide a much-requested empirical analysis of some of the future uses of AI.

As the inventory of collected use cases[4] is available as open data, other researchers could examine the collected use cases more in-depth or conduct additional quantitative analyses on the database to gain more insights.

The findings show that most of the identified use cases were conducted to improve public service delivery to citizens (46%), most commonly through providing information to citizens through AI or by supporting existing service delivery processes with AI. As noted in **III**, a large number of chatbots are being deployed to do so, although, as illustrated in **VII**, these chatbots may not be adequate to do so effectively. In general, however, there is a relatively positive notion of using AI in improving the delivery of public services, as it allows for more personalised services through connecting different data sources, clustering citizens into groups, and, as a result, better meeting their needs (Pencheva et al., 2020; Veale & Brass, 2019). Reducing the need for citizens to visit offices in person or fill out repetitive forms may be possible when administrations use AI technologies. Users' feedback, complaints, sentiments, and concerns may be better understood with the use of AI technologies, which improve their satisfaction with public services.

[4] European Commission, Joint Research Centre (JRC) (2021): Selected AI cases in the public sector. European Commission, Joint Research Centre (JRC) [Dataset] PID: http://data.europa.eu/89h/7342ea15-fd4f-4184-9603-98bd87d8239a

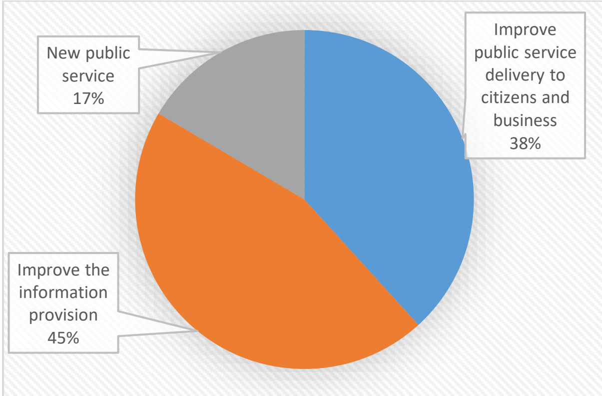

*Figure 10 Purposes of AI for public service delivery (N= 115) (in **III**)*

However, for purposes of public service delivery, it is also possible that the biases of historical data may not improve the quality of services as they mirror discriminatory features in historical public service decisions. One particular risk of (over)reliance on AI for public services is that rather than becoming more responsive to citizen needs, their data determines the provision of services, even when it is incorrect (Rik Peeters & Widlak, 2018). Another risk that has emerged is that, despite the interest in augmenting civil servants in the provision of public services and thus augmenting them (Veale & Brass, 2019), in practice, they might be deployed with efficiency goals in mind, leaving limited opportunities for civil servants to contest the recommendations of the system (Kuziemski & Misuraca, 2020). A significant portion of AI technologies is seemingly being used to improve the internal management of public administrations (30%), most commonly to improve procedures, improve the allocation of human resources, fraud detection, and maintenance, among many others.

One of the essential goals of using AI for these internal purposes is to have a more effective and efficient allocation of often-scarce resources with which these public administrations have to do their tasks. This, ideally, leads to better performance by staff members, the organisation, and consequently also by citizens and businesses. Whereas the procurement of AI was regarded earlier as one of the main drivers for facilitating the adoption of AI, these use cases also illustrate how the use of AI could be used to improve the procurement processes themselves by having better procurement offers, making the procurement processes more efficient and open for other market actors (van der Peijl et al., 2020).

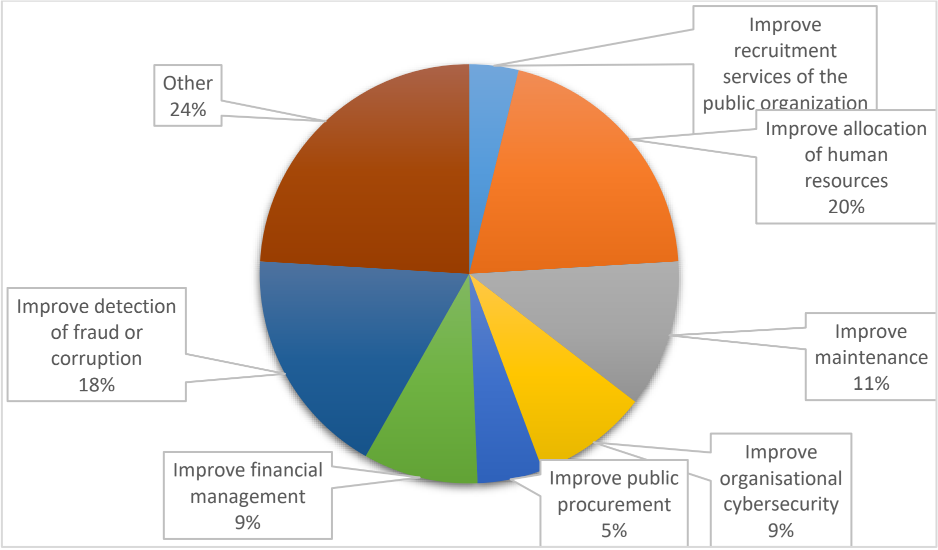

Figure 11 Purposes of AI for internal management (N = 76) (in ***III****)*

Lastly, AI is also being used for policymaking purposes, mainly to enhance the decisions of policymakers or to enforce existing policies more effectively, yet seemingly less frequently than the other applications (24%). It is likely that this has to do with the different definitions and conceptualisations behind what is and is not reported as AI, as public administrations may deploy many statistical techniques that are considered AI as part of the policymaking process, but there is no notion of automation or the delegation of these tasks to AI systems, which are thus not regarded as such. The interest in examining the impact of AI technologies on the policymaking cycle is linked to previous studies on evidence-based policy and policy analysis, in which there is a promise of better policy decision-making through the use of "rational-logical" research, often supported by technology and scientific evidence (Vydra & Klievink, 2019).

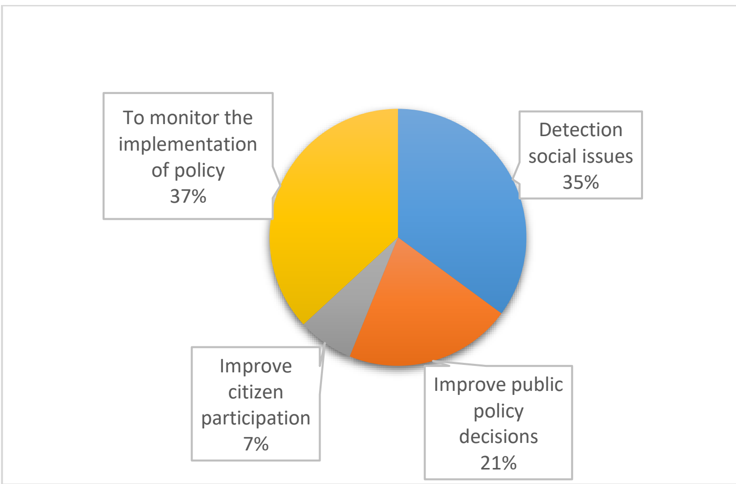

Figure 12 Purposes of AI for policymaking (N = 59) (in ***III****)*

In diving deeper into the various ways in which AI could play a role in the policymaking process, taking note of the possibilities and limitations of AI for policymaking as mentioned in **III**, Newman and Mintrom (2023) propose eight different frames for how AI could support policymakers, depending on the supportive role AI plays (either supportive or critical) and whether AI supports evidence-based policy or not. What is illustrative of this work is that it not only provides an overview of the different potential applications of AI in policymaking but also allows a frame to study one specific case study through these different lenses. By examining the controversial SyRI use in the Netherlands more closely, elements of each of these frames can be identified in the case study, highlighting the importance of understanding that AI can bring various insights depending on how its use is examined (Newman & Mintrom, 2023).

There are significant limitations to providing a clear answer to whether AI technologies are creating public value or not, as there are many other considerations to be made. The first limitation in assessing the public value is, as also emphasised in **IX**, the difference between AI's potential and its realised public value. Most of the research, including the research done in this thesis, relies on the assumptions and expected impact on public value rather than an empirical test if it does so (Ballester, 2021; Sharma et al., 2020), with very few empirical studies that validate these positive or negative effects on these broader public values (Sienkiewicz-Małyjurek, 2023). It is challenging to do these assessments as it remains an emerging field, and it is too soon to draw any conclusions about its realised value. Therefore, an analysis of the potential value is more commonly available and conducted. Assessing the realised public value is challenging due to the lack of sustainable implementation of AI in the long term rather than from an assessment of the pilot as emphasised in **III** or because the effects materialise over a more extended period, as mentioned in **IX,** which may be unintended, unexpected, and not in line with the intended reforms (Giest & Klievink, 2022). There is a significant lack of understanding of this process (Bailey & Barley, 2019) and existing research shows that assessing the realised public value of AI is further limited by additional barriers.

6 Limitations

Despite contributing to the potential and conceptual value that AI could create, this thesis is unable to provide a concluding argument on what the public value is created when it is put into use.

First, this is partly due to the focus on the various barriers that public administrations faced during the research period, shifting the focus from the effects of AI in public administration to the barriers. As such, it remains challenging to fully assess the public value that AI creates when implemented (Bailey & Barley, 2019). More is known about the technical aspects of AI applications than the postadoption phase, with an emerging need for understanding what effects occur after the adoption (Sharma et al., 2020), taking into consideration that the same deployed AI system can have different effects in different contexts (Meijer et al., 2021). Thus far, this limits generalisations based on specific case studies of AI in government.

As a result, even the potential effects identified in the thesis research from the gathered use cases in **III** and **IX** do not provide a clear claim to the actual effects that occur following the use of AI in these organisations. The qualitative studies focusing more on the experiences of specific use cases in **VI**, **IV**, **and XI** further primarily relate to experiences or expected results rather than a clear overview of the positive and negative consequences, either due to the early phase of most of the initiatives, the lack of assessing the effects either in general or among different stakeholders, or since the initiatives were already cancelled before such an evaluation could take place. Those who had some insights following the deployment often highlighted the contextual factors that play a role in obtaining value from the technology, such as the willingness to use the systems by the civil servants, the acceptance of citizens, performance in specific contexts, and the need to strengthen the capabilities and workflows of the AI and the civil servants.

For instance, one crucial consideration is to examine how civil servants deploy these AI technologies within their work and, thus, whether the intended goals align with the actual work processes. In recent research findings, it is apparent that the actual use of AI does not always align with the intended use of AI. For instance, recommendations provided by AI systems tend only to be taken into account by civil servants if they align with their previous insights (Selten et al., 2023). Such findings pose questions about whether AI technologies may overcome and correct human biases or if AI can override human decision-makers.

Even better-known cases of AI, such as the recidivism prediction tool used in the United States called COMPAS, known for discriminatory features (Dressel & Farid, 2018; Larson et al., 2016; Washington, 2018), have been thoroughly examined in the research. However, empirical research on how the decision-makers used the software and how it may or may not create public value is often out of the scope of such studies. An exception by Christina (Christin, 2017) indeed illustrates that legal professionals contest the data and methods used by the COMPAS system. They do not trust the recommendations and instead use their own judgement rather than those of a computer system. As such, there remains much to understand about how these professionals use these technologies in their operations and whether the values of the design, development, and implementation of the technologies align with the values that are being created following their actual usage, supporting the “algorithms-in-practice” type of research as introduced by (Meijer et al., 2021).

Second, as many theories and research on public value creation emphasise, public value is created if it impacts citizens positively (Twizeyimana & Andersson, 2019). However, whether deployed AI aligns with citizens' expectations remains highly unclear. In most of the examined AI use cases in **IX** or **V**, citizens are usually excluded from most of the design and development decisions, and thus, perspectives on whether they appreciate the solutions are lacking. This becomes even more crucial when the use of AI is primarily aimed at providing services to citizens. Nevertheless, similar to previous research, there is a focus on the supply-side of the technologies rather than the demand or actual use (MacLean & Titah, 2022; Savoldelli et al., 2012). Limited information is usually available on whether the chatbots are valued or considered helpful by the users. Challenges concerning the digital divide (Ebbers et al., 2016) may make it difficult for those with limited digital skills or those with challenges understanding government information to use these chatbots. Furthermore, researchers have started to explore under which circumstances citizens would prefer to talk to a person or a chatbot (Aoki, 2020).

Most of the existing studies researching citizen perspectives do so more to understand under which conditions they would prefer AI or not than on specific applications or deployments. A precise evaluation of particular implementations of AI and whether they created service- or engagement-related public values is less common. For instance, Gesk and Leyer (2022) highlight that, in general, citizens accept the use of AI, yet are more likely to prefer to choose whether to be assisted by AI or not (Starke & Lünich, 2020), and citizens perceive the use of AI within European policymaking processes as illegitimate when AI is used as the leading decision-making actor. What is interesting from this study, however, is that no difference regarding the throughput and output legitimacy of EU decision-making was found when it was done by a human decision-maker or in a hybrid fashion, illustrating that citizens find a combination of AI and humans legitimate for policymaking.

Work on the acceptance of chatbots by citizens in China further highlights that citizens tend to be more accepting of them when they provide direct value for them (Wang et al., 2021). Citizens prefer to have chatbots designed with proactivity in mind by providing additional information, being conscientious by having a multiturn conversation mode, and having a high level of emotional intelligence by expressing empathy and using more informal language (Ju et al., 2023). However, whether these preferences for using chatbots or other forms of AI within public administrations translate from one country's context to another remains unclear. As Kaun et al. (2023) highlight, there can be important differences between countries regarding the use of automated decision-making systems within public administrations due to historical differences. Citizens may be less willing to delegate decisions to AI systems when they have high trust in institutions and civil servants. Previous attitudes towards digitalisation may also influence the willingness to accept AI systems. As a result, it is more likely that citizens who have been more supportive of past digitalisation will also be more accepting of AI. However, as previously mentioned, there remain limited insights on the use and acceptance of specific applications beyond these more general preferences.

Third, there is a considerable risk of techno-solutionism in addressing societal challenges with technology. Techno-solutionist tendencies include wanting the "latest and greatest shiny object" without considering the additional work to integrate such digital solutions (Obendiek & Seidl, 2023).

This rising tendency among policymakers creates the mindset that solving social problems requires deploying the correct algorithm (Morozov, 2013). Yet, societal challenges are often complex, interconnected, and evolving (Kim & Zhang, 2016), and the deployment of AI changes the dynamics but does not necessarily solve the issue. Recent research has illustrated that public administrations might be overexcited by the promises of (emerging) technologies without truly considering what they could mean for their organisations (Obendiek & Seidl, 2023).

Data analytics is proclaimed as a "magical" or "ceremonial" tool to solve organisational challenges (Obendiek & Seidl, 2023). Only later, after purchasing, does the public administration examine how the technologies could be used, because they are not aware of the specific problems they actually want to solve with them. Such tendencies were also noticeable in the findings of the thesis, as there seemed to be a notion of using AI for the sake of it, where the value being created is being innovative rather than having a clear link to what the innovation was intended for, as highlighted in **IX.** The "magical" belief in AI and data analytics (Veale, 2020) was also identified in many of the use cases in **V**. There seemed to be the aim of doing the data analysis or the development of an AI system, often in the form of a dashboard, with the hope that some results will be achieved after it is developed. Usually, it is unclear how the development of these AI systems is supposed to be integrated with the organisation and what value they aim to achieve.

Lastly, as this thesis focused more on the immediate or almost immediate effects following the use of AI in public administrations, examining the public value creation over a more extended period has been out of scope as either second or third-order effects after implementation. As such, the public value examined in the research follows a rather isolated approach to public value creation, focusing only on individual transformation rather than aggregating public value by combining all public services (Panagiotopoulos et al., 2019). However, this does not mean that, in the future, other effects and consequences from the (increased) use of AI systems in public administrations may emerge, which goes even further than the impacts of AI as speculated in the research thus far.

As most of the current research highlights the complexity and unpredictability of the changes in public administrations that could occur with the use of AI (Giest & Klievink, 2022; Meijer et al., 2021), future research will likely identify challenges that this thesis has not yet mentioned. This would also require more longitudinal research to examine how AI technologies consistently create public value (MacLean & Titah, 2022). Whether the creation of an Algocracy (Lorenz et al., 2021) would, indeed, come to be and what consequences this would have for public services, public value, and changes to political-administrative structures remains to be seen. Alternatively, as alluded to in **V**, existing multilevel governance configurations within countries might change due to the increasing interconnectedness of administration, data, and AI systems, or the extent to which public administrations would be hollowed out by their increasing reliance on digital systems from private companies (Andersen et al., 2020), introducing potential long-term effects.

Whereas existing data protection rules are hindering unwarranted data sharing, at least in the European Union due to the GDPR, preparing the required infrastructure, data resources, and legal frameworks to facilitate widespread data sharing across administrations alone would have an impact on public values, but this is beyond the scope of this thesis.

However, given the potential impact that increased digitalisation may have on the environment, privacy, and human rights, not taking into account the impact of the conditions that may favour the increased use of AI, such as the policy initiatives described in **IV**, would provide a view of all the positive and negative impacts that AI will have on public administrations in the coming years that is too limited.

7 Conclusion

Improvements in AI have fascinated researchers, businesses, and policymakers worldwide. There are many expectations for this technology to improve economies, societal well-being, and public services. The use of AI technologies in public administrations can enhance the effectiveness and efficiency of government operations, increase possibilities for citizen participation, make policy and services more data-driven and accountable, and have many other potential benefits. However, there is limited understanding and research on how public administrations adopt AI technologies and the value their use can create. Technological progress in AI technologies does not necessarily translate into their adoption in public administrations or into a clear or straightforward creation of public value.

There has been a long-standing interest in using digital technologies in public administration to achieve public value from their deployment. Since the 1990s, policymakers and researchers have focused on promoting, researching, and understanding how digital technologies can positively contribute to government operations and create public value. Key limitations in this e-government research field include a lack of clear theoretical foundations, a focus on descriptive research of digital technologies, and limited research on the actual uptake and acceptance of these technologies by public administrations and citizens. As a result, the digital government research field has often had an overoptimistic view of the contributions of digital technologies. This tendency is also present in emerging technologies such as blockchain, big data, and AI. Given the high expectations of these new technologies and the challenges of previous digital government research in creating public value effectively, examining AI used in public administration to see to what extent it can deliver these promised benefits and create public value is crucial.

Moreover, despite the significant interest in AI, there has been a limited translation of this interest into the research field of AI within a public sector context, as the leading research on AI almost exclusively focuses on the technological aspects of AI or its application within a business context. Before 2019, research on the use of AI within the digital government field was extremely sparse, with almost all publications in this field being published after 2020. While this does signify the rising research interest, especially during the research process for this thesis, the limited research on and understanding of AI in the domain initially prompted an exploratory research design to examine various aspects of the adoption, use, and creation of public value from the use thereof. The often-expressed call for empirical research on the use of AI in governmental organisations, as almost no empirical studies existed, was the basis of the research objectives of this thesis.

The main research objective has been to explore the use of AI in public administrations to gain a better understanding of how the technology is adopted in public administrations, which factors influence the adoption and use of the technology, and to gain a first understanding of the public value that could be created when these organisations use these technologies and how. Public value creation with digital government initiatives requires the organisational capability to develop, adopt, sustain, and implement AI innovations in public administrations. The research in this thesis emphasises the importance of these organisational capabilities to create public value with AI technologies, yet they are, surprisingly, often overlooked in practice.

The primary methodological approach follows the interpretivist research philosophy, which aims to understand complex social phenomena rather than predict and establish causal relationships. This approach has allowed for a deeper exploration of the current experiences of using AI in public administrations and the factors influencing its adoption and the creation of public value, especially considering the lack of prior research. In doing so, this thesis predominantly includes qualitative research methods, particularly multiple case studies, to allow for this exploratory research. These case studies allowed for a more in-depth examination of the current use of AI technologies in public administrations and provided insights into the factors leading to public value creation. In support of these studies, the doctoral thesis utilised quantitative research methods through an analysis of collected AI use cases, a content analysis of published AI strategies, and a survey, supporting the generalisation of the research findings despite their exploratory nature. As such, the research methods utilised in the thesis are varied and diverse, including case studies, document analysis, literature reviews, and workshops, allowing for a multifaceted exploration of the rising use of AI in public administrations.

Main findings

Three main research questions underpin the thesis to unravel the puzzle of public value creation in public administrations with AI technologies. First, to better understand what AI in public administration is, what it means, in which forms it is being deployed, and how public administrations perceive it to be AI. This is crucial, considering the wide variety of definitions and interpretations in society and the research on what is and is not considered AI. As such, the first research question, *How is AI in public administrations understood by civil servants, considering the varying definitions and interpretations of AI?,* was answered through an examination of existing research articles on AI and a survey among Belgian civil servants.

Research on the use of AI in government is plagued by two sets of challenges regarding the definition of AI. On the one hand, many existing publications discuss AI generally but do not provide a clear explanation of or specify what type of AI they are talking about. On the other hand, many definitions of AI often describe the latest technologies at the time of writing, leading to a somewhat fragmented overview. This leads to a great deal of conceptual unclarity and makes it difficult to determine which type of technology should be studied when examining the use of AI in public administration. Some regard AI as futuristic technologies or technologies with capabilities that are similar to human intelligence, whereas the current academic and policy focus lies on narrow AI – applications that are conducting specific tasks argued to require human intelligence, but this AI is not intelligent. In doing so, various classifications have been proposed to create structure in these multiple forms of narrow AI. These may include classifications around the type of learning methods deployed to develop the AI, such as the type of machine learning methodology.

However, these classifications are often highly technical and not aligned with how public administrations perceive AI. The technical classifications usually do not describe tangible technologies but rather goal-oriented methodologies to develop a new system, making it challenging to research empirically. Instead, civil servants associate AI more with systems with the capability to perform tasks previously regarded as requiring human intelligence.

As such, there are also several classifications based on the type of AI application, such as chatbots, voice assistants, image recognition software, recommendation systems, RPA, autonomous vehicles, other robots, or certain IoT applications. Owing to the great variety and complexity of defining AI, some prefer to understand and research it in a flexible manner, referring to a cluster of digital technologies that are regarded as solving tasks previously thought to require human intelligence. While this flexible approach has its merits, it does not solve the conceptual ambiguity in the field. It may include applications that are not considered AI under all classifications or research fields. Yet, due to the exploratory nature of this thesis, this flexible approach was followed in line with other recent publications examining the use of AI in public administration.

Second, noting the past insights of digital government research on the challenges of adopting innovations in public administrations, the second research question aims to understand the various drivers and barriers that influence the adoption of AI in these organisations by examining the following question: *What are the drivers and barriers to the adoption of AI in public administrations?* The findings highlight the significant gap between the availability of AI technologies and the adoption of AI by governmental organisations. The advances and wider availability of AI technologies in the technological sense do not guarantee their adoption in public administration, similar to the gaps in previous availabilities of other technologies in the digital government field.

Instead, the adoption of AI technologies results from a complex interplay of various technological, social, institutional, environmental, and historical factors. Adopting AI technologies is not a straightforward process, and it requires the right conditions and factors to overcome several critical barriers to adoption. The first barriers are connected to initiating AI-enabled innovation in public administrations. Limited organisational awareness of what AI is – or is not – and a lack of incentive to start the innovation process limit public administrations' adoption of this technology.

However, awareness and willingness to adopt AI are insufficient, as wider enabling conditions and foundations were identified. These include the right infrastructural conditions, organisational resources, and other environmental conditions that support the start of AI-based innovations. AI strategies from governments are playing a pivotal role in supporting the creation of these framework conditions. They include policy initiatives to overcome these initiation barriers despite their predominant focus on assisting businesses in developing AI or regulating AI in their society rather than supporting the use of AI in public administrations.

After the initiation, public administrations may encounter other adoption-related barriers. While AI is often regarded as a novel and transformative technology, the findings of this thesis suggest that AI technologies are a form of public-sector innovation and that insights from public-sector innovation theories apply to understanding the drivers and barriers that underpin the adoption of AI technologies in public administrations. The findings further highlight the broad interdisciplinary challenges that limit the adoption of AI in government. While data, computing power, and algorithms are often regarded as the sole or main drivers of AI technology adoption, this thesis emphasises that environmental, organisational, and individual factors also play significant roles. These antecedents to AI-enabled public sector innovation are related to existing theories of public sector innovation, yet some AI-related antecedents are also found. These include having adequate data governance in the organisation to ensure high-quality data and internal data management, as well as the willingness and ability of organisations to share data to promote innovation through AI technologies.

However, the findings of this thesis indicate that, despite adopting AI technologies, they are often small-scale pilots or tests, which fail to translate into a more structural and integrated use of these technologies in public organisations. As such, there is often an overemphasis on showcasing these short-term pilots or tests as successes of AI innovation as they were capable of overcoming the initiation and adoption barriers, yet they do not provide insights on how these innovations are consequently used in the organisation and capable of providing additional value to the organisation.

The integration and actual deployment of these AI technologies are limited, which creates hurdles to the creation of public value for these technologies. This is due to various issues that constrained public administrations' capability to develop and deploy AI technologies effectively. These factors play an even more crucial role in the later phases of implementing AI technologies than in the early stages. The doctoral thesis highlights that implementing AI technologies requires significant organisational resources and capabilities that public administrations do not necessarily have or are overlooked during the early stages of the innovation process. For instance, data-related barriers may be overcome in an early stage of using AI technologies, yet AI initiatives may require additional data that is challenging to collect, or the assumed data quality is not as high as expected, requiring governance practices after AI is developed to avoid errors and misuse of the system. Most development and testing of AI are often done in an isolated setting, and integrating it into existing systems is challenging.

Furthermore, there is an underestimation of the diffusion of developed AI systems in the organisation, such as ensuring the adoption of civil servants who are supposed to work with such systems. Financial constraints that can be overcome through external funding to support the development of an AI system may recur in the later phase when there are no funding sources available for the implementation of the system or to ensure adequate internal human capability to work with AI technologies. In general, there seems to be a tendency to test pilots of AI to experience the potential benefits of the technologies or to show the innovative nature of the organisation. The absence of a public administration strategy or plan for continued usage of AI increases the risk of only focusing on the pilots rather than a comprehensive transformation of the operations.

The third research question follows from the examination that adopting digital and AI technologies does not necessarily create public value. As such, by examining which factors contribute to the public value creation of AI in technologies, the following research question aims to understand both the positive and negative contribution of AI technologies to public value and the factors that affect this: *What is the expected public value creation of AI in public administrations?* In doing so, the thesis highlights both the positive and negative narratives surrounding the creation of public value through AI technologies in public administration. While there are benefits, such as achieving efficiency and improving performance, making organisations more effective, reducing administrative burdens, and making the operations of public administrations more data-driven than based on personal assumptions, there are also many negative consequences of using AI in public administrations.

In particular, the use of AI technologies in government can create transparency and accountability challenges as it is difficult for citizens to understand when and how public administrations use AI technologies, and the obscure nature of the inner workings of the technology may make it difficult to understand the decisions taken by the organisations using them.

Privacy concerns due to the sharing of data across public administrations or other social actors and the possibilities for increased surveillance with AI technologies may further limit the creation of public value, as well as the challenges of increased discrimination through biassed AI systems, which can constrain the objectives of more neutral and effective operations.

Following the empirical insights from the landscaping exercises conducted, it was identified that the main public values driving the current AI initiatives in public administrations in Europe are predominantly efficiency-related, which could pose risks to other public values in pursuing efficiency goals. In addition, by adopting a more practical lens of public value theory, the thesis provided more insights into the specific areas of government operations where AI is currently being used. These include using AI to improve public service delivery, improving the internal management of public administrations, and supporting policymaking.

However, despite the empirical insights gathered as part of the thesis, it is challenging to provide a clear answer regarding whether AI technologies are creating public value or not due to the limited number of empirical studies validating the positive or negative effects, and the practice of assessing the realised public value was proven difficult due to the limited amount of long-term implementation of AI at this phase. Even the results from the case studies do not provide a clear result as to which effects occur following their implementation. This occurs due to the early stage of these initiatives, the lack of an assessment of the impact of the AI system, or because the use cases were discontinued before such an impact assessment could take place.

In addition, various stakeholders affected by the use of AI technology may have different perspectives on the positive and negative consequences, yet this could not be explored in depth in the doctoral thesis. In particular, the view of citizens is often excluded in research but also in the practical applications of AI. This is surprising, considering the core objective of creating public value is matching citizens' expectations. Moreover, as this thesis focused on the immediate or near-immediate effects, it excluded the influence of AI on public value creation over a more extended period as well as the broader second- or third-order effects of the increased digitalisation and use of AI in general, beyond specific individual applications.

Other limitations include data collection challenges, as there remains only partial reliable information available about the current use of AI technologies in public administrations, and public administrations have little transparency about their use of the technology. Most of the data collected in the case studies is based on self-reporting by public administrations as well as their experiences in the use of technology, which may be too positive or incomplete, especially regarding the negative consequences of using the technology. Furthermore, as the thesis is exploratory in nature, it could limit the generalisability of the research findings, as other public administrations may have different experiences with the use of AI.

Recommendations for future research

As such, it is likely that the thesis barely scratched the surface of the use of AI in public organisations, which allows for much more follow-up research. The increasing interest and academic publications will allow for more rigorous theories on the use of AI in government.

This includes more systematic literature reviews on specific topics, hypothesis testing, and more thorough and generalisable research claims on how AI is being used in public administrations and, more importantly, what public value it can contribute to. More recently, other publications have gone more in-depth into specific topics following the findings of the thesis, showing how the field is already advancing. However, many research areas remain that could be explored more substantially in the future.

This includes progress on various research projects on defining and understanding what is and is not considered AI in public administration. It is apparent that the different definitions and classifications of AI limit the generalisability of varying research findings on AI, yet a better assessment of these different definitions and, consequently, how they are utilised in digital government research is still missing. However, how other civil servants, ranging in professional backgrounds, perceive AI and how they consequently determine which use cases of AI they regard as AI would further provide valuable insights. How the concept of AI relates to other emerging research topics related to this activity, such as algorithms, algorithmic management, and automated decision-making, would become an increasingly crucial research task. Furthermore, while there is an increasing amount of research examining the barriers to AI adoption in public administrations, there is still very little understanding of the relative importance of these different barriers and how to overcome some of them.

For instance, how AI strategies have supported the implementation of AI in specific organisations, or how they might not have, remains unclear. Specific policy initiatives to support AI development and implementation in government remain unexplored. This includes how ethical guidance and a focus on the governance of AI in public administrations may lead to more responsible and trustworthy use of AI by these organisations. While there has been a great deal of research on the ethics of AI, there is minimal evidence on how these ethical recommendations are used by public administration and how they, in practice, support the development and uptake of the technology. Other topics that might be illustrative to understand these choices taken by governments are to examine how past e-government progress and policy styles limit or stimulate AI adoption in their administrations, as well as the link between past digitalisation efforts and the possibilities of using AI.

Therefore, greater insight is needed into understanding the long-term adoption of AI in public administrations. While the concept of AI capability is explored in this thesis, there remains significant room for examining this concept from different research perspectives, taking note of the potential differences between the capability to develop AI and implement AI in public administrations, respectively. This might account for additional resources and organisational capabilities that the current research has not yet identified.

Such research could also consider specific types of AI, as it is more likely that different types of AI have different barriers to their adoption and, consequently, various resources and capabilities within the AI capability frameworks. How and to what extent public administrations change their structures, processes, human resources, recruitment, and many other activities as the uptake of AI in their organisation requires increasing resources related to AI capability has not been thoroughly examined. In addition, taking note of many discontinued AI use cases, there is room for reviewing the non-adoption of AI by public administrations. This does not only include the barriers experienced by the initiation of AI but also the obstacles to the long-term adoption of the technology and the main reasons why its sustained use has been challenging thus far.

This might further create insights into whether bureaucratic factors play a role in the limited long-term uptake of AI in public administrations or whether ethical concerns or other negative consequences are the main reasons.

In that respect, much more research is needed to gain a better understanding of the public value created by these administrations. This includes exploring more deeply what the main public value drivers of AI initiatives are, what considerations public managers initiating AI in public administrations have, and how certain public values may influence the decision to adopt and use innovations. Furthermore, given the emergence of several negative examples of AI and its negative effects, it remains unclear why AI is, in some cases, capable of providing positive effects, whereas, in other cases, this is more negative. It remains unclear if this is the direct result of the technical design decisions, the organisational capabilities to effectively use the AI systems, the context of the deployment, or simply the perception that key actors have of the effects of the technology.

List of figures

List of tables

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Abstract

Public value creation with Artificial Intelligence technologies in public administration

This doctoral thesis investigates the expected creation of public value through the use of Artificial Intelligence technologies within public administrations. There is great academic and societal interest in the development and use of Artificial Intelligence technologies as they are frequently mentioned to be the start of a new industrial revolution and able to provide many benefits for governments and citizens. However, historical developments in eGovernment have shown that most of the claims of new technologies are not realized in the public sector. Often technology is not adopted in governmental organizations or organizational processes are not altered, limiting the actual changes and value for citizens. Learning the lessons from previous research on the impact and effects of ICT in government, it is likely that the creation of public value of Artificial Intelligence will not be as might be expected from the inherent technological properties of AI. However, despite the interest in Artificial Intelligence, there is a dearth of research on its usage in public administrations and limited validation regarding both positive and negative consequences. Employing an exploratory research approach, this study examines diverse definitions and understandings of AI, investigates the factors influencing its adoption, assesses public administrations' capability for effective AI development and deployment, and analyses existing use cases and their contribution to public value. The empirical evidence greatly benefited from a landscaping exercise of AI use cases within the European Union conducted in collaboration with the European Commission's AI Watch.

In the first publication *"Evaluating the impact of artificial intelligence technologies in public services: towards an assessment framework",* a conceptual framework is proposed to research the effects from the use of AI in government based on a public value approach, which takes into account the drivers needed for adopting AI and the need for organisational changes.

The second publication, "*Conceptual challenges of researching Artificial Intelligence in public administrations"* explores the various interpretations of AI within the Information Systems and eGovernment research domain. Through a survey amongst Belgium civil servants, the findings highlight that civil servants tend to associate AI with being able to conduct intelligent tasks or as certain IT applications, rather than the underlying learning methods to create them.

The third publication *"Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union"* explores based on a sample of 250 use cases of AI within public administrations in the EU how AI could contribute to core governance functions. The findings highlight that various types of AI applications can be used to support various functions, such as policymaking, public service delivery and internal management.

The fourth publication *"Policy initiatives to advance on the AI-enabled government: analysis of European AI strategies"* analysis AI strategy documents which have been published by governments within the European Union. By assessing the plans to overcome challenges of developing and adopting AI in public administrations, the findings highlight a strong focus on overcoming data-related barriers yet limited activities to support internal capability and funding possibilities to do so.

The fifth publication "*The Dynamics of AI Capability and its influence on Public Value creation of AI within public administrations"* explores how AI capability within public administrations influences the organisation's capability to effectively develop and implement AI technologies. The findings found that there are several resources, which include human resources, technical, non-technical and intangible resources, are essential for the successful implementation of AI in public administrations yet are often lacking.

The sixth publication "*Exploratory insights on artificial intelligence for government in Europe"*, the adoption of AI in public administrations is examined through a public sector innovation lens. The findings note that the adoption AI in government follows previous theoretical insights on public sector innovation. The adoption of AI results from environmental, organisational, innovation-specific and innovation-specific antecedents.

The publications of the doctoral thesis provide a crucial contribution on the various interpretations of AI in public administrations, drivers and barriers that influence the adoption thereof and novel insights into the challenges public administration face in utilising AI technologies in their organisations. The research emphasizes the importance of the internal organisational factors that determine the use of AI technologies and the public value that could be derived following this use. The findings of the research provide an empirical foundation on the challenges of the adoption of AI in public administrations and the expected public value creation of AI in public administration.

Lühikokkuvõte

Avaliku väärtuse loomine tehisintellekti tehnoloogiatega avalikus halduses

Käesolev doktoritöö uurib tehisintellekti tehnoloogiate kasutamisega seotud oodatavat avaliku väärtuse loomist avalikus halduses. Teaduslik ja ühiskondlik huvi tehisintellekti (TI) tehnoloogiate arendamise ja kasutamise vastu on üha suurem. TI-d peetakse sageli uue tööstusrevolutsiooni alguse tähiseks, kuna TI tehnoloogiad pakuvad olulisi eeliseid nii valitsuste kui ka kodanike jaoks. Siiski on e-valitsemise ajaloolised arengud näidanud, et enamik uute tehnoloogiate lubadustest ei pruugi avalikus sektoris realiseeruda. Põhjuseks on see, et sageli ei võeta uusi tehnoloogiaid valitsusasutustes vastu või ei suudeta organisatsioonilisi protsesse muuta selliselt, et need ei piiraks muutusi, mida soovitakse rakendada, ega vähendaks uute tehnoloogiate loodavat väärtust kodanikele. Tuginedes varasematele uurimustele, mis on keskendunud info- ja kommunikatsioonitehnoloogiate (IKT) mõjudele valitsusasutustes, pean tõenäoliseks, et tehisintellekti avaliku väärtuse loomine ei pruugi olla sirgjooneline, nagu võiks oodata tehisintellekti tehniliste omaduste põhjal. Hoolimata üha suuremast huvist tehisintellekti kui uurimisteema vastu, napib endiselt uuringuid selle kasutamise kohta avalikus halduses. Samuti on suhteliselt vähe tõendusmaterjali selle kohta, millised on TI avalikus halduses rakendamise positiivsed ja negatiivsete tagajärjed. Kasutades uurimuslikku metodoloogilist lähenemist, püüab käesolev väitekiri neid lünki varasemates uuringutes täita, kaardistades erinevaid tehisintellekti määratlusi ja arusaamasid, uurides TI-i avalikus sektoris vastuvõtmist mõjutavaid tegureid, hinnates avaliku halduse võimekust tõhusalt tehisintellekti arendada ja rakendada ning analüüsides olemasolevaid kasutusjuhtumeid ja nende panust avaliku väärtuse loomisse. Töö empiiriline alus tuginev peamiselt TI kasutusjuhtumite kaardistamisele Euroopa Liidus, mis viidi läbi koostöös Euroopa Komisjoni tehisintellekti jälgimisrühmaga AI Watch.

Esimeses publikatsioonis "Tehisintellekti tehnoloogiate mõju hindamine avalikes teenustes: kontseptuaalne hindamisraamistik" (ingl. k. *Evaluating the impact of artificial intelligence technologies in public services: towards an assessment framework*) pakutakse välja kontseptuaalne raamistik tehisintellekti kasutamise mõjude uurimiseks valitsusasutustes. Artikkel kasutab avaliku väärtuse teoreetilist lähenemist, mis rõhutab tehisintellekti vastuvõtmiseks vajalike tegurite ja organisatsiooniliste muutuste olulisust. Artikkel pakub originaalse kontseptuaalse raamistiku, mis on käesolevas doktoritöös olnud aluseks erinevate artiklite ühendamisel ühtseks tervikuks.

Teine publikatsioon "Tehisintellekti uurimise kontseptuaalsed väljakutsed avalikus halduses" (ingl. k. *Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union*) uurib erinevaid TI tõlgendusi infosüsteemide ja e-valitsemise valdkonnas. Artikkel tugineb Belgia riigiametnike seas läbiviidud küsitluse empiirilistel andmetel. Uuringu tulemused näitavad, et riigiametnikud kipuvad seostama tehisintellekti võimega teostada intelligentseid ülesandeid või rakendusi konkreetsetes valdkondades. Vähem seostavad riigiametnikud tehisintellekti selle loomise aluseks olevate tehniliste arvutuslike meetoditega.

Kolmas publikatsioon "Tehisintellekt avalikus sektoris: tehisintellekti kasutamise ülevaade Euroopa Liidu valitsusasutustes" (ingl. k. *Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union*) uurib Euroopa Liidu avalikes institutsioonides kasutatud 250 tehisintellekti rakenduse näitel, kuidas TI saab toetada keskseid valitsemise funktsioone. Uurimistulemused rõhutavad, et erinevat tüüpi TI rakendusi saab kasutada eri funktsioonide toetamiseks, näiteks poliitikakujundamine ja avalike teenuste osutamine, aga ka sisemiste juhtimisprotsesside tugevdamiseks.

Neljas publikatsioon “Poliiitikameetmed tehisintellekti võimaluste avardamiseks valitsusasutustes: Euroopa tehisintellekti strateegiate analüüs” (ingl. k. *Policy initiatives to advance on the AI-enabled government: analysis of European AI strategies*) analüüsib tehisintellekti strateegiadokumente, mille on välja töötanud ja avaldanud Euroopa Liidu liimesriikide valitsused. Hinnates plaane tehisintellekti arendamiseks ja kasutuselevõtuks, näitavad uurimuse tulemused, et valitsused keskenduvad eelkõige võimalike takistuste ületamisele, mis on seotud TI arendamise aluseks olevate andmetega. Samal ajal näitavad tulemused, et valitsusasutuste fookuses on oluliselt vähem olnud need tegevused, mis on seotud sisemise võimekuse ja rahastamisvõimaluste toetamisega TI-ga seotud arendusteks.

Viies publikatsioon “Tehisintellekti võimekuse dünaamikad ja selle mõju avaliku väärtuse loomisele avaliku halduse asutustes” (ingl. k. *The Dynamics of AI Capability and its influence on Public Value creation of AI within public administrations*) uurib avaliku halduse asutuste võimekust tehisintellekti tehnoloogiate tõhusaks arendamiseks ja rakendamiseks. Uurimistulemused näitavad, et mitmesugused ressursid, sealhulgas inimestega seotud, tehnilised, mitte-tehnilised ja intellektuaalsed ressursid, on hädavajalikud tehisintellekti edukaks rakendamiseks avaliku halduse asutustes, mida aga sageli napib.

Kuuenda publikatsiooni pealkiri on “Ülevaade tehisintellekti kasutamisest Euroopa valitsusasutustes” (ingl.k. *Exploratory insights on artificial intelligence for government in Europe*) käsitletakse tehisintellekti kasutuselevõttu avalikus halduses läbi avaliku sektori innovatsiooni lähenemise. Uurimuse tulemused näitavad, et TI kasutuselevõtu mustrid valitsustes on kooskõlas varasemate avaliku sektori innovatsiooni teoreetiliste põhimõtetega. Tehisintellekti kasutuselevõtt oleneb valitsusasutuste eelnevatest organisatsioonilistest eripäradest ja innovatsiooniga seotud kogemustest.

Käesoleva doktoritöö publikatsioonid annavad olulise panuse tehisintellekti erinevate tõlgenduste ja arusaamade mõistmiseks avaliku halduse asutustes. Samuti selgitab väitekiri tegureid ja takistusi, mis võivad TI vastuvõtmist avalikus halduses mõjutada. Väitekiri pakub olulist teadmist erinevatest väljakutsetest, millega avalikud institutsioonid seisavad silmitsi, kui arendavad ja kasutavad TI tehnoloogiaid oma organisatsioonides. Uurimuste tulemused rõhutavad organisatsioonisiseste tegurite tähtsust, mis määravad TI tehnoloogiate kasutamist ja sellega seotud avalikku väärtust. Empiirilise uurimistöö tulemused pakuvad olulist teadmist selle kohta, milline on TI oodatav avalik väärtus avaliku halduse institutsioonides. Väitekiri annab aluse tulevasteks uuringuteks, mis keskenduvad tehisintellekti kasutamisega seotud eelistele ja riskidele avalikus halduses.

Appendix

Publication I

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Evaluating the impact of artificial intelligence technologies in public services: towards an assessment framework

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ABSTRACT

Many governments are exploring applications of AI technologies to improve their public services. While AI has the potential to radically improve governmental processes, services and policy, limited studies empirically validate the effects of the use of AI. In this research paper, a first discussion on the development of a conceptual framework to research more rigorously the effects of AI in government is proposed. The proposed elements of the framework build upon the current understanding of the drivers influencing adoption of AI and takes into account the need for complementary organisational changes for increasing impact. The model follows a public value approach to understand the possible impact of AI on both the internal mechanism of the organisation, public service quality and broader societal effects.

CCS CONCEPTS

• **Applied computing** → **Computers in other domains** → Computing in government → *E-government*

KEYWORDS

Artificial Intelligence, impact, public sector, framework, public administration

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1. INTRODUCTION

Artificial Intelligence (AI) is assumed to have great potential to enhance public services, both increasing the quality and consistency of services delivered and improving the design and implementation of policy measures [1]. This is expected to improve efficiency of government operations and ensure more personalised public services.

In turn this should enhance the efficiency and effectiveness of public procurement, strengthen security, improve health and employment services and facilitate the interaction with wider audiences, bringing solutions to many societal challenges and becoming potentially the main driver of economic development [2].

But of course this does not happen as magic!

The application of AI for public administrations fits the more established tradition of eGovernment: the practice and study of using ICTs in order to improve government services [3].

If we look AI in public services from this perspective, we can easily notice that the promise of AI is not new, as there has always been great enthusiasm to introduce new digital technologies within governmental organisations in order to improve effectiveness and efficiency of service delivery, make organisations more citizen-centric and improve trust in government [4], [5].

However, many researchers have questioned whether the great investments in Information and Communications Technologies ICTs by governments over the past decades have actually achieved the significant impact it was supposed to bring [6], [7].

Along this line, to better understand the potential of AI to support the digital transformation of government, AI should be assessed in the realm of public administration operations and related public service provision. The uptake of the use of AI applications in public administration in fact is not yet fully understood [8]. Intuition says that public administration uptake of AI applications falls well behind the advances of technologies and that the potential of AI is not exploited at its best [9], [10].

Literature and practice in the field also show that even when AI is introduced as a 'new technology', previous challenges encountered in the eGovernment research field are still often present [11]–[13]. Much of the current research on AI or algorithms in fact often focuses solely on the technology itself, but fails to take into consideration the complexity of implementation of ICTs - or in this case AI – and interactions with people within public administrations [14]–[16].

For example, recent research shows that data management competences are highly needed before any governmental organization could even consider using AI technologies and as a result, make any meaningful impact [17]. Others emphasize the need for citizens to be able to use, adopt and value online governmental services. Arguably, when governments will provide with or by AI technologies, trust and willingness of citizens to use these services will be even more crucial.

In order to validate and truly assess the impact of Artificial Intelligence in government, an approach which takes into consideration the previous challenges of implementing ICT in government is required. Understanding the effects of Artificial Intelligence by empirical means has been promoted by authors from other fields as well [18].

This paper aims thus to present and discuss the main elements for building a conceptual framework to assess the impact of Artificial Intelligence in public services and to facilitate future research on the impact of this new set of technologies.

Following this introduction, a brief overview of the current state of AI in the public sector is presented. After, the proposed preliminary framework is introduced and explained. The article concludes with a brief discussion of potential future applications of the framework and its policy relevance.

2. AI IN THE PUBLIC SECTOR

AI has a tremendous potential to benefit European citizens, economy and society, and already demonstrated its prospective to generate value in various applications and domains [19]. However, AI is not a well-defined technology among academia, policy makers and society as it changes its meaning as a science or as a technology. This makes it already challenging to narrow down the scope of what is meant with it [20], [21]. Some refer to AI as the broader science and practice of making machines intelligent, a research field which has been active since the 1950's [22]. Even in this research field, different methods, aims and goals within the realm of AI exist [23].

At the same time machines and industrial processes, that are supported by AI systems are augmenting human capacities in decision-making and providing digital assistance in highly-complex and critical processes [24]. Within this context, there is a great interest by government institutions to harness the potential benefits that AI can bring. Many European AI strategies seem to focus on creating favourable conditions to enable private companies to develop AI to boost their business operations and create better services with less policy devoted to stimulating AI within government. A recent literature review on AI in the public sector reflects this imbalance; out of 1438 AI research articles between 2000 and 2019, 1142 focused on the private sector. Only 59 studies had a specific application or focus on the public sector [25]. Early landscaping show that government are starting to experiment and implement AI-technologies. While this study only has identified 85 cases so far – with most applications using Natural Language Processing – it is likely that many more implementations will follow in the near-future [26]. In this perspective, there is a great demand to understand the drivers, barriers, opportunities and risks to the adoption of AI in government. In addition, there is a need to understand the potential impact of the usage of AI in the public sector, either positive or negative [8].

An early study [13] shows that there are numerous, interdisciplinary challenges surrounding the adoption of AI in government which do not solely focus on the technology. To further illustrate the key elements underpinning the design of a framework to analyse use and impact of AI in the public service, the figure below outlines the relationships between drivers and barriers of implementing AI in government, and the effects and impacts that can potentially be generated.

3. PROPOSED CONCEPTUAL FRAMEWORK ON THE IMPACT OF AI

The proposed conceptual framework (Figure 1) takes insights from earlier research on eGovernment and public sector innovation to further enhance the need to first have sufficient enablers in place before AI could make an impact. Secondly, the framework draws upon research on technological impact assessments and aims to be more empirical in basis. Existing research approaches of assessing the impact of ICT in government have been deemed insufficient due to limited availability of indicators, data or research with a counterfactual to create causal links between ICT investment on one hand and impact on the other [27], [28].

As a matter of fact, AI, just like any other ICT, is a General Purpose Technology. These technologies enable new actions, but this enablement does not necessarily result in effective implementation. It is not the technology itself which makes an impact, but rather how it is used and transforms existing processes and structure [29], [30]. This makes the actual impact of any technology differ per organization and per context.

Citizens might respond differently based on their location, culture or their characteristics [31]. Indeed, even civil servants might change their behaviour unexpectedly when AI-systems are introduced, influencing work flows and input data, which in turn impact AI technologies [32], [33]. Consequently, the impact of AI technologies in government thus far more nuanced and more challenging to assess than other reports might suggest. Any form of assessment of AI impacts should thus research the AI-system ‘in the wild’ to really understand the effects [18]. Such an approach would be highly benefited by empirical policy evaluation techniques due to the quasi-experimental research design one could set up.

Systematically comparing the policy or organisational situation ex-ante and ex-post the introduction of AI would significantly increase our understanding of the short-term impact of AI. Such a practice-oriented and empirical-based research approach has been used before in research of algorithms – especially in more critical studies [34] – and could be well-suited to be combined with existing policy research methods. However, the framework should not be regarded as an operational framework, but merely a conceptual framework to invite other researchers to critically assess commonly made assumptions on researching the impact of AI in government.

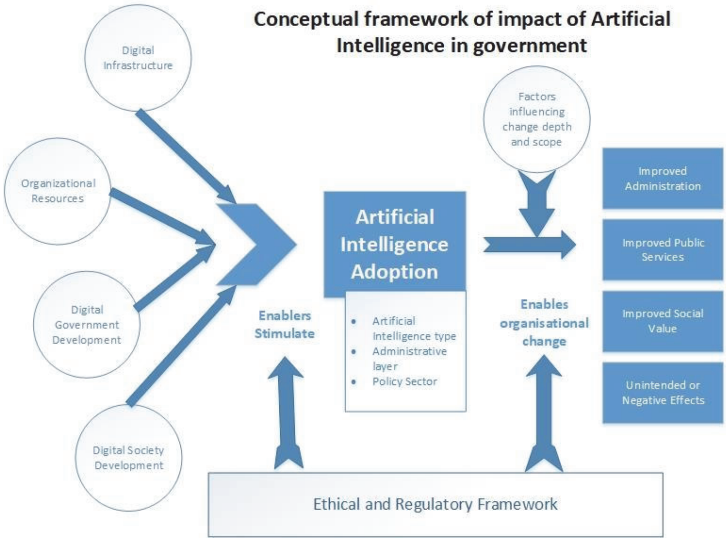

Figure 1 Conceptual Framework of Impact of AI in Government

In the following sections, the different elements of the framework are discussed more in depth.

4. ENABLERS OF AI IN GOVERNMENT

There are a number of factors mentioned in the current literature and policy documents which are argued to influence the adoption of AI in governmental organizations. These could be grouped in digital infrastructure, organizational resources, digital government development and digital society.

4.1. Digital Infrastructure

Most often mentioned is the importance of the availability of a strong technical infrastructure to support the development of AI. This technical infrastructure is required in order to obtain, manage and store various data which AI requires to learn. AI always appears in existing IT systems and never in isolation, which requires hardware and software [35]. Governmental organization should therefore have (access to) an infrastructure with high connectivity, enough bandwidth, processing power server hardware, networks and database management technologies to facilitate the storage and analysis of large datasets needed to develop AI [24], [36]. High quality datasets are also a must: without high quality, trusted data, it is likely that AI will not be implemented [13]. Naturally, there should be data available for the goal of the analysis in large volume. If this data is not available, proxies could be used as a replacement or considerable efforts should be done to obtain large datasets of the phenomena [24]. However, governments have been mentioned to have plenty of data in their systems, but due to poor data management practices, they might not always be usable or understandable [17]. Others highlight the complementarity of AI with the development of the Internet of Things (IoT) within governments: with untrustworthy sensors, the data will be flawed as well [12]. Furthermore, the digital infrastructure should be able to integrate different datasets which capture different elements suited for analysis. Integration of different datasets is however not always a given due to different standards, formats or unwillingness to share datasets [12], [37], [38].

4.2. Organizational Resources

Even when the media describes AI as machines learning on their own, there are still humans involved in the all processes of development and deployment. Numerous organizational resources are thus required to develop and integrate AI in government and public services. Even with a technical infrastructure already in place, there should be human resources available who understand how to develop AI systems [13].

There is a very high demand for experts with such AI-related expertise, while there are currently not many experts available to fill in all these positions [24]. Furthermore, the salaries these experts are able to ask for are frequently a lot higher than is common in public organizations, making it quite challenging to obtain AI- related expertise within the government [24], [39].

Others have also mentioned the need for other IT-skills in order to create and maintain a high-quality technical framework [17]. This requires sufficient expertise within the organization on data management and governance, engineering and other IT-skills [17]. Civil servants without specialized IT-skills should still have enough expertise on how to work or use AI within their day-to-day processes [24]. This is unfortunately not a given, since the usage of ICTs within the public sector is lacking behind the private sector [7].

Even with enough technical and human resources available, there should also be enough financial resources in order to implement AI technology. The lack of funding or having inadequate budgets to implement AI is a huge barrier in many organizations [13]. Having inadequate financial resources is in fact a common problem in implementing changes or innovation with the public sector [40].

4.3. Digital Government Development

The organizational resources required to adopt AI within government institutions are closely related to the development of Digital Government.

This is not unusual, as it has been mentioned that competences, both in technical and organizational terms, needed for Digital Government practices are highly relevant for the adoption of new innovations, including AI. As AI systems requires many large datasets, it is recommended having the core processes as digital as possible to process large amounts of related data usable for analysis [24], [41].

The academic field of eGovernment has noticed the transition towards eGovernment 3.0: the use of disruptive ICT's, in particular AI, in combination with existing ICT to tackle social problems and improve citizen's well-being [42]. While the research activities of eGovernment 3.0 are new, there is an understanding that the use of Artificial Intelligence and other data analytics is built on top of earlier eGovernment investments [43].

Following this logic, our understanding is that without sufficient investments in traditional eGovernment ICTs, the infrastructure, digital services availability, expertise and available data will be limited, thus reducing the potential of using Artificial Intelligence.

Furthermore, adoption of AI within the government requires an innovative mind-set within the public sector [40]. This aspect is highly related to existing practices of adopting and developing new innovations within public service delivery [41].

The organizational culture is an important element in facilitating the adoption or rejection of new technologies such as AI in day-to-day operations [44], [45]. If the usage of AI is perceived as risky, dangerous or against organizational interests, it is probable that no AI will be adopted, as seen with other ICT technologies [46], [47]. In line with this argument, we argue that governmental organizations who have already have higher degrees of maturity of eGovernance and have more experience in ICT in their day-to-day work, will have the required mind-set, skills and required infrastructure to implement AI technologies.

4.4. Digital Society

Since AI requires a lot of data in order to give valuable insights, this data first has to be available. Most of data available today has been gathered only in the latest years due to the increased datafication of social and economic processes. In the year 2000, for instance, only 25% of the world's data was stored on digital media, but at the moment, almost all of the information in the world is digital [48].

This shows a massive change in the way how we store information. However, digital data is not just a swift in how we store data, but also in what kind of information is captured and stored [49]. Due to the increased penetration of digital technologies in many kinds of social interactions, it is now possible to store quantifiable data from social processes not possible before [48]. The more and more economical and social interactions are conducted online, the more and more aspects of life are possible to be converted into machine-readable formats and stored digitally [49]. It is likely that the more digitally advanced the society is, the more the quantity, quality and diversity of the data available is for analysis for AI.

This would be reflected in the availability of companies operating in the digital sphere, the usage of digital technologies by citizens and other usages of digital technologies across the society. Even when there might not be specific AI skills present within governmental institutions, public organizations are able to collaborate with private organizations in order to share expertise in AI. Private organisations have been known to stimulate the adoption of technologies in governmental organisations and it is likely this will be the same for AI [50]. In particular, one could focus on the number of AI-related start-ups in the area as an indication of AI expertise in society [41].

Arguably, the more digital advanced and the more data is available in a particular country, the more likely it is that there will be sufficient technological skills available to analyse all this data with expertise in AI. Thus governments are setting up collaborations to stimulate AI adoption [51]. These collaborations allow different actors to share different data sets to create data-driven innovations [52]. This enables private companies to use their expertise on governmental data sets while governmental institutions will gain access to datasets of private organisations which could potentially be very valuable for them [52]–[54].

4.5. Different forms of AI technologies and usage

To improve our understanding of the different effects of AI technologies, it's needed in order to first assess what kind of AI is being used in governments, a categorization is needed in order to classify the different types of use and impact. AI in fact could refer to many different forms of technologies and it is commonly used as an umbrella term for a set of technologies and methodologies.

Furthermore, the field of AI suffers from what has been defined the so called "AI-effect": an effect that explains that technologies which were once referred to as AI are not called AI anymore since societies got so used to them. In a sense, once we get used to a certain kind of technology, we do not refer to it as AI anymore [21]. As a consequence of this, what we call AI differs over time [20].

It is thus important to keep in mind that any classification used now might be invalid in 5-10 years when the field has developed further. Early frameworks have already started to distinguish between AI learning methods and functional applications/capabilities [13], [25].

There is also an interest to assess in which policy sector the AI technology is used [25]. Certain industries or policy sectors have been argued to be more suitable for AI (such as healthcare, agriculture and transport) than others due to the current availability of data in this field [24], [25]. By analysing the different policy domains in which the AI systems are active, this assumption could be tested. Furthermore, it allows the detection of policy sectors where there is significant lack of AI adoption.

This in return invites additional research to identify specific factors which are related to the adoption and impact of AI in these specific policy domains.

4.6. The enabling factor: organisational change

Despite the abundant positive discourse of the potential of ICTs and investments made to digitize government operations and public service delivery, still little is known about the actual effects and impact these have on citizens and society [28]. Recalling the "productivity paradox" established by Solow in the late 1980's, who famously mentioned that despite many investments in ICTs, very little productivity gains have been found in the statistics, a similar phenomenon has been recently indicated for investments in AI: despite the massive investments and interest by companies, policy makers and academics, very little improvements on the productivity have been measured so far [55].

In many discussions however, there is a general understanding that using ICTs in government will establish more efficiency and cost-effectiveness, leading towards the conclusion that more ICTs is better. This is reflected in many of the statistical analyses conducted by international organizations: most reports measure the readiness and intensity of use of ICTs, but rarely assess how the technologies are used or implemented.

This is highly problematic, as there is a general understanding that simply adoption of technology does not always lead to any effects. In fact, many argue that it's the transformation enabled by technology which determines the effects of technology [29], [56], [57]. E-Government innovations tend to simply copy existing practices in an online form, rather than redesigning and reorganizing the work [3]; a tendency seen even with the use of advanced technologies such as Chatbots [9].

Whereas it is understandably difficult to evaluate impacts of ICTs due the micro, meso and macro levels of possible effects, it is recognised that in order to assess the impact of technology on society, more evidence is required, but different impact assessment approaches may also be needed [28]. Within the eGovernment research field, in particular, there is very little evidence on the impact of ICT-enabled services.

4.7. Public Value

One way to assess the multidisciplinary impact of AI in government and public services is by assessing the public value of its implementation. The concept of public value has been gaining increasing attention in researching the effects of ICT in government [58]. As one of the most important elements of introducing ICT within government institutions is not the implementation of the technology, but rather to assess what the value the technology is able to bring towards citizens [59].

Public value here is a broad concept, which focuses on the expectation's citizens have towards the government and public services [30]. These expectations are not solely based on economic values such as efficiency and effectiveness, but also on democratic and social values such as trust, engagement and respect for the rule of law [60].

Public value creation through ICTs is therefore distinctively different from value creation in the private sector, where the ultimate end value is profit. In order to meet the expectations of citizens, public organizations should aim for the creation of public value in all of their services [61].

In practical terms it is to be considered that all ICT-enabled projects within government are initiated with certain goals in mind, whether explicit or implicit. All these projects are aiming to achieve a certain goal upon its completion, whether it is to improve efficiency, reduce waiting time, increase citizen satisfaction or others. These project objectives could be abstracted towards a more general, abstract public value in order to assess what kind of public values current projects in the government regarding AI aim to achieve.

Three general value drivers to assess impact of ICTs within the government from a public value perspective are Performance, Openness and Inclusion [62]. These drivers assist in understanding the vision and purpose of including AI within public services. After an assessment of the goals of the AI-related initiative, specific AI implementations in the public sector could also be evaluated upon project completion in order to evaluate whether the introduction has achieved the expected goals and what other - unexpected - results might be generated both in the short and in the long-term.

Frequently, in fact, only the potential impact of technologies is taken into consideration when assessing the effects of technology [7]. Evaluations on the actual impact based on empirical data are often neglected. If empirical studies on certain expected technological effects, such as filter bubbles, are conducted, they tend to show that the effects as less than expected [34]. At the moment, this same tendency is visible in the field of AI in the public sector. As we have seen before, while there are many things AI could do or is supposed to do, there is a significant lack of research on the empirical validations of the potential of AI [8].

Using the concept of public value is also very suitable to research the social and political impact of ICTs use in government and public services as it provides a broad overview of the different expectations of citizens impacted by its introduction [30].

An essential factor in researching the impact of ICTs in government is that the effects depend on the social and political context it is embedded in: public value is highly interconnected with the expectations of citizens, which could vary across time, location and based on citizen characteristics such as age, as earlier mentioned [61].

This requires a strong understanding of the context in which AI is deployed, before concluding what kind of impact it is bringing, thus requiring some flexibility in the research approach. Certain public values are more important in some cases than in others. Nevertheless, the ability to produce public value is a purposeful and insightful way to evaluate the impact of potentially disruptive technologies – such as AI - on government and society at large.

Whereas a specific operational definition for Public Value is not agreed upon, a recent literature review on public value in e-Government provides a comprehensive overview of the key dimensions of public value: a) Improved Administration; b) Improved Public Services; and c) Improved Social Value [61].

4.7.1. *Improved Public Administration*

The introduction of technologies such as AI into public organizations has in fact the potential to improve the inner organizational processes. ICTs, and AI in particular - are able to improve the efficiency of administrative processes by reducing administrative burdens, process bottlenecks and queues in the delivery of services as well as enabling better communication, collaboration and cooperation within the organisation as well as with other public organisations [58], [61]. Others mention that the adoption of technology within government institutions support them becoming a more Open Government; transparent, open and more participative with others [63]. Lastly, it has been argued that the introduction of ICTs and especially AI could assist in improving the ethical behaviour of civil servants by limiting the risk of corruption and abuse of the law [61].

Common indicators which are used to assess the improvement of administrative procedures and that will be considered in developing a set of indicators for evaluating use and impact of AI in public services are [61]:

- Increasing efficiency, effectiveness and quality
- Lowering the cost of internal services
- Making government operations more systematic, sustainable, flexible, robust, lean and agile.
- Reducing administrative burden
- Reducing bottlenecks, queues and waiting times.
- Better communication, collaboration and cooperation throughout public administrations
- Increasing transparency
- Greater fairness, honesty, equality due to elimination of corrupt human actors

Naturally, improved administrative processes are likely to contribute to increasing the quality of the public services they are embedded in. Improved Public Services here refer to the improvement in services provided by the government institutions towards citizens.

4.7.2. *Improved Public Services*

Improving public services has been argued to be one of the main sources of public value creation, but this value is dependent on the quality of the service delivered by the public organization [59]. Improvements by ICTs, in particular AI, could thus improve the quality, quantity, accessibility and personalization of existing public services. Common indicators used to assess the improvement of public services are [61]:

- Better service to citizens due to better communication, interaction and access.
- More responsiveness, increased effectiveness and/or higher efficiency
- Improving collaboration with citizens in the delivery of public services
- Higher quantity of public services and information
- More inclusive public services

4.7.3. *4.7.3 Improved Social Value*

The Improved Social Value in turns refers to the ability of public institutions to support the overall social value and well-being of people by achieving better outcomes in peace, security, economy, health, safety, environment and much more [61]. It has been argued that ICTs used within government institutions could improve the well-being of citizens [64]. One way to assess whether AI contributes to the Social Value is by assessing its impact on a number of common indicators such as [61]:

- Improved public trust
- Improved citizen's experiences of governmental service provision
- Increased reliability of governments to deal with social challenges
- Improved knowledge of citizens of governmental operations
- Increased social status
- Improved social and economic opportunities
- Improved public health
- Improved security and safety

- Improved general well-being and happiness
- Improved ease of doing business
- Better economic conditions
- Poverty reduction
- Improved environmental standards
- Improved educational achievements

5. APPLICABILITY OF FRAMEWORK IN FUTURE RESEARCH

While AI-technologies have the capability to generate tremendous benefits for individuals and society, they also give rise to risks and challenges that should be properly managed and anticipated [65]. One of the biggest challenges of AI systems at the moment is the characteristic of machine learning technologies to be like a 'black box' [66]. It is extremely challenging, even for the programmers, to understand how machine learning algorithms function, posing challenges in terms of accountability, liability and trust [65].

There is also the risk of bias of AI-systems when they use historical data [67], [68]. Historical data sets reflect historical biases which users might be unaware of. Once the AI-system learns from this historical data, they are prone to incorporating these biases within their system and amplifying them [13], [33]. Another challenge of AI is the perseverance of privacy when many of our devices are increasingly becoming connected to the internet and each other. Many devices or services gather data without the user's full understanding of what is done with the data after it has been gathered [67], [69].

Lastly, there are economic and social concerns linked to the deployment of AI. In particular, there are considerable fears of job losses once AI takes over many tasks previously conducted by humans [65], [70].

To this end, it is crucial to understand how policy makers and regulators shall cope with the changes that AI-enabled public services are bringing to society and economic systems [19]. As a matter of fact, since policies and regulations are made to guide human behaviours, the use of AI both for enhancing services to citizens and monitor/control human activities has implications in the way these systems are designed and controlled. It is thus important to assess the influence of AI governance against the backdrop of the practices of data controllers, data protection authorities and individuals, but also highlighting the opportunities that AI can unleash for revitalising governance and democracy by harnessing citizen participation and 'collective intelligence' [71].

AI in fact is not only a policy challenge to be tackled, but also an opportunity to empower individuals and civil society as it offer a tremendous potential for innovating the way data are gathered and processed, thus paving the way to real-time informed policy-making based on predictive analytics and next generation computational modelling [1]. This in turn could ultimately contribute strengthening government 'legitimacy' in the digital world and helping 'finding a more humane government'.

In order to assess the different ways AI technologies could impact our societies, multiple approaches of research are before any generalizable conclusions could be provided.

First, there is a need to understand the technological artefact of AI. This requires a technical understanding of what kind of AI-technology is being used, but more importantly, an understanding of how it was possible to develop and implement this AI-technology. Artificial Intelligence requires a significant technological infrastructure, both software and hardware, in place before it is able to function.

Second, there is a need to understand the legal dimensions and regulatory governance mechanisms which either support or hinder the implementation, use and impact of AI. This requires a strong understanding of the different regulation directly or indirectly impacting the usage of AI in government. Regulation on data gathering, data sharing and reuse such as the GDPR have already been mentioned as a regulation significantly impacting the development and usage of AI [72].

Third, there is a need to assess the impact AI brings to the organizational structure and processes within public sector organizations. This requires research on organisational structures, processes, changes and culture in order to obtain a better understanding of how AI technologies are able to ultimately provide value to citizens.

Fourth, in order to understand what the social and economic impact of AI implementations truly is, social and economic impact indicators, from both the local setting of implementations as well as societal indicators – in an attempt to capture the broader implications on society - are needed.

This comprehensive approach however would require different methodological approaches to be combined and all contribute to a piece of the puzzle of assessing what the impact of AI in the public services truly is. Naturally, the model still suffers from some limitations as the research on Artificial Intelligence in governments is only recently gaining more attention.

It is very likely that certain developments such as renewed procurement processes or renewed forms of public-private partnerships assist the adoption of AI. Other current limitations are on various social and historical factors such as institutional trust.

The lack of citizen’s trust has been mentioned before to be hindering eGovernment development and is arguably even more important for AI development. In this notion, the acceptance of citizens in general, both during the development, adoption and retrieval of AI based public services is even more crucial. Already have we witnessed the (risk of) termination of some AI projects due to a lack of public trust after its deployment, such as the case in Gladsaxe, Denmark or in the Netherlands with SyRi [73], [74]. Lastly, while the framework acknowledges the need to have organisational changes to gain public value out of AI implementations, the factors influencing, stimulating or hindering this change are so far outside the scope.

6. CONCLUSIONS

Artificial Intelligence is here to stay and many governmental organizations are aiming to or already experimenting with this set of technologies. In general, there is a positive expectation of the effects of AI as it enables governments to improve efficiency, effectiveness and responsiveness to citizen's needs. On the other side, there are concerns of negative effects when governments implement AI technologies. Both of these perspectives are understandable and often presented, but there is still a lack of empirical validations on the "real" effects a n socio-economic impacts of AI.

This paper, as part of a broader endeavour to set the foundations for more rigorous scientific analysis of the added value of AI in public services, thus aimed to be a first step towards a research conceptualization and method definition in order to assess the impact of AI in government.

This framework builds on top of the existing knowledge of eGovernment and public sector innovation and takes into consideration the different enablers required to adopt AI in the first place. Furthermore, this framework emphasized the need to understand the conducted organisational changes which enable the impact of AI.

We argue in fact that the impact of AI could be well researched from a public value perspective as it focuses at the same time on the internal efficiency of public administration on the one side, and on the service quality and broader societal effects on the other side. In doing this it should be however also acknowledged the need to always take into consideration the local context in which the system operates. In addition, the framework takes into account that negative or unintended effects of using AI thus paving the way for the discussion on countermeasures and ex-ante risk management.

To this end, future research on the impact of AI in government should be combined with empirical analysis so to understand how the different AI systems operate in their socio-technical domains, and what effects and alternative impacts they can generate.

Ideally, the impact should be researched from an ex-ante and ex-post policy perspective, and numerous research approaches could be used. From our side, we aims to further develop the proposed framework as part of the broader research agenda of the European Commission's AI-Watch[2], applying it to assess the impact on various cases of AI currently in use by governments. Based on these research activities, the feasibility of the framework will be tested and adjusted as appropriate, and possibly leading to a validated approach setting the basis for a common roadmap at European level.

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DISCLAIMER

The views expressed in this article are purely those of the authors and may not be regarded as stating the official position of the European Commission.

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Conceptual challenges of researching Artificial Intelligence in public administrations

Definitional challenges and varying dimensions on the meaning of AI

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Abstract

Research has been advancing on the development and deployment of Artificial Intelligence (AI) in public administrations. However, there is limited consensus and agreement on what is considered Artificial Intelligence, as different understandings and approaches in research and practice exist. This paper explores and compares the varying ways AI has been described and understood in previous Information Systems and eGovernment research. Following, a survey amongst Belgium civil servants is analysed to assess what they associate with the term Artificial Intelligence. The findings show that many civil servants tend to associate the AI with being able to conduct intelligent tasks, have certain capabilities or are specific applications they are familiar with. Specific algorithms or learning methods, often included in research papers, are not associated with the term AI. These results show that researchers and policymakers may have opposite or even paradoxical views on what is or is not AI, which could have significant consequences for researching the adoption of AI in government, as well as comparing different research findings. To this respect, the paper proposes to use an integrative lens to studying AI in government, by including different dimensions and understandings.

CONCEPTS • Artificial Intelligence • Public Sector Innovation, • Technology adoption

KEYWORDS

Artificial Intelligence, Public administration, Perceptions, Civil Servants, Machine Learning

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1 Introduction

Artificial Intelligence (AI) has grasped the attention of many people across the world. Many governments have been writing specific AI-strategies, conferences on AI are held frequently and new articles are being written in rapid succession [1]. All in all, there is a general understanding that Artificial Intelligence is going to transform our societies and that governments should do everything to harness its full potential [2]. Time will tell whether these transformative predictions will be correct, as often the transformative potential of new technologies do not live up to its expectations [3]. In fact, it is not the first time we are discussing the potential and challenges of AI in the public sector as older research articles show us [4, 5].

However, despite this immense hype and efforts to be the best in Artificial Intelligence, there is very limited and clarity of what is exactly meant with the term, with different audiences using the term in different ways [6]. The lack of unclarity has led to a variety of critical remarks, stating that people only refer to software as Artificial Intelligence when there is funding to be held -otherwise, it would just be said to be statistics [7]. This is not to say that there are no articles or reports present which describe definitions of AI, in fact, the opposite is true. There are incredibly large volumes of publications on Artificial Intelligence, especially in the recent years [1]. Despite the great amount of publications, the term remains unclear and contested due to the various backgrounds and interest using these terms with many reports referring to AI as forms of 'intelligent machines', 'machine learning' or similar terms [6, 8–11].

Many of these new applications, systems or applications are considered AI as they can conduct intelligent tasks [9]. Existing studies already highlight that there are many, varying forms of technologies and applications considered to be AI, which may not be alike [12–14]. What is the most fundamental for research on AI in the government, however, is that civil servants themselves may use different terms and concepts to understand and describe Artificial Intelligence. Researchers who are researching the next algorithm to extract patterns in large data sets will use the term AI in very different ways (usually related with data science) than policymakers would refer to it [15, 16]. Now that there has been increased interest in researching AI in government, one of the more fundamental research gaps relates to the empirical examples and insights of how AI can create public value [17, 18]. With such strong research needs for additional empirical works, ensuring consistency and generalizations of what is and is not AI in government within the scope of the study is crucial in advancing knowledge. As Krafft et al., 2019 already indicate, many governmental documents do include policy recommendations on AI, but do not define their understanding of the term, raising concerns what exactly policy makers attempt to govern. Already, as a result, discussions on the impacts and consequences remain to be of general nature, more focused on ethics or the development of fair AI and large efforts are required for any form of systematic and comparative studies; especially cross-domains [19, 20]. Furthermore, it is likely that in the coming years, more and more governments will use some form of AI to improve their practices [21], further emphasizing the need to create a common baseline of definitional convergence to understand and explain what and how AI develops in the government, and whether this is desirable [22].

To highlight how different civil servants define and understand AI, this research is built on two steps. Firstly, an exploration of the different understandings and definitions of Artificial Intelligence as discussed in existing literature are introduced and discussed, illustrating their main differences and similarities, and, in doing so, provide a fresh and new perspective on the topic [23]. Secondly, a survey has been conducted among Belgium civil servants, asking them what they understand with the term "Artificial Intelligence" in an open-response format. Using a deductive coding technique, an overview with different understandings of AI is introduced to assist further research in on AI, as well as to highlight a challenge of how civil servants perceive AI could significantly influence research on the adoption of this technology. As such, the article concludes with a discussion and concluding remarks on the potential research and policy implications of the different perceptions in policy and research.

2 Challenges of the term "Artificial Intelligence"

Despite the historical works on AI, there is still no commonly accepted definition and many studies consequently do not provide a clear definition of AI. If a definition is given, already as many as 28 different definitions were identified [24]. In that respect, research could describe AI in many different ways. Some papers aim to highlight the difference between the AI as a SuperIntelligence, General Intelligence or as a Narrow Intelligence, to avoid potential confusion on these different types. Discussions on *AI as a Superintelligence* often refer to the futuristic robots which are far more intelligent than humans [25]. This type of AI belongs in the realm of science fiction – although the potential futuristic way AI could look like has been at the basis for some ethical discussions on how to 'control' AI even if such a moment comes to pass [26]. Like this type of Superintelligence, research could also discuss *Artificial General Intelligence*. Unlike the Superintelligent variant, this type of AI refers to robots (or other systems) which are just as intelligent as humans. This type of AI is commonly capable of learning and transferring its previous thought knowledge into new domains [27, 28]. More relevant for current research on the adoption and the type of AI applications belongs to the *Artificial Narrow Intelligence* or 'weak' AI understanding. This is often understood as machine intelligence that is equal or (slightly) superior to human intelligence – but only for a specific task , predictive, reactive and based on rules [29–31].

Within this field of current or Narrow AI, papers often describe *AI as the learning methods or techniques* used to make the AI systems 'as AI'. At the moment, machine learning is the most popular form used as the learning method in AI, or considered as a subset thereof [24]. What makes machine learning distinct from 'traditional AI' is that machine learning algorithms learn by 'themselves' on (very) large datasets. The field of machine learning, however, consists of many different approaches and specific analytical techniques. Often, a distinction is made between supervised machine learning, unsupervised machine learning and reinforcement learning. In supervised learning, labelled training data is used in order to predict new cases based on the existing information whereas in unsupervised learning insights from the data without a clear output are derived [32]. In the reinforcement learning approach, an AI system learns how to do a task well by giving a "reward" based on the output of the task [31]. Within these broad approaches, a massive amount of different analytical techniques belongs to this realm. For instance, the following terms have been used by Sousa et al., 2019 to measure the progress of AI in public sector research, such as: *case-based reasoning (CBR); cognitive mapping fuzzy logic (FL), machine learning (ML), artificial neural networks (ANN) genetic algorithms (GA), multi-agent systems (MAS) and natural language processing (NLP),* amongst many others [33]. These methods are often included in the keywords of larger comparisons such as the OECD [34] or described in the proposed AI regulation[1] from the European Commission as AI techniques or approaches.

Commonly, the use of these AI learning techniques aims to enable an *AI system to gain an ability in order to conduct specific tasks*. These abilities, or capabilities as others also mention, are what defines for some whether we classify

ANNEX 1, ARTIFICIAL INTELLIGENCE TECHNIQUES AND APPROACHES IN: PROPOSAL FOR A REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL LAYING DOWN HARMONISED RULES ON ARTIFICIAL INTELLIGENCE (ARTIFICIAL INTELLIGENCE ACT) AND AMENDING CERTAIN UNION LEGISLATIVE ACTS, COM(2021) 206 FINAL something as AI or not [35]. These capabilities or abilities gained from the learning techniques described earlier allow the AI to conduct tasks considered to require intelligence or for the AI to behave rational [22], or to think and learn [36]. Consequently, it is not so much the question how AI learns – but what it is possible to do following the learning– and whether it does so successfully. These abilities include, but are not limited to, perceiving, reasoning, learning, interacting, problem solving, decision-making or being creative [24].

Related, but not entirely similar, are some publications which refer to AI as specific applications which are consequently used by public administrations and considered AI [37]. Often, these are special IT, software or hardware which are used to improve government's processes or decisions. It has been argued that approaching AI as a tangible technology such as is more preferred for research and regulatory purposes as it is more concrete [38]. Currently, applications mentioned as such include voice assistants, facial recognition software, recommendation software, chatbots, robotic process automation among others [13, 30].

Lastly, some tend to refer to *Artificial Intelligence as the general academic field* – not specific to any kind of applications, but rather the full study domain as it has started since the 1950s [39]. Despite the status as an emerging technology, the study of AI already started in the 1950s with various researchers such as Gregory Powell, Mike Donavan and Alan Turing publishing works on intelligent machines [25, 35]. Not much later in 1956, the term Artificial Intelligence was first brought up during the Dartmouth Summer Research Project on Artificial Intelligence, often seen as the 'starting moment' of the study of AI.

An overview of these different understandings, which at times can overlap, can be found in Table 1 below.

Table 1: Varying perspectives of AI, author's own elaboration

Understanding of AI	Explanation	As seen in:
AI as Superintelligence	A futuristic machine or computer which (far) surpasses human intelligence	[13, 25, 26]
AI as General Intelligence	A futuristic machine or computer which displays equal human-like intelligence in a variety of domains	[31, 40]
AI as Narrow Intelligence	Current artificial intelligence in which systems display human-like intelligence in one specific function	[41, 42]
AI methods/techniques	Techniques and methods that allow the analysis of large volumes of data to develop AI such as case-based reasoning, cognitive mapping, fuzzy logic, machine learning, multi-agent systems, rule-based systems amongst many others. These may fall under supervised, unsupervised and reinforcement learning methods	[14, 27, 32, 43–45]
AI as human-like cognitive capability	Ability of machines to carry out tasks which require human capabilities, by displaying human-like behaviour, to behave rationally, the ability to solve hard problems	[22, 35, 46, 47]
AI as applications	A special form of IT systems, applications or software that are capable of performing tasks that normally need human intelligence	[12, 13, 30, 38]
AI as a science	The general study and science behind the pursuit of making machines or computers intelligent	[5, 39, 48]

As can be seen by this overview, the term of Artificial Intelligence is highly fluid and changing – even over time, depending on the latest state of the development [49].

3 Methodology

To assess how civil servants perceive Artificial Intelligence, this research uses data from a survey conducted amongst Belgium public administrations in April and May 2021, part of the Belgium AI4GOV programme. The AI4Belgium community is an ecosystem of researchers, policymakers, civil servants, and citizens interested in advancing AI within Belgium, and has a strong interest to research and examine the current use of AI in Belgium and is actively putting policy in place to boost the uptake of AI in society. As such, there is a strong need to identify what is considered AI by civil servants themselves, as they would play a key future role in examining the current level of uptake and impact of this technology. The survey also included various questions to the respondents regarding the current level of use of AI in their organisation, and which perceived drivers and barriers are influencing the use of their organisation. However, one of the crucial elements of the survey was to gain a comprehend how civil servants, with varying backgrounds, perceive the term "Artificial Intelligence". This question was stated: "*What is according to* *you Artificial Intelligence (AI)? Please provide a short answer.”*. Respondents were given the opportunity to provide a short, open answer as a response.

A web survey was chosen to gain answers on how civil servants from the survey, as the aim was to gain as many civil servants participating, in a relatively short time. While a survey may not lead to the same amount of detailed understanding and conceptualisation of AI as one may obtain in an interview or in a focus group due to the limited opportunities to express their thoughts, a survey is an excellent research methodology to many people in a short amount of time, and to this extent, a great research method to research general perceptions to AI [50]. Naturally, one of the key requirements of a survey design is to obtain a representative sample of respondents. To do so, various distribution channels were chosen to target a diverse number of civil servants as possible, ranging from local, regional, and federal levels of government, and also civil servants who may have limited formal education in Artificial Intelligence. Firstly, all the members of the AI4GOV network were requested to respond to the survey by email. Secondly, the survey has been distributed within the internal communication networks of the Belgium government, to also target the various public organisations which may not be active members of the AI4Belgium network. Lastly, the survey has been shared on social media and the newsletter of the Belgium Digital Government Administration (BOSA) and AI4Belgium. Since the Belgium public administrations have different working languages (mostly Dutch and French), the survey has been translated from to Dutch and to French, giving respondents the option to answer in English, Dutch or French, depending on the respondent’s preference, in order to obtain a higher response rate. The full survey was proof tested and reiterated various times to make the questions relatively easy and quick (within 15 minutes) to answer, common characteristics of mail-based surveys [51].

The question was answered by different 134 respondents, from the municipal, regional, and federal levels of the Belgium government – although most of the respondents were from the Belgium Federal government. Following a review of the answers, 18 questions were either blank or a duplication from another answer, which were consequently removed. This left 116 answers on what the respondents found to be “Artificial Intelligence”. As the answers were provided in both Dutch and French, they were both translated to English using DeepL machine translation. Following this translation, the answers were deductively coded and analysed using MaxQDA software on the basis of the categories identified in Table 1 with the exception of the Narrow Intelligence, as the techniques and applications categories overlapped strongly with this category since they described current techniques and applications considered AI and should be better understood vis a vis General or Superintelligence, rather than a category by itself. As each of the answers could be coded one, or multiple times, the final number of codes was 159 out of the 134 answers, meaning that there were several answers which referred to one or more of the categories identified below.

4 Findings

4.1 Artificial Intelligence as a future Superintelligence or General Intelligence

Despite that some academic literature strongly focus on the futuristic general or even superintelligence as Artificial Intelligence, only one of all the answers retrieved was coded as such. This respondent critized the use of the term Artificial Intelligence as part of the survey, as according to him, it did not exist. Rather, the respondent preferred that the term “Super Robots” would be used instead. Unfortunately, it is not entirely clear why the respondent found the use of the term AI so problematic, nor is it completely straightforward if “Super Robots” would be in scope of the futuristic AI or the current robotic applications that are already being used. The answer “*Super robots are capable of doing things much better than humans but none of them are capable of doing anything they were not designed to do”* given does, on the one hand gives the reference to superintelligence, as they are better than humans, but at the same time, seems to refer to existing applications due to the incapability of doing actions they are not designed for.

However, in any case, this suggests that for most civil servants, AI is not associated with a futuristic technology. General and superintelligent AI doesn’t exist now and is likely to not make its appearance for many decades (or even centuries), although some reports and authors do refer to AI as the futuristic possibility of superintelligence [26]. For the respondents, however, this is not the case, and questions regarding the use of AI thus refer to more practical experiences of technologies they now consider AI, rather than this potential futuristic technology. At the same time, there are discussions regarding the ethics of AI and the academic debate on the AI alignment problem tend to discuss this form of AI. These discussions within the academic community may refer to totally different iterations of AI with other challenges and governance difficulties [31] – and this may not fully align or even cause confusion as civil servants have a different perception of what is AI technology [20, 52].

4.2 Artificial Intelligence as a learning technique:

A substantial part of the respondents responded to the question what they consider to be Artificial Intelligence a variety of answers linked algorithms, methods and techniques to learn systems and to possible mimic human intelligence. These answers (29 out the 159 coded answers) referred to this theme. Often, this included answers such as “*A set of algorithms capable of solving problems by connecting various sources of information and drawing conclusions from varied or* *incomplete information"* or "*Machine and deep learning tools that allow learning from an algorithmic point of view from input data, or iterative learning loops, to provide a result as close as possible to the expert's expectations."*.

These answers could be well interpreted as understanding AI as the algorithms or techniques dominant in the development of AI systems. This, as such, thus focuses on the *creation and design* of technological tools which can conduct intelligent tasks. Traditionally, the field of AI has always been about the creation of intelligent machines and finding the appropriate techniques, methods and algorithms to do so [25]. This art and science of creating intelligent machines are therefore referred to as AI [53], which is in line with an answer which mentioned the "*training of computers to perform intelligent actions by themselves."*.

In this perspective, the *methods or tools* during the creation are leading in explaining AI such as Machine Learning, Deep Learning, Bayesian methods, Conventional Neural Networks and more, changing over time [14]. In general, discussions within this perspective will focus mostly on the methods used to create the AI such as the various algorithms or approaches used to create higher-performing models [43].

One consequence here for research on the adoption of AI is the assumption that AI thus is used when an organization is utilizing these (one or more) analytical techniques on their data. The understanding AI as a learning technique is highly dynamic – as in the past other techniques were considered AI. Especially AI research up to 1980s, Symbolic AI research was the leading method into creating intelligent applications (Stone et al., 2016) – but may not be considered as such anymore.

Some of the respondents referred to these algorithms as *'intelligent algorithms*', which branch a variety of different backgrounds together, including mathematics, logic, computer science, cognitive science and neuroscience. In some cases, specific algorithmic techniques (considered to be AI) were mentioned in the answers of the respondents, such as machine learning, deep learning or neural networks, but more advanced jargon or specific statistical techniques, such as Bayesian methods, conventional neural networks amongst others, were not mentioned once. This is, however, in rather sharp contrast with some of the measurements currently in use to track "AI", as highlighted earlier.

4.3 Artificial Intelligence as an ability:

Most of the respondents answered various types of abilities and capabilities that are linked to the term "Artificial Intelligence". Following the coding process, 59 of the 159 codes are considered to describe some form of ability, the highest number of coded groups. In contrast with the previous set of answers, these respondents do not refer to the algorithms or techniques used in the development of the systems, but rather what AI can – or should - do. A consensus of the different abilities of AI was not found amongst the respondents, as many highlighted different actions that they consider AI to do, although several were mentioned a couple of times. These include, amongst others:

- Performing tasks are previously done by humans or imitating human intelligence
- Learning new things, learning from experience, and improving itself
- Conducting tasks autonomously or without human interference
- Capable of automating repetitive tasks
- Find connections, recognise patterns (in data), derive trends, create or predict

If computers, systems, or other forms of ICT are thus capable of portraying one of the following abilities, the more likely it is that they are considered Artificial Intelligence. In this perspective, the *ability to conduct intelligent tasks* determine whether we regard technology like Artificial Intelligence [54]. These unique capabilities are often enabled by the AI learning methods combined with the relevant data [43]. Most AI now tend to be able to do the tasks such as digital media recognition, pattern recognition, detection of speech and text, clustering and the detection of anomalies in large datasets [55]. Many respondents of the survey also identified more specific abilities other than the ones described above linked with AI, such as *"draw conclusions from data"*, "*capable of solving problems"*, "*detecting certain actions by analysing data"*, "*enabling the exchange of data safely and efficiently", (…) "report deviations (large or small) to the product owner or support"* or "*the possibility of having value-added tasks performed automatically"*.

It is possible that thus, solely assessing the AI learning technique is thus insufficient to identify AI, but its abilities and what tasks they perform should be regarded as the leading factor. It may be very well possible that some AI learning techniques are used – but that alone is not sufficient to regard something as "AI". In particular, the answers showed a strong tendency that Artificial Intelligence is either replacing or acting without the supervision of humans. In some way, AI could thus be better understood as 'automation' – which could be done by technologies that are based on techniques other than the learning techniques described before. However, not all – and especially AI used in the public sector – is acting completely autonomous, but often acts as decision support in combination with human expertise [56]. This may thus lead to difficulties in researching the adoption of AI in the public sector, since certain applications are not see perceived as AI due to lack of autonomous decision-making.

Similarly, as several respondents were mentioning that AI is capable of mimicking human intelligence or performing tasks requiring human intelligence, it may lead to challenges in defining if this task truly requires "intelligence" to be completed. There is not a sole answer to what can be considered intelligence. In fact, there seems to be little consensus whether machines will ever be able to be intelligent at all or whether an AI can be considered "rational'' creates further difficulties which exact abilities should be included [38]. Indeed, one respondent even mentioned that AI is to "*have non-intelligent machines do intelligent tasks*".

4.4 Artificial Intelligence as an application:

Many of the respondents also described a variety of systems, programmes or applications that they considered to be Artificial Intelligence. In this sense, 53 out of the 159 answers to the question were coded to be considered part of this theme of answers. The type of applications referred to be Artificial Intelligence varied greatly, but often referred to either programmes or computer systems, that are capable of adapting or learning to their own needs. Respondents would mention specific applications, such as "*A prediction tool created by humans to assist them in their prediction tasks based on input data"* or "*A system that answers your questions from a computerized system such as a chat box"* are examples of such answers given by the respondents.

Here, applications are considered differently from the learning techniques or algorithms that were described before. Instead, it focuses on the technological artefacts which are referred to as Artificial Intelligence [46]. These are the 'final products' such as applications, ICT-systems, interfaces or innovations in which AI capabilities are embedded and with whom users interact with [13]. These applications are services, products or information systems which enable – autonomously or in combination with people – the AI to provide services, insights or make decisions. Hence, respondents sometimes mentioned this integration of (machine learning) algorithms other times of software and hardware as AI, such as "*technology based on algorithms to enable machines/computers to analyse data, calculate, decide" "(…) is software that you can use not only to perform repetitive tasks, but that can quickly learn new tasks (…)"* or "*a function you can assign to a program, app, game, machine etc. to create or predict systematic things*". To a certain extent, some of the applications already identified by Wirtz et al., 2019 were also mentioned by some of the respondents. For instance, answers mentioned a system that automatically recognises a system through a recognition matrix, facial recognition, a system for preventing diseases, robots, and virtual assistants or chatbots.

Commonly these applications combine other software and functions in combination with the insights of the AI learning methods, creating a blurry field of how much the system is actual "AI" [57]. Furthermore, there are so many different types of applications that could be considered "AI" that it broadens the scope of the number of applications perhaps too wide. Indeed, one of the answers given highlighted this issue: "*Very broad: the word suggestions on my mobile phone, Google Home, a chatbot (…).*".

Each of these applications functions very differently, and one may only wonder if agreement can be found whether each of these specific applications is considered "AI" by all – and if so, whether the effects as discussed in the existing literature and policy discourse will apply to each of them. Even with chatbots, while the application and purpose may be the same, research has already highlighted the variety of complexity and functionalities each of these chatbots may have, leaving one to wonder if all chatbots are truly AI or not. The same accounts for the use of robotic process automation, which is considered to be AI by some [58] and not by others due to the lack of 'cognitive' decision-making [27].

4.5 Artificial Intelligence as a science:

There were 4 answers out of the 159 coded referring to the overall branch of science of Artificial Intelligence, a small minority. One of these answers, for instance, mentioned that Artificial Intelligence is "*A branch of computer science covering many different techniques that rely on data and learning to mimic human intelligence"* whereas another highlighted the *"set of theories and techniques for developing complex computer programs (…)"* which derive from the academic discipline. One of the respondents referred to goal and progress-oriented research focus of the field of AI, as he responded: "*Working towards the most autonomous technology possible based on self-learning algorithms*", highlighting the alignment of the goal-oriented field of study. However, in general, based on the responses, many civil servants do not often refer to the overall academic discipline or the science of Artificial Intelligence when asked what they mean with AI. Similarly, to the associations given with Superintelligence and General Intelligence, most of the associations that the respondents have with AI are practical – related to applications, capabilities, and the applications. One may find these the results or the output of the science of AI – rather the academic field itself.

4.6 Other:

Lastly, there were 13 answers coded in the residual category of "Other", as these answers did not fit in any of the other categories identified above. Some of these answers referred to what AI enables for society, such as "*A way to save time and jobs"* or *"A necessity"*. These residual answers show that despite the broad and diverse meanings and understandings that already exist in the literature, civil servants may still have a different association with the term. Future research could dive more deeper into other, less usual associations that civil servants may have with AI.

5 Implications for research and practice

As the responses show, the term Artificial Intelligence indeed has many different concepts and understandings amongst Belgium civil servants, and, consequently, when asked whether these civil servants are using AI could lead to a plethora of different answers and examples. However, based on the answers given, there are some main dimensions of categories on which to understand how policymakers may associate the term of AI with. In this respect, this may either AI as specific learning techniques, AI as an ability, AI as a specific application or a futuristic form of AI, or a mixture between them, as these dimensions support and even expand upon another. Each of these concepts also follow on the different stages of the adoption; from development & design towards the application and implementation of AI, with each phase having different requirements or study perspectives as a result [32].

More fundamentally is that, when researching the use of AI by civil servants for instance, is that merely using general definitions of AI may thus be insufficient to account for all the different ways this term is used. It thus, may be more fruitful to be more specific in the research and aim to differentiate between the different types of AI – whichever is the aim of the researcher – as to assist respondents into associating the requested 'kind' of AI. This is even more crucial due to the apparent gap that already in some surveys on 'general' AI usage and more specific applications, as can be seen in the latest European Commission survey on the uptake of AI in businesses [59]. A somewhat paradoxical finding of this survey was that a significant number of businesses reported that they are using AI already (45%), but when asked about specific applications, such as sentiment analysis or Chatbots, the percentage was much significantly lower, sometimes ranging in less than 5%, making the reader wonder if specific applications of AI are so rarely used, how come organisation report such a high uptake of AI?

Furthermore, similar difficulties could be identified if one would research the adoption of machine learning or other statistical techniques within public organisations. It is, indeed, very possible that organisations are using these statistical approaches within their organisation – logistic regressions, Bayesian methods or other quantitative analysis tools are commonly used within private and public organisations. However, just merely using these statistical approaches may not necessarily lead to the development of an AI application, or active use of the output of such models. As such, the uptake of AI learning methods may thus be higher than AI applications, as there may be various challenges from moving to the development of models using AI learning methods to practically using applications built on those. This dilemma can already be seen in various measurements based on tracking the 'progress' of AI. Most of these track the use of various machine learning terms or methods in scientific papers. This, however, says very little about what is the result of these models, how these models are consequently finalised and whether they are in active use in (public) organisations. It seems by some existing research that the uptake of the final applications seems much lower and more problematic indeed. For the research on the uptake of AI, one should also keep in mind that many of the 'successful' pilots of AI usage in government discontinue or are not used anymore after a while. In such a scenario, indeed, the learning methods of AI have been used in a government context, but real adoption and integration of the applications did not happen [56].

The same accounts for the potential reverse definition difficulties of these dimensions. If, for instance, a civil servant is asked about their organisation's use of AI applications, it may be possible that a response consisting of software, machines or other applications is given – but these may not necessarily be (fully) based on the learning methods considered AI by others. These applications may still be able to do tasks successfully or considered novel enough to appear like it is AI but may lead to disagreements to which extent it can be seen as AI by all. An example of such disagreements are recent articles highlighting that a large portion of "AI" start-ups may sell software or applications they sell as AI, but in fact, are not based on AI learning methods, leading to sharp criticism as not being 'truly AI'[2]. Future research could focus more deeply in the professional and/or academic backgrounds of the respondents, as this could shed a light how some identify Artificial Intelligence more closely with the learning methods, applications and/or other identified categories of this paper.

These limitations could significantly affect nuanced discussions on the uptake, effects and governance of the different facets involved with AI, as there are indeed many different challenges which require more research to understand the consequences of AI on society [60]. In this respect, much can for instance be learned from previous unclear concepts used in eGovernment research, such as Smart Cities. This has also led to various critical reflections of the term, as a recent publication on smart cities highlights as well [61]. Researchers as well as policymakers can have complete different understandings of what is considered a smart city, as well as how it should function [62]. What may be a potential solution for this issue is to conduct research with a more integrated view on AI, which aims to combine the different dimensions as discussed in this paper. It may thus be

[2] See e.g. "About 40% of Europe's "AI companies" don't use any AI at all, MIT Technology Review: https://www.technologyreview.com/2019/03/05/65990/about-40-of-europes-ai-companies-dont-actually-use-any-ai-at-all/

extremely worthwhile in research to describe a specific AI system with his ability, as well as which AI learning methods were used. Such an integrated approach also fits the definition as proposed by the High-Level Expert Group on AI by the European Commission, as well as the OECD.

With this paper, the research as well as policy community may be better equipped with additional insights on how different groups perceive AI differently – and the need to ensure comparability of the findings. This is not only crucial for improving the generalization of research findings beyond individual case studies, surveys or other studies, but also in ensuring that any negative consequences following the use of any AI system does not lead to unnecessary restrictions on the many other times of technology referred to as AI, which do other tasks and are developed in a different way. Future research may further explore why these different perceptions differ between civil servants, and to which extent professional backgrounds, familiarity with AI as well as how civil servants work with AI in their job influence how they perceive what is to be considered AI, and what is not. Furthermore, there is also room to explore differences in understanding of other concepts related to AI such as bias, AI governance, manipulation or exploration various unethical forms of AI uses in a follow-up study.

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Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union

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ABSTRACT

Artificial Intelligence is increasingly being used by public sector organisations. Previous research highlighted that the use of AI technologies in government could improve policy making processes, public service delivery and the internal management of public administrations. In this article, we explore to which extent the use of AI in the public sector impacts these core governance functions. Findings from the review of a sample of 250 cases across the European Union, show that AI is used mainly to support improving public service delivery, followed by enhancing internal management and only in a limited number assist directly or indirectly policy decision-making. The analysis suggests that different types of AI technologies and applications are used in different governance functions, highlighting the need to further in-depth investigation to better understand the role and impact of use in what is being defined the governance "of, with and by AI".

1. Introduction

Governments across the world have been highly interested in exploring the use of Artificial Intelligence (AI) to enhance their public services. Recent developments in machine learning, increased processing powers and the increased volumes of data availability through the widespread datafication of societies enabled the rise of a large variety of new AI applications. The combination of large, high quality datasets with machine learning enables these applications to complete tasks with similar or higher accuracy than humans, possibly leading to large disruptions in society (Craglia et al., 2018).

For public institutions, the integration of AI technologies within their public services could provide large benefits and public value to citizens, depending on the way they are used. Some highlight the potential value of AI technologies in the policy making process by making it more data-driven, enabling faster detection of social issues, better analysis of potential policy solutions with faster feedback loops after the deployment of new policy (Höchtl, Parycek, & Schöllhammer, 2016). Others stress how the adoption of AI technologies in government will make operations more efficient and effective, since common processes could be automated, staff augmented and empowered through the recommendations of AI systems (Mehr, 2017). Compared to other Information and Communication Technologies (ICTs) used by government, it is argued that AI will be much more impactful for citizens due to its possible deployment in core functions of governmental organisations and the learning character of the technology, likely to increase public sector performance over time and to influence decision making (Engstrom, Ho, Sharkey, & Cuéllar, 2020; Veale & Brass, 2019).

However, despite the positive claims often mentioned by the literature, vendors, consultants, and policy makers, very little is still known regarding the impact and value of the use of AI in the public sector (Bailey & Barley, 2019). This is partly due to the lack of effective adoption of AI technologies within the public sector due to various challenges hindering their uptake (Bérubé & Giannelia, 2021; Sun & Medaglia, 2019), but also due to the lack of comprehensive impact studies of AI in a public sector setting (Kuziemski & Misuraca, 2020). Studies which do explore the use of data-driven technologies within the public sector often highlight that their integration into existing work practices is troublesome (Bailey & Barley, 2019; Kolkman, 2020) or find that the political and unstructured nature of policy making contrast the technical-rational viewpoint of improving decisions with data (Vydra & Klievink, 2019). A recent overview by (Zuiderwijk, Chen, & Salem, 2021) shows that the existing literature on AI in government describes various categories of potential benefits that AI could bring, but that there are risks to the use of AI in government as well.

The aim of this paper is to build on this narrative, and builds on an

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enriched review of the cases gathered by the AI Watch landscaping in 2019–2020, following the insights from a preliminary analysis on the use of AI in public services. This analysis showed in fact AI technologies and application are currently used for many different goals but little evidence of their impact exists yet. This limits generalizations and theory building on how AI gets used by government actors, but also for which function and with which effects. Hence, in this paper, an attempt is made to highlight to what extent AI is used to support specific governance functions, namely, policymaking, public service delivery and internal management, illustrating the potential of impact with some cases. To this extent, this research aims to understand how AI could be used to improve governance functions of public administrations and the broad underlying research question could be framed as follows:

What evidence exists of the effects of using Artificial Intelligence for improving core governance functions in the public sector in the European Union?

In doing so, firstly, an overview of the analysis of recent literature on AI in government is provided to understand for which governance functions AI could be used. This is followed by an overview of the specific benefits and risks of using AI for the three main governance functions of government defined in relevant literature and categorized as: policymaking, public service delivery and internal management by (Misuraca & Viscusi, 2013). Some short case studies of AI use in each area, selected from the sample analysed as part of the landscaping of AI in the public sector underpinning the research are then described to illustrate how some of these benefits and risks as described in the literature manifest themselves in practice and to which extent current use of AI relates to the different functions of governance. The paper concludes outlining the key findings and drawing some recommendations for policy and future research.

2. Strengths and shortcomings of AI in government

Despite the recent high interest into Artificial Intelligence, the concept is still ill-defined and has changed over the last decades. It is generally accepted that the term AI and the dedicated research has its origins in the 1950s, when many scholars started publishing new research on the creation and design of intelligent machines (Stone et al., 2016). Current advances in learning and development of software systems capable of doing "intelligent" tasks often is the result of large datasets combined with machine learning algorithms (Desouza, Dawson, & Chenok, 2020). Given enough data, machine learning algorithms can in fact discover patterns in the data themselves, leading to the creation of highly predictive models (Preece, Ashelford, Armstrong, & Braines, 2018). Combined with existing software and/or hardware, it is increasingly possible to let the machine provide advice, predict next steps, or even make decisions by themselves, with little human supervision, if any.

In doing so, AI is considered in as a 'special form' of ICTs, capable of displaying intelligent behaviour and completing tasks normally said to require human intelligence. As a result, AI applications are often capable of perceiving and detecting contents from audio, visual and textual information (Agarwal, 2018; Sun & Medaglia, 2019), detect anomalies in the data and make more substantive predictions (Centre for Public Impact, 2017), predict, plan, control and many other applications (Mikalef, Fjørtoft, & Torvatn, 2019; Zuiderwijk et al., 2021).

This classification also complies with the definition advanced by the European Commission in 2018[1] and builds on findings from exploratory research that identified a number of common 'types' of AI in the public sector, in which these capabilities embed themselves, such as Virtual Agents, Recommendation systems, Cognitive robotics & autonomous systems and AI process automation systems (Mikalef et al., 2019).

In general, the use of AI in the public sector will either be used to automate processes or to "augment" human decision makers (Veale & Brass, 2019), by for example making redundant activities less cumbersome and by serving as decision-making tools for experts (Mikalef et al., 2019). Interestingly enough, in the past, similar discourse can be found on the benefits and risks of using AI in government, despite this 'AI' refers to traditionally programmed ICT systems rather than those based on machine learning that are being discussed mostly today (Barth & Arnold, 1999; Susskind, 1990).

Many of the benefits ascribed to AI for the public sector are not always based on empirical data, but often rely only on assumptions. Validation of their expected positive effects are so far limited due to, first of all, the limited adoption of AI in public administrations and the lack of thorough impact assessments which indeed highlight the effects of AI after their effective deployment (Kuziemski & Misuraca, 2020).

In fact, most of these mentioned benefits are overshadowed by various challenges which can limit their results, also because many AI innovations do not reach scalability (Zuiderwijk et al., 2021). This could be due to data issues, the quality of the AI application itself, unintended consequences through human interactions or simply the fact that structural social issues remain unsolved, despite AI (or other technology), or even reinforced and emphasising possible social biases and discriminations. As a consequence, still little is known about the actual effects following the implementation of AI within government processes (Bailey & Barley, 2019), and it is likely that positive or negative effects will depend on the time, function, kind of AI, used data and many other environmental factors. The many research gaps present in this area of analysis are therefore calling for further in-depth investigation and experimentation, which is demonstrated by the great interest in better understanding the effects of using AI for the public sector, as it is argued it can greatly improve policy making, enhance public service delivery and strengthen internal management, as we illustrate in the following sections, based on our extensive review of literature and cases.

2.1. AI supporting policy making

One of the potential impacts of Artificial Intelligence in government is to improve the various stages of policy making. Researchers have traditionally been keen on using the policy cycle theories to describe and understand the different processes of how public policy gets designed and implemented, as it provides an comprehensible conceptualization of the complexity of policymaking: agenda setting, policy formulation, decision-making, policy implementation and evaluation (Bridgman & Davis, 2003; Höchtl et al., 2016). AI applications for policy making functions follow this existing research agenda on data-driven policy making and evidence-based policy as they continue the trend of making governmental policy more based on 'facts', make decision making based on better analytics, more accurate or less uncertain (Vydra & Klievink, 2019). In this respect, it is argued that the key benefits of using AI in the policy process is to increase the effectiveness, efficiency and legitimacy of the various 'steps' in the policy making process (Pencheva, Esteve, & Mikhaylov, 2020), which in return will make the resulting policy better as it is more data-driven which augments the decision-making capacity of people (Mcneely, Hahm, & on., 2014).

As such, it is highlighted that the use of big data technologies and AI can facilitate the detection of social problems and the preferences of citizens more accurately, faster, and efficient than traditional techniques such as surveys (Pencheva et al., 2020). The inclusion of various online data sources and/or through the sensory input provided by AI applications further assist in gaining insights from sources previously not considered in policy making (Kankanhalli, Charalabidis, & Mellouli, 2019). By detecting social problems more accurately and faster, it could enable quicker policy responses before they escalate (Höchtl et al., 2016). Similarly, it could be possible to forecast social problems by

[1] 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 on Artificial Intelligence for Europe, Brussels, 25.4.2018 COM(2018) 237 final

combining data together so that policy may be enacted to ensure that these issues do not manifest themselves (Margetts & Dorobantu, 2019), giving birth to what has been termed anticipatory governance (Guston, 2014) or Policy Making 2.0 (Misuraca, Mureddu, & Osimo, 2014).

Following, AI could also assist in the decision making process by devising policy alternatives, providing more in-depth ex-ante policy evaluation, enabling analysis of sentiment of citizens on various policy options or improve the participation of citizens in designing policy alternatives (Desouza & Jacob, 2017). AI based on data mining techniques on large datasets which may lead the way to new understandings of a policy problem – including a new solution (Mehr, 2017). The use of algorithmic models – which could be based on various machine learning techniques – are used extensively within policy making to predict ex-ante what the effects of policy will be such as expected costs (Pencheva et al., 2020) or can help in discovering variables influencing the results (Loukis, Maragoudakis, & Kyriakou, 2020). Their usage in policy making can assist in placing issues on the policy agenda, aid in consensus forming and adoption in all stakeholders while creating a perceived objectivity in their results (Kolkman, 2020). For complex modelling functions, AI could potentially assist in creating potential future scenarios (Margetts & Dorobantu, 2019; Misuraca, Geppert, & Kucsera, 2018).

The use of AI within the policy making process has also been argued to make its process more inclusive, as it enables new ways to include the participation of citizens and to include the voices of citizens who may be overlooked using traditional methods. Automatic translation of documents may allow minorities to express their preferences and AI may enable citizens to be more engaged to their politics and be more informed (Savaget, Chiarini, & Evans, 2019). The analysis of social media data may bring the preferences of citizens into the design of new policy proposals and allows the consideration of discussions on social media within the policy domain (Cardullo & Kitchin, 2019). AI technologies may also assist policy makers in analysing large volumes of citizens' input through online consultations, facilitating to gain insights despite the wide scope and nuance of some of the contributions (Chen & Aitamurto, 2019).

However, administrations must be mindful with using AI for policy making, as there is the tendency to believe that automated decisions based fully based on data are automatically better than human decisions. In reality, this is not necessarily true, and in fact in most cases these decisions are based on data of poor quality, or biases, which may emphasise the risks of taking wrong decisions based on an inaccurate or partial picture of reality.

Several researchers have in fact pointed out that data is never neutral but has always intrinsic biases due to the culture in which they are generated, collected and analysed (Janssen & Kuk, 2016; van Dijck, 2014). There are demographics within societies which are structurally less involved in formal and data generating activities, and thus, provide less data, negatively impacting policy making and public services (Giest & Samuels, 2020), which is especially relevant for the use of social media data (Boyd & Crawford, 2012). Consequently, some data may be outdated, incomplete or wrong, which leads to biased results. Using biased input data for AI– even when actors are not aware of this – will therefore lead to unreliable or discriminatory results (Barocas & Selbst, 2016). Furthermore, given enough data, AI will always find some correlations – but it is very questionable if these insights are actionable, truthful or even correct and not just 'fool's gold' (Smith, 2020) and not as regarded by many the 'ground truth' for data-driven decisions.

2.2. AI for improving public service delivery

AI-systems could be used to improve the delivery of public services to businesses and especially citizens directly, either by using Chatbots or through personalized services based on the citizen's characteristics and information available (Androutsopoulou, Karacapilidis, Loukis, & Charalabidis, 2019). The combination of Big Data and AI has been argued in fact to have the potential to greatly enhance government performance and public service delivery efficiency, saving money and increasing productivity (Pencheva et al., 2020). By connecting various data sources and clustering users into specific groups, public services may be changed to facilitate personal needs, potentially making the effectiveness and acceptance of these services higher (Veale & Brass, 2019). This may be combined with making public services more proactive; AI-enabled public services could automatically allocate services rather than that citizens ask for the services themselves (Kuziemski & Misuraca, 2020). In particular, public services which rely heavily on (accurate) data benefit significantly, as information can be gained at a lower cost (Pencheva et al., 2020).

Consequently, the automation of public service delivery can reduce the need for businesses and citizens to meet civil servants face to face, or potentially avoid the need to go to an administration's office at all as transactions can be fully completed online. Mundane and repetitive tasks, such as responding to frequently answered questions, could potentially be automated by AI technologies to free up time for civil servants for other tasks (Mehr, Ash, & Fellow, 2017). Ideally, the time which made free enables civil servants to dedicate more attention on value-adding activities they otherwise would not be able to do, such as personalized care for citizens which require it (Sun & Medaglia, 2019).

The removal of human decision makers through automation with AI technologies could also improve the legitimacy and trust in the delivery of public services, especially since the use of automated decision makers create a tendency of neutral decision making – even when the machines are biased. This may be particularly true for citizens with distrust in the bureaucratic decisions or to control and reduce corruption (Miller & Keiser, 2020). Moreover, through the monitoring capabilities provided by AI and/or the combination of sentiment analysis of complaints or users' requests, it may be possible to further understand and improve citizen's satisfaction with public services.

However, the use of AI in public service delivery is not without its challenges. Like with policy making, AI systems could provide biased recommendations or enabling making biased decisions. This could lead citizens being trapped in 'bureaucratic digital cages' where not their voice but their data – even when incorrect – is the leading factor in the provision of public services (Peeters & Widlak, 2018). Similarly, the design of the AI systems requires developers to make political decisions which may be difficult to detect or correct when wrong (Mulligan & Bamberger, 2019), changing the political decisions underpinning an existing public service. This is especially relevant as there is often limited political or citizen oversight in the design and the deployment of where, when, and how AI systems get used in government services.

Despite the intention that civil servants should be working "with" AI, the lack of transparency and explainability of automated systems, as well as the impossibility to contest the results and the strong managerial pressure to follow the "machine" recommendations, could lead to a scenario where the AI system is ultimately "making the decision", turning the intention of governing with AI into governing "by AI" (Misuraca, 2020). In practice, machines then determine and administer the rules of a state (Danaher, 2016). Having many, expensive and opaque algorithmic systems of which the performance is unclear may finally reduce, rather than improve, the effectiveness and legitimacy of government organisations (Andersson, Hallin, & Ivory, 2021).

2.3. AI for enhancing internal management

The use of AI technologies is also a great driver to automate and enhance the internal management operations of the public administration which in turn will improve the organisational effectiveness, efficiency and quality of the services delivered to businesses and citizens (Engstrom et al., 2020). Commonly, AI used for internal management can be utilized for a more effective and efficient allocation of resources, including financial and human resource management, leading to an overall better administration and staff performance. AI is also increasingly being for inspection or policing tasks, to decide for instance where staff has to inspect, which areas to prioritize or even which individuals to keep in check (Benbouzid, 2019). For operational tasks, AI models can be used to assist in observing how civil servants are performing (Pencheva et al., 2020) and how resources are used, helping in the elimination of repeated activities or other inefficient processes. AI technologies are also deployed to identify objects in need of maintenance (van Veenstra, Grommé, & Djafari, 2020) and improve the security – especially cybersecurity of the internal networks of the public administration by anticipating and detecting cyberattacks (Mehr, 2017). One of the most common mentioned benefits of using AI in the public sector is in fact the possibility to detect fraudulent transactions; either fraud from citizens (Eggers, Schatsky, Viechnicki, & Eggers, 2017) or by tackling corruption of staff (Lima & Delen, 2020) and increasing the possibilities for conducting audits (Bullock, Young, & Wang, 2020).

Another upcoming use for AI is within public procurement, by supporting procurement processes in a variety of different ways, such as the drafting of contracts, providing information, assisting in procurement decisions to acquire the best value deals, identify tenders at risk of corruption and automating processes for reducing risks of errors or wrongdoings. This can enable more correct and accurate procurement offers, less projects going over budgets, improving the efficiency of the procurement processes, save costs and eliminate administrative burdens (van der Peijl, O'Neill, Doumbouyam, Howlett, & de Almeida, 2020), and (Mcbride, van Noordt, Misuraca, & Hammerschmid, 2021).

An overview of the use of AI in each governance function (according to the categorisation made by Misuraca & Viscusi, 2013 and following the descriptions of AI deployment in government identified in the mapping conducted as part of the research underpinning this paper can be seen in Table 1:

3. Methodology

This paper is based on an enriched review of the analysis of the data set of cases built over time as part of the AI Watch research on the use and impact of AI in public services. Following the insights from the landscaping of the use of AI in public services in the EU the analysis expanded the number of cases and the scope of the review. In doing so, the use and potential impact of AI to support specific governance functions, have been researched and findings are illustrated with some qualitative cases.

Building on this exploratory analysis, as anticipated in Section 1, this paper thus addresses the following broad research question: *What evidence exists of the effects of using AI for improving core governance functions in the public sector in the EU?* The original inventory of cases was gathered

Table 1
Overview of AI functions in government, authors' own elaboration.

Governance function	Potential AI use
Policy making	1. To detect social issues more quickly 2. To improve public policy decisions (and to estimate potential effects of policy) 3. To monitor the implementation of policy (and to evaluate existing policy) 4. To enhance citizen participation in policy making
Public Services	1. To improve the information services of the organization 2. To improve public service delivery to businesses and citizens 3. To develop new innovative public services
Internal management	1. To improve the allocation of human resources 2. To improve recruitment services of the public organization 3. To improve financial management of the organization 4. To improve the detection of fraud and/or corruption 5. To improve maintenance 6. To improve public procurement processes 7. To improve organisational (cyber)security 8. Other

as part of the dedicated research strand of the AI Watch, an initiative of the European Commission's Joint Research Centre and DG CONNECT. The AI Watch is a research unit within the Joint-Research Centre tasked with monitoring the industrial, technological, policy and research AI Landscape within the EU (European Commission, 2018). As part of these activities, the AI Watch is conducting research into the use of AI in the public sector in collaborating with Member States, allowing for a reliable overview of various case of AI use in government.

The cases were collected with variety of data collections methods over a period between 2019 and 2020, through a combination of desk research on policy documents, AI strategies, the EU AI Alliance, academic sources as well as practitioner reports on the use of AI in government. Additional information regarding cases of AI used in government were gathered through the organization of a workshop in February 2020, interviews and a survey circulated among representatives from Member States in which additional cases of AI where collected. Duplications collected in this period referring to the same AI use case have been removed from the inventory. The research activities of the AI Watch are still ongoing, and cases of AI are still being collected and analysed. A subset of the cases collected in the database can be found as open data[2] on the JRC Open Data Catalogue for additional analysis.

Following a review of the cases for this paper, some initiatives referring to the use of AI within hospitals were also excluded for the inventory, leaving to an analysis of $N = 250$ cases of AI currently being deployed within EU public administrations.

However, several limitations hamper the in-depth analysis of the dataset. First, given the broad spectrum of countries under review, not all information regarding AI-cases is available in languages accessible to the researchers, limiting understandability of specific details needed to assess possible results and impact.

Likewise, Artificial Intelligence is an umbrella term for many different technologies and applications. There is currently no consensus on what kind of technologies or applications could be considered AI or not. Some member states might refer to some applications as AI whereas others would not classify this application as such. This is especially relevant as some make distinctions between the use of AI methods (de Sousa, de Melo, Bermejo, Farias, & Gomes, 2019), the use of AI applications (Wirtz, Weyerer, & Geyer, 2019) or have a completely different understanding of what is to be considered AI or not (Krafft, Young, Katell, Huang, & Bugingo, 2019).

For this reason, instead of attempting to propose a specific definition on AI for the public sector, we adopted the classification already proposed in based on 10 application domains – called 'AI typologies' (see Fig. 2 below) which is broadly aligned with both the operational taxonomy proposed by the AI Watch and that one, specific for AI in government - also based on 10 domains, by Wirtz et al., 2019.

Moreover, to perform the specific analysis for this paper, each case in the dataset has been coded with regard to the use of AI to support specific governance functions, namely policy making, public service delivery and internal management. The coding was based on the description provided on each of the AI use case, as often it said for which goal the AI has been developed or is being used within the public administration. In some cases, due to ambiguity of the function of the AI use case, additional information was gathered through the links and sources of the AI use cases to build the classification. Future research should however possibly contrast the findings with interviews to case owners and in-depth case studies.

[2] The subsection of AI cases in the public sector can be found here: https://data.jrc.ec.europa.eu/dataset/7342ea15-fd4f-4184-9603-98bd87d8239a

4. Findings

4.1. Overview

As can be seen in Fig. 1, the inventory covers 30 European countries, including all the 27 Member States of the European Union, Norway, Switzerland and the United Kingdom. The sample however is not statistically representative as there are significant differences between the various countries with regard the number of cases, especially if compared with their population or other socio-economic indicators, including the GDP expenditure in the public sector. Many cases in the inventory come in fact from small countries, such as the Netherlands, Portugal, Belgium, Denmark and Estonia, whereas some countries, such as Greece and Luxembourg are only represented with 1 case in the inventory. It is very likely that more AI is being used in all of the countries and that this inventory should be only the surface and should have been used as a first baseline to start a structured monitoring exercise over time.

Based on the classification adopted in the inventory classifies the different use cases in 10 AI typologies. The typology of AI most included (57 out of 250) in the inventory, as can be seen in Fig. 2, belongs to the category of "Chatbots, Intelligent Digital Assistants, Virtual Agents and Recommendation Systems", which refers to the different virtual assistants or Chatbots used to provide advice to their users. This is followed by AI classified as some form of predictive analytics and those using Computer Vision.

Although this classification was proposed as initial and may be changed in the future once a better classification will be developed based on further evidence collected as part of the AI Watch, or other efforts at pan-European level, it proves functional to the scope of our investigation as it allows to discern what type of AI is used to support the different governance functions.

In this respect, the analysis shows that some types of AI applications are more used for some governance functions than for others, as seen in Fig. 3. For example, 10 out of the 13 AI use cases classified as Security Analytics and Threat Analysis are used to support the internal management of the public administrations, while all the AI types belonging to "Audio Processing" and almost all the Chatbots (53 out of 57) are introduced for improving public service delivery rather than for policy making and internal management functions.

This confirms that, while AI could be used for many different goals as highlighted also in recent literature (e.g. Valle-Cruz, Criado, Sandoval-Almazán, & Ruvalcaba-Gomez, 2020), it seems that specific AI applications are used and are likely to have a major potential impact for dedicated governance functions. Knowing for which function of the government AI is being deployed within the public sector is of high importance to better design strategic interventions and tailor impact assessment studies to understand their effects and ((Kuziemski & Misuraca, 2020) and possible replicability in other contexts and areas.

A more in-depth overview allows us to provide specific insights for each function.

4.2. AI for policy making

From the analysis of the sample, 59 (24%) cases seem to be used to support policy making, seen in Fig. 4. In the cases reviewed, however, AI often takes a supportive role within policy making processes, rather than fully automating or 'taking over' political decision making Clearly, to really measure the effects and impact of AI within the decision-making processes is challenging, as policy decision making is influenced by a large variety of factors of which the insights of the AI could be only one of the elements to be considered (Bailey & Barley, 2019; Vydra & Klievink, 2019). Nevertheless, the use of AI to improve policy making processes seems to be already expanding as demonstrated for instance by the overview on the use of AI in the United States federal agencies (Engstrom et al., 2020), and it is expected to further grow in the future, as anticipated by some scholars, (Sætra, 2020), calling for better understanding the governance "of, with and by" AI (Misuraca, 2020).

More specifically, 20 out of these 59 cases could be understood as using AI to detect social issues faster than before. As discussed earlier, this may be done through detect issues through data analysis or by including more 'eyes and ears' within the policy domain. These 'perceiving AI' could for example be cameras with object detecting capabilities. These systems could assist monitoring what is occurring in the policy domain and the data obtained from AI could then consequently be analysed again in combination with other data sources to better understand the specific social issue at stake. For instance, in Tallinn, the city administration deployed an AI system to analyse data from traffic cameras to detect different types of vehicles driving across the city. These were then used as input for road building planning and traffic management decisions[3]. While the system has a satisfactory accuracy rate, it is reported that the accuracy of the detection is affected by weather conditions and currently does not include all traffic users, such as pedestrians and bikes. Therefore, a significant subset of traffic users is not represented in the use of this AI application for policy making, which may lead to more decisions that do not take into account all their traffic behaviour.

Other cases (12) in the sample have a more direct relation to the process of decision making, either by assisting in the preparation of policy options or by creating models used for ex ante assessment of alternatives through simulation. For example, in Malta, the Pharmacy of Your Choice platform planned to use AI to devise new preventive care models to create better health outcomes for the Maltese society[4]. This application of AI is expected to be able to use data of over 143,000 different citizens from over a period of 10 years. In particular, it is assumed that the use of these models will make healthcare more effective and less costly. However, quite surprisingly, not many examples of policy modelling are found in the dataset, apart from the platforms which are developed to enable policy makers to make new policy models through AI. This could be in part due to the fact that the use of policy modelling could not be reported as "AI", despite the fact that the analytical techniques underpinning the approach are based on machine learning algorithms. Adoption more in depth investigation is therefore required to shed more lights on this issue.

The majority of AI applications included in the sub-sample related to policy making is instead concerned with monitoring the implementation of a specific policy – and to possibly measure its effect (21 out of 59). One example is the use of cameras using Computer Vision to detect whether drivers are holding a mobile phone while driving their car as can be seen in both the Netherlands[5] and in Belgium[6]. These systems are implemented to assist the police in enforcing the existing regulation on the use of mobile phones while driving. Enforcement by human police officers is in fact resource intensive and this is why police agencies find great merits in the use of these AI applications, despite the need to careful manage risks of privacy intrusion and protect individual liberties and human rights. Other AI applications are being deployed to measure the success of policy, such as in Cyprus where an AI system has been developed to systematically assess the effectiveness of social protection services by collecting and analysing different data regarding health and social care.

While AI could greatly facilitate citizen participation, only 4 cases of AI used to increase citizen participation were found. One example is CitizenLab, which is a citizen participation platform which is currently

[3] https://www.kratid.ee/tlt-kasutuslugu

[4] https://malta.ai/wp-content/uploads/2019/11/Malta_The_Ultimate_AI_Launchpad_vFinal.pdf

[5] https://www.om.nl/actueel/nieuws/2020/11/12/openbaar-ministerie-start-digitale-handhaving-op-handheld-telefoongebruik-achter-het-stuur

[6] https://www.vias.be/nl/newsroom/succesvolle-test-met-camerasysteem-om-gsm-gebruik-achter-het-stuur-te-detecteren-/

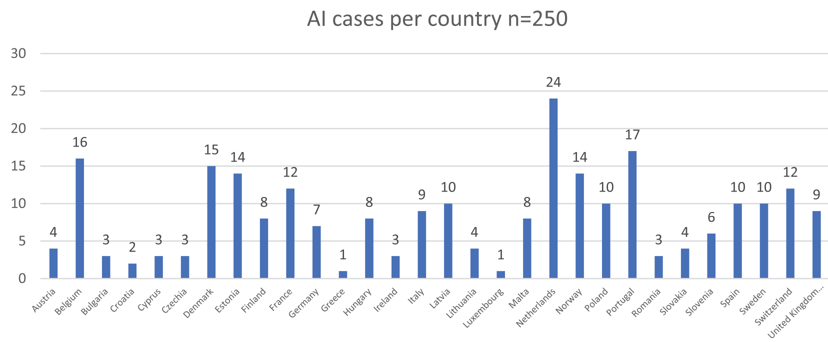

Fig. 1. AI cases per country in the inventory.

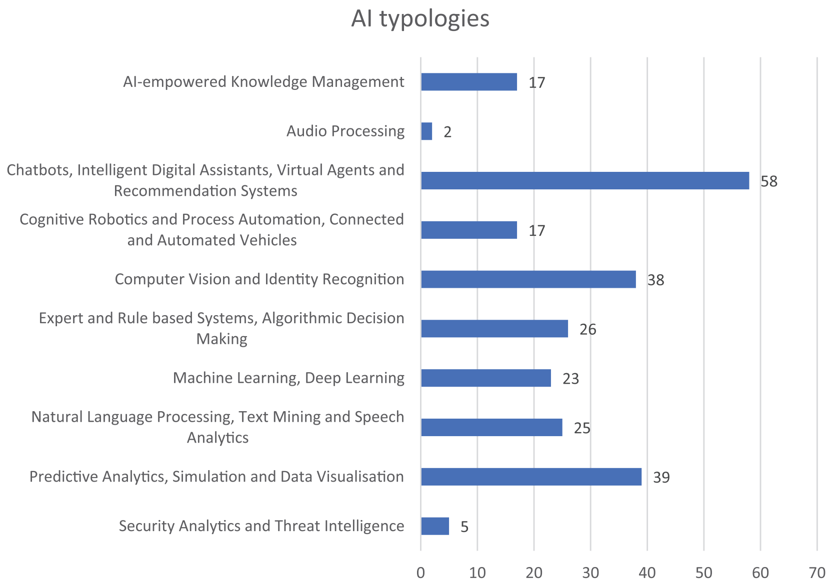

Fig. 2. AI typologies in the inventory.

used in over 275 different municipalities. The platform offers AI functionalities to analyse the input of citizens and to aggregate the feedback given to municipalities. Similarly, the app "Tvarkau Vilnių[7] (I fix Vilnius)" used in Vilnius, Lithuania, is introducing AI-elements to further improve the information provided from citizens regarding the issues citizens encounter in the city and requires action from the municipality, making emerge the need to better structure the knowledge gathered through interaction with different stakeholders, with the administrative processes and the policy making mechanisms (Misuraca, Barcevičius, & Codagnone, 2020). An overview of the use for policy making purposes can be found in Table 2below:

4.3. *AI for public service delivery*

With regard to the use of AI to support the delivery of public services to citizens and businesses, the sample includes 115 cases, seen in Fig. 5. In this respect, however, a differentiation should be made between cases where AI is used to improve information provision to citizens (51 cases) and those cases in which AI play a supportive role in the delivery process and/or to automate the transaction of services (44 cases). In many of the cases in which AI is assisting in the information provision to users, Chatbots represent the great majority. These are often seen as simple but easy to implement AI application which can help citizens search the information that they may need. For instance, several Chatbots were introduced in public administrations to answer questions regarding the Covid-19 crisis.

Chatbot "Mona", as used on the Austrian Company Service Portal (USP)[8], is one example of such a Chatbot. Mona was introduced to answer questions for companies regarding changes due to the coronavirus crisis, such as labour law, subsidies, organising teleworking and more. The service of the Federal Ministry for Digitization and Business Location (BMDW) is available online on the "Unternehmens Service Portal" (USP, Company service portal) website and can also be used on mobile devices. In practice, in addition to a classic information channel

[7] https://tvarkaumiesta.lt/

[8] https://www.usp.gv.at/index.html

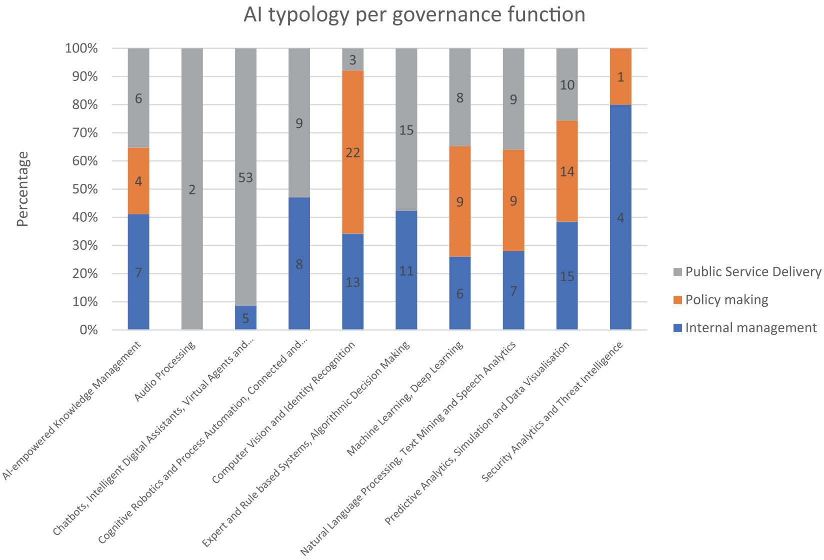

Fig. 3. AI typology per governance function.

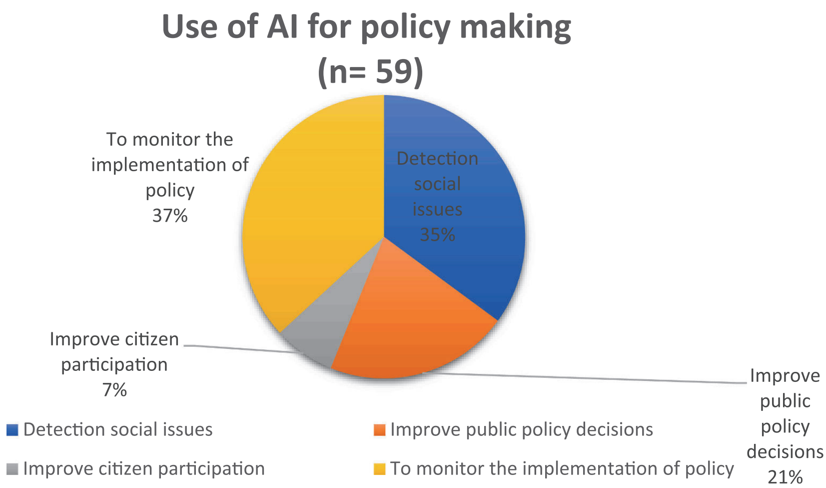

Fig. 4. Use of AI for policy making.

in which more detailed information is provided step by step, users can ask freely formulated questions and answered "in real time".

As mentioned before, other cases of AI are used directly to enhance public service delivery mechanisms or aim to assist the civil servants providing the public service by "augmenting" their skills, replacing mundane tasks or providing insights on the citizen or business requesting the service. One example is the JobNet AI system[9] used in Belgium. This is an AI system which assist the civil servants at the Flemish Employment and Vocational Training Service (VDAB) in the reskilling, upskilling and retraining of citizens. Following other examples also experimented in the USA, UK, France and The Netherlands, among others, Jobnet combines many different AI-models and data sources into one AI application which helps citizens to better identify their own skillsets, which jobs fit their skillsets and which jobs they could do with some minor reskilling.

Alternatively, AI can be used to completely introduce new public services (19 cases). This may be the intention – but not yet the reality – as can be seen with the AI experiment of Espoo[10], Finland, where social care and healthcare data was analysed to detect patterns of service provision. This analysis would be the basis for providing new proactive

[9] https://www.agoria.be/nl/VDAB-gebruikt-AI-om-jobmatching-te-verrijken

[10] https://www.espoo.fi/en-US/City_of_Espoo/Innovative_Espoo/Glimpses_into_the_future/AI_experiment_phase_1_Helping_artificial(133974)

Table 2
Overview of use AI for policy making.

Use of AI for policy making	Illustrative example	Description
To detect social issues more quickly	Traffic Detection, Tallinn	Cameras installed in the city assist in the detection of traffic load, which may lead to new traffic management policy.
To improve public policy decisions (and to estimate potential effects of policy)	Pharmacy of Your Choice policy models, Malta	Use of policy models based on AI and large health data is expected to lead to better healthcare policy.
To monitor the implementation of policy (and to evaluate existing policy)	Detection of driving with a phone, Netherlands and Belgium	Implementation and enforcement of traffic regulation is enhanced through cameras with Computer Vision.
To enhance citizen participation in policy making	CitizenLab	Contributions from citizens on the citizen participation platform are analysed through AI.

currently being evaluated to assess whether the care robots do improve the quality of life for the elderly. If the results are positive, there is the intention from the city administration to use more robots within the city as part of their social services provision.

An overview of the cases for public service provision can be seen in Table 3 below:

4.4. AI for internal management

Out of the sample under analysis, 76 cases out of the 250 (30%) have been classified as being used for internal management by the public administrations to streamline and improve their administrative procedures and organisational structures, seen in Fig. 6. This is done by using AI to improve the recruitment services of the public administration (three out of 76), such as the robot Tengai used in the Swedish municipality Upplands-Bro to make the recruitment processes less biased. AI technologies could also be used to improve the allocation of human resources (16 out of 76) to better match skills and expectations with job tasks and career perspectives A more sophisticated, though controversial

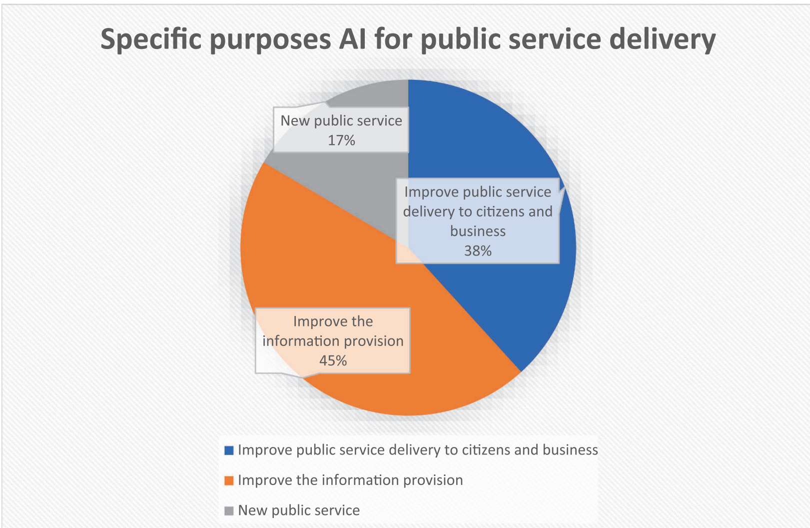

Fig. 5. Use of AI for public service delivery.

public services, mostly acting as a preventive measure to anticipate or limit future conditions of illness of unemployment for instance. Following the analysis however, no further implementation has taken place as the change towards preventive public services based on the data analysis was controversial from an ethical perspective and more research was deemed necessary to better understand how such services should be implemented in full compliance with data protection rules, while balancing the collective interest with the respect of individual rights (on this see Misuraca, 2021). Nevertheless, robots are already being used successfully to deliver new public services, such as the case of Barcelona demonstrates. The robot Misty II[11] is being in fact tested by the Municipality to see whether it can be used in elderly care, by tackling loneliness, helping the older adult population live longer at home and overall improving their quality of life. The experimental use of Misty is

[11] https://www.barcelona.cat/infobarcelona/en/tema/senior-citizens/misty-ii-the-social-robot-becomes-part-of-the-lives-of-twenty-senior-citizens_907645.html

approach, is that of AI systems such as the Early Help Profiling System (EHPS) which was used in London, United Kingdom, to help public managers analyse a large variety of data to identify children and families which are vulnerable or at risk of child abuse. With the support of the

Table 3
Use of AI for public service delivery.

Use of AI for public service delivery	Illustrative example	Description
To improve the information provision services of the organization	Chatbot Mona, Austria	Assists public administrations in providing trustworthy information to companies about related issues.
To improve public service delivery to businesses and citizens	Jobnet AI, Belgium	JobNet assists citizens and civil servants in making more tailored retraining or job suggestions based on AI.
To develop new innovative public services	Misty II, Barcelona	The deployment of robots in elderly care to improve the quality of life and wellbeing.

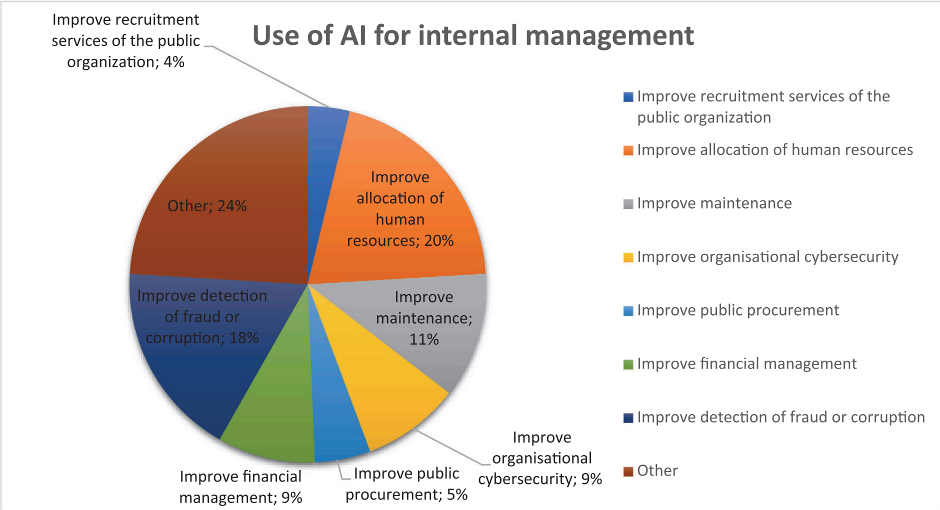

Fig. 6. Use of AI for internal management.

analysis, social workers can focus their attention on the selection of families provided by the system, and then decide which family to provide with an early intervention support programme, with the assumption that it is more likely to have more impact. Needless to say is that the system is currently not in use anymore following critical remarks and failing to realise expected benefits (Dencik, Redden, Hintz, & Warne, 2019).

Another common use of AI for internal management is related to those cases where of assistance in the maintenance of assets and other resources the public organization manage, directly or indirectly (nine cases). While quite like the allocation of human resources – as often predictive maintenance requires someone to do the maintenance - it was chosen to differentiate these functions as one is clearly more connected to the distribution of time of personnel while the other is mostly concerned with the maintenance of assets, as the example in the city of Stockholm[12] shows. Here an AI system is being used to provide better predictions to reduce water leakages and to plan maintenance accordingly.

The sample also includes seven cases in which AI is used to improve organisational (cyber)security by, for example, automatically detecting security risks, cyberattacks or other irregularities on the organisational IT systems. For example, the AI application used within the X-Road IT system and the related network of computers of the Estonian government, the Estonian Data Exchange Layer, is being monitored by an AI application used by the Information System Authority (RIA) to detect anomalies on their network[13].

In four cases there was a clear goal to improve public procurement processes of the public administrations. One such example is the AI application “QuickScan Organisaties” made available for use in Belgium[14]. The aim is to automate the business assessment process during public procurement so to reduce the time for the procurer and the supplier of the service using a risk-based approach.

Another use of AI to support internal administration regards financial management, with seven cases identified in the sample. An example of this is a system used in the Norwegian Government Agency for Financial Management, where AI is used to help customers with the correct posting of invoices to avoid having to spend time and resources on incorrect invoices[15].

Similarly, a sizable portion of AI cases are used to improve the detection of fraud or corruption (14 cases). While this domain of use is part of the financial management, due to prevalence of systems being used for fraud prevention and the hot debate it has generated, it was decided to make it a separate group. Some examples include the use of a fraud detection algorithm in the French Customs to help detect false or fraudulent declarations in import processes[16], or the well-known. SyRi case in the Netherlands, which showed the potential threat for public governance, of the use of combined multiple data sources to identify welfare fraud. The system was in fact dismantled following a court ruling[17] where it was ruled that the financial benefits for the state did not weigh up to violation of the privacy rights of citizens due to the large scale collection of data.

Lastly, a residual category of use of AI for internal management was identified, with 19 different cases addressing a variety of other goals to improve the internal performance of public organisations. These, for example, include the use of AI to improve data processing requests, digitalizing internal documents or facilitating internal information sharing between different state information services. For instance, Estonia developed an AI system to remove personal data from official documents which are then published as open data[18].

An overview of the illustrative cases mentioned above is reported in Table 4, highlighting the expected potential impact of the use of AI:

5. Discussion and conclusion

The adoption of Artificial Intelligence by public sector organisations to improve various aspects of governance is growing fast. Recent

12 https://www.swedenwaterresearch.se/wp-content/uploads/2019/05/Rapport_AI_2019-ny.pdf
13 https://www.kratid.ee/ria-kasutuslugu
14 https://innovatieveoverheidsopdrachten.be/projecten/quickscan-organisaties
15 https://www.regjeringen.no/en/dokumenter/nasjonal-strategi-for-kunstig-intelligens/id2685594/?ch=6#id0043
16 https://www.aiforhumanity.fr/pdfs/MissionVillani_Report_ENG-VF.pdf
17 https://uitspraken.rechtspraak.nl/inziendocument?id=ECLI:NL:RBDHA:2020:1878
18 https://git.texta.ee/texta/texta-rest

Table 4
Use of AI for internal management.

Use AI for internal management	Illustrative examples	Description
To improve the allocation of human resources	Early Help Profiling System, London	Helps civil servants prioritize which families are at higher risks following the AI's recommendations
To improve recruitment services of the public organization	Tengai, Sweden	Assists in the recruitment services of the public administration by making it less biased to improve internal competences.
To improve financial management of the organization	Assist payment of invoices, Norway	Use of AI to improve the handling of invoices to reduce the amount of errors or delayed payments.
To improve the detection of fraud and/or corruption	French Customs	Assistance in the detecting of fraudulent declarations in the customs agency.
To improve maintenance and asset management	Mains leakage prediction, Stockholm	Assists in the prioritizing of which mains to maintain following AI's recommendations.
To improve public procurement processes	QuickScan Organisaties, Belgium	Assists public administrations in evaluating offers from companies to ensure higher quality procurement offers.
To improve organisational (cyber) security	AI in X-Road	Use of AI in the detection and mitigation of cyberattacks on the internal data exchange network.

academic publications highlight the potential benefits that AI could have for policy making, making it more dynamic and data-driven (Valle-Cruz et al., 2020), improving public service delivery (Aoki, 2020) and the internal management of public administrations (Medaglia, Gil-Garcia, & Pardo, 2021). Others highlight various application areas in which Artificial Intelligence could improve the functioning of various government domains, such as the judiciary (de Sousa, Fidelis, de Souza Bermejo, da Silva Gonçalo, & de Souza Melo, 2021), policing (Meijer, Lorenz, & Wessels, 2021), social care (Andersson et al., 2021) as well as many others (Wirtz et al., 2019). However, the potential benefits are overshadowed by research highlighting various barriers to the use of these technologies by government, such as the need for the right capabilities (Mikalef et al., 2021), attention (Alshahrani, Dennehy, & Mäntymäki, 2021), data governance (Janssen, Brous, Estevez, Barbosa, & Janowski, 2020), ethical concerns (Zuiderwijk et al., 2021) as well as other factors hindering or facilitating its use.

As such, while the potential is great, there is a disconnect between the expectations as highlighted by the literature and the empirical research assessing to which extent AI is currently being used in public administrations (Medaglia et al., 2021). More specifically, there is a gap in understanding the effective impact and transformative potential of AI technologies and application on government and society. As recently underlined by Zuiderwijk et al., 2021: "*a large portion of the research, debates, and influence towards AI's progress across the governance ecosystem is documented in practitioner and policy documents*".

While more in-depth academic reviews are therefore needed to also consider the time lag of scientific publication, this study aims to shed lights on the effective use and potential impact of AI to support core governance functions, as they emerge from a review of 250 cases of AI in public administrations in 30 countries, including all the EU27, Norway, Switzerland, and UK. The dataset has been gathered through a combination of desk research, interviews and a survey to government representatives and, although it has limitations about the statistical representativeness of the sample, it represents yet a unique mapping exercise in Europe having such a broad spectrum in terms of coverage and scope.

The findings from the analysis confirms that AI is indeed used to support a variety of different aspects of each governance function, although it is mainly found as a tool to improve public service delivery and, to a lesser extent, to enhance internal management, On the other side, a limited number of examples are directly or indirectly aiming at helping policy decision-making. In this respect, usually AI is used to detect new social issues for policymakers to base new policy on or to assist in the monitoring of the implementation of existing policy, and to possibly measure its effects. To this end, more research needed to illustrate or analyse which governance functions AI improves - but also if, and how, under which conditions and which capabilities administrations require to work with (each type of) AI technology (Mikalef et al., 2021).

Particularly surprising is the fact that there are only few cases of policy modelling used to support the design and formulation of intervention strategies, apart from the computerised platforms which are developed to enable policy makers to make new policy models through AI. This could be in part because the use of policy modelling could not be reported as "AI", even though the analytical techniques underpinning these approaches are based on machine learning algorithms. This is clearly an area which requires more in-depth investigation to better understand the linkages between the automated data analytics processes and the computerised predictive modelling and simulation methodologies and tools implemented for policy making.

For public services, instead, AI is most often deployed to enhance delivery mechanisms and promote information provision to citizens and businesses. The introduction of new public services using AI are not very common – potentially due to ethical risks and/or discomfort with proactive service delivery approaches. How public administrations thus change from receptive to more proactive public services or how AI technologies are used in the creation of new public services requires more academic inquiry and policy experimentation. Similarly, still much is unknown if citizens value these services (Chatterjee, Khorana, & Kizgin, 2021), how they respond to AI-mediated public services and how new ways of citizen participation with AI applications are perceived.

For internal management purposes, AI has also many diverse applications – ranging from supporting recruitment, cybersecurity, financial management to the better prediction of which assets require maintenance. The analysis shows that however, most AI applications are being used to allocate internal human resources, such as helping to allocate inspection or police staff, or to assist in the detection of fraud by either citizens or internal staff. How public administrations change (Meijer et al., 2021), facilitate such organisational change (Andersson et al., 2021), how civil servants' jobs change or how civil servants collaborate with their AI systems (Ahn & Chen, 2021) is still in an exploratory phase and in much need of additional academic inquiry.

However, the increasing use of AI to allocate the staff may have consequences to which data gets gathered as a result, potentially leading to more bias through feedback loops. In addition, the widespread use of AI to tackle fraud may lead to conflicts with other public values, such as privacy or the right to a fair trial. Citizens who are wrongly classified as being fraudulent may have extreme difficulties trying to prove administration's wrongdoings, which may very well harm the legitimacy of public administrations. Whilst ethical guidelines and principles are widely known and available, how they are followed in public administrations and which other actions are taken to mitigate risks of AI requires more investigation, such as ensuring that AI used is explainable (de Bruijn, Warnier, & Janssen, 2021).

In summary, the analysis suggests that different types of AI technologies and applications are used in different governance functions, highlighting the need to further in-depth investigation to better understand the role and impact of use in what is being defined the governance "of, with and by AI" (Misuraca, 2020) and to further understand what evidence is available to assess the use and impact of AI for the public sector, in the EU and worldwide. Therefore, in terms of future research, while the current dataset analysed includes a sample of 250 cases, much more effort is required to collect additional cases of AI as to have a wider and more representative sample, include more information on each of these cases in order to provide more in-depth insights regarding the potential goals, benefits, risks and effects of AI used in government. This is a pivotal task that policy-oriented research should facilitate, so to provide further ground for academic investigation and scientific analysis. In fact, in some cases having the AI systems being implemented within the public administration was regarded as the goal in itself – without having a clear connection with any of the core governance functions or how AI was supposed to improve public administration's practices. While learning from experiments and use of new technologies could be worthwhile in itself, from a value perspective innovation for the sake of innovation may not be the best use of public resources (Meijer & Thaens, 2020).

Similarly, some initiatives are not implemented anymore following controversy or poor results, and often without evidence deriving from proper impact assessment and simulation of alternative options. This underscores the fact that there is still a substantial research gap in trying to understand whether the potential of AI in government gets realized – and if so, how. It may very well be that initial expectations of AI may thus not get realized due to a lack of sustainable implementation in the long run. Research is thus highly needed to understand how AI – as well as other digital – innovations go beyond the pilot phase and truly get incorporated within operations (Kuguoglu, van der Voort, & Janssen, 2021).

As a result of our analysis, we assume that there are specific risks to the use of AI for the different functions of governance which require further investigation, such as the potential threats of deploying AI to prevent fraud in government, which are clearly different from risks emerging from the use of AI for providing information to citizens. Follow-up research should thus clearly take into consideration the additional, context and purpose related risks of AI deployment in a government setting. This does not require solely more academic investigations, but also is an invitation to public managers to be more transparent and informative about which AI they are using within their organisations and to which extent this is having a positive impact, or rather could produce unexpected consequences and generate negative side effects. In doing so, researchers should also take into consideration the potential negative effects the increasing use of AI in government may have on the environment and consequently include environmental costs in impact assessments as well.

This is exactly one of the main limitations of this research as the analysis could not evaluate whether the cases investigated really achieved their intended goals and what are the possible negative impacts produced. In this respect, the lack of a clear understanding of the impact following AI use in government remains one of the greatest research gaps (Medaglia et al., 2021; Zuiderwijk et al., 2021). While work has progressed on conceptual work in understanding potential consequences, actual impact studies remain scarce at this phase. In addition, some cases may fit multiple functions of governance but, in part due also to the relative lack of information on some of the cases, it was decided to have a unique classification. This may of course be further investigated in a follow-up study so to outline better the relationships between various governance functions, and the multiple use and impact of AI.

Despite these limitations, however, this paper provides a first and unique original overview on the current use of AI within governmental organisations in Europe, with a specific focus on the way it supports different core governance functions. AI technologies are in fact used for various purposes in government, and a clear overview of the different positives and negatives for each governance function allow more detailed follow up research on the use of AI, with potentially additional drivers, barriers, consequences, and risks for each different deployment – in additional to broad general risks applying to 'all' AI. This is a valuable contribution for researchers and policy makers to gain a better understanding of the potential impact of AI for the public sector, in Europe and as benchmark for other world regions.

Author statement

Colin van Noordt: Conceptualisation, Writing – Original Draft.

Gianluca Misuraca: Writing, Review & Editing, Supervision.

The drafting and work put into the paper has been a close cooperation.

Disclaimer

The views expressed in this paper are those of the authors and cannot be regarded as stating the official position of the European Commission or any organization they are affiliated to.

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Policy initiatives for Artificial Intelligence-enabled government: An analysis of national strategies in Europe

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Abstract

Governments have been putting forward various proposals to stimulate and facilitate research on Artificial Intelligence (AI), develop new solutions, and adopt these technologies within their economy and society. Despite this enthusiasm, however, the adoption and deployment of AI technologies within public administrations face many barriers, limiting administrations from drawing on the benefits of these technologies. These barriers include the lack of quality data, ethical concerns, unawareness of what AI could mean, lack of expertise, legal limitations, the need for inter-organisational collaboration, and others. AI strategy documents describe plans and goals to overcome the barriers to introducing AI in societies. Drawing on an analysis of 26 AI national strategy documents in Europe analysed through the policy instrument lens, this study shows that there is a strong focus on initiatives to improve data-related aspects and collaboration with the private sector, and that there are limited initiatives to improve internal capacity or funding.

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Keywords
AI barriers, AI strategy, Artificial Intelligence, digital government transformation, public setor innovation

Introduction

Artificial Intelligence (AI) technologies are gaining extraordinary momentum. After a period of relative neglect, commonly referred to as the “AI winter”, in the past few years, technologies such as Machine Learning, intelligent chatbots, and image and speech recognition have reached a new peak in mainstream visibility, user expectations, and global investments. Such renewed focus is shared by governments worldwide, who are swiftly buying into a discourse on the potential of AI to achieve public sector goals. AI represents “*an ideal technology to be applied to the public-sector context, where environmental settings are constantly changing, and pre-programming cannot account for all possible cases*” (Sun and Medaglia, 2019: 370). AI applications can potentially increase the efficiency and effectiveness of service delivery (Mikalef et al., 2021), but also support government decision-making by simulating different policy options (Margetts and Dorobantu, 2019). Examples of government AI applications include the prediction of crime hotspots (Goldsmith and Crawford, 2014), supporting cancer treatment choices by doctors in public hospitals (Sun and Medaglia, 2019), recommending hygiene inspections in restaurant businesses (Kang et al., 2013), and responding to enquiries in natural language on waste sorting, taxes and parental support (Aoki, 2020), amongst many others (Pencheva et al., 2020; Van Noordt and Misuraca, 2022).

The potential of AI for enhancing social benefits and economic growth has been stressed in many research papers (Zuiderwijk et al., 2021) and policy documents (Jorge Ricart et al., 2022), with governments across the world aiming to prepare their country for the introduction of AI and be the leading country in AI (Toll et al., 2020a). In this respect, governments have been putting forward policies and strategies to stimulate and facilitate research on Artificial Intelligence, developing new solutions and adopting these technologies within their economy and society (Fatima et al., 2020; Guenduez and Mettler, 2022). Despite this intent, however, the adoption and deployment of AI technologies within public administrations face many barriers, limiting administrations in drawing on the benefits of these technologies (Mikalef et al., 2021; Schedler et al., 2019). Recent academic literature has highlighted the various barriers public administrations face in developing and using AI technologies, ranging from the lack of quality data, ethical concerns, unawareness of what AI could mean, lack of expertise, legal limitations, and the need for inter-organizational collaboration (Campion et al., 2022; Fatima et al., 2020; Medaglia et al., 2021; Van Noordt and Misuraca, 2020b; Wirtz et al., 2019). As a result, there are limited insights into implementing AI in public administrations, and the uptake thereof is still in an early phase (Mergel et al., 2023; Tangi et al., 2023). While many private sector organisations, and especially small and medium enterprises (SMEs), face similar challenges in using AI technologies within their business processes, governments are actively introducing policy initiatives and measures to make it easier for businesses to develop and use AI technologies, as many of the national AI strategies describe (Fatima et al., 2022).

In this respect, the public sector is only mostly regarded as a facilitator or regulator of AI technologies in the private sector. Far less attention is given to the government's role as an AI user and on how governments aim to overcome public organisations' barriers to using AI for societal benefit (Kuziemski and Misuraca, 2020). The use of AI by governments themselves is thus not often within the scope of the discussion (Guenduez and Mettler, 2022), which limits the potential transformation impact that this technology can have (Pencheva et al., 2020). Little is understood of how governments aim to facilitate and stimulate the use of AI within their own administrations, as a consequence of scarce research on the use of AI in government and on how various barriers to public sector innovation of AI have been overcome (Medaglia et al., 2021). This article thus aims to contribute to this research gap by providing a noteworthy empirical basis of activities governments set out to stimulate the use of AI in public administration and overcome these barriers, by reviewing published AI strategies through the policy instrument lens.

These strategy documents include plans and goals in which governments describe how to overcome various issues and barriers to introducing AI in their societies. Despite that published AI strategies often hold a mythical discourse about the opportunities of AI (Ossewaarde and Gulenc, 2020), researchers have already started analysing the AI strategies, in an effort to gain new understandings of the role of governments in AI. In this emergent phase, these efforts include analyses based on general categories, such as policy areas (Fatima et al., 2020; Valle-Cruz et al., 2019), and narratives (Guenduez and Mettler, 2022). Other analyses adopted grounded approaches by looking for textual patterns (Papadopoulos and Charalabidis, 2020), focusing on ethical principles (Dexe and Franke, 2020), and on which public values are most referenced in AI strategies (Robinson, 2020; Toll et al., 2020b; Viscusi et al., 2020).

Whilst research has examined the policy instruments described in AI strategies (Djeffal et al., 2022; Fatima et al., 2020), these studies examine the AI strategies in general, without a specific focus on AI implementation in public administration. To tackle this issue, this study analyses 26 AI strategies from 25 European countries, focusing on the activities related to stimulating the development and adoption of AI within the public administration, with the research question: "*What are the main policy initiatives proposed in AI strategy documents by European governments to facilitate the development and adoption of AI technologies within their public administrations, and how do these initiatives aim to address the barriers faced in the implementation of AI in government?*"

The strategies analysed in this study have been published following the momentum of the Coordinated Plan on Artificial Intelligence by the European Commission, where European Member States have committed to introducing AI strategies (or other programmes) in which they specify investment plans, implementation measures and other initiatives related to AI (European Commission, 2018). We aim to understand the main policy initiatives that Member States designed to make the European public sector a "trailblazer" in the use of AI, as stated in the Coordinated Plan (European Commission, 2018).

Our previous research (Tangi et al., 2022; Van Noordt et al., 2020) showed significant differences in the extent to which national strategies address the use of AI in public administrations, and in which initiatives governments propose to overcome barriers. In this study, a systematic content analysis has been conducted over 26 AI strategies to identify which initiatives administrations put forward to facilitate the development and adoption of AI in their public administrations. An inductive coding of 816 segments of texts describing plans to introduce AI in government across 26 documents reveals similarities and differences in the approaches that governments are taking.

This paper is structured as follows. First, we provide an introduction to public administrations' barriers to using Artificial Intelligence. Next, we connect the barriers faced in the implementation of AI with the literature on policy instruments. Afterwards, the coding methodology and approach are described. Next, the main findings of the coding process are presented and explained. The paper concludes with the core take away points of the study and proposals for further research on overcoming the barriers of AI adoption in government.

Literature review

Challenges to the use of AI in the public sector

The term Artificial Intelligence still holds many different interpretations (Collins et al., 2021; Noordt, 2022) and is commonly used as an umbrella term to describe software and hardware that is capable of conducting tasks which previously were thought to require human intelligence (Tangi et al., 2022). Machine Learning algorithms "*find their own ways of identifying patterns, and apply what they learn to make statements about data*" (Boucher, 2020: 4). For the public sector, AI holds promises of improving the internal efficiency of public administrations, improving decision-making, enhancing citizen participation, improving legitimacy, making public services more personalised, and removing redundant tasks and activities for public workers (Dwivedi et al., 2019; Eggers et al., 2017; Mehr et al., 2017; Valle-Cruz and García-Contreras, 2023; Van Noordt and Misuraca, 2022). As a result, AI technologies can provide far greater public value than other digital technologies (Li et al., 2023).

Because of this high potential of AI technologies to improve various functions of governance in the public sector, preliminary research has emerged, analysing the use of AI technologies by government authorities, which challenges they face, and which consequences occur from their deployment (Kuziemski and Misuraca, 2020; Medaglia et al., 2021; Neumann et al., 2022). In fact, despite earlier enthusiasm for the benefits of AI technologies, a substantial body of research has highlighted the risks and dangers of AI technologies, such as the risk of algorithmic bias (Bannister and Connolly, 2020), opaque decision-making (Janssen et al., 2020b), rapid loss of jobs, risks to citizen's privacy (Yeung, 2018), radicalisation, and the spread of fake news (Dwivedi et al., 2019). While many of these ground-breaking findings correspond to the use of AI technologies by larger technology companies or government authorities outside the European Union, scandals and controversies regarding the use of AI by public authorities within the

European Union have started to emerge, highlighting the fact that the potential benefits of AI may be offset by its negatives if not used appropriately.

Whilst the possible negatives effects - or even dangers of the irresponsible use of AI – should not be ignored in the academic debate on the use of AI in government (Chen et al., 2023; Schiff et al., 2021), this paper dives deeper into the various challenges governmental organisations face with adopting these technologies, rather than into the consequences following the deployment of AI. As the existing digital government literature has researched extensively, public organisations often face many hurdles in using innovative technologies (Cinar et al., 2018; De Vries et al., 2016). A technology may be available on the market, already used extensively in the private sector and create expectations on how public services and governments ought to facilitate services, but government organisations may still face difficulties in adopting the technology in their organisation (Meijer and Thaens, 2020), even more so in a way that changes organisational work practices (Gieske et al., 2020; Schedler et al., 2019).

Similar barriers exist for using AI technologies within the public sector, as early research has shown (Neumann et al., 2022; Rjab et al., 2023; Van Noordt and Misuraca, 2020b). Following a review of existing studies on AI in the public sector, Wirtz et al. (2019) found four main streams of challenges that hinder the implementation and use of AI applications in the public sector: technology implementation, legal, ethical, and societal challenges. These streams have been found in other studies, highlighting that it is difficult to start with AI (Bérubé and Giannelia, 2021; Schaefer et al., 2021; Van Noordt and Misuraca, 2020b) or scale up following a successful pilot (Aaen and Nielsen, 2021; Kuguoglu et al., 2021; Tangi et al., 2023).

In particular, some technological challenges identified refer to a lack of good data (Janssen et al., 2020a). Deploying AI technologies requires public organisations to have robust data management practices, as data is the backbone of many AI applications (Valle-Cruz and García-Contreras, 2023). A lack of sufficient data, poor data quality, or difficulties in obtaining the necessary data – due to issues in sharing data between various public organisations and adherence to multiple data-related regulation, such as the GDPR – limits public organisations (Agarwal, 2018; Harrison et al., 2019; Sun and Medaglia, 2019). Data-related challenges emerge if a significant portion of public services is not digitised and, thus, little to no data is available on these services for AI development and adoption. Some of the legal barriers public administrations face are legal restrictions hindering their use of AI technologies, such as privacy legislation or the mandate of public authorities to deploy AI technologies (Burrell, 2016; De Bruijn et al., 2022).

Public procurement regulation has been regarded as unfit for public authorities to stimulate AI technologies, as it often requires more flexible innovative procurement processes (Madan and Ashok, 2022; Mcbride et al., 2021). Legal uncertainties may also hinder the use of AI in government, as unclarities regarding the responsibility, liability and accountability of AI-enabled decisions in the public sector may lead to hesitation among civil servants to adopt AI (Alshahrani et al., 2021).

Related to legal concerns are various ethical concerns that raise barriers to using AI in government (Danaher, 2016). With AI, there are concerns about whether the development and use of AI are ethically and morally justifiable, which values are pursued during the development of AI, and whether AI follows social norms and obligations (Bannister and Connolly, 2020; Hartmann and Wenzelburger, 2021; Ju et al., 2019). Public administrations may thus be hesitant to use AI technologies as they may threaten the privacy of citizens, make decisions more opaque, biased, or because there is a general distrust towards having machines or computers play a more substantial part in the delivery of public services (Sigfrids et al., 2022).

Citizens may be hesitant to have AI play a significant role in public administration's decisions and operations, as highlighted by the various concerns citizens have shown about the role of AI in society (Schiff et al., 2021; Wang et al., 2023). A general lack of understanding of how AI works among citizens may make them hesitant for public authorities to use AI, limiting the possibilities for authorities to use these technologies. Civil servants themselves may also not fully understand the opportunities and consequences of AI, as there is a general lack of AI-related skills in the public sector (Mergel et al., 2019; Mikalef and Gupta, 2021; Wirtz et al., 2019). This limits the opportunities to spot potential use for AI, develop new innovative AI applications and use AI in civil servants' work.

Policy tools to overcome barriers to AI in government

Despite these known barriers to AI adoption limiting the ability to create public value from these technologies (Van Noordt and Misuraca, 2020a), little is still known about how public authorities aim to overcome them (Medaglia et al., 2021; Wirtz et al., 2021). Some public administrations may have conducted successful trials with AI, but face difficulties in scaling up the results across the organization or across organisational boundaries (Alexopoulos et al., 2019; Kuguoglu et al., 2021; Van Winden and van Den Buuse, 2017). In the discourse on AI, the role of government in AI is often only regarded as a regulator in society, or as a facilitator of AI for the private sector, and many of the policies as proposed in national strategies are linked to these two roles (Kuziemski and Misuraca, 2020; Zuiderwijk et al., 2021), leaving limited insights on what governments plan to do to support their own use. A recent analysis of AI policies found that European countries do not often highlight the potential of AI technologies to improve their services (Guenduez and Mettler, 2022). Despite these limitations, what is mentioned in AI strategies may thus provide valuable insights into what actions governments are planning or doing to tackle the existing challenges public administrations themselves face in developing and implementing AI technologies.

Such an inquiry into understanding public policy has been of interest in the public administration field for a more extended period, as research on "*anything a government chooses to do or not to do*" (Howlett and Cashore, 2014), and in particular, the policy instruments chosen, provides insights on which goals governments aim to achieve and through which means (Howlett and Cashore, 2014). In general terms, policy instruments are referred to as "*techniques of governance which, one way or another, involve the utilization of state resources, or their conscious limitation, in order to achieve policy goals*" (Howlett and Rayner, 2007). Often, these are studied in the instrument choice approach, where particular attention is given to selecting and implementing these policy instruments as the decision to choose a specific instrument from those available. In doing so, policy instruments are researched for different purposes, such as whether they are fit for their deployment, how policy issues are framed, and how social and power dynamics play a role in the selection of the instrument (Kassim and Le Galès, 2010). The choice of preferred instruments has been linked to more comprehensive governance models, as a shift from more network-styled governance models requires policy tools to follow accordingly, since the decision for specific policy instruments is constrained by the higher-level policy and governance regime (Howlett, 2009).

In this sense, policy instruments are considered as "tools of government" to give effect to public policies and the practical means of how policy is to be achieved and how governments intervene in society (Howlett, 2004). Several classifications of policy instruments have been introduced to categorise the wide variety of actions governments could take. These include: classifications based on the extent of government coerciveness, such as in the Doern continuum (Bali et al., 2021); on the resources behind each tool, such as the carrots, sticks, sermon and organization framework (Bemelmans-Videc et al., 1998; Howlett, 2004); and the NATO taxonomy by Hood (1983), where governments use the resources (Nodality, Authority, Treasure and Organization, hence the NATO acronym) either to monitor or to alter behaviour (Hood, 1983; Howlett, 2018). The work by Hood (1983) has been more recently revisited to capture the unique characteristics of the digital era (Hood and Margetts, 2007). The theoretical framework by Hood and Margetts draws on the four categories of tools of government available (Nodality, Authority, Treasure and Organization), and has been fruitfully used to analyse government strategy and policy (Acciai and Capano, 2021), although in limited form about digital innovation (Mukhtar-Landgren et al., 2019; Reid and Maroulis, 2017). A key exception is the analysis of policy instruments to identify modes of AI governance in analysing AI strategies, ranging from self-regulation, market-based, entrepreneurial and regulatory governance approaches (Djeffal et al., 2022).

Nodality-related instruments refer to the government's property of "being in the middle of a social network" (Hood and Margetts, 2007: 21) and include instruments associated with such capability, primarily retrieving or sending information. Common instruments in this category include, for example, information campaigns, sending reminders to taxpayers, or receiving information on tax evasion. As such, this is the main instrument governments can implement concerning spreading information and know-how about the topic they aim to address (Hood and Margetts, 2007). Recently, attention has been given to how the internet has affected the use of nodality instruments by governments (Castelnovo, 2021; Margetts, 2009). However, nodality-based instruments are also limited as they only deal with the provision of information and are not sufficient if the government is not seen as a credible source, or when actors are not capable or willing to act on the information provided (Howlett and Mukherjee, 2018).

Alternatively, the state may provide more coercive instruments, described as Authority-related instruments. These include all instruments that draw on legal powers to require and condition behaviours, such as introducing laws and regulations to demand or forbid certain outcomes (Hood and Margetts, 2007). Authority-based tools are only effective when the government is considered legitimate and require high amounts of monitoring and enforcement to be effective (Howlett and Mukherjee, 2018).

Governments may also utilise their financial resources to achieve policy goals. Such Treasure-based instruments allow governments to influence behaviour, such as providing monetary incentives, funding, or applying taxes (Hood and Margetts, 2007). Through financial incentives and disincentives, actors can be persuaded to do certain actions. Providing grants, loans, charges, tax reliefs or funding interest groups or other organisations belong to treasure-related instruments (Howlett and Mukherjee, 2018). Such financial instruments can be based on certain conditions – increasingly allowing for more refined conditions through the advance of data gathered through digital devices.

In addition to these resources, governments may also use Organization-based instruments, which refer to the government's ability to possess or have easy access to resources and capabilities (Hood and Margetts, 2007). These tools allow governments to act through devices or mechanisms to ensure a change of behaviour in actors. This may occur through creating new agencies, restructuring past agencies, introducing new tools, or deciding to provide services directly. However, lately, Organization-based instruments hardly refer to fully-owned government organisations anymore, as there have been several organizational policy tools which result in a combination of public and private actors (Margetts, 2009).

In practice, policies often combine these different types of instruments. With the advance of digital government studies, the policy instrument literature has been combined to include new instruments from the digital era (Waller and Weerakkody, 2016). In fact, even AI technologies are likely to be deployed by public administrations as part of their policy instrument "toolkit" by, for instance, improving Nodality-related instruments by personalizing information to citizens and thus providing more effective results (Van Noordt and Misuraca, 2022).

Policy instruments are often used to change citizens' and businesses' behaviour to meet governments' policy goals. However, there is limited research on how policy instruments could be utilised to understand and explain how public administrations steer *themselves* to achieve digital government goals, such as AI-related policy goals. This may be because public administrations have traditionally been regarded more as an instrument themselves (as an Organisation-related instrument) or as the organisations that a deciding and implementing the instruments, rather than being at the receiving end thereof (Waller and Weerakkody, 2016). Nevertheless, considering the substantial barriers public administrations face in AI implementation and general digital government transformation, there may be much value in understanding how governments facilitate such activities through policy and strategies.

Methodology

Data collection

The methodology adopted in this study consists of two parts: the collection of AI strategies, and the coding and analysis of the strategy documents. First, the national AI

Table 1. Examined AI strategies.

Country	AI Strategy
Austria	Artificial intelligence mission Austria 2030
Bulgaria	Concept for the development of artificial intelligence in Bulgaria until 2030
Cyprus	National artificial intelligence (AI) strategy: Actions for the utilization and development of AI in Cyprus
Czechia	National artificial intelligence strategy of the Czech Republic
Denmark	National strategy for artificial intelligence
Estonia	Estonia's national artificial intelligence strategy 2019-2021
Finland	Leading the way into the age of artificial intelligence
France	For a meaningful artificial intelligence. Towards a French and European strategy
Germany	Artificial intelligence strategy of the German federal government: 2020 update
Hungary	Hungary's artificial intelligence strategy: 2020-2030
Ireland	AI - Here for good: A national artificial intelligence strategy for Ireland
Italy	Strategic programme on artificial intelligence
Latvia	Informative report "on the development of artificial intelligence solutions"
Lithuania	Lithuanian artificial intelligence strategy
Luxembourg	Artificial intelligence: a Strategic vision for Luxembourg
Malta	A strategy and vision for artificial intelligence in Malta 2030
Netherlands	Strategic action plan for artificial intelligence
Norway	National strategy for artificial intelligence
Poland	AI development policy in Poland 2019 – 2027
Portugal	AI Portugal 2030
Slovakia	Action plan for the digital transformation of Slovakia for 2019 –2022
Slovenia	National program for the promotion of the development and use of artificial intelligence in the Republic of Slovenia until 2025
Spain	National artificial intelligence strategy
Sweden	National approach to artificial intelligence
United Kingdom[1]	Industrial strategy: Artificial intelligence sector deal

strategies of countries that are part of the Coordinated Plan on AI of the European Commission were collected. As of February 2022 (Jorge Ricart et al., 2022), there are 25 countries in the EU27+UK+CH that have published their national AI strategies, as can be seen in Table 1.

What counts as a national AI strategy is not always straightforward, as many policy documents, reports and other documents describe AI initiatives (e.g., the countries and initiatives overview of the OECD).[2] In some countries, influential AI documents are published by expert groups or civil society, often in collaboration with the government, which may be regarded as the national AI strategy. Governments may have released numerous AI policy documents in other countries, such as minor updates of the main AI strategy. Hence, to ensure comparability and validity of the analysis, only the AI strategies that were published by the government and can be considered formal AI strategy documents as indicated by the European Commission[3] are considered for this analysis. In

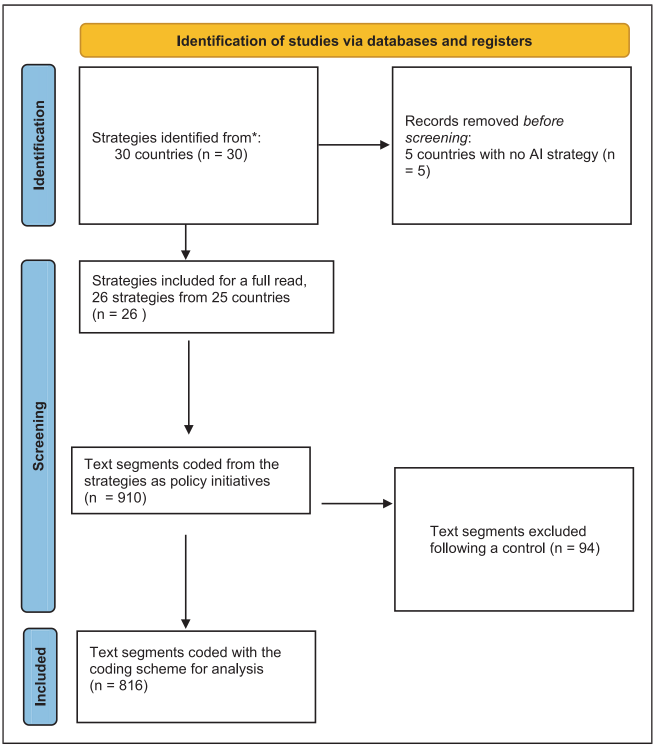

Figure 1. Steps taken to collect AI strategies and analyse the policy initiatives regarding AI in public administration.
Note: *The AI Watch of the European Commission https://ai-watch.ec.europa.eu/countries_en

this respect, we thus do not include certain documents that other studies have included in their analysis of AI strategies, such as Fatima et al. (2020), consequently limiting comparability with these studies and highlighting the need to find consensus in what is considered the national AI strategy of a country. Since some of the strategies were published in languages other than English, machine translation was used to translate the text through either DeepL, Microsoft Office or Google Translate, depending on the document format and the language supported by these platforms. Figure 1 provides an overview of the steps taken in collecting and analysing the national AI strategy documents.

To analyse national AI strategies, we adopted a qualitative approach, given the novelty of the phenomenon (Yin, 2013). In particular, we conducted a content analysis of the published AI national strategy documents. A content analysis follows a systematic approach to extract patterns of meaning around emergent themes through an iterative process (Flick, 2014; Hsieh and Shannon, 2005) and is a well-established method adopted in a variety of studies on strategic plans in the areas of public administration (Mazzara et al., 2010) and Information Systems research (Nasir, 2005). Following the collection and identification of national AI strategies, the research team included each document for a full reading. In the first step, any text section describing actions, initiatives, or suggestions to facilitate, stimulate or reinforce the development and uptake of AI in the public sector was coded as a "policy initiative", using the coding software MAXQDA™ (La Pelle, 2004).

In this respect, a rather strict reading of the text was included, and only explicit references (either in the text or through the context of the paragraph) to actions and the public administration, state administration, public services, or other related terms, were included. The strategy documents hold many activities, but most target the private and academic sectors. Other measures are more general, such as increasing the number of AI courses in education. While public administrations may indirectly benefit from these activities, these initiatives have not been included in the review, unless they explicitly referred to the public administration. Alternatively, the strategies highlight the benefits or risks of AI for the public sector but do not explain how this ought to be achieved or mitigated.

Following an internal control of the coding process, 94 initiatives were excluded from the analysis because of duplications, or because they were too abstract to classify. This process resulted in the coding of 816 policy initiatives across the 26 documents, with an average of 31.4 initiatives per strategy document, with the Lithuanian strategy having the fewest initiatives (14) and the French the most (77). Some strategies include fewer initiatives to analyse, such as Bulgaria, Czechia, Italy, Lithuania, Portugal, and the United Kingdom, featuring fewer than 20 policy initiatives; on the other hand, Cyprus, Denmark France, the Netherlands, Norway, Slovenia, and Spain all have over 40 policy initiatives, which should be kept in mind when comparing the relative occurrence of policy initiatives in the strategies. In addition, it is to be noted that governments may have conducted other initiatives to support the uptake of AI within their public administrations that are not highlighted in their strategy and, thus, are not within the scope of this analysis.

Data analysis

In the second step, using the software MAXQDA™, the policy initiatives were assigned a first-order coding. The coding scheme development followed a process divided into phases (Dey, 2003), adopting an inductive coding strategy. Every policy initiative coded in the first step was assigned to one or multiple of the first order coding, as the initiative categories described in the text sometimes overlapped. This led to 1050 coded policy initiatives, compared to the 816 initiatives identified before. Divergences in coding were discussed among the two researchers until a consensus was reached. Following the agreement, a second-order coding was conducted on the first-order coding to better identify the nature of the policy initiative within the category.

An overview of all the policy initiatives and their corresponding first and second-order coding can be found in the Appendix.

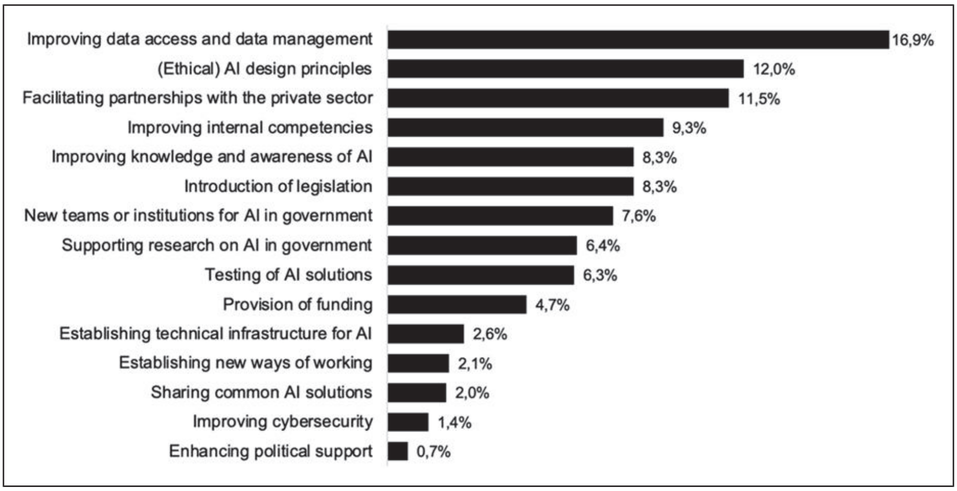

Figure 2. Categories of policy initiatives – frequency of mentions in strategy documents expressed as percentages (*N* = 1050) of coded policy initiatives.

Findings

Policy initiatives to improve the use of AI in public administration

The inductive coding exercise led to identifying 15 types of policy initiatives that aim to tackle challenges to AI development and implementation in the public sector. The frequency of the initiatives in the strategy documents is illustrated in Figure 2, represented as percentage values of the total number of mentions of initiatives in all the strategy documents (*N* = 1050).

Improving data access and data management

Most of the identified policy initiatives in the AI strategies are related to improving the data infrastructure of the public administrations to provide the required data needed to develop Artificial Intelligence. A high percentage (16.9%, 177 out of 1050) of the coded policy initiatives refer to improving data access or management in one form or another. Improving data access relies on introducing or advancing existing initiatives to provide more open data for reuse to develop AI or new data-sharing mechanisms. Examples include the MyData data-sharing system of the Finnish government, and the introduction of a data market platform, as described in the Hungarian AI Strategy. Other initiatives relate to improving the data governance of the public sector, to enhance the quality of data and its suitability for AI. This could be done, for example, by introducing a data management standard in the public sector, as described in the Czech AI Strategy, but also by ensuring that data is adequately anonymized so that it can be reused, as the German and the Polish strategy describe. A subset of these initiatives can be seen in the Table 2.

Table 2. Examples of data-related policy initiatives.

Country	Finland	Hungary	Czechia	Germany	Poland
Selection of coded policy initiatives	Promotion of the utilisation of data modelled after MyData activities, including the establishment of MyData global	The instrument of this action is the introduction of a data market platform (adatpiac platform)	Developing a binding public administration data availability plan for AI use, including data standards	We will assess whether it is possible to make available datasets that have been generated by government-financed research projects to third parties, whilst ensuring data protection interests	Guidelines for the provision and use of data anonymised by private entities for the public good (medicine, social research)

Whilst, in general, data-related initiatives are frequently mentioned, there are several strategies in which a fair amount of all the initiatives described therein refer to improving data access and management. In the strategies of Germany,[4] Italy, Hungary, Latvia, Luxembourg, Norway, and the UK, more than 25% of all the coded initiatives refer to data. Hungary, in particular, stands out, with 38.7% of all the initiatives referring to actions to improve data quality and access. From this, it becomes clear that one of the main initiatives of moving forward with AI in government seems to be improving the public administration's data ecosystem. However, it is possible that overreliance on solely improving the data ecosystem, as these countries seem to do, could lead to a lack of investment to overcome other vital barriers, such as funding, expertise, legal barriers, and administrative culture.

Ethical AI design principles

Another cluster of policy actions (12%, 126 out of 1050) refers to the establishment or use of various ethical AI design principles introduced to assist public organizations to develop and implement AI ethically. Strategies often describe actions to establish a set of ethical AI principles, often aligned or similar to the guidelines[5] proposed by the High-Level Expert Group on AI (AI HLEG) from the European Commission, or include the recommendation, obligation, or other actions to follow these established AI principles. Examples include an ethical framework and methods for the public sector described in the Danish strategy, supporting the implementation of the AI HLEG recommendations in the Slovakian strategy, and establishing principles for the responsible use of data in the Estonian AI strategy. The Austrian strategy describes that design, development, and application (the entire life cycle of AI) should be transparent, trustworthy, legal, and secure, which is why framework conditions will be created.

A smaller subsection of these initiatives also describes non-ethics-related guidance for AI projects as a way to ensure positive effects from the use of the technology, such as how to conduct public procurement of AI (e.g., the Norwegian and the Maltese strategies), or providing guidance on how to implement AI solutions into public sector processes, as the Spanish AI strategy mentions. The Irish strategy highlights that AI-enabled government services should also have adequate arrangements for ensuring accountability and traceability. In Table 3, a selection of the coded policy initiatives can be identified.

Such activities are in line with the vital role of governments to create ethical and trustworthy AI prevalent in many of the AI strategies around the world (Guenduez and Mettler, 2022) – but it is possible that the conflict of roles of governments as a regulator and as user of these technologies creates tension (Kuziemski and Misuraca, 2020), which is why there may be a high prevalence on ensuring ethical AI in the strategies, but there is less attention given to the use of ethical AI by public administrations themselves.

Interestingly, almost half of all coded initiatives in this category (48.4%) were present in only four countries: the Netherlands, France, Finland, and Norway. In these strategies, having solid ethical frameworks and guidance for civil servants to overcome the ethical concerns of civil servants in developing and using AI were often mentioned. In contrast, in the Estonian, Lithuanian, German, Bulgarian, Czech and Polish strategies, only one

Table 3. Examples of ethical AI policy initiatives.

Country	Denmark	Estonia	Austria	Norwegian	Spain
Selection of coded policy initiatives	On the basis of the ethical principles, the government will ensure that common public-sector methods and guidelines are drawn up which support the statutory requirements for transparency	Develop principles for responsible use of data	The design, development and application of AI should be carried out in a transparent, trustworthy, and legally secure form. For this purpose, framework conditions are created that ensure compliance with human rights and security of the use of AI during the entire technical life cycle	Give guidance to public agencies on how they can ensure access to data when entering into contracts by, for example, proposing standard clauses	One of the tasks carried out will be the ethical and legal evaluation of systems whose objective will be to reinforce the legitimacy and trust in automated systems of the public administration. The ethical framework must consider the specificities in the case of the use of AI in the public administration

initiative referred to establishing and using ethical AI principles for the public sector to follow. Many strategies do mention the need to develop ethical frameworks and follow ethical guidelines. However, often they do not specify whether public organizations must do so, or only describe that private organisations should develop and use AI ethically. It may also very well be the case that most governments do not see a need to ensure the ethical use of AI in the public sector more than in other domains, which is why there is no specific focus thereof.

Facilitating partnerships with the private sector

Public administrations are encouraged in the AI strategies to work with the private sector to develop and adopt AI technologies for use in their own organisation: facilitating partnerships with the private sector is often (11.5%, 121 out of 1050) mentioned. AI strategies often describe how innovative the private sector is in developing AI applications, which consequently could be procured by public administrations. In the Polish strategy, for example, great emphasis is given to the establishment of GovTech Polska, a new organisation which will assist public administrations in working together with the private sector for innovative AI technologies. The Irish strategy, amongst others, also mentions that mechanisms will be developed to support the public procurement as a catalyst for trustworthy AI.

Private organisations are also often mentioned in the strategies to share expertise in AI-related projects in the public sector, assist in testing new AI technologies, better understand which government-to-business public services may be improved through AI technologies, following an ecosystem-driven approach to AI. The strategies highlight the sharing of privately held data with the government, with governments introducing new mechanisms for companies to share their data for the public good. A few of these highlight initiatives that aim to stimulate the supply of private-sector AI solutions – specifically for the public sector. For example, as the Italian strategy proposes, this may be strengthened by having calls to identify and support start-ups that could bring AI-based solutions for public administrations through accelerator programmes. Such activities can often be seen in light of the narrative to ensure the economic success of the country in AI, where the government has to act as an enabler for companies to thrive in the "global AI race" (Guenduez and Mettler, 2022) by using the procurement purchasing power to support local AI companies. AI strategies generally have an overemphasis on supporting economic value creation, which may explain this strong focus (Wilson, 2021). Some examples of these policy initiatives can be found in Table 4.

Some countries emphasise facilitating partnerships with the private sector more than others. For example, the United Kingdom and the Italian strategy have 25% of their initiatives referring to actions to strengthen collaboration with the private sector. Portugal, Czechia, the Netherlands, and Poland also have over 15%. There is a risk, however, that these countries put too much emphasis on gaining innovative solutions from the private sector but do not place enough investments into obtaining the adequate skills to work with AI, procure AI effectively, or have a general level of understanding among civil servants about the potential and dangers of AI.

Table 4. Examples of initiatives facilitating partnership with private sector.

Country	Poland	Ireland	United Kingdom	The Netherlands	Italy
Selection of coded policy initiatives	Recognising the achievements of GovTech polska in the field of animation and support for the public procurement process. This program has been included in the strategy for the development of AI. This will support the public administration's demand for AI solutions and improve the process of acquiring contractors for such solutions	Instruments such as dialogues, hackathons and pre-commercial procurement of innovative solutions Will enable suppliers to respond better to public procurement requests, and also assist public authorities to better understand the market and formulate targeted procurements	The industry will work closely with the government, through the AI council, on broader questions related to AI, such as data ethics and the role of AI in the public sector	When using algorithms by the government and in PPP (public-private partnership) constructions experiments, BZK (the ministry of internal affairs) stimulates the use of tools such as the AI impact assessment and quality marks/ audits	Introduction of periodic calls to identify and support start-ups with potential AI-based solutions to the public administration's pain points, through an accelerator-like programme that turns ideas/research projects into applicable solutions and scalable companies

Improving internal competencies

To tackle the lack of expertise in AI within public administrations, strategies describe various actions (9.3%, 98 out of 1050) to improve the competencies of civil servants within public administrations, distinct from enhancing the competencies of businesses or citizens. The French strategy, for example, highlights that it is vital for the government to be a key driver in the societal transformation with AI, but that it requires human resources. Similarly, the Danish strategy describes that digital competencies, and not just AI-related skills, are of high importance to have more public authorities work with AI technologies. It is not always clear what competencies should be improved, but this may be done by facilitating AI training courses, hiring AI experts or making the public sector a more attractive employer for AI-experts to work for. For instance, the Portuguese strategy mentions that existing AI and data science skill qualification programmes for the public sector should be reinforced in order to improve public sector capacity in AI. Some examples of these initiatives can be found in Table 5.

Significant differences can be found in the frequency of policy initiatives – both in absolute and relative terms – hinting towards different approaches in boosting the uptake of AI in government. For example, the Spanish AI strategy includes most policy initiatives to improve public administration's internal competencies (11 out of 63, 17.5%). This is in stark contrast with other strategies, such as the German,[6] the Bulgarian, the United Kingdom and the Swedish, with only one such initiative referring to improving internal competencies. In the Czech strategy, no such initiative was identified.

Improving knowledge and awareness of AI

Related to the training activities are initiatives aimed at increasing general awareness and knowledge of the possibilities of AI for the public sector. Hence, the strategies mention several initiatives (8.3%, 87 out of 1050) to support these – different from obtaining expertise and skills, as described earlier. These include actions to strengthen international collaboration on AI in the public sector, sharing best practices on AI in government or carrying out activities, such as events, awareness campaigns or creating new platforms, to make the opportunities of AI more known among public managers and civil servants. For instance, the Bulgarian strategy highlights that awareness-raising campaigns at local, regional, and national level for public service institutions should be made to provide tailored information on the use of AI. The sharing of best practices may include sharing expertise on how to do public procurement of AI, as highlighted in France, creating success stories of AI to inspire other administrations, as in Estonia and Norway, or setting up a "transparency lab.", as in the Netherlands, where state administrations can share knowledge on the transparency and accountability of AI. Several examples of these initiatives can be found in Table 6.

In particular, the Maltese and Slovenian AI strategies stand out, with many of their policy initiatives described as improving knowledge and awareness of AI.

Table 5. Examples of policy initiatives to improve internal capacity.

Country	France	Denmark	Portugal	Slovenia	Spain
Selection of coded policy initiatives	Public authorities must therefore equip themselves with the skills required to better understand, identify and fight against forms of algorithmic discrimination, particularly when it affects access to basic services, such as housing and energy, healthcare, employment, and training, and credit	In order to improve the competencies of government IT specialists, the government will engage in dialogue with Danish universities working with artificial intelligence at a high level, with a view to developing courses aimed at IT specialists	Reinforce public sector skills and capabilities with respect to AI and data science	Support for professional education programmes (seminars, courses) of specific models, methods, and algorithms of AI in the selected priority areas for the deployment of AI for enterprise and public sector development groups	The training plans provide the personnel of the public administration with the necessary knowledge that allows them to incorporate solutions based on AI, at all levels, including executive positions, to improve the service to citizens

Table 6. Examples of initiatives to improve awareness.

Country	Malta	Estonia	Bulgaria	Norway	Slovenia
Selection of coded policy initiatives	An awareness campaign will be launched for public officers to build capacity, knowledge and understanding of what AI is, why it is important, and the benefits of public sector adoption	Organizing the spread of knowledge and exchange of experience, to introduce the possibilities and examples of AI in different networks and formats	Planning initiatives and awareness-raising campaigns at local, regional, and national level, to provide information in an appropriate way depending on the respective use of AI.	Facilitate cooperation and exchange of experiences and best practices for AI in both central and municipal administrations	Support for activities (conferences, workshops, etc.) to raise awareness in the economy, the public sector, and among the public about the strengths, weaknesses, opportunities, and dangers of AI.

Introduction and review of legislation

To overcome some barriers to developing and using AI in the public sector, a sizable amount of the coded policy initiatives describe the introduction of legislation, regulation, or certain rights to tackle some legal difficulties (8.3%, 87 out of 1050). The content of the initiatives varies greatly, as some of the initiatives describe new legislation to follow when public authorities will be using AI – such as regulation that prevents risks of AI, as highlighted in the Swedish strategy – or the obligation for public administrations to provide insights in the AI applications they are using, as in the Dutch public law. Several policy initiatives describing new legislation concern improving data access and sharing – overlapping firmly with the first cluster of data-related initiatives described. Another set of legislation is related to public procurement and aims to review, change, or introduce new competition or procurement law to reduce administrative barriers in procuring AI. Hence, a new form of innovative procurement contract could be stimulated to create more favourable conditions for experimentation during a procurement process.

A few strategies describe the introduction of new legislation to encourage investment and testing, such as in the Norwegian AI strategy, where it will be considered if testing with AI could be part of the existing pilot schemes legislation. A selection of these policy initiatives can be seen in the Table 7.

Within this category, France stands out with 20 policy initiatives related to this (17.2% of all of France initiatives), such as referring to the revision of the reuse directive to open additional public data, the new laws on individual data portability for local authorities to develop AI, and the concept of data of public interest, as highlighted in the Law for a Digital Republic. Other countries mention far fewer initiatives referring to introducing new legislation to support the introduction of AI in public administration.

New teams or institutions for AI in government

To implement many of the other actions, some strategies describe that new teams, institutions, departments, units, or other organizational structures will be set up (7.6%, 80 out of 1050). These new organisations often act as a central hub for public administrations to find AI expertise or assist them in identifying new use cases. Of these initiatives, many describe the establishment of a new organization, outside of the existing administrative structures, such as the Office for Artificial Intelligence in the UK, the Lithuanian Artificial Intelligence Advisory Board, a committee for ethics (Table 8) or a body of experts for auditing AI in France. Other initiatives refer to the Digital Innovation Hubs[7] from the European Commission as central hubs which, among many other tasks, aim to assist public administrations to develop and deploy AI, such as in Cyprus, Spain, Norway, and Bulgaria. In other cases, the strategies describe initiatives to create new AI teams inside existing public administrations, such as the establishment of a working group for digital transformation in Slovakia, the creation of Chief Data Officer positions in Estonia, or a Joint Centre of Excellence for AI to share expertise across the whole French public sector.

Table 7. Examples of initiatives to introduce legislation.

Country	Sweden	The Netherlands	Luxembourg	France	Austria
Selection of coded policy initiatives	Sweden needs to push for Swedish and international standards and regulations that promote the use of AI and prevent risks	Companies and governments have a (legal) responsibility to provide adequate insight into the (procedure surrounding) AI applications they use	Identifying innovative regulation in the context of data marketplaces in order to increase legal certainty and transparency of data economy participants	Regulating the use of predictive algorithms. To prevent these situations arising, citizens should first of all be informed about their right in these two instances: The right to an effective remedy, and the right to explanations concerning the processing of data on which surveillance is based	The federal government will refer to loopholes in the existing legal framework or obstacles in the development and application of trust

Table 8. Examples of initiatives to introduce new teams.

Country	United Kingdom	Lithuania	France	Cyprus	Ireland
Selection of coded policy initiatives	The government will establish a new office for artificial intelligence to work with the AI council to create and deliver the AI strategy, and collaborate with other relevant initiatives, such as the GovTech catalyst	Establish a Lithuanian artificial intelligence advisory board that will assist government in decisions on future AI policy. The board can be split into national and international levels	DINSIC[8] could incorporate a hub of excellence for AI internally and coordinate a network of skills found within administrations and their operators. Composed of 30 or so officers, their tasks could be to steer advisory assignments within administrations, ensure monitoring and mapping of innovations accomplished by the state, and also to create proofs of concepts and assist implementation on a larger scale in the event of success	These infrastructures will be the link between different bodies that develop and apply AI technologies, such as research centers, businesses, the public sector, and other stakeholders, and with this cooperation these ecosystems will actively contribute to technological and practical development of AI.	The government plans to establish a GovTech delivery board, which will lead the digital transformation of the public service. The GovTech delivery board will consider AI adoption in the public service as part of its work, providing strategic leadership and ensuring a coherent and cohesive approach by the public service in adopting AI as part of its toolkit for addressing societal issues

Supporting research on AI in government

Advancing research on AI is often the cornerstone of many AI strategies, with descriptions of how the academic sector will be strengthened to become a pillar of AI research. However, how much of this research focuses on AI used or for usage in public administrations is often not described. We identified 67 out of 1050 (6.4%) initiatives for supporting research on AI in government. Initiatives include setting up an R&D project for the implementation of AI in government, as in the Estonian strategy, investing in research for applications for civil defence, as in the German strategy, supporting research on Smart Cities, as in Malta, or on how to implement research findings quickly in the public administration, as described in the Dutch strategy. Promoting or facilitating research on AI for or about the public sector is mentioned the most in the Netherlands, Spain, and Germany, but only mentioned once in the French strategy, despite the fact that the French strategy describes how to boost France's academic capacity on AI to great extent. Several examples can be seen in Table 9.

Testing of AI solutions

Another type of initiative described in the strategies is to enable the testing of AI for usage in the public sector (6.3%, 66 out of 1050). It is expected that through testing and experimentation, public administrations will learn more about the effects of AI and gain more experience with this technology. The testing of AI usually is described through two different instruments: the introduction of regulatory sandboxes to provide an environment for the safe testing of AI for the public sector before they are implemented; and the rolling out of various pilot projects. In respect to the latter, these are initiatives that stimulate public administrations to conduct pilots with AI. For example, in Slovakia flagship pilots represent a standard feature in public sector innovation. No country stands out, although Sweden, Czechia, Finland Lithuania have a relatively high amount of these initiatives in their strategy (>12%). Some of these are mentioned in Table 10.

Provision of funding

The provision of funding for AI in the public sector is not mentioned often in the AI strategies, and was only identified 49 times (4.7%). This is surprisingly infrequent, as the lack of funding is one of the often-cited barriers to public sector innovation. Funding is sometimes aimed at research purposes, such as in the Portuguese strategy, in which 19 R&D projects between academic and public administrations are funded, instead of AI pilots and deployments, for instance as in the Polish strategy, which states that 10% of each department and municipal procurement budget should go to AI-related purposes. Other funding possibilities are, for example, for public officials who want to obtain AI-related certifications, as in the Maltese strategy, for open data regardless of the earned revenue, as in the Latvian strategy, or to support projects with private companies, as in the Dutch strategy. A selection of these initiatives can be found in Table 11.

Table 9. Examples of initiatives to support research.

Country	Estonia	Germany	Malta	The Netherlands	Spain
Selection of coded policy initiatives	R&D project under the RITA[9] programme to finance research on implementation of automatic AI-based decision-making support in Estonian state institutions	We will invest in research and development into AI-based technologies for civil security	An EU-financed research on smart cities project is currently underway. The project aims to assess the latest advances in Europe in the development of smart cities and determine which are most applicable to Malta, along with how much they would cost to implement and sustain	The knowledge center 'data science, artificial intelligence & quantum technology for military applications' develops AI applications for defense and works together with TNO[10]	Promote national strategic missions in the field of public administration where AI can have an impact to improve the services to citizens (areas such as health, justice, employment, etc.)

Table 10. Examples of initiatives to test AI solutions.

Country	Sweden	Czechia	Finland	Lithuania	Slovakia
Selection of coded policy initiatives	Sweden needs pilot projects, testbeds, and environments for the development of AI applications in the public and private sectors that can contribute to the use of AI evolving in a safe, secure, and responsible manner	Elaboration of AI pilot projects in public administration and health care	Different network of networks' data lake trials and test environments (sandboxes), with examples such as the use of social welfare and healthcare data in the city of Espoo and the HUS[11] diabetes trial	Create a regulatory sandbox that will allow the use and testing of AI systems in the public sector for a limited time frame. This will allow the developers to test out their product in a live environment and allow the public sector to determine what solutions can be integrated	The public administration will learn to innovate: We will significantly reduce the time for deploying innovations. Testing pilot solutions will become a common practice in the public administration

Table 11. Examples of funding initiatives.

Country	Poland	Malta	United Kingdom	Latvia	Estonia
Selection of coded policy initiatives	Each department and its subordinate public finance units, but also each local government unit, should allocate at least 10% of its public procurement budget for the development of AI technology in principle	The public service training curricula will be updated in 2020 to include AI-related courses. AI training courses will commence in 2021. Furthermore, financial support will be made available to public officers wishing to obtain external certification and qualification in AI-related areas	Create a £20m GovTech fund, supported by a GovTech catalyst, which will support tech businesses to provide the government with innovative solutions for more efficient public services and stimulate the UK's growing GovTech sector	In Estonia, separate funding is available to public service providers to test new electronic solutions in the provision of public services in the form of pilot projects. It would be valuable for Latvia to take over this experience and create an analogous programme	Ensuring flexible and sufficient funding opportunities for pilot projects within funding measures for digital government development (including after the current EU structural funds period), including for AI projects that have a higher-than-average failure rate possibility

Regarding the funding of AI for use in the public administration, Estonia and Latvia often refer to it within their strategies. Many other, in fact, hardly refer to the availability of funding to assist in the uptake of AI in government, or do not make clear whether this funding is for research purposes, pilots or assisting in implementing new AI solutions within the government.

Other initiatives

Lastly, a residual category includes initiatives with less than 3% representation, which are nonetheless worth mentioning. A set of initiatives (27) refer to other technical, infrastructural actions needed for public administrations to develop or adopt AI. These include preparing some form of technical, analytical layer (11) to ensure compatibility of AI, such as reviewing the architecture of AI in Malta, the BüroKratt AI concept for interoperability of public sector AI in Estonia, or creating a structured public database ecosystem to overcome technical barriers for AI in Luxembourg. Alternatively, this may include initiatives to enhance or establish cloud computing for the public sector's usage, improve the availability of high-speed internet in public administrations, or make high-performance computing available for government use. The Hungarian strategy lists that those public institutions should be provided with whichever hardware they require for AI R&D activities, such as supercomputers or other cloud-based software. Other initiatives to support AI within the government include actions to change the working practices and culture of public administrations (22), sharing of standard, reusable AI solutions, such as language models or datasets across the public sector (21), enhancing cybersecurity (15) and ensuring sufficient political support (7) to advance with the plans of the strategy.

Discussion and concluding remarks

As our analysis shows, there is a fair diversity between the different strategies in how they discuss plans to facilitate the use of AI technologies within public administrations, in the kind of actions they propose to overcome various barriers to AI adoption, and in the propensity to highlight some policy initiatives more than others. It has to be noted that, following a full read of the strategy documents, there are many passages in the texts that are rather generic, with a lack of concrete descriptions on what are the plans, mixing intentions, wishes and active policy, and are unclear on whether specific initiatives target public sector organizations, private or academic organizations, or society as a whole. This lack of clarity of strategies on the goals, targets, and instruments has been highlighted by other studies – for example, many strategies often lack details on implementations and metrics (Fatima et al., 2020) – but it is arguably even more unclear with understanding the various policy instruments and goals for stimulating public sector AI (Zuiderwijk et al., 2021). Often shortcomings or challenges are highlighted in the strategies that public administrations face in using AI technologies. However, concrete measures to overcome these barriers are omitted, or initiatives lack information or depth, although some exceptions exist.

Given the difficulties that public administrations face in developing and deploying AI technologies, this study analysed which activities AI strategies describe to overcome these difficulties with the research question: "*What are the main policy initiatives proposed in AI strategy documents by European governments to facilitate the development and adoption of AI technologies within their public administrations, and how do these initiatives aim to address the barriers faced in the implementation of AI in government?*". Many governments seem to favour an approach heavily focused on improving data and other data-related factors to overcome existing barriers to AI development and adoption within their administrations. Such a focus on data is not unexpected, as one of the essential preconditions for AI is access to adequate volumes of high-quality data (Janssen et al., 2020a; Van Noordt and Misuraca, 2020b; Wimmer et al., 2020). The focus on data might be related to the year of publication of the strategies: also considering that some strategies were published a few years ago, data were essential as the fuel for moving the first step towards AI. However, nowadays, as also highlighted by several studies, public administrations should realize that for fostering the adoption of AI, data policies need to be complemented by policies that tackle other implementation barriers, such as organizational barriers, lack of skills, or lack of coordination (Giest and Klievink, 2022; Maragno et al., 2022). Therefore, there is a possibility that this reliance on improving data quantity, quality and access may not boost the adoption of AI as much as anticipated, if many other significant barriers remain. Such a risk is particularly true for countries with many initiatives within this category without policy initiatives to tackle other implementation barriers.

Furthermore, there seems to be a strong focus on GovTech and the private sector to assist public administrations in overcoming development and adoption challenges. There appears to be an underlying assumption that developed innovative solutions will eventually find their way into public administrations by supporting the AI private sector ecosystem. However, challenges to procurement, such as the legal use of data (Harrison and Luna-Reyes, 2022), ownership (Campion et al., 2022), opacity and secrecy (Mulligan and Bamberger, 2019) can bear serious risks if public administrations themselves cannot manage such partnerships successfully (Tangi et al., 2022).

This requires policies that foster internal capacity, ensuring the presence of internal competencies and awareness of AI solutions, stressed in policy documents (Kupi et al., 2022; Tangi et al., 2022) as well as in academic work (Desouza et al., 2020; Mikalef and Gupta, 2021). Ensuring that there is no dependency on the private sector in the field of AI may also further ensure that the governments' approaches are aligned with public values, such as increasing inclusion and engagement, rather than the current emphasis on efficiency values that AI is set to achieve now (Toll et al., 2020b; Wilson, 2021). In this direction, readers of the strategies could also notice many actions aimed at boosting the opportunities for the development of AI in the private sector, but similar initiatives aimed at boosting the public sector use of AI are lacking (Guenduez and Mettler, 2022). For instance, opening public data seems primarily a strategic goal for private organizations' development of AI solutions and providing economic growth – not to improve public services or policymaking through better reuse and sharing amongst administrations.

The severe lack of reference to funding programmes for public sector AI may make it challenging for public administrations – even if data is available – to move forward with initiating AI development. Overcoming implementation barriers and changing work practices beyond the scope of a single pilot require resources to implement organizational changes (Kuguoglu et al., 2021). A mix of policy initiatives that rely strongly on improving awareness and information to act upon often requires adequate financial resources to be successful (Hood and Marge'tts, 2007), as only introducing many "soft" instruments with a lack of financial or regulatory incentives may run the risk of having them be ineffective in overcoming the barriers faced by public administrations (Van Noordt et al., 2020).

In fact, AI strategies have been mentioned as unrealistic funding strategies, despite aspirations to pour many resources into AI (Fatima et al., 2020). Whether the investment is thus aimed at research, the private sector, or the public sector remains unclear. For the public sector specifically, strategies may refer to the Digital Europe Programme[12] or the Recovery and Resilience Facility[13] as potential funding sources for public sector AI – but often lack specifications on what exactly the funding will be used for. Alternatively, it may also be possible that strategies are not the documents describing funding strategies and opportunities, but the noticeable absence requires further investigation.

Limitations and future research

This study features some limitations, which must be taken into account. First, some countries are not included in the analysis, as they have not published an AI strategy yet or are not members of the Coordinated Action Plan of AI. This excludes all non-European countries, which may have different approaches or plans to overcome the barriers to AI development and adoption. Future research may thus require the inclusion of other regions and countries to compare findings between regions, especially since differences between regions have already been identified (Guenduez and Mettler, 2022). Furthermore, as the only documents used were the national AI Strategies, other policy actions, such as eGovernment strategies, may have been overlooked. It may very well be those countries' eGovernment strategies hold additional information on how AI in the public sector will be facilitated. Further research may include a more comprehensive coverage of actions to describe a full spectrum of a specific country or region, as done in Sweden (Toll et al., 2020b). It is also possible that national AI strategies focus more on the apparent data-related challenges as a main priority, and that other documents could include more concrete actions on the identified areas, as these barriers become more visible after experimenting with AI for a while (Kuguoglu et al., 2021).

While this study aims to contribute to the identified research gap on implementation strategies for AI use in the public sector (Wirtz et al., 2021; Zuiderwijk et al., 2021), it still barely scratches the surface in understanding how governments perceive the use of AI, which expected benefits they aim to gain, how they overcome barriers to innovation, and whether the proposed initiatives, in fact, sufficiently tackled the implementation barriers. All these questions remain essential and require further inquiry (Medaglia et al., 2021). It may be possible that certain "styles" or approaches to stimulating AI in government are emerging, with some governments focusing strongly on improving data ecosystems, the private sector and/or internal competencies, similar to the strategic stance towards AI identified earlier (Viscusi et al., 2020) – although in this study a clear distinction between countries could not be found. Furthermore, it is unclear whether previous institutional arrangements, such as historical eGovernment progress or public management reforms, influence the likelihood of proposing certain initiatives and not others. It is indeed possible that approaches followed in past eGovernment strategies will be followed with AI technologies as well, since a lot of the discourse of AI in strategy documents is in line with that of eGovernment (Toll et al., 2020b). What wider consequences to public administration capacity and governance capabilities will be when AI becomes increasingly used in public administration processes is still an open research question.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. In the new Coordinated Action Plan the United Kingdom is not listed as member anymore, while in an earlier study of the AI Watch project by the European Commission the AI strategy has been included (van Roy, 2020). In this study, we decided to include the AI strategy of the United Kingdom. However, the new National AI Strategy, released in September 2021 has not been included in this analysis, as it is not part of the Coordinated Action Plan anymore.
2. https://oecd.ai/en/dashboards/overview
3. As described in the new Coordinated Action Plan https://digital-strategy.ec.europa.eu/en/library/coordinated-plan-artificial-intelligence-2021-review
4. The first German strategy.
5. Ethics Guidelines for Trustworthy AI, https://ec.europa.eu/futurium/en/ai-alliance-consultation.1.html
6. In both the first as well as the second German AI strategy only one initiative was identified referring to improving internal competences.

7. The European Digital Innovation Hubs https://digital-strategy.ec.europa.eu/en/activities/edihs
8. Direction interministérielle du numérique et du système d'information et de communication de l'État (DINSIC), the French Interministerial Digital Department.
9. Valdkondliku teadus-ja arendustegevuse tugevdamine (Strengthening sectoral research and development activities).
10. Netherlands Organisation for Applied Scientific Research.
11. Hospital District of Helsinki and Uusimaa (HUS).
12. The Digital Europe Programme of the European Commission https://commission.europa.eu/funding-tenders/find-funding/eu-funding-programmes/digital-europe-programme_en
13. Recovery and Resilience Facility (RRF) https://commission.europa.eu/business-economy-euro/economic-recovery/recovery-and-resilience-facility_en

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The dynamics of AI capability and its influence on public value creation of AI within public administration

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ABSTRACT

Artificial Intelligence (AI) technologies in public administration are gaining increasing attention due to the potential benefits they can provide in improving governmental operations. However, translating technological opportunities into concrete public value for public administrations is still limited. One of the factors hindering this progress is the lack of AI capability within public organisations. The research found that various components of AI capability are essential for successfully developing and using AI technologies, including tangible, intangible, and human-related factors. There is a distinction between the AI capability to develop and the AI capability to implement AI technologies, with more administrations capable of the former but finding difficulties in the latter. A lack of in-house technical expertise to maintain and update the AI systems, legal challenges in deploying developed AI systems, and the capability to introduce changes in the organisation to ensure the system remains operational and used by relevant end-users are among the most critical limiting factors for long-term use of AI by public administrations. The research underlines the strong complementarity between historical eGovernment developments and the capability to deploy AI technologies. The study suggests that funding alone may not be enough to acquire AI capability, and public administrations need to focus on both the capability to develop and implement AI technologies. The research emphasizes that human skillsets, both technical and non-technical, are essential for the successful implementation of AI in public administration.

1. Introduction

The advent of Artificial Intelligence (AI) is seen as a new and novel game changer in the public sector. The promises of AI are about using intelligent machines to take over human tasks and perform them more efficiently and effectively with tangible results and create public value (Schiff, Schiff, & Pierson, 2021; Sun & Medaglia, 2019). However, public value creation with AI technologies also requires organisations to introduce additional complementary changes, such as organisational or cultural changes (Tangi et al., 2023; van Noordt & Misuraca, 2020b), and those changes require a varied set of resources, from technological to human and more intangible resources, like the proper skillset and inclination towards innovation. The required resources for AI implementation are referred to as *AI capability*, conceptualized and measured in earlier research (Mikalef et al., 2021).

This perspective is quite in contrast with the more technologically deterministic viewpoints of technological change (Luna-Reyes & Gil-Garcia, 2014), which suggests that AI will be a societal change 'by itself', disregarding the institutional dynamics facilitating or hindering its uptake (Ahn & Chen, 2022), or those which argue that AI will automatically provide benefits (or harm) to society, without considering the complexity of the socio-technical interactions of AI and public administrations through which this occurs (Rinta-Kahila, Someh, Gillespie, Indulska, & Gregor, 2021; Sanina, Balashov, & Rubtcova, 2021). These perspectives offer a minimal view that pulls out the implementation from the context, ignoring the in-house capability of the organisation leading to low uptake of the technology (Mergel, Dickinson, Stenvall, & Gasco, 2023). Nowadays, AI can no longer be considered an emerging technology, but rather a set of more mature technologies already used in several public administrations (Tangi, van Noordt, Combetto, Gattwinkel, Pign, & Pignatelli, F., 2022) but also with many pilots that do not succeed in scaling-up, limiting the impact (Medaglia & Tangi, 2022) of AI and not matching the expectations in terms of public value creation. This lack of effect is mainly due to contextual – and not only technological – factors (Mikalef & Gupta, 2021; Schiff et al., 2021).

There is still a lot unknown about the processes of how AI initiatives

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develop and are implemented, which AI capability public administrations have, and how this influences the choices regarding this development and the outcomes of such initiatives (Madan & Ashok, 2022; Mikalef et al., 2021; Neumann, Guirguis, & Steiner, 2022; van Noordt & Misuraca, 2020a). As such, this research aims to investigate the dynamics of how various components of AI capability influence the development and deployment of AI within public administrations. Furthermore, this research aims to contribute to what AI capability is, how this can be acquired and how this contributes to the value creation with AI technologies in a governmental context.

Through an analysis of 15 case studies of public administration's current use of AI technologies through desktop research and expert interviews, this article explores AI capability in government and how this influences public value creation with AI technologies. Such insights interest policymakers and public managers by making them aware of the various factors needed to create public value – particularly from an internal capability perspective. This paper provides additional insights and room for future research to dive deeper into the presence and influence of these factors to ensure AI technologies positively contribute to the administration implementing them.

2. Theoretical background

2.1. AI capability for public administrations

Considering the current and practical research endeavour, AI is regarded as an umbrella term for "*a special form of IT systems, applications or software that are capable of performing tasks that normally need human intelligence*"(Tangi et al., 2022). Often, these systems are based on machine learning methods – but not exclusively. This aligns with other research on AI in government to define AI more flexibly (Madan & Ashok, 2022) and includes various technologies and methodologies to enable computers to perform these tasks that generally need human-like intelligence (Chen, Ahn, & Wang, 2023). Current research on AI does not have a universal definition or approach to what is or is not AI (Collins, Dennehy, Conboy, & Mikalef, 2021), as observed in research on AI in government (Sienkiewicz-Małyjurek, 2023). Whereas technical differences between AI approaches and AI systems have been pointed out, such a deep classification is not always needed for understanding perceptions and experiences of AI (Gesk & Leyer, 2022) and may limit researching technologies which public administrations themselves regard as AI regardless whether this AI label is accepted by all (Aoki, 2020). However, such a flexible approach to AI does come with challenges, as it may cover too many applications and technologies which, despite a similar umbrella term, are noticeably distinct from each other (Wang, 2019), potentially requiring different components and supportive factors to ensure that public value can be created yet this is still a field of inconclusive research.

In general, AI applications could potentially increase the efficiency and effectiveness of service delivery and support government decision-making by simulating different policy options (Mehr, Ash, & Fellow, 2017; Pencheva, Esteve, & Mikhaylov, 2020). Researchers have pointed out the potential of improving policy-making with AI technologies (Valle-Cruz, Criado, Sandoval-Almazán, & Ruvalcaba-Gomez, 2020), augmenting civil servants with additional data-derived insights (Veale & Brass, 2019), automating mundane tasks and processes (Ranerup & Henriksen, 2022), improve the information provided to citizens, making services more personalized (van Noordt & Misuraca, 2022) and understanding citizen sentiment and needs better, such as through the analysis of social media data (Alomari, Katib, Albeshri, & Mehmood, 2021; Cresswell et al., 2021).

However, most of the potential effects of AI (whether positive or negative) have yet to be confirmed and assessed on an empirical basis (Kuziemski & Misuraca, 2020; Anneke Zuiderwijk, Chen, & Salem, 2021). This is due to the various barriers public organisations face in innovation, which include several factors coming from the environment, organisational context, innovation-level as well as individual related factors (de Vries, Tummers, & Bekkers, 2018), to an extent unique to the public sector context compared to the private sector (Bertot, Estevez, & Janowski, 2016). Some note that applying AI in the public sector may not be as distinct from the private sector, such as argued by some CIOs (Criado & Ode Zarate-Alcarazo, 2022), and the challenges in obtaining value from AI innovations in private sector organisations are similar (Mikalef & Gupta, 2021; Shollo, Hopf, Thiess, & Müller, 2022). Other researchers do point out noticeable differences between the public and the private sector, such as the public sector's need to maximise public value, rather than commercial value when they deploy AI technologies (Fatima, Desouza, Buck, & Fielt, 2022), the difference in the motivation of personnel, goals and intentions of the organisation (Schaefer et al., 2021), the presence of unique barriers limiting the uptake of AI in public administrations requiring a dedicated review (Madan & Ashok, 2022), which explains why public sector adoption of AI has been slower than in the private sector (Anneke Zuiderwijk et al., 2021). Others point out that expectations from citizens (Gaozhao, Wright, & Gainey, 2023) as well as having higher transparency and explainability requirements compared to the private sector (de Bruijn, Warnier, & Janssen, 2022; Janssen, Hartog, Matheus, Yi Ding, & Kuk, 2020), of both the functioning of the AI systems themselves (Criado, Valero, & Villodre, 2020) as well as higher transparency of knowing how public resources are being spent and why (Fatima et al., 2022) creates different demands surrounding the deployment of AI in public administrations compared to private sector organisations. As such, while some challenges of using innovations, including AI technologies, may be comparable to both the private and the public sector, the context in which public administrations operate is different and thus, findings from the private sector may not be directly translated to the public sector without adjusting for this contextual difference.

Overcoming these challenges is essential to ensure the sustainable implementation of AI in the public sector. Scholars are now beginning to argue that public administrations can no longer rely solely on the capacities developed in recent years for the adoption of digital technologies: a new and different type of capability is needed, namely AI capability (Mikalef et al., 2023; Mikalef & Gupta, 2021). Following earlier work by Mikalef & Gupta, (2021), AI capability is defined as the innovation capability needed to uptake Artificial Intelligence. So far, research has only scanned detailing what AI capability is, which factors characterise it and *why* this is still lacking. This research is going in this direction and will provide further insights into how public administrations acquire and use AI capability to develop and implement AI technologies in their organisations.

The concept of AI capability has been introduced to determine better which resources organisations should acquire and develop to obtain benefits from the acquisition of AI technologies (Mikalef & Gupta, 2021), noting that despite much excitement about the technology, many organisations face challenges in gaining performance gains from the use thereof (Mikalef & Gupta, 2021; Shollo et al., 2022). AI capability is based on the Resource-Based Theory (RBV), the innovation capability theory, and the Technology-Organisation-Environment Framework (TOE). The Resource-Based View (RBV) of organisations (Madan & Ashok, 2022; Wade & Hulland, 2004) highlights the complementarity of both IT assets and capabilities with the organisational capabilities to achieve an increase in performance (Pang, Lee, & DeLone, 2014). This organisational capability to spot, develop, test, use and integrate innovations into the organisation has also been conceptualized by research as innovation capability (Bekkers, Edelenbos, & Steijn, 2011; Lewis et al., 2015; Lewis, Ricard, & Klijn, 2018), which describes various resources and capabilities a public administration should have to be innovative, take risks and use innovations to improve its operations and create public value (Boukamel & Emery, 2017; Gieske, Van Buuren, & Bekkers, 2016). These organisational factors explain why this historical progress in eGovernment is unbalanced across public administrations, despite the availability of these technologies (Zheng, Chen, Huang, &

Zhang, 2013). The fundamental notion of this approach is that the effective use and management of these technologies can lead to value creation – not the technology by itself (Pang et al., 2014).

Just having AI within a public administration does not necessarily lead to public value (Alshahrani, Dennehy, & Mäntymäki, 2021; Meijer, Lorenz, & Wessels, 2021), as different capability factors play a role in determining the decision to adopt AI technology and the performance of AI. For instance, research on the use of Chatbots has shown that significant environmental pressure may lead to the decision to use Chatbot technologies initially, but the performance of these Chatbots differs greatly based on the level of economic development and the organisational readiness of the organisation (Y. Wang, Zhang, & Zhao, 2022). Other work on incorporating Chatbots in government organisations also highlights the additional organisational work required to keep the performance of the technology high such as the need to assign new positions to work and train with the Chatbot technology and to review its performance as an 'organisational agent' (Maragno, Tangi, Gastaldi, & Benedetti, 2022). Even the same AI system used in different organisations can have different effects due to the organisational and environmental contexts it uses (Meijer et al., 2021).

In their exploration of AI capability, Mikalef et al. (2021, 2023) noted that to be able to deploy AI solutions that improve the quality and efficiency of the organisation, in-house competencies are effectively needed, which goes beyond merely the motivation to use AI technologies (Mikalef et al., 2021). Other studies stress further stress to derive value from AI technologies, it is not only needed successfully develop AI (Campion, Gasco-Hernandez, Jankin Mikhaylov, & Esteve, 2022; Mikalef et al., 2021; Neumann et al., 2022; van Noordt & Misuraca, 2020a) but also to integrate them in the organisation on a more structural basis (Aaen & Nielsen, 2021; Kuguoglu, van der Voort, & Janssen, 2021; Meijer & Grimmelikhuijsen, 2020).

However, despite this, there is still a strong need to understand better the different dynamics that shape and form AI capability within public organisations over a more extended period or specific factors that have been overlooked so far (Mikalef et al., 2021), utilising interpretivist approaches to gain a better understanding of the trajectories of deploying AI technologies, facilitated or hindered by the organisational resources (Mikalef & Gupta, 2021). This study aims to provide such a closer perspective by utilising case study research to examine better how AI could give value to public organisations through the lens of AI capability (Mikalef et al., 2023) and, in doing so, contribute to the research gap of limited empirical evidence on how AI is used in public administrations, how, why and to which effects (Medaglia, Gil-Garcia, & Pardo, 2021; Anneke Zuiderwijk et al., 2021). In doing so, this research adopts this earlier developed conceptual framework on AI capability (Mikalef & Gupta, 2021) based on three main components: tangible, intangible and human resources, each of which has been complemented with additional theoretical insights.

2.1.1. Tangible resources

These factors include various organisational resources considered tradable on the market, such as physical assets, IT resources, and more relevant AI data infrastructure. Tangible resources are often regarded as available for all organisations in theory and are necessary, yet insufficient, to create capability (Mikalef & Gupta, 2021). For the successful initiation and development of AI, data of adequate quality, meaning that the data is accurate, representative, consistent, relevant, complete and ready for use (Janssen, van der Voort, & Wahyudi, 2017), and of adequate volume, are crucial to initiating AI-related development.

Such availability of data-related resources often requires the presence of a developed technical infrastructure internal to the organisation (Desouza, Dawson, & Chenok, 2020), with enough connectivity, bandwidth, processing power, and database technologies, among others (Bertot et al., 2016; Janssen et al., 2017; Mikalef & Gupta, 2021). Moreover, the infrastructure should be flexible and capable of handling and processing high volumes of data, which may require a dedicated infrastructure for the use of AI (Bertot et al., 2016; Janssen et al., 2017). This need widens the possibilities for a public administration to develop and use AI. Often, the data and technical infrastructure builds on top of previous digitalisation activities due to the interconnectedness of AI technologies with the data collected and infrastructure (Lachana, Alexopoulos, Loukis, & Charalabidis, 2018), such as the use of the Internet of Things which data could later be used for AI (Kankanhalli, Charalabidis, & Mellouli, 2019). As such, public organisations which have done insufficient work in ensuring previous eGovernment progress may thus find a significant disadvantage to starting with AI technologies as their infrastructural resources are limited.

Public administrations often have to juggle time and resources to complete their existing work tasks. They may thus have little time and resources available for exploring and experimenting with new technologies (Palm & Lilja, 2017). As seen in some cases of AI used in government, these activities are often done outside the scope of existing work hours and are sometimes even voluntarily by enthusiastic individuals (van Noordt & Misuraca, 2020a). Without enough financial resources and time for AI, it is challenging to identify AI applications which could be utilized in the organisation (Mikalef & Gupta, 2021; Pang et al., 2014). However, such resources should also be available to integrate successful AI into the organisation – these activities also require considerable financial and human resources to facilitate the change, sometimes (much more) than the development (Kuguoglu et al., 2021; Real & Poole, 2004) – yet this is often overlooked or outside the scope of projects, limiting the final take-up and potential for value creation. Many innovations within the public sector often fail to scale up following their development and/or pilot (Kuguoglu et al., 2021; van Winden & van den Buuse, 2017). As a result, many initiatives remain in a small-scale implementation, limiting their potential benefits only to a small scale, or even ending after a period of time.

2.1.2. Human resources

Whilst Artificial Intelligence is often discussed in replacing or automating human activities, human resources and skillsets are invaluable in AI capability. AI does not get developed without the involvement of human experts and workers (Maragno et al., 2022; Mikalef & Gupta, 2021). This requires public organisations to have staff with expertise in the development of AI, staff with skillsets in managing the (existing) IT infrastructure and any other supplementary technical positions which facilitates the development and implementation of AI (Mikalef & Gupta, 2021). Public administrations struggle greatly to acquire such technical expertise in-house due to a lack of (financial) benefits, recognition and supportive culture for these already scarce experts (Mergel, 2019; Mergel, Edelmann, & Haug, 2019; Wirtz, Weyerer, & Geyer, 2019), creating dependency on external parties to manage the technical infrastructure and/or provide technical expertise to for AI applications (Duhamel, Gutierrez-Martinez, Picazo-Vela, & Luna-Reyes, 2014; Mikhaylov, Esteve, & Campion, 2018; Moon, Choe, Chung, Jung, & Swar, 2016).

Not just for developing AI is human expertise important, but also – and more generically - for facilitating the actual digital transformation in the organisation (Mergel et al., 2019; Tangi, Janssen, Benedetti, & Noci, 2021). Whereas technical skills for the development of AI need to be stressed, the need for public managers able to align AI's technological possibilities with the organisation's goals is just as critical (Alshahrani et al., 2021; Mikalef & Gupta, 2021). Such leaders should be encouraging and supportive in changing ways of working with AI systems and capable of identifying the right skillsets and people to work well with AI (Kaplan & Haenlein, 2019). Unrealistic expectations of AI technologies by management or a willingness to try AI for the status but not for actually introducing change in the organisation often leads to a failure of AI in government later on (Kuguoglu et al., 2021).

However, AI competencies go beyond just management, and every civil servant needs some form of AI-related competencies. Civil servants must find new ways of working with AI systems, changing their traditional working routines (Maragno et al., 2022) and their attitudes to including new technologies to improve their practices (Kaplan & Haenlein, 2019). Some form of creativity is needed within the staff to detect new situations in which AI could be applied to. Whilst creativity may be an individual characteristic, public administrations could greatly support public sector creativity. They can provide additional resources for staff members who are eager to do so, such as by facilitating a human resource management system and by encouraging staff to come up with innovations to improve existing practices. (Houtgraaf, 2022; Mikalef & Gupta, 2021).

2.1.3. *Intangible resources*

Most AI projects rely strongly on internal and external collaboration between academic, private, and other public administrations. The networks in which public administration operates and how the administration leverages the expertise from these networks are crucial for many innovations to initiate and succeed (Cordella & Hesse, 2015), requiring the organisation to be able to collaborate with different actors (Picazo-Vela, Gutierrez-Martinez, Duhamel, Luna, & Luna-Reyes, 2018). Such collaboration is not straightforward, however, as privacy and security when sharing data, a lack of understanding of what data is needed and available, misalignment between organisations and a lack of engagement from the hierarchy limits such collaborations (Campion et al., 2022). Introducing organisational routines to overcome these challenges may help to facilitate trust, make clear responsibilities and achieve AI's success (Campion et al., 2022). As such, the organisation has to have the ability to detect challenges in the current state of operations, construct a vision of where to go with AI technologies, and layout and implement the steps needed to facilitate such a change (Barcevičius et al., 2019; Mikalef & Gupta, 2021). Such change often requires overcoming various cultural barriers internal to the organisation as well, as there may be widespread risk aversion, low commitment to learning, low openness to new ideas, cultural traits limiting cooperation across horizons, vertical levels, low level of success (Boukamel & Emery, 2017), particularly of innovation of which their effectiveness is unknown of such as AI (Doberstein & Charbonneau, 2020).

At the same time, it is to be highlighted that AI innovations in a public administration context do come with some considerable risks (Dwivedi et al., 2019). Rushing through innovation, especially with AI, brings public administrations in a precarious position where they have to balance the severe risks to fundamental human rights through irresponsible deployment with the desire to be more risk-taking and efficient (Kuziemski & Misuraca, 2020). As such, becoming less risk-averse does not mean that there will be a complete disregard for the potential negative consequences which may occur because of AI deployment, highlighting the importance of being aware of the risks of AI and taking appropriate action to mitigate them.

While there is a general understanding in the literature about what kind of resources, skills and organisational factors are needed to move forward with using Artificial Intelligence in public administrations, it is still somewhat unclear how the presence or lack of components assist in the development and use of AI, how public administrations may acquire these components and which factors may limit the acquisition thereof.

3. Methodology

3.1. *Case selection*

To gain a better understanding of the acquisition of AI capability in public administration and how it leads to the creation of value with AI technologies, this study uses insights from 15 case studies of the use of AI technologies by public administrations within the European Union. These cases were selected from a large database on AI in public services published by the Joint Research Centre of the European Commission [4]. To our knowledge, the database represents the largest and more complete source of information at the disposal of the research community on the use of AI technologies in public administrations. While the organisations using AI and consequent source of information is limited to European countries, at the same time it allows for higher homogeneity in the policy background and the legislative boundaries that strongly influence the implementation challenges.

The analysed organisations have been selected following a pragmatic approach. Firstly, potentially relevant organisations with already several detailed information about their use of AI available on the web, considering that the original database already included a link pointing to a website with information on the case, were identified to ensure that the contacted public administration has experience with using AI. Secondly, the study aimed to identify those public administrations with a more advanced maturity in using AI as they likely have more insights on gaining the resources needed for AI deployment. However, despite best attempts, not many of these organisations were identified. Thirdly, we reduced the list to include only the organisations where contact details of at least one person working on the organisation's AI projects were available to contact them. Lastly, only the cases where at least one interview with an expert involved in the development and/or implementation of the system was possible were included. As a result, the study consists of insights from 15 public administrations that have developed one or multiple AI systems. Whilst the study aimed to keep a diverse subset of public administrations, utilising different AI systems, in different countries and various administrative levels to have generalizable findings and to provide insights into this early phenomena, other administrations not included in the study, those without AI adoption yet may hold different experiences on how they face challenges in acquiring the right resources to use AI effectively.

A short overview of the selected organisations, as well as an example of the AI that they use or have used is found below:

- **Case 1**, the Danish Business Authority in Denmark. This organisation has been using different AI-based models, put together in the Intelligent Control Platform that provides an automated assessment of how a selected company is more likely to commit fraud compared to others.
- **Case 2,** the Greek government. An example of AI used was an AI system in border control points that help with the selection of travellers to test upon arrival. The purpose was to effectively allocate the scarce PCR tests within the summer tourism season.
- **Case 3**, the municipality of Leuven, Belgium. The municipality was developing sound meters installed and development of an application for citizens to report noise in the street. The results will allow proper corrective actions, also through nudging.
- **Case 4**, the Finnish Tax Authority, Finland. This organisation has been exploring applications of AI among which an AI system is based on understanding speech and transforming it into text. It is used to provide subtitles on all the videos and is part of a wider initiative within the administration to use Speech-to-Text technologies in various use cases.
- **Case 5,** the Luxembourg National Library, Luxembourg. This organisation has been using an AI system that operates on top of the results of the different OCR (Optical Character Recognition) used over the years for digitizing historical newspapers and books. The system aims at improving the quality of the result, identifying and correcting mistakes.
- **Case 6,** the Estonian Unemployment Fund. This organisation has been deploying Ott, an AI system used to assist consultants with unemployment by providing insights predicting the chances of their client – an unemployed person - getting a new job.
- **Case 7**, the municipality of Amsterdam, the Netherlands. This public administration has been trailing multiple AI systems and is considered one of the leading cities in AI. One example is an AI solution to detect garbage. The AI solution automatically identifies trash on the street and shares this with the garbage management services of the city to act and solve the issue.

- **Case 8,** the Spanish Tax Authority, Spain. This administration has been using an AI system to estimate the income of Small and Medium Enterprises and self-employed individuals who pay taxation under a module taxation scheme.
- **Case 9,** the Estonian Parliament, Estonia. This organisation has been deploying a speech recognition tool called Hans to assist in the transcription of the parliamentary sessions.
- **Case 10,** the National Library of Estonia, Estonia. This organisation has been developing several AI projects among which an AI system supporting the automatic keywording of publications of the organisation.
- **Case 11,** the EtaLab within the French Interministerial Digital Directorate, in France. This is a supporting organisation of the national government which has been supporting 24 different AI projects across different French public administrations. One example is the development of an AI system which removes identifiable personal information from court decisions to support the publishing of open data.
- **Case 12,** Estonian Customs and Tax Board in Estonia. This organisation has trialled a couple of AI innovations before developing its internal AI strategy. One example of AI that was explored was the use of AI to assist in risk determination.
- **Case 13**, the Flemish Unemployment Organisation, Belgium. This organisation is relatively advanced in AI with over 30 people working on AI initiatives, with 14 of them in active deployment. One of these AI systems is an AI system which supports the unemployed in finding a fitting job according to their competencies and interests.
- **Case 14,** the municipality of Strängnäs, Sweden. This municipality is the sole smaller/medium-sized municipality part of the AI Sweden network and is in an experimental phase with AI technologies. One example of AI that has been explored was the use of NLP to support the protection of children.
- **Case 15,** Federal Public Service Policy and Support, Belgium. This federal administration supports other administrations in their digitalization efforts and has been exploring using AI to support their own activities as well. One AI system in the organisation is a Chatbot supporting citizens in creating tickets for the help desk.

3.2. Data collection and analysis

The primary data consisted of semi-structured interviews with 19 different informants, often the project manager, developer, or manager otherwise responsible for (some) of the organisation's AI activities, as can be seen in Table 1 below:

Table 1
Case and their interviewees.

#	Organisation	Interviewee
Case 1	Danish Business Authority, Denmark	Chief Advisor
Case 2	Greek government	Main developer, University of Southern California, United States
Case 3	Leuven, Belgium	Project Coordinator
Case 4	Finnish Tax Authority, Finland	Director Product Management
Case 5	Luxembourg National Library, Luxembourg	Deputy Head IT and Digital Innovation
Case 6	Estonian Unemployment Fund	Senior researcher, University of Tartu, Estonia
Case 7	Amsterdam, Netherlands	AI City Lead
Case 8	Spanish Tax Authority, Spain	Head of Systems and Communications
Case 9	Estonian Parliament, Estonia	Administrative Director
Case 10	The National Library of Estonia, Estonia	Chief Data Officer
Case 11	EtaLab, France	Head of AI Lab
Case 12	Estonian Customs and Tax Board, Estonia	Head of Business Technology / Development Specialist
Case 13	Flemish Unemployment Organisation, Belgium	Manager AI Center of Excellence
Case 14	Municipality of Strängnäs, Sweden	Head of Digital Strategy
Case 15	Federal Public Service Policy and Support, Belgium	AI4Belgium Lead / Director General Digital Transformation

The interviews were conducted between October 2021 and October 2022. The interviews were following a pre-designed protocol, with a semi-structured approach following an earlier exploration of the use of AI in the organisation through desktop research. This allowed for more robust, generalizable and replicable findings rather than solely exploratory case studies alone (Baxter, Jack, & Jack, 2008). Both authors have conducted the interviews, to avoid as much as possible any interpretation biases.

The interviews included questions (see also in Appendix A) focusing on the use of AI in the organisation and the experiences regarding their usage. In addition, the interview included questions on various components of AI capability and how this was acquired. If necessary, follow-up questions touching upon the specific points that came out from the existing literature have been mentioned or, in the case of an absence or a lack of insights, moved to other topics. From the interviews, it sometimes emerged that examples of AI described were, however, not in use anymore. Consequently, insights on why these systems were not implemented after a seemingly successful trial have been incorporated into the research findings as well. Only in case 6 was a video interview not possible, but the questions were answered through a mail interview to gain some insights into the system. The interviews were supplemented with additional material on the case as well as follow-up exchanges through e-mails. The transcripts were consequently thematically coded to identify the various components of AI capability and their additional insights on each component of AI capability. Through the coding process, subcategories of the AI components were identified and through revising each case to compare and verify the occurrence of the coding, relationships and logic between the components of AI capability were determined. However, due to the broad nature of AI capability, each component could only be touched upon briefly in the data collection, leaving room for more in-depth analysis and insight into how specific resources are acquired, sustained, and how they influence the development and implementation of AI.

4. Findings

The findings gathered from the interviews show that AI capability within public administration is not straightforward nor advanced, even among organisations deemed as frontrunners or mature in their country. The several components of AI capability are not immediately present within public organisations, or they are faced with several difficulties in obtaining, requiring and maintaining these resources.

4.1. Tangible resources: a sporadic continuation of past eGovernment legacy

Most cases follow the use of AI technologies after several years, if not decades, of digitalisation of their administrative services. All the cases used some, or mostly, internal administrative data to base their AI systems on. Often this required several years of having digital processes to capture the data stored in data warehouses or other databases. As such, long progress in digitalisation, as seen in (Case 5) or managing administrative data due to the nature of the tasks of the institutions such as (Case 6 and 13) often provides the data needed for the initiation of AI. As illustrated by case 13 "*Well, at the VDAB there was always a lot of data because they work with job seekers, use applications and then the data was stored in a data warehouse*". There is a strong connection between the willingness and ability to use AI and the public administration's historical interest in using data. In several cases, the use of AI follows the organisational tasks in supporting the open data ecosystem, such as seen in (Case 11), *The first mission at the lab was the open data policy for the French government, but after a few years it was clear to the team that it's also* *very useful to help administrations use their data"*.

While first, the role of these institutions was to promote general data quality and accessibility, over the years, a shift occurred from the interest of publishing open data towards analysing them, with increasingly more advanced technologies, showing the evolutionary trajectory from early eGovernment progress towards the use of AI – the use of AI is a continuation of a more extended period of digitalisation rather than the starting point. Often, however, new data had to be collected for the project, even with the general history of digitalisation of the administration. Yet, public administrations often face challenges in acquiring new data as they may not be allowed to do so. In (Case 3) for instance, regulatory restrictions limited the collection of audio data from their citizens for the use of AI development – altering the overall approach of the development: "*We had an extensive study to see if there was a way to tap some audio from time to time (…) but this was not possible privacy-wise."* Alternatively, data collection may be legal but not considered ethical. Therefore, the development of the AI system in (Case 2) excluded the collection of some personal information through the Passenger Locator Forms whilst it was legally possible to collect. "*We prioritised transparency and simplicity to figure out which data is reasonable to get and what is still informative."* A legal framework which allows the sharing of administrative data among public administrations, clearly highlighting which data and for which purposes it can be shared, both facilitates and restricts the initiation of AI systems, as a legal framework was the main enabling factor allowing the Intelligent Control Platform in (Case 1) to be developed and used legally: "*We also needed to have the legislation in place in order to gain access to the necessary data. Now, we have legislation allowing the Business Authority to gain data from all other authorities within the scope of the Danish Business Authority's area of operation"*.

Programmes which aim to support the organisation's data readiness, such as introducing more robust data governance mechanisms and quality, help the organisation organise the data needed for AI projects and significantly support the initiation and reliability of the AI systems. At the same time, data quality for AI is not easily objectively measurable and should not be assumed by having data governance alone. Having a baseline of data governance to ensure decent data quality is essential. However, several cases, such as (Case 13 and 14), showed that every piece of data requires some inspection, assessment, and deliberation on whether it could be suitable for AI and the goal it will be used for. For instance, as stated in Case 13: "*A large part of our time goes to correcting and preparing data so that we can use it within an AI model. I believe you can minimize that time (by strong data governance practices) but it will always be a part of the time of data scientists. You cannot expect a wonder from these people (the team responsible for data quality) so that they are able to do that part of the job."* Cases 7 and 14, for instance, highlighted that seemingly high-quality datasets might turn out not to be suited for AI systems, which may only be discovered in a late phase of the development process: "*When you try and improve the process with language models, you could have surprises when 80% of the project time has passed. Maybe it shows that the data quality or data amount was not good enough."*, Case 14.

From this data collected, we can draw the following proposition:

Proposition 1. Digitalisation is crucial for developing AI capability in public administrations. These resources emerge from a past eGovernment legacy, although new data for AI are often still required as well as ensuring legal/ethical controls.

While the data is a crucial component to have as part of the AI capability of these organisations, a supporting technical infrastructure is required as well. The data collection infrastructure often grew over time as the data quantity increased. How this infrastructure is managed, however, varies per administration. Some administrations host their technical infrastructure mostly internally such as (Case 5, 8 and 13), allowing for general flexibility and access to data needed for the development of AI systems. Case 1 and Case 15 also stored the data of other public administrations or had access to these for AI-related initiatives. In other administrations, such as in (Case 12), the technical infrastructure is completely outsourced to another public administration. This may not be a problem per se, but as (Case 2, 10 and 13) showed is that challenges may appear when the technical infrastructure is managed by different partners that may or may not be incompatible with each other, introducing additional coordination challenges and costs when data collection, infrastructure and computational resources are all outsourced: "*And then (before outsourcing) it was very simple to implement. If you wanted to, you could go to another department and say I need this and that. (…) But right now, it is not so easy to implement something new."* Case 10.

However, what stood out was the ad-hoc nature of the computational infrastructure for AI development and implementation in these organisations. As (Case 11) highlighted is that in France, administrations are themselves responsible for the technical infrastructure for their AI projects, which greatly vary in maturity: "*A difficulty is that we don't have one infrastructure where we can do any machine learning project easily. (…) and it can be problematic to send the data to cloud providers. So now, anyone is doing the machine learning with its own infrastructure*". Smaller public administrations, like municipalities (Case 14), are at risk due to the lack of computational resources, which increases their reliance on external companies to develop and train their AI systems. Computational resources are also needed beyond the first development when systems need to be retrained, as seen in (Case 6): "*The retraining is not automated, but we thought it was better if a human did this regularly to add new variables and take others away. (…) They do this every quarter."*

The cases also highlight a dilemma for public administrations to base AI systems on cloud-based infrastructure or their own internal resources. Some (Case 13, 14 and 15) stressed that the use of external cloud providers for AI development is forbidden, limiting their possibilities to develop AI without the presence of an adequate internal technical infrastructure: "*When we use personalized data, we cannot go to the cloud"* (Case 13). In other cases, external cloud providers were one of the main contributing factors leading to the successful implementation of AI, such as in Case 4, which combined a cloud provider with their internal systems. A government community cloud, as (Case 15) is responsible for, may provide the right balance of allowing computational resources without requiring smaller administrations to procure these resources themselves, as mentioned: "*What we are interested in is to have analytics on all the data across all organizations. Then we have the data and the tools in our cloud, so we provide the digital solutions to get the input of the data"*.

From the data collected, we can draw the following proposition:

Proposition 2. AI requires a powerful infrastructure, both for the development and the continuous training of AI systems. This can be acquired either through internal infrastructure, or through an external partner– with different effects on their AI capability.

Despite the importance of providing adequate financial resources for AI development and funding, it is not common for public administrations to have this structurally available. Most funding for AI development and implementation is ad-hoc and sporadic, often through external funding sources rather than structurally from inside the organisation itself. For instance, for (Case 5), funding came from a national AI4GOV funding programme to finance the development and pilot of the study, while Cases 6 and 10 were developed due to one-time funding through European funding. Case 11 was even an entirely voluntary project with no budget. Some exceptions exist, for instance, as Case 15 provides funding for several years for AI, allowing them to create an internal AI team and initiate several AI-related activities: "*The government decided to provide a budget divided in two categories, one dedicated to hire people and the second one to support implementation in the field"*.

The lack of this structural funding may allow for the development of the pilots, as most of the external funding resources kick-start the development. However, challenges occur in implementing and maintaining AI systems later on. Some AI projects were designed only to be developed as a prototype, as seen in Case 7: "*So the funding available is always only for experiments in piloting and then they stop, which of course* *gives the issue that after you need structural budget. (…) When it's gone, you also have to let people go, or you need to find budget to hire them, which is not always possible"*, or in Case 3: *"So the funds that we have now is 80% funded by the Flemish Government and 20% by the municipality. For implementation, it is 50/50 funding so we have to look if we have funding available to fund the bigger implementation"*.

Exploration and experimentation lead the narrative, goals and funding requirements. Implementation of said developed solutions would thus require additional external funding or resources from the internal budget, which were not always available, leading to their discontinuation. It may well be the case that the costs for implementing developed AI systems may be more than the development (e.g. Case 10), which makes it challenging for public administrations to decide whether the benefits of using AI outweigh the costs, such as seen in Case 7: "*Because the moment is no longer a pilot, there are more people that are going to be responsible for it. And I think a lot of people don't want to take that risk. And maybe it's also good because there are a lot of unknowns using this technology and the effects of it. So, putting it on hold sometimes is a wise decision to wait and see until it's actually, you know, a good idea to do it"*.

In fact, in those organisations where financial resources were available for both the development and the implementation, such as in Cases 8, 9 and 13, it allowed for more structural and sustainable use of the AI systems, such as illustrated by Case 13: "*In a lot of organizations there you have one budget everybody has to fight for. But we have an innovation budget so there is so much money for innovation and nobody can take something from that budget. So, we actually have that budget and we can do our experiments and projects"*. Alternatively, the implementation followed from the regular IT budget, such as in Case 9: "*This was done from the IT budget, but for that time we had some additional budget from the main budget."* Other organisations, such as Cases 5 and 6, managed to find internal resources available after the external funding ended. In Case 10, funding for implementation would have to come from another organisation which may not immediately see the value of AI implementation following the pilot. Not having adequate internal resources available for the post-development phase is thus a major limiting factor in the AI capability of public organisations and crucial to consider obtaining value from AI.

From the data collected, we can draw the following proposition:

Proposition 3. Financial resources affect the AI capability greatly. Adhoc and sporadic funding creates challenges in maintaining and scaling up AI systems, whereas stable resources allow a structural and sustainable use of AI inside the organisation.

4.2. Human resources: balancing between internal and external expertise

Human skillsets are also a crucial component in ensuring AI capability within public administrations, but all the researched administrations have difficulties acquiring AI-related expertise, both technical and non-technical, limiting their possibilities to understand where AI could be deployed, how to develop and implement these systems and how to change their organisation accordingly. Even organisations with bigger AI teams internally present such as (Cases 1, 7, and 13) regarded themselves as 'lucky' to attract so many data scientists especially considering in some countries AI experts are few and challenging to hire, such as those experienced by (Cases 6, 9, 12 and 14): "*We don't have the specialist who can work on AI tools in our system. This is one of the biggest problems that we have. (..) I can calculate on 10 fingers how many data scientist specialists we have in Estonia, and to have them in our organisation is a big challenge*" – Case 12.

To do so, a lot of work was done to make the organisations attractive workplaces for data scientists (Cases 1 and 7). Many, such as highlighted in Cases 11 and 15, noted that the financial capability to hire data scientists is very limited in public administrations, only allowing for (very) small teams internally with AI-related expertise. Although even those organisations with bigger teams notice this difficulty, such as Case 7: "*When we go to a more senior level, we notice that we cannot compete with the private companies in terms of salary."* Sometimes, however, just one individual is sufficient to start the development of some of the AI applications, as seen in Case 5. Other institutions acquired their AI expertise through internal training, learning by doing (Case 8) and upskilling of employees with some data-related expertise already: "*An initial set of skills was acquired by means of prior training in technological foundations provided to the team members. Some team members deepened their knowledge driven by personal interest and the remaining expertise was acquired during the development of the project; we learned by doing."*

Not all administrations had the technical expertise internally present. For instance (Case 3, Case 4, Case 9, and Case 14) relied on external private sector expertise to develop the AI systems, although this comes with challenges. As Case 3 highlighted, the lack of internal capability led to risks in managing the technical parts of the tendering process as there was not sufficient internal know-how to evaluate the process: "*So whenever we have meetings with the technology partner (…), it's also a bit difficult let's say. A data scientist is actually something that we would really like to have. (…) I have not heard from other cities that they have a data scientist, but it would be really welcome*." The experiences from (Case 7) showed how varying levels of technical expertise present in partner municipalities limited collaboration: "*But what we notice is that in every city they had very different levels of technical knowledge. (…) So, you can put them in the same room and say you have to collaborate, but you need to be on the same level in order to be able to really collaborate. So, I think that was the biggest issue in trying to get people to work together when they were in different phases of technical knowledge within their organisations."*

In the worst case, as experienced with Case 12, private vendors may only deliver the final product, leaving limited opportunities for learning inside the organisation. Public procurement rules, as mentioned in (Case 15) may also make private sector involvement in AI close to impossible.

As such, a preferred arrangement of working is to have a core AI team present with several individuals who know how to develop, implement, and maintain AI systems while being responsible for working with externals, as seen in (Cases 1, 11,13 and 15): "*At the moment 25% of the AI team is internal, and 75% is external"*- Case 13. However, even then, working with academic institutions rather than with businesses, such as in (Case 6 and 7) is more suited for the relatively unknown results of AI projects: "*A risk I have experienced often is that there is a promise of over-delivery and there seems to be not so much flexibility after a tender has been closed. If then (the contractor) doesn't deliver, you are still stuck with the tender, and working with academics gives you a bit more flexibility or a different kind of contract or collaboration* – Case 7.

Nevertheless, even these organisations highlight that technical expertise for the maintenance of systems, which is essential to ensure the effectiveness of the AI systems over time, is challenging as it is relatively dull work and takes up a fair amount of resources (e.g. Case 6, 13): "*75% of our resources go to the maintenance and improvement of the applications (…), if we still want to stay developing new things or experiment with new things, then our team will have to grow because we cannot do both*" – Case 13. While in this research, a clear overview of supplementary IT skills did not become apparent, the cases did suggest the importance of having additional technical skillsets such as for maintaining data warehouses (Case 13), the integration of AI in existing software (Case 4) and others, depending on the task needed (11 and 15).

Proposition 4. A functional arrangement is to have a core AI team to develop, implement, and maintain AI solutions while being responsible for working with externals. Full reliance on third parties, given difficulties in hiring people with the right profile, affects the AI capability of public administrations greatly.

However, the experiences in all the cases emphasized management's importance in initiating and implementing AI. Whereas technical expertise may be acquired through outsourcing, internal leadership cannot. As such, they are crucial to take the lead in AI development and implementation, build momentum around AI in their organisation and allow staff members to experiment and explore AI technologies (e.g. Case 1, 4 8, 9). Without top management involvement in creating an AI strategy and vision (which was done in cases 12, 13, 14, 15), there is a risk that strategic alignment of the technology with the organisational goals will be limited or that support for components of AI capability will not be acquired: *"The reason why we turned to the AI strategy is to understand who will be the owner, what we need to do with it and have next steps to be successful with projects and to implement them all over the organizations because we understood also that we need to, you know have some new rules in our organizations"*- Case 12. Senior management is crucial for improving the overall AI capability of their organisation, though, for instance, setting up dedicated AI teams in their organisation (Case 1, 15) or allowing hiring individuals with AI skills not done before (Case 5).

Tactical level management needs to be able to bridge technological opportunities of AI with the tasks of the organisation (Case 7, 13, 15), understand the trade-offs of AI for use in the organisation, demystify AI and remove assumptions that AI will solve all challenges by itself (Case 1) and realize and understand the complementary work needed to make AI contribute to the organisation (Case 13). When this awareness is lacking, there is a risk that the organisation is only keen on trying out new pilots and innovations without considering the additional work to implement the solutions, as seen in, for instance (Case 10): "*No, only until the pilot because we don't know what the result is.*"

Civil servants also require complementary skills to work with the AI systems to derive value. However, they are often overlooked as innovations can be pushed down with enthusiasm from management rather than from the end users. For instance, remarked in Case 6: "*We see a different attitude within the institution depending on the level. The street-level bureaucrats are somewhat sceptical, and it has taken a lot of time with training but they still see it as a relatively abstract tool with some features that are not really useful, depending on the experience and region. (…) If you move up higher at the managers, they like it a lot*". Especially with the risk of AI innovation being done for the sake of innovation, end-users may not be so interested in using the system as it can be seen as "*just another pilot*" (Case 7). In that sense, the cases show the difficulties of ensuring civil servants can work effectively with AI systems as changing work routines is difficult (Case 1, 12, 14), even when other components of AI capability are quite mature (Case 7, 13). However, civil servants with AI expertise are crucial for developing AI capability and critical to ensuring ethical and responsible use of AI (Case 1, 6), which is why domain expertise involvement is seen just as critical to have in the AI Team rather as data expertise (Case 1, 13 and 15): "*We emphasised that of course the main domain specialists are always involved in developing models and are also invested in monitoring the models.*" – Case 1.

Creativity was seen as implicit within the organisations to ensure AI initiation. However, in some cases, active work was being done to provide an open and facilitate organisational culture to discuss potential applications of AI and criticisms (Case 9). Ensuring creative civil servants can approach the AI teams requires creating an environment where exploring and such contact is facilitated (Case 13). In their experiences, suggestions from AI often come from entrepreneurial civil servants who kickstart the process (Case 11) or provide a large pool of potential use cases to develop further (Case 12).

Proposition 5. Non-technical employees, both civil servants and managers, play a crucial role in the AI capability. They require understanding and knowing the features of AI technology, bridging the technology to organisational tasks and the responsible use thereof.

4.3. Intangible resources: the invisible link between initiation and implementation

The intangible resources are seen as more difficult to acquire but are often the most crucial resources present in the organisation to gain value from AI in public organisations. Indeed, as already identified, solely technical investments do not necessarily translate to the value of AI but require a complimentary culture within the organisation (Mikalef & Gupta, 2021). In these cases, it was often the intangible resources which made the crucial difference in the organisation of achieving experienced success or difficulties in AI. In particular, the interviewees pointed out the importance of ensuring collaboration within the organisation, such as a healthy understanding between domain experts and data scientists during the development of the AI systems (Cases 13, 15). AI development is distinct from regular IT development, which could develop more 'at a distance' of the organisation (Case 12). Being open, communicative, and allowing all stakeholders to participate in AI development processes helped acceptance (Case 9): *"We listen to the Parliament members and listen also our working organization to how they respond to these the new kind of things and if I found something new, then we, of course, we will present it to them. (…). We started having a little preparation before the actual software development, we had several meetings to discuss about this artificial intelligence, and we had a seminar about the very creating some ideas on what kind of artificial intelligence we could use in the Parliament. This is preparation for AI but also for the mindset"*. Including (all) relevant actors too late then lead to a lack of interest in, or even flat-out rejection of, the AI system later (Cases 7, 9 and 10): *"The first thing they asked: Okay, do you want to fire us, or are we not needed? What we must do if the next day AI takes all the work. They don't understand it"*. - Case 10.

Co-creation in AI has been stressed by other research work (Campion et al., 2022) to ensure the expertise of domain and data scientists are combined. However, the findings also highlight the post-development collaboration as critical to ensuring the implementation of AI systems after. IT and business departments must work more closely together to ensure the system is used, adequately updated the system, and the results can be trusted (Case 12). Such post-development collaboration is further critical to avoid risks as domain experts work differently with systems than expected or reuse models in ways they were not intended (Case 1) or need to falsify the outputs from the AI systems as the developers often do not understand all nuances during the employment (Case 6, 9): *"The trouble obviously is, is that taking a data scientist from outside always comes with the problem that he doesn't know the domain and some of these models are really domain-specific. (…) We don't only need to be good at predicting but also at explaining to the consultants. If you do not have the domain knowledge, you do not know the business process well. Then you can create a perfectly accurate model at prediction that provides completely useless information"*. Validation processes of results often require different organisational units to come together, which may not work on a day-to-day basis (Case 8), must integrate different perspectives and experiences (Case 2) or even must be put together in a new governance team to supervise the performance of the AI (Case 15).

Still, public organisations should ensure solid internal collaboration; external collaboration with different stakeholders during the development and deployment of AI systems is crucial. Involvements of partnerships, networks, ad-hoc teams and outsourcing are all essential for AI. Being involved in related AI networks (Case 14) or being the main initiator for such a dedicated AI-in-government network (Case 11, 15) is considered a vital resource for know-how and partnerships – although many public administrations are not yet part of such networks *" I think that we are still the only small-medium sized municipality to be member, but Stockholm municipality and most of the governmental agencies are"* – Case 14.

Being open to working with other public administrations to share data, computational resources, and additional expertise (Case 11), able to write adequate tenders and understand private sector needs (Case 4, 7) or work with academic institutions (Case 3, 7 and 13), are essential components of AI capability. Citizen involvement is uncommon; if there is any, it is at a later phase of the project rather than at the start, where they can steer important design considerations or help annotate unstructured data resources (Case 3, 7, 11 and 14). The same cases did highlight that widespread collaboration with citizens could have facilitated more trust and acceptance in some of the AI systems and is an area they work on in future projects. Managing partnerships is thus crucial and might even become more complex as additional actors become involved during the implementation process, not to be underestimated.

Proposition 6. Being capable of managing co-creation and collaboration is a strong component of AI capability. Internal collaboration between IT and business departments is needed to ensure the quality of AI in the organisation, while external collaboration allows for data sharing and summing computational resources. Collaboration with citizens, however, is still uncommon.

Just as how being collaborative acts as a strong facilitator, administrations should also have the capability to introduce complementary changes to acquire value from AI technologies. From the findings, it emerged that this component is one of the more crucial factors which determines to sustainable implementation of the developed AI systems. This begins with being able to understand what AI technologies could be used for in the organisation, which can be done by management in a higher-level context through a vision, strategy (e.g. Case 12, 14, 15) or through experimentation by staff members (11,13), or both, although in the researched cases only a few have this vision. In most cases, AI is initiated on an ad-hoc and fragmented basis, leaving much room for administrations to strategize which challenges they face and where AI could contribute. For instance, Case 2 was discontinued as the problem the system was developed for was not considered to be present anymore. Alternatively, a simple change of management or the departure of one individual may also stop the implementation of an AI system and thus too strongly influence the implementation of the AI system in public administration (e.g. Case 7).

As a result of the lack of this strategic vision, many organisations reported difficulties in having the ability to change the organisation accordingly. Actors in charge of developing the AI system may not be able to change the organisational structure. However, exceptions exist (Case 9), as they do not have the autonomy to make decisions or resources to scale up (Case 11). Changing the organisation is even more challenging to accomplish when the complementary changes require the involvement of external actors, such as outsourced IT providers (3), other public institutions (Case 10) or the political authority (7), even when plans are available for implementation as in Case 10: *We made a prototype, but it's not working in real life. Of course, there is a prototype, what is working, and everyone can just try it, how it works, and we have documentation of how it can be put into production"* .

These changes may be relatively small-scale, such as deciding to keep the data scientist, train the civil servants to work with the system, expand the scope of the pilot and provide equipment for data scientists. However, the administrations with several AI systems in place show a need for co-evolution of the organisation along with the growth and depth of AI implementation. Otherwise, the possibilities to continue with AI are challenging, as noted in Case 11: *"The good thing is that we have now a real community of data scientists inside the state, and it can really bridge projects. But of course, if you think about maintaining a lot of projects and going to scale, it's more difficult. If you want to go there, you have to have bigger teams. Very often, the data science lab is like four or five people, sometimes eight to ten, but it's not much if you have to run many machine learning projects in your ministry. So I think it is still fragile compared to the private sector where you sometimes have very big teams to manage one algorithm."*

Such a co-evolution includes the growth in personnel with AI expertise, the technical infrastructure to allow (re)training of the systems, and change in work processes and organisational structures, as new teams need to be formed or positions created (Case 12, 13). Administrations may not be able to set up a dedicated team to monitor and evaluate the models used in the administration (as done extensively in Case 1) or underestimate the complementary roles and time needed to integrate AI successfully into the organisation. Creating an agreement on the importance of maintaining developed systems and allocating (human) resources to these tasks can be difficult to accomplish (Case 13). It may, in a future phase, even be required to completely reimagine the goals of the whole organisation in the broader public governance sphere as the role and autonomy of public administrations, such as municipalities, could completely change because of the increasing role of AI in society and their organisation (Case 14): "*It is going to take time to implement it, and it would help to understand how the architecture in the future would look like. Who will do what? What will be a municipal core business and what will, for instance, the digitalization agency provide? So who does what? I think we would need to know what this future target architecture looks like – both the infrastructure, processes, applications and who will do what"*.

As expected, the organisational culture favouring AI's use assists in the exploration, initiation, and use of AI technologies in public administration. Many administrations highlighted that their organisation has a general supportive culture of innovations, which often results from the historical interest in technology throughout the years. Including dedicated innovation departments (Cases 7 and 11) further supports spreading the overall positive atmosphere surrounding technology. An innovation culture follows from the innovation practices as mentioned in Case 13: "*Within our team, we get a lot of freedom in innovation and it's also creating an innovative culture where freedom to innovate is one of its core principles. So, every member of our team can freely experiment for 20% of his or her time"*. An open, transparent, and supportive culture facilitates trust between the various actors and supports the use of innovation (Case 9). However, at the same time, this supportive culture of public sector innovation has nuances. For instance, there may be a great difference in support between different groups within the organisation, ranging from (top) management seeing AI as the 'dream' to achieve (Case 15) and, in contrast, other departments or staff members not necessarily seeing the need for the technology (Case 3, 7, 13) or even as a threat to their work (Case 10).

It may also be that there may be a culture favouring innovation in general – but not for AI per se. AI innovations can be regarded as significantly different than other types of innovation and met with additional scepsis as it is opaquer and more intrusive (Case 14)*: "RPA is in production and they're very happy with it and they want to improve it further. But for AI, I guess that it is going to be challenging to put it in production. (…) With RPA you could predict quite well how things would turn out with. But with AI, you get surprises. It's not enough to be sharper – it is really challenging."* Alternatively, the organisation could be very supportive of 'innovations' as the topic is exciting, but not the complementary changes needed to use it effectively. This may create a situation where public administrations are content with following the trends of new technologies yet establishing little internal know-how and adoption (Case 7, 10).

Proposition 7. The ability to conduct complementary changes often determines the success of AI and is thus a leading component in AI capability. A co-evolution of AI technology, personnel, leadership, work processes and organisational structures is difficult to achieve yet crucial to achieving positive results.

5. Discussion

5.1. Reflection on theoretical insights

The study brought the following propositions, that engage with the existing literature, adding new insights on AI adoption in the public sector with a specific and novel focus on AI capability.

Tangible resources *A sporadic continuation of past eGovernment legacy*	*Proposition 1*. Digitalisation is crucial for developing AI capability in public administrations. These resources emerge from a past eGovernment legacy, although new data for AI are often still required as well as ensuring legal/ethical controls. *Proposition 2*. AI requires a powerful infrastructure, both for the development and the

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(*continued*)

	continuous training of AI systems. This can be acquired either through internal infrastructure, or through an external partner– with different effects on their AI capability. *Proposition 3*. Financial resources affect the AI capability greatly. Ad-hoc and sporadic funding creates challenges in maintaining and scaling up AI systems, whereas stable resources allow a structural and sustainable use of AI inside the organisation.
Human resources *Balancing between internal and external expertise*	*Proposition 4*. A functional arrangement is to have a core AI team to develop, implement, and maintain AI solutions while being responsible for working with externals. Full reliance on third parties, given difficulties in hiring people with the right profile, affects the AI capability of public administrations greatly. *Proposition 5*. Non-technical employees, both civil servants and managers, play a crucial role in the AI capability. They require understanding and knowing the features of AI technology, bridging the technology to organisational tasks and the responsible use thereof.
Intangible resources *The invisible link between initiation and implementation*	*Proposition 6*. Being capable of managing co-creation and collaboration is a strong component of AI capability. Internal collaboration between IT and business departments is needed to ensure the quality of AI in the organisation, while external collaboration allows for data sharing and summing computational resources. Collaboration with citizens, however, is still uncommon. *Proposition 7*. The ability to conduct complementary changes often determines the success of AI and is thus a leading component in AI capability. A co-evolution of AI technology, personnel, leadership, work processes and organisational structures is difficult to achieve yet crucial to achieving positive results.

The different components of AI capability, both tangible, intangible, and human-related factors, highlight the variety and diversity of the multidisciplinary requirements these organisations should have – going beyond merely acquiring data and technical infrastructure, as also noted in the recent literature review by (Madan & Ashok, 2022).

In addition, this research found that there is an apparent distinction between the AI capability to develop, and the AI capability to implement AI technologies, with more administrations being capable of the first but finding difficulties in the latter as the lack of some components of AI capability could be challenging to acquire structurally. This novel finding is consistent with previous work highlighting that the challenges of AI implementation also differ between development and implementation (Tangi et al., 2023). So far, scholars working on AI capability often discuss it as a static element that does not have different declinations in the different stages of the implementation process.

This distinction has a clear impact on the – still limited - value that AI has so far created in the public sector (Sienkiewicz-Małyjurek, 2023). This may further help explain why the use of AI in organisations fails to integrate after an early trial (Kuguoglu et al., 2021) and are noteworthy elements to further examine in future research on AI capability. In particular, a lack of in-house technical expertise to maintain and update the AI systems, a lack of strategic alignment between the possibilities of the system, legal difficulties in deploying developed AI systems, and the capability to introduce changes in the organisation to ensure the system remains operational and used by the relevant end-users are among the most important components strongly limiting long-term use of AI by public administrations yet are perhaps of little contribution during the development. The findings may further provide grounds for additional research and understanding why limited empirical studies support the claim that AI is giving value to administrations and which kind (Mikalef et al., 2023).

The findings further stress the strong complementarity between historical eGovernment (Proposition 1) developments and the capability to deploy AI technologies. There is a need to examine previous eGovernment waves to understand the use of emerging technologies going beyond merely IoT or other data-gathering sensors (Kankanhalli et al., 2019).

The availability of tangible resources, in particular data, for AI follows the development of open data ecosystems and the promotion of data quality and accessibility done previously, yet as research has shown is not apparent as well (Tai, 2021; A Zuiderwijk & Janssen, 2014), which is to be taken into consideration when aiming to understand the ecosystem, or even country-level, inquiries into driving factors of AI adoption in public administrations (Neumann et al., 2022; Wirtz, Langer, & Fenner, 2021). Furthermore, new data often had to be collected for developing AI in the public sector, which can be challenging due to regulatory and ethical restrictions; complementing existing studies supporting the importance of solid data governance mechanisms can facilitate the initiation of AI systems (Alshahrani et al., 2021; Janssen, Brous, Estevez, Barbosa, & Janowski, 2020). However, the research emphasizes that data quality should always be carefully evaluated to ensure it is suitable for the intended purposes, even when data governance practices exist. In addition, our findings confirm existing studies on AI in government that often highlight the need for technical AI infrastructure (Proposition 2) (Alshahrani et al., 2021; Desouza et al., 2020). In this respect, the effects and trade-offs of using cloud service providers on AI capability have not been explored. From the cases, it emerges that while using external cloud providers may be beneficial to overcome technical limitations, it is not always possible to do so due to legal restrictions.

This study underlines that funding may not be enough to acquire AI capability in contrast to existing innovation adoption theories (de Vries et al., 2018). Funding for AI development and implementation in public administration is often ad-hoc and sporadic (Proposition 3), mostly coming from external sources rather than from within the organisation itself. This lack of structural funding can lead to challenges in implementing and maintaining AI despite overcoming earlier barriers to AI initiation and adoption. As such, future research on the use of AI technologies and future works focusing on the AI readiness of public administrations for using AI technologies should not solely focus on the capability to develop AI technologies alone, which may be more challenging to measure yet more crucial to assess a proper level of AI capability in the organisation. Such work should also take into consideration the potential fragility of the AI capability in public administrations, as it could only be acquired temporarily, leaving public administrations ill-prepared for more structural use of AI.

Human skill sets, both technical and non-technical, are essential for successfully implementing AI in public administration. Our findings suggest that non-technical expertise is necessary to work with AI, and public employees need to understand and know the features of AI (Proposition 5). This confirms previous research on considering AI an organisational agent to work with (Maragno et al., 2022), the lack of digital literacy on AI (Medaglia & Tangi, 2022), and strengthen the policy recommendations on the need to promote a general awareness on AI features (Tangi et al., 2022). Acquiring technical AI expertise is challenging, however, due to the limited availability of skilled individuals and the financial capability to hire them, as many other articles have highlighted (Madan & Ashok, 2022; Medaglia et al., 2021). Our findings suggest several emerging organisational configurations to overcome the skills acquiring AI capability within public administrations, such as those who entirely depend on external expertise, others who have a small core internal team working with externals on request and externalising as much AI capability as possible to externals. The findings suggest that the latter would be the ideal configuration, even though hard to achieve in practice (Proposition 4). Further investigation into these internal-external configurations in public administrations related to AI development and implementation, such as in benefits, preferences, challenges, and consequences to long-term AI capability, could provide critical new insights into how AI materialises in governmental organisations. Such insights are highly welcomed in further understanding the changes before, during and after AI gets deployed within public administrations (Giest & Klievink, 2022; Meijer et al., 2021).

The intangible resources are often the informal underlying foundations which make the various components of AI capability work, which makes it more challenging to acquire or change easily. Collaboration, for instance, both internally and externally of the organisation, is crucial for the successful implementation of AI in public administration. Co-creation between domain experts and data scientists is essential for developing AI systems, and post-development collaboration is critical for their successful implementation. Whilst it may sound straightforward, initiating and managing such collaborations is complex, as noted in (Campion et al., 2022). Being able to do such collaborations, however, seems an increasingly important field of importance and also academic inquiry, such as the growing research on business-to-government data sharing (Rukanova et al., 2023) as well as ensuring that citizen perspectives of the deployment of AI match those of the administrations (Schiff et al., 2021; Wang, Guo, Zhang, Xie, & Chen, 2023).

Similarly crucial is that AI capability requires the ability to conduct complementary changes, yet many organisations reported difficulties in making the necessary changes to their organisation to fully benefit from AI – a difficulty which has hindered the success of eGovernment innovations as well (Nograšek & Vintar, 2014). With AI innovations in particular it seems often due to a lack of strategic vision and the inability to make decisions and allocate resources. Instead, a co-evolution of the organisation is necessary to support the growth and depth of AI implementation, including the growth in personnel with AI expertise, new work processes and organisational structures, and the allocation of resources for maintenance and evaluation – all of which complementary organisational changes. Such a co-evolution of the organisation has been studied in the development of internet portals yet seems a promising research topic for AI as well (Luna-Reyes & Gil-Garcia, 2014). Such insights are crucial for further academic inquiries and valuable considerations for public administrations interested in deriving public value from the use of AI technologies.

5.2. Theoretical implications

The paper makes several contributions to the existing academic debate on the use of AI in public administrations in an area where the literature is still scarce yet growing (Medaglia et al., 2021; Wirtz et al., 2021; Anneke Zuiderwijk et al., 2021). So far, research on AI in the public sector has lacked insights based on empirical findings from real-life examples of the use of AI in government (Medaglia et al., 2021; Wirtz et al., 2019), which led to little evidence on the value of AI (Mergel et al., 2023). This paper aims to enrich the current research insights from real-life experiences using AI technologies in public administrations. With our comprehensive perspective, we confirm and enlarge the empirically-based body of literature, which has so far been mainly based on theoretical studies (Wirtz et al., 2019), or focused on specific AI technologies (e.g., chatbots, Maragno et al., 2022) or AI features (e.g., explainability, (de Bruijn et al., 2022; Grimmelikhuijsen, 2023). Research on the implementation of AI, or implementation-related issues is lacking (Mergel et al., 2023). Second, the research builds on the emerging concept of AI capability. Consistent with previous research, we argue that AI implementation lacks AI capability in public administrations (Mikalef & Gupta, 2021; Neumann et al., 2022; Sienkiewicz-Małyjurek, 2023). However, few studies have explored this issue in depth. This is the first study to disentangle this issue by identifying which capability resources are needed and currently lacking, through a qualitative research perspective.

Third, we highlight that AI capability encompasses a very diverse set of resources, tangible, intangible and human. We emphasise that implementing AI in the public sector is a complex endeavour. All these resources must be present and adequately assembled to ensure a sustainable and trustworthy use of the technology. Despite general agreement on the complexity of AI implementation, academics have so far lacked this helicopter view, which combines all the pieces of the puzzle to provide a comprehensive picture of all - or most - of the AI capability factors required. Fourth, we argue that AI capability varies with the technology's implementation cycle. Having - or acquiring - the right capability to develop an AI solution does not automatically lead to the assumption that this capability will enable its use. In other words, the capability to develop AI and the capability to use AI are different things. We did not limit ourselves to pointing out this difference but also clarified their differences. This novel view has not been included in previous research on AI capability yet is crucial to consider in researching, developing and using AI in public administration.

Finally, we highlight the need to link existing research on AI with previous research on e-government. Scholars often frame their research within the current literature on AI in the public sector. In doing so, the debate seems to forget about two decades of research on digitisation and e-government. Our studies highlight how the past legacy of e-government is necessary to explain the current dynamics of (lack of) public value creation through AI. Therefore, the need emerges to merge the two fields of academic insights further and to better understand the influence of past e-government practices with AI technologies.

6. Conclusions and limitations

Artificial Intelligence technologies continue to grasp the interest of many public administrations due to the technological prowess and progress of the last decade. However, the translation from the technological opportunities provided by the technology into concrete business value for companies and public value from public administrations utilising this technology to improve their operations has been limited. One of the crucial factors hindering the progress in incorporating AI technologies within public administration is the lack of AI capability within the organisation. Whilst possibly often seen as the organisational, technical expertise in developing AI, such as having adequate data scientists who know how to deploy machine learning algorithms, AI capability is understood more broadly. It includes various technical and non-technical components that public administrations should possess to develop and use AI technologies effectively. This study adds novel insights in this direction focusing on 15 public administrations regarded as relatively highly mature in AI in their countries.

The study is limited, as it only extracts insights from several case studies. The small sample size of 15 organisations limits the generalizability of the findings and may be biased towards public administrations who are ahead in the use of AI technologies. The acquisition of AI capability and the complementarity and interactions between the various components in public administrations not using AI technologies yet may yield different results. Furthermore, as noted, the current deployment of AI technologies within public administrations is in an early yet maturing stage. It may well be that several of the highlighted challenges identified in the research may have been overcome already or newly identified as the field progresses. At the same time, the qualitative nature of the research complements and strengthens the existing quantitative studies on AI capability done in (Mikalef et al., 2021, 2023; Mikalef & Gupta, 2021). Another limitation of the finding is the relatively broad nature of the analysis, as the research examines several components of AI capability rather than a subset of these resources in more depth to better understand the dynamics and contributions to organisational performance and value creation through AI technologies.

As the findings suggest, several sub-components and challenges were identified through this closer examination of the AI capability components, which could not have been examined as in-depth as desired in this scope of research. This leaves, however, much room for future research to look into specific challenges of acquiring AI capability in various ways. Furthermore, AI and AI capability are treated holistically, covering an umbrella of different technologies, which are AI by researchers and the public administrations deploying them. Specific AI-type related resources or differences depending on the nature of the underlying machine learning algorithm, design, data sources, or deployment context may provide additional insights on the resources public administrations might acquire to deploy them. Despite these limitations, the work offers fruitful new insights into the current state of AI capability and a deeper understanding of present experiences of the deployment of AI in public administrations, serving as a starting point for future research, both qualitative and quantitative and provides practical insights for public managers interested in improving the AI capability within their organisation.

CRediT authorship contribution statement

Colin van Noordt: Conceptualization, Methodology, Data curation, Writing – original draft. **Luca Tangi:** Data curation, Writing – review & editing, Supervision.

Declaration of Competing Interest

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Appendix A. Template of interview questions

1. Could you describe level of maturity regarding the use of AI technologies in the [**Name Organisation**]?
2. How would you describe the organisational capability to develop and implement AI technologies in the [**Name Organisation**]?
3. How does your organisation manage to have adequate volume and quality of data ready for (supporting) the development and implementation of AI technologies?
4. How does your organisation acquire the necessarily technical infrastructure needed for the development for AI?
5. How does your organisation manage to dedicate sufficient time, staff members and financial resources to the development and implementation of AI?
6. How does your organisation manage to acquire the technical skillsets needed for the development and implementation of AI?
   a. To which extent are the skillsets needed for the development and implementation of AI in-house (in the administration developing the system), outsourced to you or to third parties?
   b. Is there a preference for working with externals or developing AI in-house?
7. How does your organisation work for having (senior) management ready, acceptive and supportive of using AI in their organisation? How about other civil servants?
8. How would you describe the level of creativity in your organisation to come up with new AI innovations?
   a. How was this achieved?
9. How would you describe the current organisational culture in your organisation to collaborate with external departments or organisations for AI projects?
   a. Do you know of any activities which enabled this culture to flourish?
10. What other factors would you consider crucial for your organisation's capability to use AI technologies?

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Exploratory Insights on Artificial Intelligence for Government in Europe

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Abstract

There is great interest to use artificial intelligence (AI) technologies to improve government processes and public services. However, the adoption of technologies has often been challenging for public administrations. In this article, the adoption of AI in governmental organizations has been researched as a form of information and communication technologies (ICT)–enabled governance innovation in the public sector. Based on findings from three cases of AI adoption in public sector organizations, this article shows strong similarities between the antecedents identified in previous academic literature and the factors contributing to the use of AI in government. The adoption of AI in government does not solely rely on having high-quality data but is facilitated by numerous environmental, organizational, and other factors that are strictly intertwined among each other. To address the specific nature of AI in government and the complexity of its adoption in the public sector, we thus propose a framework to provide a comprehensive overview of the key factors contributing to the successful adoption of AI systems, going beyond the narrow focus on data, processing power, and algorithm development often highlighted in the mainstream AI literature and policy discourse.

Keywords

artificial intelligence, public sector innovation, adoption, AI-enabled innovation, digital transformation

Introduction

Advances in machine learning have led to increased interest in artificial intelligence (AI) over recent years by all sectors of society, expecting it to become the key technology driving the next industrial revolution (Chui et al., 2018). Public organizations have also recently caught up on the promise of AI and started coordinating their efforts to use it to improve government administrative processes and services to the citizens (Mehr, 2017). AI technologies, in fact, hold the potential of improving the effectiveness, efficiency, and personalization of public services (Mehr, 2017).

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Therefore, there is a great interest in understanding how it could be used in the public sector and what value could be gained from its adoption. Nevertheless, previous research on eGovernment has shown that there are considerable challenges for public sector organizations adopting innovations, especially when it involves information and communication technologies (ICTs; Agarwal, 2018; De Vries et al., 2016; de Vries et al., 2018).

We still understand very little about how and why emergent technology—such as AI—is used within government (Kankanhalli et al., 2019). As the expectation is that AI will be used in more fundamental governmental processes (Engstrom et al., 2020), we believe that researching AI use could give valuable insights for policy makers to help understand which factors are more likely to support its adoption in the public sector.

To this end, our analysis follows an exploratory case study research design on three different applications of AI within the European public sector, addressing our main research question: "Which antecedents of public sector innovation enable the adoption of AI in public administrations in the European Union?" Such exploratory research is well suited to gain a broad understanding of emerging social phenomena such as AI, as it allows for a more in-depth understanding of the factors contributing to the adoption of innovations (Meijer, 2015).

The article aims to contribute to the academic debate on how antecedents of public sector innovation, which are already established in the research field, could be extended in order to better understand under which conditions AI innovations develop. In fact, the public sector is often left out of scope in most AI-related research as a recent review highlighted (Sousa et al., 2019). Only recently, more researchers have started exploring the actual applications of AI in the public sector, which highlights that the use of AI is less sophisticated or radical as anticipated as there are numerous barriers hindering its use (Engstrom et al., 2020).

The article is structured as follows: After an introduction of how AI is defined in this research, the different factors contributing to innovation in the public sector are discussed. A brief overview of our methodological approach is then presented, and the analysis of three cases of AI in use in different public administrations in Belgium, Estonia, and the Netherlands are described from the perspective of public sector innovation theory. The article ends with discussion of the findings and a conclusion outlining future research directions and implications for policy in the European context.

Literature Review

Conceptualizing AI in the Public Sector

Due to recent advances in computing power and algorithms, and the explosion of data availability, many applications using machine learning have been introduced in different areas of the economy and our daily life. This made the term AI revamped, and it has been associated with several new products that often use the terms big data, machine learning, or deep learning interchangeably with AI (Katz, 2017; Makridakis, 2017).

As a consequence of the lack of a clear conceptualization, however, researchers refer to AI in very different ways (Krafft et al., 2019). Some describe AI as software able to do intelligent tasks (Russel & Norvig, 2016; Sousa et al., 2019). Others prefer to research AI as a tangible technology rather than a goal-oriented tool (Scherer, 2016). In this article, we focus on the adoption of AI applications or ICT systems with capabilities, such as perception, learning or understanding, commonly regarded as human-like (Wirtz et al., 2019), and not so much in the development of models using machine learning (Desouza et al., 2020).

Despite the lack of a clear conceptualization on AI, scholars argue that AI technologies are able to provide value and benefits to government organizations in numerous ways (Alexopoulos et al., 2019; Eggers et al., 2017; Stone et al., 2016; Sun & Medaglia, 2019). AI applications are expected to be well suited to tackle common governmental problems in resource allocation, gaining insights from large databases, a shortage of experts to tackle certain problems, doing many repetitive procedural tasks and handling diverse data (Mehr, 2017), tackling corruption (Lima & Delen, 2020), and achieving social development goals (Vinuesa et al., 2020), although limited empirical proof is available. As an example, Chatbots are seen to be able to improve the communication between citizens and government agencies (Androutsopoulou et al., 2019) but might not live up to these expectations due to existing eGovernment challenges (van Noordt & Misuraca, 2019).

Much attention has also been given to possible negative effects of using algorithms within public sector organizations, as it creates opaque decision-making processes (Craglia et al., 2018; Pasquale, 2015; Preece et al., 2018), challenges in accountability and trust in AI-enabled decisions (Burrell, 2016), and risks to privacy due to sensitive, granular, and in-depth data collection practices (Floridi, 2017; Mittelstadt et al., 2016). In addition, the frequently mentioned risk of discrimination due to bias is another possible negative effect that attracted much attention in research and policy (Barocas & Selbst, 2016; Veale et al., 2018). These different perspectives on the value and risks of using AI are likely to influence the choices to adopt this technology within the public sector and the acceptance of innovation in society.

Understanding the Antecedents of Public Sector Innovation

In fact, one of the main challenges for governments is to adopt and use ICT innovations in their operations (Kamal, 2006; Potts & Kastelle, 2010). Hence, numerous scholars attempted to understand the conditions that make it more likely for innovation to occur in the public sector, defining the factors that act as a barrier or as a driver (also referred to as antecedents), which influence the adoption and diffusion of innovations in public organizations. Following the seminal work of Borins (2000) and Rogers (2010), a coherent framework has been developed by De Vries et al, (2016).

In this article, we follow this approach with the aim to unravel the “black box” of AI adoption within public organizations, considering it as a form of public sector innovation. This is in line with recent research from Schedler et al. (2019), stating that barriers to adoption of innovations in government remain the same, no matter what kind of innovation is introduced. We thus consider the following antecedents influencing the adoption of AI in the public sector: environmental, organizational, innovation-related, and individual.

Environmental antecedents. The working environment in which public organizations operate has significant effects on their innovative capacities. Most innovations are coming from a specific local context where numerous pressures from the environment, such as public opinion, media, or political activity, result in innovation (De Vries et al., 2016; Sørensen & Torfing, 2011). The networks in which organizations operate are also an important driver for innovation. Public organizations involved in frequent contact with other innovative organizations usually take over their norms and practices, as they are perceived to be legitimate or better, a process called mimetic isomorphism, resulting in organizations developing more innovative practices themselves (De Vries et al., 2016; Hinings et al., 2018).

In addition, when organizations in a network perceive that they are mutually dependent on each other, they are more likely to explore new innovations by sharing organizational resources (Bekkers et al., 2013; Bertot et al., 2016). These networks could also involve private vendors. Private sector organizations have been argued to play a major role in promoting and consulting the adoption of eGovernment services (Jun & Weare, 2011). Lastly, regulation is generally seen as a hindering factor to facilitate innovation, but it may also be a driver for innovations to occur as a result of the need to deal with imposed restrictions (De Vries et al., 2016).

Organizational antecedents. At the organizational level, there are numerous structural and cultural factors contributing to the adoption of innovations within the public sector. The more influential antecedent is the disposal of appropriate organizational resources (De Vries et al., 2016). In order to adopt innovations, there should be an adequate amount of time, money, and people available, something that is often limited in the public sector. Having an inadequate budget to adopt AI is in fact a huge barrier in many public sector organizations (Wirtz et al., 2019). Naturally, for adopting ICT-enabled innovations, there should also be enough staff available with appropriate competences (Cinar et al., 2018; Meijer, 2015). However, the demand for experts with AI skills is extremely high, whereas their availability is low. Getting the necessary expertise to develop and adopt AI might, therefore, be challenging and expensive in the short term (Centre for Public Impact, 2017; Susar & Aquaro, 2019).

Another often-mentioned antecedent is the participation of relevant stakeholders in the development process as it makes adoption of the innovation more likely (Lewis et al., 2018). If end users do not have the skills to use the innovative product or service as intended, there should be training and support available to increase acceptance (de Vries et al., 2018).

There should also be a supportive technical infrastructure with enough processing power, storage, bandwidth, and connectivity for digital innovations to emerge (Bertot et al., 2016). For AI applications using data from different sources, it is necessary that the systems are interoperable, including the capacity for different data to readily work with each other across different systems (Kankanhalli et al., 2019). This requires sufficient expertise within the organization on effective data management, complemented by technical skills, as the data used for AI need to be cleaned, integrated, structured, and secured (Harrison et al., 2019).

A lack of management support and/or credible leadership with a vision for integrating new solutions in the administrative processes is another frequently mentioned barrier (Meijer, 2015). The organizational culture could stimulate the adoption of innovations, possibly when accompanied with financial incentives or other rewards (De Vries et al., 2016).

Innovation-related antecedents. Innovations need to be perceived as "value adding" by all stakeholders involved in the adoption process. Innovations should also be regarded as easy to use and to experiment with and compatible with the organizational values and, to a certain extent, historical experiences, in order to facilitate their adoption (Cinar et al., 2018; De Vries et al., 2016). This is of particular importance for AI-enabled innovations as the potential for radical innovation is high and their adoption could disrupt existing processes and in turn change previous administrative practices that with time may have become established cultural norms, considerably.

Individual-related antecedents. Lastly, there are specific factors regarding the role of individuals involved in the process of innovation that is crucial for its adoption. Frequently, it is argued that creative leadership is needed in order to overcome the previously mentioned environmental or organizational barriers. An individual within an organization, no matter their position in the hierarchy, can be seen as the informal leader of and an important factor in innovation (De Vries et al., 2016). It is in fact often the case that within an innovation process, there is an individual who spots the potential of a new technology and persuades their colleagues to adopt it (Kamal, 2006).

Although the environmental and organizational antecedents play the largest role in enabling different forms of innovation (De Vries et al., 2016), it is the combination of all of them which provides a view of how and why innovation in the public sector occurs.

Methodological Approach

To answer our research question, we conducted an exploratory multiple case study on three different adoptions of AI within public sector organizations in EU countries. Since AI within the public sector

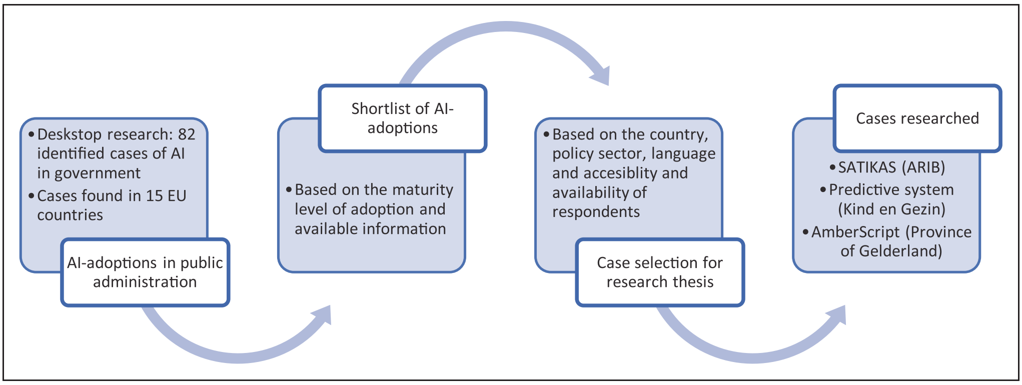

Figure 1. Case studies selection process.

has received little attention from scientific research, following Yin (2018), the exploratory case study design allows an early examination of this relatively new phenomenon, with the aim to test current theories and generate new ones (Flyvbjerg, 2006).

The use of multiple case studies is also expected to offer more replicable, reinforced, and robust findings that help to provide a more generalizable contribution to academic research (Baxter & Jack, 2008). In our research, however, we consider it crucial that different AI technologies—as well as the context in which they operate—are comparable with each other, as the term encompasses multiple technologies that might not be alike. While the analytical framework can thus be applied universally, we acknowledge that historical, institutional, and cultural elements are not captured in this study, influencing the findings.

To facilitate the case study selection, the research built upon the cases gathered by the European Commission's Joint Research Centre's AI Watch and the AI Alliance. The AI Watch has been set up to monitor the AI landscape in the European Union (EU) in both the private and public sectors (European Commission, 2018). Most of these cases are self-reported by the Member States as being AI. As summarized in Figure 1, three of the 82 cases gathered in the period February–May 2019 have been selected based on the following criteria: the country adopting the technology, accessibility and availability of information about the potential candidate case, language and quality of the documentation available online.

The cases selected are the SATIKAS system in Estonia which use AI technologies to check land mowing, the predictive system for day-care services inspection used in the Flemish Child and Family Agency in Belgium, and AmberScript, an automatic transcription tool to provide subtitles for video recordings of political council meetings used in the Province of Gelderland in the Netherlands.

Once the cases have been selected, the analysis of the AI applications and their adoption has been done in three steps, through desk research, interviews, and validation.

First, a document analysis was conducted on available material online or provided by other means to gain a brief overview of the main purposes of the AI application. SATIKAS, for example, was presented by the Estonian government during the Tallinn Digital Summit 2019 and has been described in policy reports (Network of European Regions Using Space Technologies [NEREUS], 2018; Organisation for Economic Co-operation and Development [OECD], 2019). This document analysis was conducted through a snowball method using both Google Scholar and Google search engine.

To complement the analysis, four semistructured interviews with the persons responsible for introducing the innovation in their organization and other experts were carried out. The interviewees were either the project managers or main contact person regarding each project. One respondent from the SATIKAS case preferred to answer questions by email while most interviews were conducted remotely, apart from the interview with AmberScript which was in person. Each interview lasted for an average of 30 min. The questions were customized based on the context of the case. They, however, remained comparable as they were based on the antecedents of public sector innovation which served to structure the interview.

The interviews have been used to complement and validate the information found in other data collection methods but were considered crucial in understanding how and why the process of innovation occurred. If there was any need of clarification, additional email correspondence with the respondents followed. Moreover, the case analysis has been reviewed by the respondents themselves in order to correct possible misinterpretations by the authors.

However, while these interviews have been insightful, there is a risk of bias that the project managers see the innovation as a great success, a perspective that might not be shared by other actors. The lack of additional interviews with other civil servants working with the AI application or users of the systems limits some of the findings regarding the perceived value of the innovation by different stakeholders.

Finally, a focus group with experts who are part of the AI Watch took place at the European Commission's Joint Research Centre in June 2019, to validate the results of the case study analysis and place them within the context of the research, as well as discussing future research and policy implications.

Case Studies on the Use of AI in Government

In this section, we briefly illustrate the three cases of use of AI in public administrations we analyzed in Estonia, the Netherlands, and Belgium. These cases are illustrative and served to start building the knowledge base for future comparative analysis and more in-depth research.

SATIKAS

In the Estonian Agricultural Registers and Information Board (ARIB), the system called SATIKAS[1] uses satellite data coming from the European Copernicus Programme to control automatically, using AI technologies, whether mowing has taken place on the Estonian grasslands (Tartu Observatory, 2019). With increasing labor costs in Estonia, it was becoming more and more expensive to have checks performed by field inspectors (NEREUS, 2018) leading to the need to reduce the number of visits while preventing farmers from not keeping up with the subsidy requirements (Bleive & Voormansik, 2016).

SATIKAS was developed gradually as part of applied research conducted jointly by ARIB, CGI, and the Tartu Observatory (Bleive, 2017), after enthusiasts met together informally in 2011. The system uses the deep learning methods recurrent and convolutional neural networks for the analysis of the satellite data (Respondent Tartu Observatory, personal communication, 2019). Data from the Sentinel-1 radar and Sentinel-2 optical satellite images, together with ground reference data of some farmer's fields, historical inspection logs of ARIB, and meteorological data from the Estonian Weather Service were used to conduct the analysis (Commission, 2017; NEREUS, 2018).

Despite the general interest for trying out new technologies, some senior officials at ARIB were not initially very hopeful about the success of the project (Respondent Tartu Observatory, personal communication, 2019). Some staff feared the creation of a "Big Brother State," while others feared that their jobs might disappear due to the introduction of the technology (Estonian Agricultural Registers and Information Board, personal communication, April 26, 2019)). Nevertheless, the project was allowed to continue as an experiment to see what was possible (Respondent Tartu Observatory, personal communication, 2019).

The project gained funding through the European Regional Development Fund to assist the development of public services with ICT (NEREUS, 2018). Different resources and capabilities from all the various organizations involved were used in order to develop SATIKAS. This included machine learning expertise from the Institute of Computer Science of the University of Tartu and the Software Technology and Applications Competence Centre. It must be noted that the technological infrastructure used to develop SATIKAS has changed over time once the project grew. The technological platform of ARIB became in fact insufficient to store and handle reliably the huge data volumes involved, leading to the use of the infrastructure of the Environmental Agency of the State Service (Respondent Tartu Observatory, personal communication, 2019).

Having access to high-quality data—from both the ground and the satellite imagery—has been an important condition for the SATIKAS system to succeed. In the beginning of the project, the data supply from Copernicus was not always of high quality due to changing formats and duplicate images, leading to a lot of work when managing the quality of the data sets (Respondent Tartu Observatory, personal communication, 2019).

Civil servants within ARIB using the SATIKAS system were partially involved during the system development, providing verification data and assessing the outputs generated. They also received training to understand how it works in order to gain trust in its results (Respondent Tartu Observatory, personal communication, 2019). After the development of the system, the field inspectors realized that fears about job losses were inappropriate as their man power was still required (Estonian Agricultural Registers and Information Board, 2019). Other stakeholders started to see more value in the system once the first results were satisfactory.

Predictive System Day-Care Services

In 2014, the Flemish Agency for Child and Family (Kind en Gezin) in Belgium started a pilot project to use advanced data analytics to create a predictive model to detect day-care services that require further inspection (Bongers et al., 2018). The Child and Family Agency does not carry out the inspections itself but works together with the regional Health Care Inspectorate of the Department of Welfare, Public Health and Family (European Commission, 2019). However, there is limited capacity to conduct inspections, which led to the need of optimizing the inspection process (Bongers et al., 2018). Data mining was thus introduced as a contribution to inspection practices based on the experience and reasoning of the staff in the Healthcare Inspection systems, in turn making them more accurate (Respondent Kind en Gezin, personal communication, April 4, 2019).

The predictive system for the Child and Family agency is based on a supervised machine learning method. A logistic regression and XGBoost were used, as these methods had the best results in early testing (Respondent Kind en Gezin, personal communication, April 4, 2019). In order to develop the predictive system, data found in the internal data warehouses and data from the Health Inspectorate were analyzed (Bongers et al., 2018). The current predictive model was released in 2017, but its development was inspired by a previous attempt. In fact, at the end of 2013, Child and Family worked together with IBM to design a predictive model to indicate which kind of day-care services should be subject to inspection. However, due to legal and organizational changes in 2014, the previous model was no longer applicable to the new situation (Bongers et al., 2018).

During the new system's development, the agency cooperated closely with the Data Science team of the Department of Welfare, Public Health and Family because of their expertise in text mining (Bongers et al., 2018). In addition, there was a strict collaboration with the Health Inspectorate, as they provided the data used in the system. A consultancy played a supporting role by giving additional expertise in the use of RStudio (Respondent Kind en Gezin, personal communication, April 4, 2019).

Despite general enthusiasm for innovations and technology within the agency, the AI application had to be seen as a tool to empower and support workers rather than replacing them or checking if they are doing their work well (Respondent Kind en Gezin, personal communication, April 4, 2019). Therefore, staff was involved as much as possible throughout the project (Bongers et al., 2018). The combination of both showing statistical proof of the validity of the system, and an emphasis on supporting human workers, rather than replacing them, further improved the acceptance of the system by the end users (Respondent Kind en Gezin, personal communication, April 4, 2019).

While a small part of the budget of Child and Family could have been made available for IT data science projects, employees worked on it in their spare time, with limited resources as the project (in its initiation at least) was initiated as an experiment so to avoid possible resistance (Respondent Kind en Gezin, personal communication, April 4, 2019). The availability of enough trustable and high-quality data was an important factor in enabling the adoption of the AI tool. This is crucial for any data mining or AI project, although some additional tasks were required in order to comply with the General Data Protection Regulation (GDPR; Respondent Kind en Gezin, personal communication, April 4, 2019).

In addition, to gain and maintain trust of users in the recommendations provided by the AI, and to ensure accuracy and reliability of data, there is a need for constant maintenance and improvement of the model. It was thus suggested that not only would poor data maintenance lead to a possible decrease in model accuracy but also a reduction in the trust of other data projects.

Amberscript

In 2018, the Province of Gelderland in the Netherlands adopted an automatic transcription tool to provide subtitles for video recordings of political council meetings. Before this, the organization's clerks usually made the transcriptions or summaries of the meetings themselves. Sometimes, other external parties were contracted to do the transcriptions, but it could take over 3 months before they would become available (Respondent Province of Gelderland, personal communication, May 6, 2019).

The automated transcription of the meetings is made possible by the AI tool AmberScript. This software uses speech recognition technology in order to interpret and convert the words spoken in audio files into text used for summaries and subtitles. At the moment, apart from the Province of Gelderland, AmberScript is already in use in around 60 municipalities in the Netherlands (Respondent AmberScript, personal communication, April 17, 2019).

In 2018, in order to provide automatic transcriptions of the meetings, AmberScript has partnered with WebCast, a private organization which provides a platform for over 150 provincial and municipal public bodies to host video and audio recordings of their meetings and to make them available to the public (Respondent AmberScript, personal communication, April 17, 2019; WebCast, 2019). For organizations already using WebCast's services, the automated transcriptions are an additional functionality which can be purchased on demand.

This partnership was needed in order to develop a specific speech recognition system since WebCast allowed access to many existing audio and video files from previous political meetings (Respondent AmberScript, personal communication, April 17, 2019). The speech recognition model was trained using a combination of the audio and text databases that had been filled with handmade or previously available transcripts of meetings. In order to train the speech recognition model for high-accuracy transcription, a data set of more than 1,000 hr of audio with transcriptions was compiled, cleaned, and processed into the AI model (Webcast, 2019). The availability of all the recordings of the council meetings was one of the key factors in the development of the system (AmberScript, personal communication, April 29, 2019).

Webcast has been providing services for the Province for more than 12 years and, due to this long-standing relationship, notions of shared trust and joint commitment can be seen as drivers for innovations to be adopted (Respondent AmberScript, personal communication, April 17, 2019; Respondent Province of Gelderland, personal communication, May 6, 2019). However, an early version of the automated transcriptions did not meet the expectations, so there were additional discussions with Webcast on how to improve the technology. Later, adjustments and pilots were proven to be satisfactory, and the decision was taken to integrate the use of the system in the transcription process of the council meetings (Respondent Province of Gelderland, personal communication, May 6, 2019).

An important factor that led to the adoption of AmberScript was a change in Dutch law due to the 2016 European Directive on digital accessibility,[2] which required websites and mobile apps of governmental institutions to be accessible for citizens with handicaps (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties, 2017; Respondent Province of Gelderland, personal communication, May 6, 2019). While this law was considered important, it was not yet in force and so the technology did not need to be fully adopted. Nevertheless, the Province wanted to stay ahead of the deadline as they agreed with the aim of the new law and saw it as an obvious mechanism to make their services as accessible as possible (Respondent Province of Gelderland, personal communication, May 6, 2019).

The other main reason for the adoption of the automatic subtitle system was the general organizational culture and practice of adopting innovation which facilitate improvements to the services of the Province. Strong beliefs were expressed that governmental institutions should keep innovating when appropriate, staying aware of what is happening on the technological market and being open to trying innovative solutions (Respondent Province of Gelderland, personal communication, May 6, 2019).

The clerks who are now using the system see it as adding considerable value since it saves them a lot of time and effort. The use of the tool has allowed them to focus on other tasks that provide more value to citizens, though they still have to check the translations for possible mistakes (Respondent AmberScript, personal communication, April 17, 2019). The system is easy to use and there was no training required for its introduction, although there was a collaboration with Webcast to help using the system (Respondent Province of Gelderland, personal communication, May 6, 2019) which shows the importance of innovative public–private partnerships and procurement models for promoting adoption of AI in the public sector.

Findings and Discussion

The analysis of case studies of ICT-enabled innovations from the perspective of the antecedents that act as drivers and/or barriers to adoption helps us to better understand what factors can hamper the full application of AI's potential and those that can, instead, facilitate its adoption on a wide scale across the public sector.

For this reason, we discuss the antecedents of innovation introduced in the literature review as they emerged in the analysis of the case studies. In doing so, we aim to discover whether any other AI-specific factor arises.

Environmental Antecedents

For most innovations in the public sector, the context in which the organization functions has a significant effect on the capability to introduce and likelihood to adopt innovations, as seen as in

Table 1. Environmental Antecedents.

Environmental Antecedents	SATIKAS	Child and Family Predictive System	AmberScript
Local pressure	Rising labor costs and regulation contributed indirectly	Pressure to improve inspection capabilities	New upcoming regulation created pressure for the organization to adopt the system to comply
Networks	Great contribution to awareness, development, and adoption	Crucial for initiation and development of the system	Crucial for awareness, development, and adoption of the system
Private vendors	Minor role	Minor role, major role in previous project	Major role in promoting, development, and adoption
Isomorphism	No isomorphism as SATIKAS was regarded as a first mover in the field	Mimetic isomorphism through conference	It is used by other organizations, but this had no recorded influence on the adoption
Regulation	Regulation increased the need for the system, but it is not hindering development or adoption	General Data Protection Regulation had an effect on handling of data	Upcoming regulation stimulated adoption of the system

Table 1. Based on the case analysis, the role of networks has proven vital in the development of AI. This shows that the local environment in which the institution operates influences their adoption of AI.

These networks not only include other public sector organizations but also private actors. In each of the cases investigated, the roles of the private companies differed, although their involvement was as a partner in the development of the AI tools rather than simply as a vendor. This shows the benefit of having collaborative partnerships between public and private sector actors, including the role of both professional and personal contacts in forming them.

In addition to the importance of networks, all adoptions were influenced by some form of environmental trigger, whether indirectly (e.g., rising labor costs and more legal requirements) or directly (e.g., regulation on digital accessibility). These pressures from the environment enabled making the usage of AI a more valuable choice, although this was not a direct consequence of this environmental pressure. However, once the AI technology became a legitimate alternative to tackle these environmental pressures, such as the case of AmberScript, adoption seems to be more likely to occur successfully.

Organizational Antecedents

Both structural and cultural organizational factors have frequently been mentioned to be an important factor in the adoption of innovations within the public sector. The cases analyzed confirm that there are numerous cultural and organizational factors that have contributed to the adoption of the AI systems within the governmental organizations examined, summarized in Table 2.

Insights from the cases also demonstrated that it is challenging to find expertise in AI. None of the organizations had (all) the necessary expertise in-house to develop the systems. Rather, there were numerous organizations contributing to the development or adoption of AI with varying levels of involvement.

In all the cases, gradual improvements on the system were required, as it was likely that mistakes would be made and poor performance is expected, at least at the start of the project. This shows, in

Table 2. Organizational Antecedents.

Organizational Antecedents	SATIKAS	Child and Family Predictive System	AmberScript
Organizational resources and funding	Sufficient but high cost of developers limit progress. Funding through European Union budget	Sufficient to develop and adopt the system. But lack of staff resources increased time	Specific budget for innovations with service provider (Webcast)
IT resources	Shared IT-resources and capabilities	IT resources and capabilities shared or present in-house	IT resources outsourced
End user participation	Partially	Close collaboration by giving multiple presentations	Close collaboration in testing and piloting
Training	Provided to enable trust in the system	No training on the use of the system	No training
Management support	Sceptical at first	Positive	N/A
Organizational culture	Innovative; eager to do more with less	Positive toward technology and innovation	Positive toward technology to improve access to information for citizens and making government open
Incentives	No financial rewards, initiation out of personal interest	No financial rewards, initiation out of personal interest	No financial rewards

part, the “learning” character of the technology, but it also means that some stakeholders may need to be more patient to wait for positive results. The role of senior management is vital in shaping such a culture. Even when senior officials might be critical of using AI technologies in administrative processes and public services, experiments should be allowed to discover what benefits a technology is able to bring to established practices and what effects it may have on the organizational performance.

Moreover, end users, in particular civil servants working with the applications, should be consulted and their feedback taken into consideration. As it emerged from the interviews, due to the acceptance from users, the added value of the AI applications is likely to be higher.

Innovation Antecedents

While the environmental and organizational antecedents play a significant role in the adoption of AI, there are some specific attributes connected to AI technologies, themselves, that have led to their adoption, as seen in Table 3.

In all the cases, AI was considered to provide value according to the project leaders. However, results from the analysis of the cases show that the perception of value is “dynamic” and may differ between various stakeholders.

For instance, at the start of the SATIKAS project, many civil servants did not see any value in the system. After showing and discussing results, the perception of the value increased. Thus, it should be explained clearly that the introduction of an AI system is an augmentation to the work of civil servants rather than a replacement. In this respect, the dynamics of the process of reducing organizational resistance toward AI-systems are not yet well understood and should be further investigated enlarging the empirical base with primary survey data.

Table 3. Innovation Antecedents.

Innovation Antecedents	SATIKAS	Predictive System	AmberScript
Perceived Value	Valuable addition to work more effectively	Valuable contribution to support staff	Valuable as it reduces work burden
Compatibility with organizational values	In line with organizational values to do more with less	Improvements of field inspection in line with organizational tasks	Fits organizational value of inclusiveness of public services
Ease of Use	Data visualization of results makes the system easy to use	Data visualizations of results make the system easy to use	Strong collaboration with end users to ensure ease of use
Security and privacy concerns	No sensitive data used, so no security or privacy concerns	No sensitive data used, so no security or privacy concerns	No privacy concerns, as it regard public meetings

Table 4. Artificial Intelligence Antecedents.

AI Antecedents	SATIKAS	Child and Family Predictive System	AmberScript
High-quality data	High-quality data to develop model and get useable results	High-quality data to develop model and get useable results	Over 1,000 hr of high-quality audio and transcription data to train the model
Maintenance of data	Work to ensure data quality from Copernicus	Work for data maintenance to ensure high-quality inputs and outputs	Continuous data maintenance to improve the system
Data sharing	Public sector data from different organizations shared with private partners	Different data from public organizations required	Audio data gained with permission from public organizations and used by a private organization
Data-driven services ecosystem	Different forms of data/ capabilities available in the local environment	Different forms of data/ capabilities available in the organization	Availability of public data/ capabilities for analysis from private sector contributed to the development of AI system

Individual Antecedents

In the different AI systems studied, we have identified certain individuals who have played a significant role in their adoption. For example, in the SATIKAS case, one representative of ARIB was mentioned as having played a significant role in its adoption, being referred to as the "soul of the development" (Respondent Tartu Observatory, personal communication, 2019). One aspect to underline related to the individuals involved in the adoption of AI was their personal interest, to the extent that some were working on the projects in their free time. This shows a strong inner motivation to do extra activities in their job such as experimenting with new technologies such as AI.

AI Antecedents

In addition to the antecedents typical for public sector innovation, we assumed that there are specific factors summarized in Table 4 that are crucial for AI adoption, and, based on the results from the case studies, we suggest that the most important is data governance.

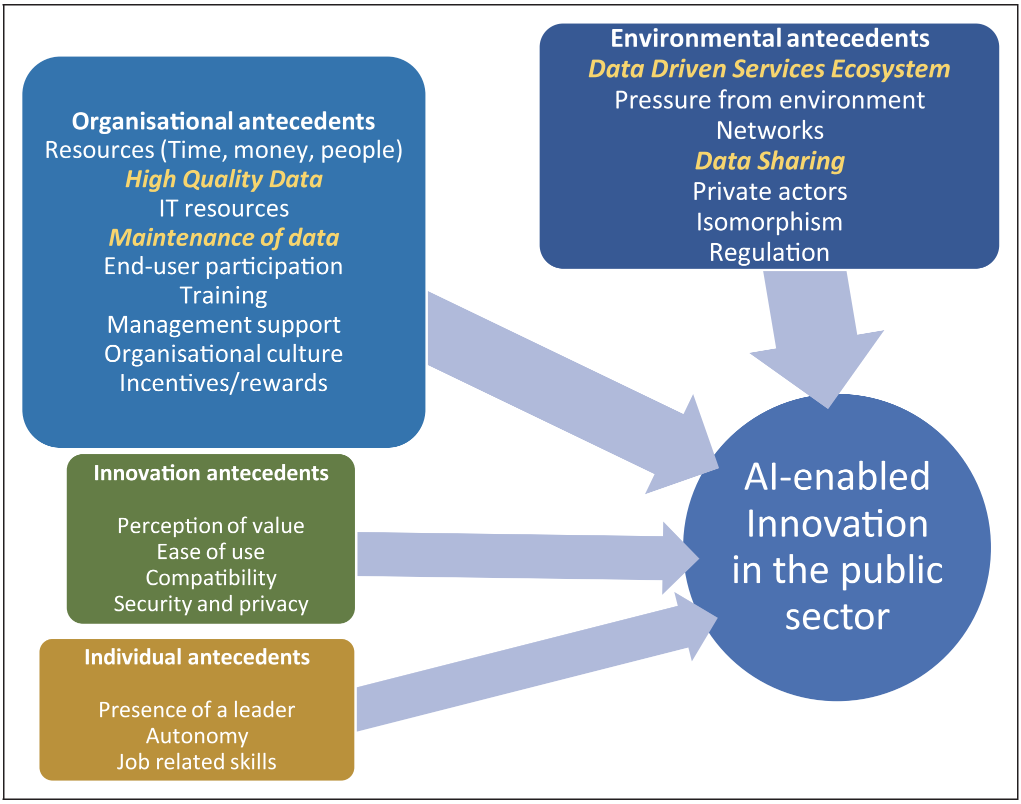

Figure 2. Revised conceptual model of innovation with artificial intelligence based on de Vries et al. (2016).

Figure 2 presents the conceptual framework revised after our case study analysis. It shows that the role of data governance is crucial for the development and adoption of AI, as most of the early literature suggests. However, as mentioned by one of the respondents, the quantity of data may not be the most important issue, as too much data could actually lessen the quality of the AI by generating correlations that are not present in reality. In contrast, high-quality data are crucial for training AI, relying on strong data management processes which may take a considerable amount of time and effort. Therefore, constant maintenance of AI systems is required to ensure high levels of performance. This is considered vital for guaranteeing trust in AI systems and for the sustainable adoption of AI.

For this reason, while sharing of data can be related to the antecedents of networks, it merits being seen as an antecedent in its own as it seems to greatly stimulate the development and adoption of AI in the case of governmental processes and public services. AI systems used within public administrations rely on interorganizational data sharing, and value can be gained by both public and private actors.

Another AI-specific antecedent to be considered is linked to the increased datafication of societal processes within the ecosystem, which would likely lead to more data becoming available for the development of AI systems, in turn increasing the interest in AI in government due to the processing support it offers. This is worth of analysis, as the contextual information around data, including metadata codification and related semantic interoperability efforts, may help organizations to be more transparent about the inputs to AI systems and how content is used, while harnessing existing digital infrastructures.

The results of our analysis based on case studies confirm findings of early literature on AI in the public sector, pointing in particular to the recognized need for gaining high-quality data, data analytics capabilities, and strong data governance (Harrison et al., 2019). Our research is aligned with the emerging perspective on how smart technologies are adopted in the public sector to achieve public value (Criado & Gil-Garcia, 2019) and start filling an important empirical gap in this stream of investigation.

As a matter of fact, compared with the existing literature on public sector innovation, the adoption of AI could be well understood and researched as a new form of ICT-enabled governance innovation in the public sector (Misuraca & Viscusi, 2015), as it is indeed influenced by the same factors that impact other forms of innovation in the public sector as described in (De Vries et al., 2016) but requires specific data-governance antecedents that are a crucial element for the use and adoption of AI in government and public services.

In line with recent literature, the results of the case studies suggest how the technical infrastructure underlying the data ecosystem is needed for AI to be used as a prerequisite for AI adoption. It can thus be argued that a mature level of digital government is required for AI to be deployed successfully and that without a functioning data ecosystem including Internet of Things (IoT) systems and digital services, AI is likely not to be adopted as there is simply no data available to train the models (Kankanhalli et al., 2019). However, the adoption of these technologies come with their own hurdles (Janssen et al., 2017), so that administrations interested in using AI face both barriers in adopting the technical digital and data infrastructure and the implementation and use of AI applications.

Another specific element of AI-enabled innovation compared to other innovations in the public sector is the increased risk of social, economic, political, and ethical challenges that may emerge following its adoption (Dwivedi et al., 2019). For instance, traditional cultural and power relationships within government or toward citizens may change with the adoption of AI, making some government actors hesitant to adopt AI solutions, while others may in fact push for adoption.

Moreover, the “black box” nature of AI-enabled decisions limits the accountability of decisions, already reducing opportunities for citizens and internal staff to challenge recommendations provided by the AI due to lack of time, repercussions from supervisors, or the perceived legitimacy of the AI (Kuziemski & Misuraca, 2020). While previous eGovernment research has highlighted that public managers may use ICTs to reinforce their position (Kraemer & King, 2006), with AI, the gap between citizens and public administrations may even increase if AI applications remain difficult to scrutinize and to explain (Kuziemski & Misuraca, 2020). How civil servants perceive the value and challenges of AI, including the changing role of government, may have a large influence on how AI and similar technologies get adopted (Guenduez et al., 2020; Sun & Medaglia, 2019).

Conclusion

While the literature on the adoption of public sector innovation is quite established, there are research gaps in the analysis of the adoption and sustainable use of AI-enabled innovation in government and public services. In fact, several use cases of AI have been canceled after an initial successful adoption due to political, legal, or other reasons (Misuraca & van Noordt, 2020). Therefore, the study of AI adoption should adopt a long-term lens in order to witness if AI applications are in fact still in use after a certain time—but also to better understand the consequences of its adoption (Bailey & Barley, 2019). Changes in law, organizational structure, data quality, citizen, or staff resistance may unexpectedly end AI adoptions but have not received sufficient research attention yet.

In this perspective, our research aims at shedding light on how the various antecedents of public sector innovation can lead to sustainable and long-term adoption of AI innovations in the government. In doing so, we focus on the specific elements that characterize AI-enabled innovation, and in particular the data governance and ecosystem underpinning its use and adoption.

In addition, the insights from the analysis of case studies provide concrete indications to policy makers aiming to stimulate and develop the use of AI within their administrations. Whereas a clear policy intention to support the development of AI-enabled services within the public sector is emerging in the EU, as highlighted in the recent White Paper on AI for instance, policy responses may be more successful if focusing on multiple innovation antecedents such as funding, public–private sector partnerships, and citizens perceptions, rather than on solely improving data quality and data quantity, as it is instead often the main concern in technical research on AI and technooptimistic policy interventions stated in strategic documents.

To this end, the holistic framework proposed in this article gives a comprehensive overview of the key factors contributing to the successful adoption of AI systems. At the same time, results from the analysis of the case studies offer valuable insights for practitioners and public managers who are interested in adopting AI in their organizations, going beyond the narrow focus on data, processing power and algorithm development often highlighted in the mainstream AI literature and policy discourse so far.

However, as the use of AI in the public sector is still in its infancy, more research is clearly needed to truly understand how systems are adopted by public sector organizations, helping to validate and potentially adjust the AI-specific innovation antecedents identified in this article. Due to its exploratory nature, the research underpinning this article has several limitations that we aim to address in further research. First, the way in which "AI" has been conceptualized may create challenges for the applicability of the findings for the broad set of AI technologies. Another limiting factor is that the research focuses on a limited set of cases with little information available on organizational and individual factors contributing to specific AI adoption. In future research, it is therefore important to look at the wider context of the adoption of any digital government project, requiring facts and opinion—gathering from several actors working with or within the administrations involved that may have shaped the adoption of AI systems in government. This would require also looking more specifically at the entire data ecosystem that nurtures the development of AI-enabled innovation in government and public services, and how different data governance regimes may stimulate development and facilitate use, while promoting cross-fertilizing mechanisms for AI adoption in the public sector.

Authors' Note

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Notes

1. SATIKAS stands for SATellIidi andmete KAsutamise Süsteem which translates to "A system that uses satellite data" (Voormansik & Bleive, 2016).
2. EU2016/2102 on the accessibility of websites of public sector bodies.

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Publication VII

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New Wine in Old Bottles: Chatbots in Government

Exploring the Transformative Impact of Chatbots in Public Service Delivery

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Abstract. Advances in Artificial Intelligence technologies have revived the interest in Chatbots in both the private and the public sector. Chatbots could improve public service delivery by being able to answer frequently asked questions and conduct transactions, relieving staff from mundane tasks. However, previous e-Government research shows that the adoption of newer technologies does not always mean public services get improved. It is therefore of interest to research to which degree newer, advanced technologies such as Chatbots are able to improve, change and restructure public service delivery. This paper gives an exploratory insight using desktop research into three Chatbots currently used in the public administrations of Latvia, Vienna and Bonn. The findings suggest that minor organisational changes are accompanied with the introduction of Chatbot-technology in public administrations, but question whether Chatbots are able to transform traditional services to digital, integrated public service transactions.

Keywords: Digital transformation · E-Government · Artificial Intelligence · Chatbot

1 Introduction

There has been a big interest in the possible gains of using Information and Communication Technologies (ICT) for the delivery of public services to citizens. Already during the 1990s, there was a strong belief that information technology services are able to create a new, better functioning government of the future [1]. Government operations would be able to become more efficient, of higher quality and also more accessible to the public.

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The internet is always available 24 h every day, so citizens would be able to avoid the slow and hierarchical structures of traditional government. They would not have to rely on the opening times of the government anymore since the Internet allows citizens to find information themselves online and is able to deliver services through the web [1, 2].

Lately, another technology has captured the attention of the field. Coming from the realm of Artificial Intelligence, advances in Natural Language Processing-technologies have revived the potential of Chatbots [3]. Early Chatbots were limited in their functionalities as they were only able to respond to simple queries. Recent advances in Artificial Intelligence technologies, in particular the ability for machines to understand the context of languages better, made it possible for Chatbots to tackle more complex tasks and host more human-like conversations [3]. The optimism for this technology is great; it has already been predicted by Gartner that by 2020, the average person will have more conversations with Chatbots than with their own spouse [4].

In this paper, three cases of Chatbot used in European public administrations are described and briefly discussed on their transformative potential and integrated service delivery. As these Chatbots are frequently mentioned and have won numerous awards, they could be an indicator of how the future of Chatbots in the European public sector might look like in the upcoming years. The main aim of this research is therefore to answer *"Which organizational changes occur within public service delivery due to the introduction of Chatbot-technologies?"*. By analysing the transformative impact of three cases, a greater understanding could be achieved on the impact of Chatbots within the public sector. In order to answer the research question, this paper follows a multiple case study design to identify which kind of changes the Chatbot technology introduced. By analysing three well-known cases of Chatbots technologies, the findings could be more robust and generalizable rather than relying on one single case study [5]. The data collection had been done by document based desktop research. While this enables research from a distance, it does limit the correct interpretation of documents found online and restricts the researcher from gaining additional information not found on websites by for example conducting interviews [6].

2 The Promise of e-Government

An ICT-driven government is argued to be more responsive to citizen-needs, more democratic, transparent and efficient than a traditional government [2]. Early e-Government documents have showed that there was a great wish that technologies would enable a more joined up government apparatus, where different sectors of the government work together across organisational barriers to tackle public problems in an integrated approach, rather than different public organisations working isolated from each other [2, 7]. Government-wide information structures would allow different departments to work together in a more quicker and efficient way as ICT would ease the communication across organisational barriers [8].

The ICT-reformed public services would then improve government-citizen relations, reducing democratic gaps and other disappointments experienced by citizens [9]. For digital public service delivery, it was expected that there would be continuous progress from information provision online to one and two-way communication between citizens and the public organisation, transactional services and lastly cross-agency integrative e-services with more citizen engagement [10].

However, many of the proclaimed benefits of e-government have not been realized [11]. Despite many investments and projects to realize new innovative forms of governance and government service delivery, no substantial gains have been made in the e-government field. While there are many government services now available online, there is a significant mismatch within the supply and the demand for these online services [11]. The techno-deterministic premise that ICT-introduction within the public sector would eventually lead to significant reforms within public organisations did not come by as expected [9]. In fact, most government agencies did not change their organizational practices towards more citizen-oriented public services if they adopted ICT as there is still a lack of integration between different public organisations [2]. When public organisations actually do provide public services online, it is frequently only possible to gain information from the website rather than being able to conduct interactions or transactions with the public organisation [1, 12]. It has been argued that this strong focus on information provision exists because it is seen as "low-hanging fruit"; implementing transactional digital services would require much more resources and effort [12].

The promise of fully integrated public service delivery, without the need to go to multiple organisations, is usually not implemented [13]. This lack of integration among different public organisations was one of the challenges e-Government was supposed to solve, but rather, it is one of the greatest challenges which hinder the potential of e-Government [2]. IT-adoption in governments rather supports current organisational practices and power rather than changing the processes towards citizen's needs [14].

The introduction of eGovernment-technologies has been argued to enable changes of different magnitudes within public administrations: at the workplace level, organisational level and inter-organisational level [15]. Firstly, technology allows for small, incremental changes by automating existing processes and thereby improving the efficiency of government operations. Secondly, ICT could allow more general organizational changes to support the introduction of newer technologies. These changes are small adaptions and internal changes, commonly referred to as first-order changes [16]. Technology introductions in the public sector frequently bring about these kinds of changes [15]. Thirdly, ICT could also enable transformative or even disruptive changes by enabling new mechanisms for public service delivery or policymaking, but limited empirical examples of these changes exist. Lastly, there could be more radical changes which change the governance systems or radically transform policy-making mechanisms [16]. These second-order changes are much more substantial as they radically alter traditional practices, but are more difficult to organize, especially in the public sector [15].

3 The Revival of Chatbots

Chatbots, shorter for conversational agents, are computer programmes which are able to detect and understand language, through text or through speech, and have the ability to communicate back [3]. Simply put, Chatbots are computer programs which are able to recognise the input from a user using pattern matching technologies, access information and reply with the information found in the knowledge database [17]. Conversational agents are not really a new technology; the first Chatbot was already programmed in 1966 in order to discover if humans would be able to find out if they would be talking to a person or a machine [18]. However, the potential for Chatbots is now taken much more seriously due to advances in AI-technologies and changing communication patterns. A lot of our daily communication occurs through messaging apps and we have grown quite comfortable with communicating with them; this makes the introduction of Chatbots quite frictionless [19]. Currently, there are already numerous applications of Chatbots used by the private sector, with the most well-known being the virtual assistants of our mobile phones: Siri, Alexa and Google. Chatbots are starting to appear into numerous other business sectors in order for people to obtain information or to complete interactions without the need for humans [3]. Common usages of Chatbots are as customer service assistants, making reservations, paying bills and allowing customers to buy products or services online [20].

The public sector has also been looking into the usage of Chatbots to improve public service delivery. The main proclaimed benefits of Chatbots are that they allow organisations to reduce their administrative burden and enhance communication with citizens [3]. In addition, Chatbots would enable people to overcome information overload; rather than having to find information themselves, the Chatbot will help them to find what they need [21]. Early use cases of Chatbots within public organisations focus on answering citizen's questions or complaints through customer support, searching documents, routing citizens to the correct office, translations or drafting documents [22]. Most Chatbots are well suited to help citizens navigate through websites with lots of information, answer simple questions or conduct transactions.

This removes the need for humans to answer the same kinds of questions over and over again, allowing human operators to spend more time on complex cases [23, 24]. Others even see the potential of Chatbots to radically improve the citizen experience, improve citizen engagement and enabling new forms of decision-making with the help of citizen's interactions with Chatbots. Chatbots could be used to conduct surveys and gain feedback on public services in a more useful way as the Chatbot would be able to ask follow-up questions [25, 26]. There is certainly a potential value for government organisations to embrace Chatbots, but based on the history of e-Government progress, there is a strong need to gather empirical evidence from its effects.

4 Current Chatbots in Government Service Delivery

4.1 UNA in Latvia

In 2018, the Register of Enterprises of Latvia introduced the Chatbot UNA to answer frequently asked questions regarding the process of enterprise registration. The name UNA has a symbolic meaning as it stands for the Future Support of Entrepreneurs in the Latvian language. This way, UNA acts as an indicator for the future of the Latvian public administration; Chatbots are available 24/7 and thus able to make communication between citizens and the state accessible and friendly [27]. UNA is available on both the website of the Register of Enterprises as well as on the Facebook page as part of the Facebook messenger application [28]. UNA is able to answer frequently asked questions about the registration of their businesses as well as the liquidation, merchants, companies and organizations. If citizens already have an application in progress, they are also able to ask about the progress of their documents. At the moment, UNA only works in the Latvian language [27].

The Chatbot has been developed because the organization had to respond to a lot of calls and emails, which were more or less the same each time. The high numbers of organizational resources spent to answering the same kinds of questions could easily be lessened by using Artificial Intelligence, especially Natural Language Processing techniques [29]. A Latvian company, Tilde, specializing in Artificial Intelligence technologies cooperated in the development of UNA. The usage of the conversational agent has been argued to be highly successful and has been nominated for numerous awards such as the OECD's Public Excellence, World Summit Awards and others [30, 31]. According to the first performance indicators, 44% of the questions asked on UNA are considered to be general of nature and easily taken care of by the Chatbot.

Other non-standard issues are still handled by the support staff, but now they have more time to focus on more complex tasks [30]. While there are plans for UMA to perform the registration of legal subjects and legal facts in the future, currently, the Chatbot is only available to provide information to commonly asked questions. Citizens are still required to collect and fill in numerous documents, sign and stamp, send the filled in documents to the Register and pay the fees using the traditional processes [32].

Another element worth considering is that UMA is not designed to assist citizens with the whole process of starting a business, but solely answers questions about the process of registering the Enterprise as this is the task of the Register of Enterprises of Latvia. Arguably, there are numerous other services which new business owners have to conduct such as applying for licenses, permits, getting a business bank account, buying property, paying taxes and others which UMA is not able to answer questions about.[1]

4.2 WienBot in Vienna

In 2017, the Chatbot WienBot was launched in Vienna. This conversational bot has been designed to provide answers to frequently asked questions people have. The City of Vienna discovered that there are thousands of searches every month on the municipal website in order to gain more information about the online services available in the city. WienBot improves this process by enabling citizens to find information "quickly, smart and on-the-go" [33]. Rather than having to search for the correct page on the municipal website, citizens are able to ask the WienBot which will provide an immediate answer. The amount of information WienBot provides is very broad and

[1] Starting a business is considered a "life event", whereby numerous processes from different (public) organizations have to be followed by a citizen. See also the Quality of Public Administration Toolbox from the European Commission about why redesigning digital services based on these events has many benefits to citizens.

diverse as the website of the municipality has many different online services [33]. At the moment, WienBot is able to provide answers to around 350 different topics and services of the city. WienBot works solely in the German language, but is also able to reply in the local dialect [34].

The WienBot has been developed in order to make the information about the different services the City of Vienna provides more easy and understandable. It follows the current trend that much more information about the municipal services is looked up on the smartphone. However, rather than having the citizen to look up the information themselves, the Chatbot will give a quick answer to any question someone might have [33].

Citizens will still be able to find additional information on the websites, but for quick information, WienBot should be sufficient. Especially information about the availability of public parking spaces in the city is mentioned as a well-desired functionality of WienBot [33]. The City of Vienna was responsible for the development of the application themselves. It won the World Summit Award in 2017 for the best Government & Citizen Engagement application [35].

Even though there are a large number of topics WienBot is able to answer, the Chatbot is solely aimed at information provision for already existing governmental information. It is not possible to transact any governmental services through the Chatbot. Instead, citizens will get a link with more information about where to go to in order to obtain certain government services [33]. While the WienBot is arguably very useful to gain information, there is no possibility to avoid going to the office by conducting transactions online through the Chatbot. It is unclear if there are future plans in order to incorporate the future of transactions through the applications. For example, if a person tells the WienBot that he has lost an item; it will provide him or her with a link to the relevant pages of the lost property office (Fundamt) rather than allowing citizens to use the services through the Chatbot [33].

The transformative potential for the WienBot is hereby severely reduced as citizens would still be required to go through the traditional public services in order to gain what they need, rather than being able to ask WienBot to conduct these transactions for them.

4.3 GovBot/Botty Bonn in Bonn

In the City of Bonn, Germany, the GovBot [36] has been implemented in order to assist citizens with their administrative services. Citizens are able to ask for application forms, opening hours or are able to book an appointment through an interactive process with the Chatbot [37]. The City of Bonn didn't develop the Chatbot themselves but are using the GovBot developed by the software companies Publicplan and Materna. They developed a Chatbot which has been specifically designed for usage in the (German) public administration. Currently, the GovBot technology is used in the search engine of the administration of North-Rhein Westphalia, the City of Bonn and in the City of Krefeld [38]. Citizens are able to access the Chatbot on a specialized website.

GovBot is a Chatbot based on machine learning and an integrated knowledge base of administrative knowledge. The main aim of GovBot is to relieve the administrative staff within the public administration with labour-intensive and recurrent tasks of handling the same kind of citizen requests. Rather than having citizens ask the civil service themselves with questions, they are able to gain the same answers immediately through the use of the GovBot [37, 39].

In addition, the GovBot is able to assist citizens with administrative processes by helping citizens fill in administrative forms. Citizens are then able to come prepared to their appointment with the documents filled in correctly, such as the application of a license plate [40]. Currently, the Chatbot is still in a testing phase and will be added with more information in the future [37].

Even though the Chatbot is still in a testing phase, the main aim of the GovBot is to facilitate better information provision to citizens about general affairs or current administrative procedures. As of now, it seemed not to be possible to conduct any transactions or government services through the Chatbot rather than scheduling an appointment at the office. There is much to praise about assisting citizens with difficult forms and the GovBot definitely could play a big role in this. However, there is no actual change on existing administrative processes with the introduction of the Chatbot; citizens still need to make an appointment at the civil service after filling in the forms and go through the standard procedure, rather than being able to finish the transaction through the GovBot.

5 Discussion and Conclusions

This brief exploratory insight suggests that current Chatbots which have been implemented within the European public sector certainty provide a certain value for the citizens. All three Chatbots aim to improve the communication between citizens and the administrative bodies by providing easy answers to often asked questions. Citizens are able to find the information they are looking for in a quick and reliable way without the need to navigate the governmental websites themselves or contact the customer service, enabling staff to spend their time on other tasks (Table 1).

Table 1. Overview of Chatbots in government

Chatbot value	UNA	WienBot	GovBot
Information provision	Yes	Yes	Yes
Transactional services	Planned	No	No
Integrated information	No	No	No
Organisational changes	First order changes by having staff focus on more complex tasks	None identified	None identified

Even with the introduction of advanced technologies, there is a significant focus on information provision towards citizens, rather than using them to provide better government services to citizens. Instead of using Chatbots in such a way that citizens don't even need to come to the administrative office, citizens are still required to follow the traditional procedures, although this time empowered by the knowledge provided by the Chatbot. It would be truly a change if citizens would be able to send the documents online as well or conduct the whole process through the Chatbot. There seems to be awareness that transactions provide more value towards citizens. The developers from UNA in Latvia aim to facilitate transactions in the future through the Chatbot, but at the moment this is not yet the case.

There are technologies in place to facilitate these transactions; most countries have some form of e-ID system in place already which citizens could use to identify themselves with. An online payment system or e-Signature system would make it possible for citizens to conduct their government transactions fully digital. However, this does require that the actual administrative procedures should be replaced, a task which is significantly more challenging to accomplish.

Just like the lack of transactions, the e-Government literature frequently mentions that the lack of an integrative approach with joined-up public services hinders the potential of e-Government services. All of the mentioned Chatbots seemed to be fully based on the knowledge from the developing organization and don't take into account the knowledge from other, relevant public organizations. This is unfortunate as citizens frequently have to contact different public institutions when they are in need of public services.

The aim of this paper was to explore whether the introduction of Chatbot-technology within the public sector woul be accompanied with transformational changes. However, based on these early findings, we suggest that only first-order occur: namely the automation of current activities and some (minor) organizational changes to facilitate or as an effect to its introduction. Civil servants would be able to devote more time towards more complex cases when many questions get answered by the Chatbots, but the actual nature of their work doesn't seem to change at all.

They are still conducting the same processes as before, even when some of these tasks could be done by different technologies too.

Our findings do not suggest that any second-order changes happened due to the introduction of Chatbots. Public service delivery has not been radically changed, nor was there any mentioning of changes in the governance system, citizen engagement or reforms of the policy-making processes due to the implementation of the Chatbot.

If these practices are left unchanged, more institutions might implement Chatbots in order to improve their information provision towards their citizens. While this goal is very noble and paved with good intentions, there is a serious chance that these Chatbots are going to reflect the current fragmented landscape of governance. Instead of the current practice that citizens have to find the information they need from 10 different government websites, they will have to "talk" with 10 different Chatbots because the knowledge bases of the Chatbots are not integrated. Each of the Chatbots will only be able to answer the citizens the questions they have that correspond to the activities of the organization, rather than giving citizens a full, integrative respond that will cover the whole journey they will take.

If there is no sufficient amount of data sharing between public organizations, citizens will still be required to provide the same kind of information multiple times. Filling in the same kind of information on a government form is, with or without a

Chatbot, a tedious and annoying task for all. Just having a Chatbot is not going to make this procedure any more value adding. If the public sector truly wants to gain maximum benefits from emerging technologies, such as Chatbots, it will require massive public reform, a change in administrative culture and a strong reflection on the current organizational practices. Rather than having technology help understand citizens with the current administrative procedures, there should be questions raised if certain administrative procedures could be made easier or removed at all!

There is much more research needed to make more valid conclusions as this paper so far briefly scanned a couple of Chatbot implementations within the public sector. The field is still rapidly evolving and the reflections given here might quickly become invalid if multiple public organisations realise the potential which digital transformation could provide them. Furthermore, the lack of interviews limits the scope of changes which might have been introduced with the Chatbot technology. Possibly, certain organisational changes did occur but were not mentioned online. This restricts the current conclusion but should be seen as an invitation to conduct further research on these cases. Artificial Intelligence technologies such as Chatbots are an intriguing set of new technologies, likely to leave a big impact on our society in the near-future. However, it is advisable to take the transformative discourse of these technologies with a pinch of salt. A true understanding of the impact these technologies will bring the public sector requires a clear and realistic view on how they get adopted and used in practice, by institutions and by citizens.

Disclaimer. The views expressed in this article are purely those of the authors and may not be regarded as stating the official position of the European Commission they are affiliated to.

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The use of AI in public services: results from a preliminary mapping across the EU

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ABSTRACT

Artificial Intelligence is a new set of technologies which has grasped the attention of many in society due to its potential. These technologies could also provide great benefits to public administrations when adopted. This paper acts as a first landscaping analysis to indicate, classify and understand current AI-implementations in public services. By conducting a desk research based on available documents describing AI projects, 85 AI applications in the public sector in selected European countries have been identified and reviewed. The preliminary analysis suggests that most AI initiatives are started with efficiency goals in mind, and they occur mainly in the general public service policy area. Findings of this preliminary landscape analysis set the basis for further more in depth research and recommendations for policy.

CCS CONCEPTS

• **Applied computing** → **Computers in other domains** → Computing in government → *E-government*

KEYWORDS

Artificial Intelligence, public administration, digital services, Europe

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1. INTRODUCTION

Artificial Intelligence (AI) is considered a 'new' set of technologies which have (re)gained great attention recently among academia, policy makers, businesses and citizens alike. As indicated by the Communication on AI Made in Europe, *"Like the steam engine or electricity in the past, AI is transforming the world"* [1]. Although many of the methodological developments in Artificial Intelligence (AI) date back more than 50 years, the reason why we now pay so much attention to AI in general and machine learning (ML) in particular is that the recent advances in computing power, availability of data, and new algorithms have led to major breakthroughs in the last decade.

This resulted in the fact that the many applications of AI/ML have started to enter into our everyday lives, from machine translations, to image recognition and music generation, and are increasingly being exploited in industry, commerce and government [2].

The opportunities are many, in some cases not yet foreseen. By enabling smarter analytical capabilities and better understanding of real-time processes, and delivering shorter and richer feedback loops for all levels of governance [3].

AI is assumed to have the potential to increase the quality and consistency of services delivered, to improve the design and implementation of policy measures, to allow more efficient and targeted interventions, to enhance the efficiency and effectiveness of public procurement, to strengthen security, to improve health and employment services and to facilitate the interaction with wider audiences [4].

For instance, AI can enable doctors to improve diagnoses and develop therapies for diseases for which none exist yet; it can reduce energy consumption by optimizing resources; it can contribute to a cleaner environment by lessening the need for pesticides; it can help improve weather prediction and anticipate disasters; and so on. The list is endless and it is expected to bring solutions to many societal challenges, becoming the main driver of economic development.

However, socio-economic, legal and ethical impacts have to be carefully addressed. Deployed wisely, in fact, AI holds the promise of addressing some of the world's most intractable challenges. But the significance of its positive impact is mirrored by its likely destabilising effects on some aspects of economic and social life [5]. In the words of the late Stephen Hawking: *'AI could be the biggest event in the history of our civilisation. Or the worst! We just don't know'*.

The European Union in particular, aims to develop trusted AI based on European ethical and societal values building on the European Charter of Fundamental Rights [6]. People should not only trust AI, but also benefit from the use of AI for their personal and professional lives.

To this end, the EU is setting out the foundations for creating an innovation friendly ecosystem for AI: an environment where economic players find the infrastructure, research facilities, testing environments, financial means and adequate skills levels to invest in and deploy AI. Public administrations have also taken an interest in using AI-enabled systems and technologies in order to improve their processes, services and policies [1].

The application of AI for public administrations fits the more established tradition of eGovernment: the practice and study of using ICTs in order to improve government services. Already since the 1990's there has been great enthusiasm to introduce new digital technologies within public sector organisations in order to improve effectiveness and efficiency of service delivery, make administrations more citizen-centric and improve trust in government [7]. However, many researchers have questioned whether the great investments in ICTs by governments over the past decades have actually achieved the significant impact it was supposed to bring [8] [9].

More recently, as a consequence of the continued datafication of society and the digitalisation of the government, there has been an increasing effort to use the massive volumes of data available in order to improve governmental practices [10]. By utilizing the data and digital infrastructure built during the previous e-government generations, public organizations are expected to become more data-driven and thus to increase their capacity for problem-solving of major societal challenges [11] [12].

Despite the potential and interest in using Artificial Intelligence technologies, literature and practice in the field also show that even when AI is introduced as a 'new technology', previous challenges encountered in the eGovernment research field are still often present [13]. Much of the current research on AI in fact often focuses solely on the role of the technology itself, but fails to take into consideration the complexity of implementation of ICTs, or in this case AI within public administrations, creating the false expectation that technology availability will always lead to its usage.

This research acts as a first landscaping attempt of the current implementations of Artificial Intelligence in public services.

It is part of the continuous landscaping task of the AI-Watch of the European Commission started beginning of 2019. This exploratory analysis in particular serves to set the ground for further in depth research building on an inventory of cases and initiatives gathered across European countries. In addition, this research paper aims to provide a preliminary understanding of some of the main drivers of the current AI projects in the EU. This would enable a broad overview of the current AI implementations in the public sector as well as what kind of objectives these AI are supposed to achieve.

To this end, the paper is structured as follows. First, an overview of the current state of play of Artificial Intelligence is presented, giving special attention to the use of Artificial Intelligence in governmental organizations. After, the classification used in the landscaping exercise to analyse data gathered is provided and the methodological approach followed for the mapping is explained. Based on the identified AI initiatives, an analysis of preliminary findings based on the AI application type, policy area and expected effects is presented. The paper concludes with discussion of findings and recommendations for future research.

2. STATE OF PLAY: AI IN PUBLIC ADMINISTRATIONS

AI has a tremendous potential to benefit European citizens, economy and society, and already demonstrated its prospective to generate value in various applications and domains [2]. From an industrial point of view, AI means algorithm-based and data-driven computer systems that enable machines and people with digital capabilities such as perception, reasoning, learning and even autonomous decision making [14]. AI is based on a portfolio of technologies including algorithms for the perception and interpretation of vast amounts of information (data), software that draws conclusions, learns, adapts or adjusts parameters accordingly and methods supporting human-based decision making or automated actions [15].

Unfortunately, AI is not a well-defined technology among academia, policy makers and society as it changes its meaning as a science or as a technology. This makes it already challenging to narrow down the scope of what is meant with it [4]. Some refer to AI as the broader science and practice of making machines intelligent, a research field which has been active since the 1950's. Even in this research field, different methods, aims and goals within the realm of AI exist [16].

Traditional AI research has focused on Symbolic Artificial Intelligence, that is, humans code their knowledge into a computer in order to make it intelligent. People programme the code which computers are able to understand, usually following "if X, then Y" rules [2]. Humans therefore have great control of computers behavior, being the ones giving instructions to the machines.

However, this approach has limits due to the complexity of transcribing human knowledge and intelligence into computer code [16]. Human intuition and emotional intelligence is very challenging to put into a computer code, especially when the environment and other factors change rapidly [17].

The recent interest in AI and what most of the current debate is about are developments in machine learning technologies. Unlike the traditional approach of a human putting the rules on how the machine should behave, machine learning allows machines to learn "on their own" by analysing massive amounts of data. By discovering underlying patterns in large datasets, machine learning algorithms are able to write their own "if X, then Y" rules [2].

However, since machine learning algorithms discover correlations or patterns in the data which humans would never be able to find, it is very difficult for humans to understand these rules. The role of the programmer is significantly reduced in this learning method; the data on which the algorithms learn from are much more important [16]. In practice, machine learning enables computer to do certain tasks with equal or superior accuracy which in the past required human intelligence to do [18].

As a matter fact, we are witnessing the rapid development of smart, intelligent or autonomous systems that do not simply execute predefined instructions or tasks. They can also learn and adapt with limited human intervention, and/or collaborate with humans to identify problems, find new solutions and execute them faster and in previously unforeseen ways, or – if used in a malicious way cause harm and/or increasingly shift the cognitive capacities of human being, having a profound impact on the world we live in, from industry and work, through our personal and social spaces to government and politics.

Despite the positive discourse, recent research has also highlighted potential downsides of using algorithms or Artificial Intelligence applications such as bias, loss of privacy, accountability due to opacity of algorithms and possible job losses [2]. At the same time machines and industrial processes, that are supported by AI are augmenting human capacities in decision-making and providing digital assistance in highly-complex and critical processes [19]. Within this context, there is a great interest by government institutions to harness the potential benefits that AI can bring.

Many European AI strategies seem to focus on creating favourable conditions to enable private companies to develop AI to boost their business operations and create better services or goods [20]. Much less attention is given on how to use AI to improve public services and government operations, despite AI could enormously increase value creation from big data and its use to rapidly emerging B2B, B2G, G2C, G2B and B2C scenarios in many application domains. In this perspective, there is a great demand to understand the drivers, barriers, opportunities and risks to the adoption of AI in government. In addition, there is a need to understand the potential impact of the usage of AI in the public sector, either positive or negative [15].

Early studies shows that there are numerous, interdisciplinary challenges surrounding the adoption of AI in government which do not solely focus on the technology [21] [22]. However, as the field of research on AI adoption and impact is still in its infancy, with many reports talking about the potential impact without empirical backing, there is a reason to be critical and flexible on the indicators given in this model. Certain factors might not turn out to be grounded whereas others might have been overlooked by the discussions so far.

To further illustrate the key elements underpinning the design of the framework to analyse use and impact of AI in the public service, the figure below outlines the relationships between drivers and barriers of implementing AI in government, and the effects and impacts that can potentially be generated.

In practical terms it is to be considered that all ICT-enabled projects within government are initiated with certain goals in mind, whether explicit or implicit. All these projects are aiming to achieve a certain goal upon its completion, whether it is to improve efficiency, reduce waiting time, increase citizen satisfaction or others. These project objectives could be abstracted towards a more general, abstract public value in order to assess what kind of public values current projects in the government regarding AI aim to achieve. Most projects are based on the broader Value Drivers: Performance, Openness and Inclusion as guiding principles in project initiation [30].

3. MAPPING ARTIFICIAL INTELLIGENCE IN GOVERNMENT

Current applications of AI have been argued to solve a number of common governmental problems such as resource allocation, managing large datasets, exports shortages, creation of scenario's and predictive, repetitive procedural tasks and managing diverse data [3]. Existing and emerging AI-technologies usually provide one or multiple of these capabilities which individuals or organisations can utilize in order to solve these problems. In summary these can be grouped as follows:

1) AI techniques could make predictions which are way more comprehensive and accurate than human-based predictions as the predictions are based on huge data volumes [14] [23].
2) AI can help in detecting anomalies within big datasets to help organizations focus on specific cases which, according to the algorithm, stand out from the rest [14]. This is commonly used in detecting (welfare) fraud [24].
3) Computer Vision technologies allow computers to collect, process and analyse information coming from large numbers of digital images or videos. When functioning correctly, a Computer Vision AI technology will be able to recognize unique features in digital media in order to identify objects, actions or unique characteristics [14].
4) Natural Language Processing (NLP) is an AI technique which allows machines to process and understand audio and text. This allows applications to have automatic translation functions to translate government information, provide interactions through Chatbots or conduct sentiment analysis of textual data [25].
5) The profiling (classification of customers or citizens) is also a potential capability provided by AI technologies. [26]. With the proper classification technologies, individual citizens could be grouped according to citizens

with similar needs or interests [21]. This opens the door for governments to provide more tailored public services, dynamic government websites or personal recommendations based upon the citizen's profile and those with similar needs [23].

In order to assess what kind of AI is being used in governments, a categorization is needed in order to classify the different types of use and impact. AI in fact could refer to many different forms of technologies and it is commonly used as an umbrella term for a set of technologies and methodologies [27].

Furthermore, the field of AI suffers from what has been defined the so called "*AI-effect*"**:** an effect that explains that technologies which were once referred to as AI are not called AI anymore since societies got so used to them [4]. It is thus important to keep in mind that any classification used now might be invalid in 5-10 years when the field has developed further.

The framework proposed thus focuses on developing an ad hoc classification framework based on the current applications domain in the public sector; and built upon research from Wirtz, Weyerer, & Geyer [21]. To provide a presentation of contemporary applications in use, a simplification of the current AI-classifications has been used. While this classification is simple, it allows for specialization and additional classifications when the field has developed further. Current AI-projects have been classified as: Image Recognition, Pattern Recognition, Natural Language Processing, Robotic Process Automation and Robotics.

There is also an interest to assess in which policy sector the AI technology is being used. Certain industries or policy sectors have been argued to be more suitable for AI (such as healthcare, agriculture and transport) than others due to the current availability of data in this field [26]. By analysing the different policy domains in which the AI systems are active, this assumption could be tested. Furthermore, it allows the detection of policy sectors where there is significant lack of AI adoption.

This in return invites additional research to identify specific factors which are related to the adoption and impact of AI in these specific policy domains. The Classification of the Functions of Government (COFOG) developed by the OECD in 1999 and since then used also by the UN (and EUROSTAT) classifies government expenditure data from the System of National Accounts by the purpose for which the funds are used.

The COFOG categorizations work as follows: There are 10 different policy sectoral groups (such as defence, education and social protection which each further splits into up to nine sub-groups to allow classification of one general policy sector which specific policy subgroups. For the preliminary analysis, only the first grouping has been used. In future landscaping reports, more nuanced views on AI could be achieved by considering the second-order policy domain as well.

4. METHODOLOGY

The documented Artificial Intelligence implementations have been gathered by an extensive review of policy and practitioner-generated documents and available publications of AI-projects in public administrations. This collection included current strategy documents, consultancy reports and other documents regarding Artificial Intelligence used in the European public administration. Most of the documents on AI have been gathered through the European AI Alliance of the European Commission. This is a stakeholder network of representatives of organisations working or interested in Artificial Intelligence to exchange information, best-practices or have discussions on various aspects of AI in society [28].

In addition to reviewing the documents and posts shared on the AI Alliance network, additional documents have been gathered by using the search engine Google on "Artificial Intelligence + Public Sector" and "Artificial Intelligence + Government".

These documents have been examined with a document review by the authors in order to identify current AI projects mentioned in these documents. Any AI projects currently being initiated by the European member states found in the documents were included in the documentation. This resulted in gathering 85 unique AI-initiatives across 15 different European member states.

This research method was chosen as it enabled a relatively easy and quick way of research, providing a starting point for future, more extensive AI landscaping studies as the document analysis is relatively easy, low-cost research method [29]. Future iterations of this study could include other key words such as "machine learning + Government" or other technologies regarded as AI by governments. At the moment, only AI regarded by the organizations themselves as AI are included.

A key focus on the collection was the implementation of AI-technologies within public administrations. AI-tools being used by private companies operating in this domain have not been considered; while AI-tools developed by private companies, but used and implemented by public administrations are. Arguably, the amount of AI-implementations by private companies in these policy domains would have been much higher, but is not the focus of this research.

Whereas numerous cases have been identified so far, it is clear that the current collection of AI-implementations is not complete. Currently, governmental reports on their AI-initiatives are still very limited and at the time of writing there were just 9 countries who adopted an official AI strategy, and not all national AI Strategies give concrete recommendations on how to improve the public sector with AI-technologies.

Naturally, it is very likely that the amount of AI-initiatives in the public sector found is much lower than the actual amount of AI-initiatives taking place in the public sector. For example, our analysis has reported 20 cases of AI-projects in the Netherlands whereas a recent survey conducted among Dutch public institutions has reported 74 AI-projects [29]. It is likely that this analysis is underreporting the amount of projects for other member states as well due to some limitations of the data collection method.

Firstly, not all AI-initiatives are mentioned or documented online. As the data collection method was by desk research, only the AI-projects which were mentioned by online sources could have been identified. This limits the amount of AI-initiatives which are already being used in public organizations, but are not mentioned in online documents.

Moreover, as not all information regarding AI-projects in governmental organizations is reported in languages accessible to the researchers involved in this first analysis, there is a possible inherent bias towards implementations from English and Dutch speaking countries, as documentation describing AI-projects in the public sector not in these languages was more challenging to assess.

As the landscaping exercise is an ongoing research project, future iterations of the analysis will involve other data collection methods such as continued surveys among EU member states, expert discussions as well as interviews to collect more cases.

Likewise, Artificial Intelligence is an umbrella term for many different technologies and applications. There is currently no consensus on what kind of technologies or applications could be considered Artificial Intelligence or not. Some member states might refer to some applications as Artificial Intelligence whereas others would not classify this application as such.

Different classifications have consequences for the analysis as they could inflate or deflate the number of AI-projects listed in the paper.

There are still challenges in assessing when an AI-project could be classified as an implemented AI-initiative. Projects currently being initiated in the various public administrations are in different phases: either in Proof of Concept stage, Development stage, Pilot testing or Implementation stage with routine usage of the system. As our analysis focuses on the implementations of Artificial Intelligence systems, cases which are either in Pilot testing or in the Implementation stage have been considered for the analysis.

5. PRELIMINARY ASSESSMENT OF AI INITIATIVES IN GOVERNMENT

This section reports a first elaboration of trends analysis based on the information gathered through collected cases so far. The analysis reflects some of the earlier discussions on AI as well as providing a starting point in assessing what kind of expected effects AI could bring.

For this, the structure of a recent literature review on Public Value was adopted, and effects of eGovernment have been classifies according to three main categories: Improved Public Services, Improved Administration, Improved Social Value [30].

In addition, the main "Value Drivers", of the projects have been assessed by the authors, building on the classification by [35].

Furthermore, different AI-types currently in use by governments have been assessed as shown in Figure 1. Clearly, while the classification of AI-technologies is an ambitious task which require further analysis, due to the different meanings and usages of the term, a first, simple attempt has been made to have a quick overview of the situation.

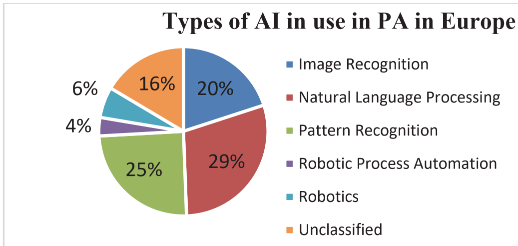

Figure 1: Types of AI technologies in use in PA

5.1. AI cases per country

As indicated in figure 2, there are currently significant differences among the European member states in terms of Artificial Intelligence implementations. While on average, each country has 3 implementations of AI-technologies, the highest amount of initiatives found was in the Netherlands with 20, followed with 19 implementations by Belgium. It is likely that these countries currently have the highest amount of listed indicators due to challenges in the data collection as described above. However, this may also due to the policy emphasis that has been put recently on developing AI in the public sector in these countries.

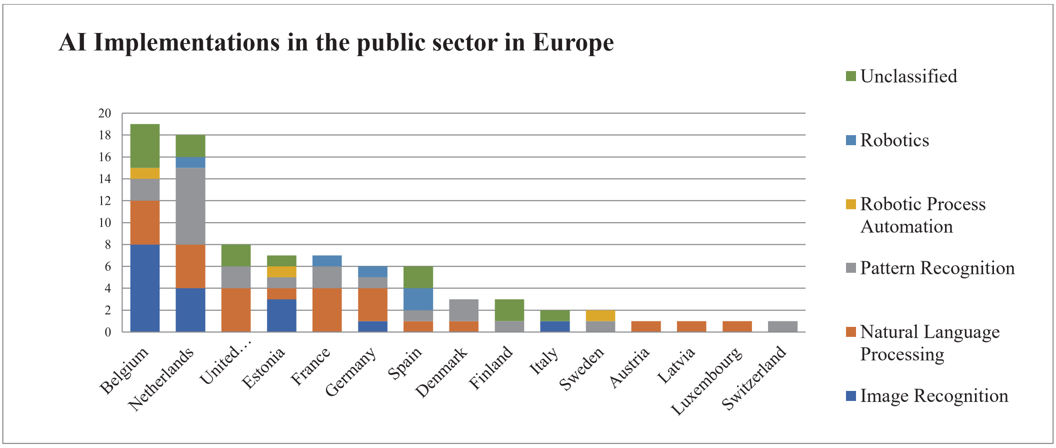

Figure 2 AI Implementations in the public sector in the EU

From the analysis it emerges that most of the AI-technologies currently in use are a form of Natural Language Processing technology, such as Chatbots or Speech Recognition (29%), followed by Pattern recognition (25%) and Image processing (20%). In practice all AI technologies that apply a form of automatic recognition in order to provide more accurate predictions seem thus to be more common place across public administrations.

This is hardly a surprise, as one of the main benefits of AI is the ability to identify patterns and make more accurate predictions based on available datasets. Implementations of Artificial Intelligence which are able to detect people or objects in images or videos are thus being introduced in many organisations, while implementations of robotics or Robotic Process Automation is less reported (16%). For 14 of the 85 identified AI-implementations, it was not very clear what kind of AI-technology was used, hence they are marked as unclassified.

5.2. AI implementations per policy sector

Based on the COFOG categorization of policy sectors (see methodology), the areas in which the AI tools are active in have been also assessed. As can be seen in Figure 3, most of the current AI applications are used in the "General Public Services" policy domain, without any direct link to any specific policy area.

With regards to the General Public Services, the greatest percentage of AI-tools currently in use is based on Natural Language Processing. One could think of Chatbots providing information about various administrative procedures or automatic translations of documents or the transcription of political debates using NLP-technologies. There are however not many Image Recognition technologies being used in General Public Services, while they are more common in the Economic Affairs policy domain.

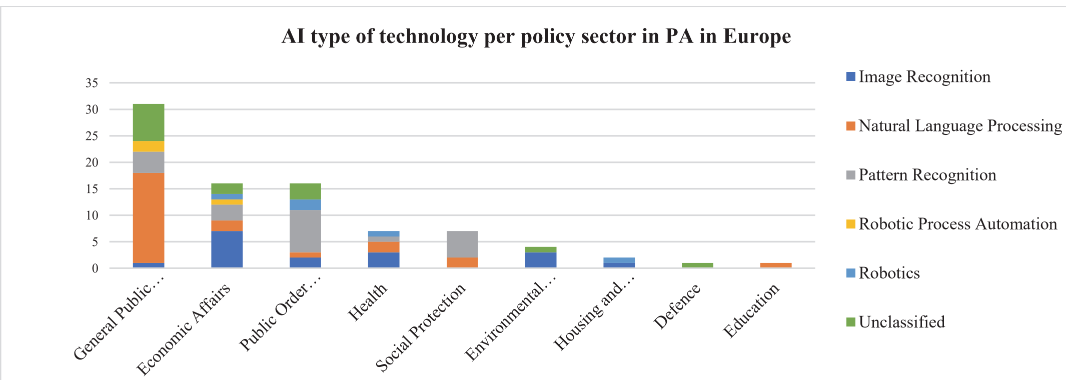

Figure 3: AI type of technology per policy sector in Europe

Despite the current debate on the positive aspects of AI-implementations in the health domain, the analysis shows that while hospitals might implement AI-technologies, public administrations operating in this domain at policy level, seem to be lacking behind as only a couple of AI-technologies have been implemented so far in the sample analysed.

Only one case of AI in the Defence sector has been identified. It is very likely that AI-projects in the Defence policy domain are not well documented online due to security concern and hence could not have been gathered in the data collection.

5.3. Expected goals of Artificial Intelligence

As it was mentioned before, projects introducing ICTs in government are aimed to achieve certain objectives. These objectives could be abstracted into broader, more abstract values. Following previous work of one of the authors [35], we have classified these in three main value drivers: Performance; Openness; and Inclusion.

A quick analysis of the current goals of the AI-initiatives mapped shows that most of the AI-technologies are implemented with efficiency gains in mind (see Figure 4).

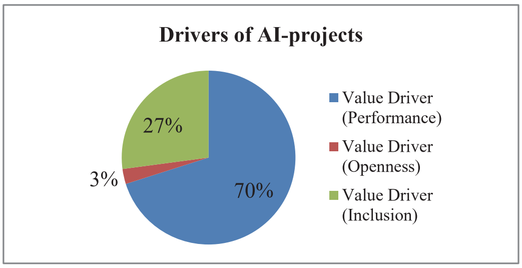

Figure 4: Drivers of AI-projects in government

In fact, 75 out of the 85 AI-initiatives are aiming to achieve efficiency goals, whereas just 29 of all the initiatives had goals related to inclusion in mind as seen more in details in Figure 5.

Only 3 aimed to make the government more open towards it citizens. This shows that the initiation of Artificial Intelligence seems to be, just like most of the historical eGovernment narratives, driven by internal efficiency gains.

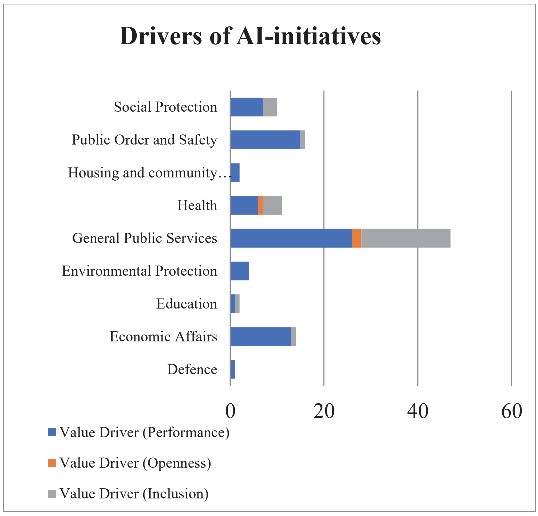

Figure 5: Drivers of AI-initiatives

With regards to the expected effects of the reforms, the AI-initiatives could be grouped according to their impact on either the administration themselves, the public services the organisation provides or a broader, social impact.

In Figure 6, one can see that most of the AI-initiatives keep a focus on the internal efficiencies of the public administrations by improving the organisational performance itself. However, 56.5% of the initiatives are aiming to provide Improved Public Services directly or as a result of these improved internal efficiencies. Surprisingly, only 27.1% of the AI-initiatives refer to one of the earlier identified Social Values.

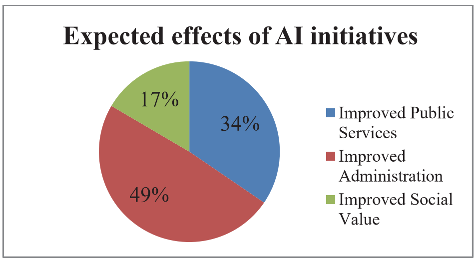

Figure 6: Expected effects of AI-initiatives

As can be seen in the figure 7 then, only a very small amount of AI-projects in the "General Public Services" realm consider the goal of improved social value as the main to achieve. Most of the projects seem to be only focusing on the internal efficiencies and administrative procedures of the organization, without taking the social value into consideration. Only projects in the "Public Order and Safety" domain do take the Social Values more into consideration, by for example directly referring to the expected impact on citizen's safety.

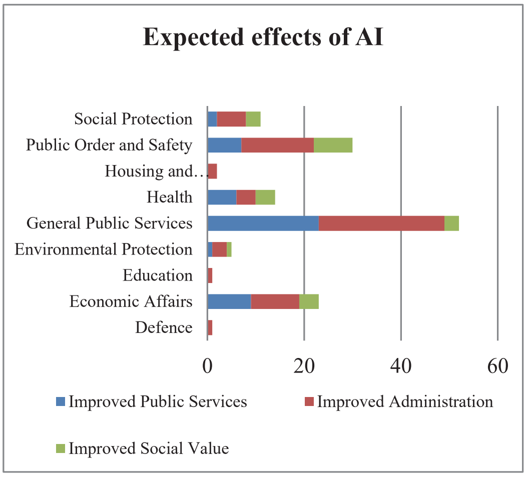

Figure 7: Expected effects of AI per policy sector

6. CONCLUDING REMARKS

The implementation of Artificial Intelligence technologies within the public sector is raising great interest among policy makers. When implemented correctly, AI-technologies are able to improve existing organisational practices and create new capabilities to solve some of society's most pressing issues.

Despite some of the challenges for public organizations to adopt new technologies, many institutions are already using Artificial Intelligence. In this paper, a first landscaping attempt has been done in order to discover how public administrations are currently using this technology.

Based on exploratory analysis and desk research, 85 different AI-implementations across European countries have been identified. While some countries clearly have more AI-implementations than others, it is likely that our mapping is limited due to underreporting of implementations online. Future iterations of the landscaping exercise will be likely to include more initiatives of Artificial Intelligence in the European public sector.

Currently, our preliminary analysis indicates that AI-technologies used the most across European public administrations are Natural Language Processing-technologies and Pattern Recognition technologies. Such NLP-applications could either be Chatbots or automatic translation tools to provide governmental information in different languages. Likewise, Pattern Recognition technologies allow governments to predict events based on various and numerous data they have collected.

Most of the AI-adoptions seem to take place in the "General Public Services" domain rather than in other policy sectors. This was somehow unexpected due to the general positive claim on the promise of AI in the health sector for instance. In this case, it could be possible that organisations operating in the health domain do have capabilities and resources to implement AI, but that the public organizations operating in this domain at policy level have yet to acquire these resources and/or expertise.

While the potential of Artificial Intelligence has been mentioned to be broad and diverse, offering many different possibilities for changing how public organizations function and deliver services, an assessment of the project's aims tend to favour that most of the AI-initiatives are aimed with Efficiency goals in mind. Only limited amounts of AI-projects are aimed at improving Inclusion of service delivery and even fewer are using AI-tools to make the organisation more open to the public.

This shows the general tendency to use technologies in the government to improve organisational effectiveness and efficiency, without taking into account how these technologies could provide avenues for increasing collaboration or inclusion of different stakeholders and citizens.

Furthermore, most of the AI-initiatives are expected to provide a positive contribution on the administration itself, while limited amount of projects directly mention some form of social value which gets improved due to the application of the technology. It is still an open question whether the projects have achieved their objectives and which unexpected effects AI-implementations have brought. In fact, little is still known about the disruptive effect of AI and whether AI technologies are capable of changing the way public services are delivered or even how the public sector works as a whole.

This research does suggest that there might be policy-domain specific factors which might affect the uptake of AI-technologies within public organizations. As of now, it is still unclear what these factors might be. In addition, certain AI-types seem to be more likely to be implemented in the public sector than others. More research should shed a light on why certain AI-types are used more than others.

As this landscaping exercise is still limited with only 85 cases, future iterations of the exercise are required to collect further data and provide more in depth insights. In particular, a more nuanced and clear analysis of the different AI-types might allow a more thorough analysis on the different AI-technologies in use, while attentional data collection methods might increase the amount of AI-implementations currently in use within Europe. The data collection through online desk research enabled in fact only a first glance of the current use of AI, but is likely to suffer from incomplete data as not all AI-implementations are described online or are described in languages accessible to the researchers.

Despite these limitations, this paper provides a first and unique original overview on the current use of AI within governmental organisations in Europe. This will be valuable contribution for other researchers to gain a better understanding of the current use and effects of Artificial Intelligence as most of the current documents tends to mention only a limited number of best-practices or describe potential cases, without any proof of its existence.

At the same time, and in line with the rationale of the research underpinning this first exploratory analysis, this mapping of cases serves to provide input to structuring the policy review that is currently being conducted as part of the European Commission's AI-Watch[2]. This is the monitoring mechanisms set up by the European Commission's Joint Research Centre in collaboration with other services of the Commission and research centres, to provide scientific support to assess the implementation of the Coordinated Action Plan on AI Made in Europe, adopted by EU Member States in December 2018 and currently under development.

In particular, as part of the AI-Watch, which has been established in January 2019 to monitor the European capacity in Artificial Intelligence, the status of technology and its uptake in the European economy and society, a specific activity is devoted to provide an overview and analysis of the use and impact of AI in public services.

This includes gathering information on all EU Member States' initiatives on the use of AI in public services and developing a methodology to identify risks and opportunities, drivers and barriers of the use AI in public service provision.

Future research will thus provide a more comprehensive overview of the use and added value of AI tools supporting public service delivery by looking at the most relevant examples in prioritized public services. Based on the results of the analysis, recommendations on the way forward for further development of AI-based systems and solutions in government will be outlined to provide insights and a possible roadmap for accelerating adoption of AI in the public sector, and its impact on society at large.

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DISCLAIMER

The views expressed in this article are purely those of the authors and may not be regarded as stating the official position of the European Commission.

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Driving public values of Artificial Intelligence in government

Analysis of driving public values of AI initiatives in government in Europe

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Abstract: Public administrations in the EU have started to increasingly adopt and mainstream implementation of Artificial Intelligence technologies. However, it is still unclear what types of AI applications are used and to what kind of public value they aim to contribute to in the public sector. We therefore set out to identify the current landscape of AI use across the EU. In total, we have identified 549 cases and coded each AI application using a public value framework. Findings from the analysis show that while the use of AI has the potential to contribute to professionalism public values, efficiency public values, service public values and engagement public values, public administrations are predominantly implementing AI in pursuit of efficiency-related objectives. The paper further describes potential risks of public value destruction of the prevalent pursuit of achieving efficiency public values when public administration deploys AI technologies.

Keywords: Artificial intelligence, public value, EU, government, data-driven policy

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Introduction

Artificial intelligence (AI) promises disruptive changes to the way the public sector designs and operates its internal processes and delivers public services to businesses and citizens. The changes range from proactive delivery of services (Androutsopoulou *et al.*, 2019) to automation of tasks (Engin and Treleaven, 2019) and disruption of work (Sun and Medaglia, 2019), among others. While some applications of data analytics based on machine learning already exist in some countries, and several pilots are emerging, in general, public administrations have only started to explore the implementation of AI technologies and have therefore not realized its potential in use. Empirical evidence is in fact missing to understand what these AI-supported public service delivery projects look like and how – or whether – they deliver public value. While some scholars argue that AI might disrupt not only how services are delivered, but also how value is created for the public (Ojo, Mellouli and Ahmadi Zeleti, 2019), we also witness potential threats to the quality-of-service delivery and emerging risks or unintended negative consequences that can be generated by the adoption of AI in the public sector, as some recent cases have demonstrated (Misuraca and van Noordt, 2020).

Whereas research on AI in the private sector is generally more widespread and advanced (Collins *et al.*, 2021; Loureiro, Guerreiro and Tussyadiah, 2021), it is questionable whether copying approaches and practices from the private sector is sufficient in understanding public sector use of AI (Zuiderwijk, Chen and Salem, 2021). The public sector operates in a unique setting, where public services and policy (supported by AI and other ICT) should not only be based on economic values such as profit, but also on democratic and social values, such as the rule of law. Innovation in the public sector has also been argued to occur differently than the private sector due to the specific culture, goals and constraints the public sector operates in (Bugge and Bloch, 2016; De Vries, Bekkers and Tummers, 2016), which is why research insights from the private sector cannot be directly transferred to the public sector context. (Medaglia, Gil-Garcia and Pardo, 2021). In fact, while a lot of attention to the potential societal impacts of AI is given in the literature (Zuiderwijk, Chen and Salem, 2021), empirical research testing these assumptions are only slowly emerging (Aoki, 2020). What this early research has found is a too limited view, focusing exclusively on the economic benefits of the use of AI systems may limit awareness and perspectives of other important public values, such as ignoring legality, within the scope of the development and implementation of such solution, leading to destructive results as seen in the case of Robodebt in Australia (Rinta-Kahila *et al.*, 2021).

As such, research on AI in government is growing, but a clear understanding on both how to assess the impact of AI in government and which effects materialize after adoption and deployment is still lacking (Zuiderwijk, Chen and Salem, 2021). It is often still unclear how positive and negative impacts can be identified, given the potential positive, negative, and unintended consequences AI brings in a public sector setting. While there is plenty of work on the theoretical effects of AI deployed in government, linking it clearly with the actual deployment of AI in government is limited. As such, research is quite aware of what public value AI *could create*, but there is limited evidence of which value *is (attempted to) being created*.

This paper therefore aims to tackle this research gap by assessing which public value existing AI use cases in public administrations around Europe aim to create. Through a landscaping exercise of AI use in public services across the EU, we have extracted cases and conducted an analysis of a set of 549 identified use cases. Using a public value framework derived from the existing literature, (Rose *et al.*, 2015), we identify how AI public service delivery plans contributes to the professionalism public values, efficiency-related public values,) the service-related public values and engagement-related public values. This is especially relevant in order to minimize 'administrative evil' and to maximize good governance, as public values may be threatened by the implementation of AI technologies (Schiff, Schiff and Pierson, 2021). Furthermore, it provides an overview of which values may be under and overrepresented, especially since in the strategic documents surrounding AI, a too strong economic perspective is often present whilst other important goals, such as strengthening the rule of law, sustainability, citizen participation and democracy, are severely overlooked in the narratives (Toll *et al.*, 2020; Guenduez and Mettler, 2022; Wilson, 2022).

Next, we provide an overview of the state of play by reviewing the literature on public sector AI, outline how various forms of public value could be created by utilising AI within public administrations. We then present the research design and our methodological approach followed by the discussion of the main findings of the analysis. Then we derive implications of the study for both policy makers and public managers who are implementing AI initiatives and propose new avenues for future research.

Literature review

AI in the public sector

The use of AI technologies and applications in government has been argued both by academics and practitioners to be capable of improving government tasks and processes in significant ways. Despite that AI is often used as an umbrella term to describe a variety of different technologies, AI is often understood as ICT systems which are capable of perceiving their environment and taking actions to complete tasks, which are regarded to require some form of human intelligence or rationality (Sun and Medaglia, 2019). In this respect, a diverse set of AI applications has been emerging in public sector settings for purposes, such as assisting in policy making processes (Wirtz, Weyerer and Geyer, 2019; Valle-Cruz *et al.*, 2020), direct public service delivery (Aoki, 2020; Kuziemski and Misuraca, 2020), internal process management of public administrations (Lima and Delen, 2020; Pencheva, Esteve and Mikhaylov, 2020), and public procurement (van der Peijl *et al.*, 2020).

Compared to other ICT used by public administrations, AI can be much more impactful for citizens due to its direct support in decisions affecting citizens, the likely deployment in core functions of governmental organizations which originally required human expertise (Veale and Brass, 2019; Engstrom *et al.*, 2020). Despite the positive potential impact and discourse, an increasing amount of research warns of the negative consequences of the use of AI within the public sector context (Hartmann and Wenzelburger, 2021). If used irresponsible, there are risks of amplifying (existing) discrimination within society by using biased data in automated decision making (Liu, Lin and Chen, 2019), making decisions opaquer, and reducing citizens' privacy through large-scale data collection, which can increase the feeling of surveillance and paradoxically reduce transparency in government (Barocas and Selbst, 2016; Dwivedi *et al.*, 2019). Moreover, the possible loss of control through AI-mandated decisions and the low capacity to manage complex AI-enabled operations may undermine the trust relationship between the public sector and the citizens (Janssen *et al.*, 2020) or even exclude citizens entirely (Larsson, 2021).

In this still emergent field, we have little empirical insights into the implications that the adoption of this new set of technologies can have in terms of public value creation in society. In general terms, it could indeed be assumed that the implementation of AI in public administrations will follow the general strategic goals and discourse laid out by policy documents. Studies reviewing AI strategy documents found in fact that AI is often described as an enabler of efficiency and effectiveness in the public sector (Fatima, Desouza and Dawson, 2020), but not regarded as an enabler for increasing citizen engagement in general (Toll *et al.*, 2019; Wilson, 2021). As there is a significant interplay between the values involved in the design and roll-out of ICT technologies, understanding which values are driving the deployment of AI in the public sector will give a noteworthy preview of the impact that can be expected from AI in general (Viscusi, Rusu and Florin, 2020), and in specific domains, such as in the case of social services and care (Misuraca and Viscusi, 2020), a domain that will likely hold a great potential for AI implementation and the possibility to enhance social values and citizens' well-being.

Public values in the use of AI

AI, similar to other types of public sector innovations are generally deemed to be "of value" because they are innovative, dynamic, change the previous status of service delivery, or are generally agreed upon as the next wave of technology use in government (see, for example, De Vries, Bekkers and Tummers, 2016). However, it is often unclear what kind of outcome new technologies have on the organization, their stakeholders or society at large.

Such a debate is like earlier discussions on the purpose and goal of e-Government initiatives, as a similar debate was held on what the main values, purposes and visions were found in such e-Government initiatives (Bannister and Connolly, 2014; Rose *et al.*, 2015). Such values are commonly associated to certain assumptions on how technology will improve the functions of government, strongly linked to the technological frames of technology, and e-Government more closely (Criado and O.de Zarate-Alcarazo, 2022). Such technological frames can provide powerful cognitive structures on the expected applications as well as consequences of their deployment, as seeing technology primarily as a tool for automation will change both the perceptions, scopes, and objectives of the e-Government initiatives.

How AI initiatives in government are thus perceived as well, and which objectives and values they attempt to achieve, further brings insights into how AI may be seen as a tool to improve the quality of government and increase public value. We therefore set out to better understand what public value might be created - or potentially destroyed - by the use of technology that replaces human interaction in public service provision processes, as it allows to better understand the underlying purposes and motivations beyond individual project goals (Rose *et al.*, 2015). In fact, first explorations on the expected benefits of AI of CIOs show that efficiency benefits are the highest perceived one, whereas citizen participation and trust were the least (Criado and O.de Zarate-Alcarazo, 2022) – which may possibly reflect in the way AI is planned to be deployed in their administrations and which public value they aim to achieve.

Public value is generally defined as the additional value that public managers provide through their actions to society – and is seen as equivalent to shareholder value held on a company's assets (see, Moore, 1995). While the research on e-Government, as well as practitioners, have aimed to follow the experiences and practices of ICT in the private sector to the public sector, directly copying the practices may not be as desirable as expected as public organisations ought to create public value – which goes beyond merely the market-related objectives that the private sector ultimately values (Pang, Lee and DeLone, 2014; MacLean and Titah, 2021).

Based on Moore's initial definition, scholars have created theoretical frameworks of public value(s), that include long lists of potentially distinguishable 'value-dimensions' in large public value inventories (see, for example, Bozeman, 2007; Jørgensen and Bozeman, 2007). Most of these values have not been empirically tested yet – given the rather implicit nature of most of them (see, for example, (Panagiotopoulos, Klievink and Cordella, 2019). However, for public value creation to occur, public administration will have implement these AI technologies, change their operations and strategy of public services to consequently improve citizen satisfaction (van Noordt and Misuraca, 2020; Chatterjee, Khorana and Kizgin, 2021).

The public administration literature distinguishes between public value and public values (Bryson, Crosby and Bloomberg, 2014; Nabatchi, 2018). Public value itself is defined as the as the beneficial outcomes through the strategic activities of public administrations. These can be numerous and more specific, which are particularly useful to analyse the success and objectives of specific AI initiatives and goals (Jørgensen and Bozeman, 2007; Rose *et al.*, 2015; Twizeyimana and Andersson, 2019). The deployment of AI, or any ICT for that matter, will have implications for public values, such as on transparency, equality, integrity, and human connectivity, amongst many others. Such (theoretical) effects have been discussed in previous literature on the implications of information systems and e-Government (Bannister and Connolly, 2014), similar to the discussions held now on how AI technologies positively or negatively impact certain public values held now (Zuiderwijk, Chen and Salem, 2021). For instance, there is the expectation that AI will have a positive impact on efficiency but a negative impact on the equity of government operations (Gaozhao, Wright and Gainey, 2023).

Public values, on the other hand, then are used as a label for the normative principles, that underly these activities and help "*to guide and justify the behavior of individuals, governments and societies.*" (Nabatchi 2018, p. 61). These values are seen as more broadly in nature and transcend specific actions and their outputs. In a way, they act as value drivers which underpin e-Government initiatives in general (Misuraca and Viscusi, 2015), linking to broader ideal public values driving such as the core values of public management of *sigma*, *theta* and *lambda*-type values (Hood, 1991), as the main 'input' for the activity (Chantillon, Crompvoets and Peristeras, 2020).

In order to understand what the values are that AI use in public administrations might follow, we follow the four value positions as identified by (Rose *et al.*, 2015), which integrated the main value traditions in public administration literature with assumptions of the benefits of technology in government.

Professionalism value ideal

The professionalism value originates from the traditional bureaucratic values as coined by Weber. These imply that decisions are based on law and policy, that decision-makers base their decision on good information. The key values of this ideal type are that governments act durable by ensuring a robust, resilient, and competent public service supported by an accurate public record, a focus on equity by ensuring honest, fair and impartial civil servants, legality and accountability so that decisions follow the chain of command and are properly documented (Rose *et al.*, 2015). These values are important to ensure that government remains "*fair and* *honest*" and "*robust and resilient*" (Hood, 1991). Technology could for support such values by that allowing a better identification of citizens, improving data security, ensuring more accountability and governance by better recording governmental actions and to support standardised administrative procedures. AI technologies could, despite the remarks that bureaucracy could disappear due to technological change, reinforce these bureaucratic values rather than replace it by making more rules and procedures formalized (Newman, Mintrom and O'Neill, 2022). Limiting, or even replacing, potentially biased civil servants using their discretionary decision making by technology could be a main driver to introduce AI technology in the administration, as consequently improving equity and procedural fairness.

At the same time, the inscrutability of AI systems and its unclear role in workflows may lead to less formalization within bureaucracies as civil servants find their work content altered in unforeseen ways (Sarah N Giest and Klievink, 2022). Furthermore, there is the often pointed out risk that despite the attempts to improve fairness, equity and objective decision-making, the use of AI may increase inequalities due to biases in historical datasets or the disproportioned targeting of certain demographics with AI (Schiff, Schiff and Pierson, 2021).

Efficiency ideal

Through New Public Management, traditional bureaucratic values were challenged by focusing more on introducing private sector values and market mechanisms within the public sector. Economic value focuses on the indicators that show how efficient and effectively public administrations deliver public services (Alford and O'Flynn, 2009) and whether they have achieved these goals. Typical goals as part of the efficiency ideal are to have adequate value for money, achieving cost reductions, enhancing productivity and performance. Efficiency values have been at the forefront of the e-Government narrative and initiatives as the main purpose of IT is often to improve the effectiveness and efficiency of the state (Cordella and Bonina, 2012). The same narrative is often highlighted in the case of AI applications, such as in strategic documents where the economic value of AI often strongly highlighted (Wilson, 2022). This is unsurprising since the main benefits of AI being able to automate or speed up tasks, a technological frame often connected with efficiency ideals (Medaglia, Gil-Garcia and Pardo, 2021). Indeed, within the debate, the main benefit of AI often focuses on the reduction of personnel through automation of tasks or decision making with the use of technology (Schiff, Schiff and Pierson, 2021).

Service ideal

As such, the too strong focus on the economic values, sometimes undermining the rule of law and decreasing accountability of government, risks limiting crucial bureaucratic values at the cost of economic interests – sometimes without empirical evidence that such privatised ways of working are in fact better (Rose *et al.*, 2015). Therefore, government officials should aim to search and implement public value; an ill-defined yet crucial objective ensuring that civil servants do not merely follow the decisions of policy or pursue the most efficient options. Instead, they should aim for commitment to the public interest, respect individual citizens and ensure that their expectations are met or consensus made (Bannister and Connolly, 2014; Rose *et al.*, 2015). Value for citizens is thus generated when citizens have access to a service, they have the right to, and access is not denied due to high expectations of administrative literacy or unreasonable administrative burden (Bryson, Crosby and Bloomberg, 2014). The role of technology in government has been further included to improve the availability, accessibility, and usability of their services to citizens compared to traditional, offline, public service delivery. Artificial Intelligence may further tap into the increased possibility to improve the quality of services, and in particular the information provision, as it could provide more accurate and relevant information for citizens (Kuziemski and Misuraca, 2020) through for instance Chatbots (van Noordt and Misuraca, 2019a; Aoki, 2020).

Through automatic translation or rewriting bureaucratic sentences, interpreting sign language or other, AI could be used to make the service and information more accessible for those facing difficulties with traditional or previous digital public service delivery. At the same time, however, is that the use of AI limits possibilities for achieving citizen value, as rather the individuals but their data points will determine how services are delivered (Peeters and Widlak, 2018), limiting human responsiveness and reactivity. Furthermore, despite the possibility to have AI make public services more citizen-centric, it is often the case that citizens are excluded from the design and development choices or only play a marginal role in the testing of the system.

Engagement ideal

Building on top of the earlier emphasis on ensuring collaboration with citizens, the engagement ideal takes it further and highlights that serving the public is through co-production and citizen empowerment. In this perspective, government should run like a democracy rather than a business (Rose *et al.*, 2015), and thus actions that support transparency, inclusive participation, democratic engagement, deliberation, and citizen rights support the engagement ideal (Bozeman, 2007, 2019). Many e-participation and e-democracy initiatives that strengthen citizen involvement in policy could be regarded as having the engagement ideal as their driver.

However, despite the potential public value creation through AI, it is important to highlight the difference between the expected, potential effects of technology (and thus the intended public value) and the actual effects and realization of public value. In fact, all too often, only the potential benefits of technology are considered and it is assumed they will (always) materialize, but it has been well established that technology used in government does not necessarily lead to any value, but the transformation enabled by the technology does (Nograšek and Vintar, 2014; Tangi *et al.*, 2020), with expected and unexpected effects only materializing over time, affecting different groups in varying ways, which depends on an interaction of various factors (MacLean and Titah, 2021). As many of the AI projects are still in an emerging stage, it is, without closer examination, too challenging to assess the realized public value, but it is possible to assess the expected and potential public value as this is more readily available.

When public values are not realized, or certain public values over or underrepresented in AI, it may lead to a failure in public value creation later on when efficiency-related values at the cost of the other main values, such as bureaucratic values ensuring fairness of government practices (Schiff, Schiff and Pierson, 2021). Conflicts may indeed emerge when multiple public values are desirable but cannot be fulfilled at the same time (Chantillon, Crompvoets and Peristeras, 2020) which is likely to occur within design considerations and objectives of AI initiatives within the public sector. Potential trade-offs within the design of AI in government could be aiming to maximize (algorithmic) efficiency and effectiveness by utilising more deep learning models at the cost of opacity and accountability (de Bruijn, Warnier and Janssen, 2021) or designing and introducing AI to augment existing workers rather than replace or overrule them (Kuziemski and Misuraca, 2020; Sarah N. Giest and Klievink, 2022). As such, understanding which public values are the main drivers of current AI initiatives within public administrations in Europe could provide a telling insight in which are the main motivations public administrations aim to introduce AI and also where possible tensions may arrive. For instance, if many AI initiatives within government are introduce with efficiency-related goals in mind, it may come at the cost of other values or may simply be wasteful endeavours (Meijer and Thaens, 2020).

Research design

In the following, we describe the overall research design including the steps of the data collection, the analytical steps and also highlight potential limitations of the chosen approach and how the research team aimed to mitigate them.

Data collection

This paper follows a mixed-method research design, consisting of a secondary data analysis of AI use cases gathered as part of the AI Watch research activities on the public sector collected by the Joint-Research Centre between 2019 and 2022. This inventory of AI use cases (N = 686) is the result of a research activity to gather and analyse adoption and implementations of Artificial Intelligence currently in use by various public administrations across the European Union, first started in (Misuraca and van Noordt, 2020) and later continued in (Tangi *et al.*, 2022). This inventory is the result of a variety of data collection efforts to fill the gap of missing structured information of AI use in the public sector.

Firstly, desktop research was used through internet search of news articles on AI use in the public sector, as well as policy documents, practitioner-generated reports describing use cases, such as those on the European AI Alliance platform of the European Commission. Several governmental innovation websites or dedicated AI registers were also included in this desktop search to identify as many use cases as possible. Secondly, additional cases were gathered was assembled based on submissions from EU country representatives who added their national cases to the resulting AI Watch database, either via email and/or shared during the 4 workshops organized by the AI Watch research group (van Noordt and Pignatelli, 2020; van Noordt *et al.*, 2020, 2021; Manzoni, Medaglia and Tangi, 2021). Thirdly, a survey was held as part of the AI Watch research to gain more information on barriers for AI adoption which also allowed for the gathering of some additional use cases which were consequently added in the inventory as well (Medaglia and Tangi, 2022).

Each of the cases went through a procedure to ensure the validation of the use cases so that all the information was double-checked and information of earlier gathered use cases confirmed later within the process to ensure the information was most up to date. Consequently, this inventory is a great starting point to assess currently known use of AI in the public sector and the public value aim to achieve. However, the inventory suffers from several limitations, due to the targeted and therefore potentially biased nature of the data collection in form of self-reports from the EU member states, making it very likely that many initiatives are not included in the inventory, especially those implemented at local/municipal level and more difficult to be identified by the research team. Other limitations might include language barriers of the research team, so that the assessment of each country's policy documents might be limited in its depth and breadth. The research team however made their best effort using deepl.com to translate as many relevant sections of websites and cases as possible.

It is also noteworthy that different initiatives are included or not included due to the wide-varying understandings of the term AI: not every administration refers to AI in the same way, but might have described other types of technologies, while those might not have fit the categories of the inventory were not included (van Noordt, 2022). Challenges also emerged in gathering reliable information with regards to the maturity and local actors involved in the implementation of AI. It is possible that not a public administration, but in fact a private vendor was tasked with developing or using the AI solution within a public service, without clear understanding if public administrations in fact, do. Lastly, it may very well be that initiatives in the inventory are already discontinued due to various reasons. For the scope of this paper, the research team decided to include the case if it had a clear public service delivery connection and thus excluded initiatives with no public service component or use, for instance when there the case was used in hospital services or in schools, not considered public administrations. This resulted in the removal of 137 cases, leaving 549 for the analysis.

Overall, the inventory includes all 27 EU countries, as well as the United Kingdom, Norway, Switzerland and Ukraine, as all countries have either submitted their current AI use case descriptions to the database or the use cases were identified through desk research. However, the inventory is not evenly distributed across the different countries, as there are more use cases of AI from the Netherlands (114), Estonia (47), Italy (43) Portugal (40), Germany (35), Belgium (34) France (32) and Finland (31), whereas in many other countries only less than 10, or even only 1, use cases could be identified. As such, the inventory should not reflect the actual status of use of AI yet merely reflect which use cases could be identified through the data collection methods. On average, of each country 18,3 use cases of AI are included in the inventory. An overview of the cases per country can be seen in the Figure below:

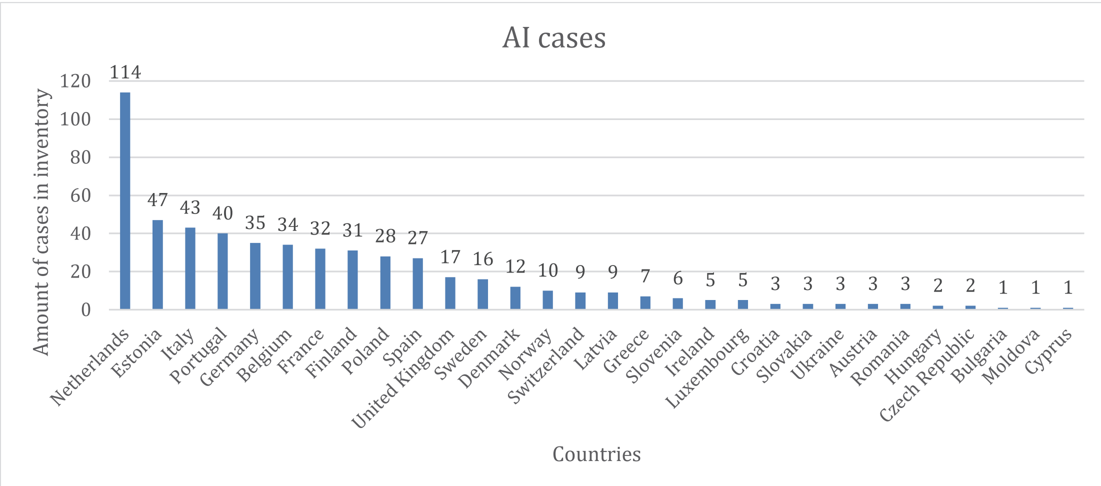

Figure 1 AI cases in inventory per country

Data analysis

Each individual case in the inventory was reviewed and assessed based on its title and submitted description to evaluate whether there is an (implicit or explicit) expectation that the AI case will add or is driven by either the professionalism, efficiency, service or engagement value, following the four types of main public values highlighted in the literature review (see Rose *et al.*, 2015). In this coding step, it became obvious that individual AI use cases be driven by one or more public values. Consequently, the analysis is not restricted to the most prevalent public value type. Each of the cases have been discussed among the authors and any differences in coding deliberated to ensure accuracy and reliability in the labelling (see, Burla *et al.*, 2008). An example of such a coding would be:

Name	Description	Value driver(s)
EE Parliament- A system for preparing of verbatim reports	The speech recognition system helps transcribe the speeches given at the rostrum of the Estonian Parliament (Riigikogu). The Chancellery of the Riigikogu is currently required to publish a verbatim report within one hour from the end of the sitting. It takes a lot of human effort to do that, and the burden falls on stenographers. By deploying speech recognition, it will increase the efficiency and accuracy in transcripts of the sessions. Also, the plan is to start providing verbatim recordings as machine-readable open data, so other systems can use that data freely as well.	Professionalism value Efficiency value Engagement value

In addition to the thematic coding described in the first step, in a second step the research team identified several illustrative cases to exemplify the resulting value categories. These cases were selected from the inventory to highlight the possible public value created by AI technologies, but also identify how these values may be challenged in practice.

Findings

In this section, we provide an overview of the main findings. These include an overview of the coded initiatives, starting with those driven by professionalism public values, then the efficiency-related public values, the service-related public values and lastly those driven by engagement-public values. In each of these sections AI use cases derived from the AI Watch inventory are described to compliment the coding. Following, a discussion is held on how some of the intended purposes of the AI systems may in fact not realise but compliment to public value destruction.

A fair portion (70 out of 549) of the cases analysed in the inventory supports the professionalism values. Many of the use cases for instance aim to strengthen the data quality of the public administration as to have more accurate records of citizens, businesses or other. Identifying and removing errors in business statements, such as used in the Danish Business Authority.

Similarly, the Swiss Federal Office for Statistics uses machine learning algorithms to improve their data quality by returning wrong or likely incorrect data to the data providers. AI may also be deployed to make public service delivery more the fair than traditional services, as in Belgium a system has been deployed to decide the registration of children in a school system. This system is based on several factors which is seem as fairer than registering children in-person as it has led to parents sleeping in tents outside of schools to secure a spot. Similarly, several AI initiatives are being introduced as to ensure whether existing rules are being reinforced, such as the use of satellite imagery to check farmers compliance to subsidy requirements as in Walloon and Estonia or the use of computer recognition to standardize the vaccination registration process in the Flemish Child and Family agency. Other use cases aim to facilitate the professionalisation of the civil service staff, such as the deployment of a chatbot called RenoiRH within the French Interministerial Center for IT Services as to provide information regarding the mobility and career development of their staff members. Lastly, there are several use cases aiming at strengthening the resilience of public administrations, in particular the cybersecurity, such as the sensor technology to detect cyber attacks in the Norwegian National Security Authority.

The driving public values identified among the cases focuses predominantly on achieving efficiency values, supporting the effectiveness or cost-effectiveness of the administration, the services or the policy. In fact, of the overall 549 cases, in 431 AI applications some form of efficiency-driven values could be identified. This shows the prevalence of the expected efficiency gains provided by AI in many of the identified and described AI use cases in the inventory and is in line with the previous dominant perspective of ensuring efficiency gains in public administration through digital technologies. This shows that public administrations are attempting using AI to create economic value to reduce costs, for example by replacing human workers by automating tasks with various AI technologies. An example of having AI take over mundane and redundant tasks of civil servants is the deployment of the Chatbot UNA in Latvia, which is now used to answer many frequently asked questions with regards to the process of registering a business. Now, public servants have freed up time to answer more specific requests which are considered more value-adding and thus reorganizing how the work gets organized internally (van Noordt and Misuraca, 2019b). Others for instance suggest the automatic processing of citizen applications, such as the case in the municipality of Trelleborg in Sweden

(Ranerup and Henriksen, 2019). Several cases further highlight making the existing policy options more effective as more data could be utilised, or the risk of fraud strongly limited, limiting the misallocation of public resources.

In 132 of the use cases references to service public values were identified. In many of these use cases, service value is expected when administrative processes will be simplified for citizens, reducing their waiting time or difficulties in filling in forms. This aim to ensure the utility of government for citizens through qualitative and accessible public service aligns well with the role of technology as a service enabler for governmental organisations, continuing the legacy of e-Government to create public value through the provision of services to citizens (Bannister and Connolly, 2014; Rose *et al.*, 2015). In this respect chatbots or other forms of virtual assistants are seen as the main form of AI technology to improve accessibility of public information or understandability of various administrative processes. Examples include the Voicebot used in the Irish Revenue Commission to provide a more efficient and effective service to citizens using their telephone services or Taxana used in the Slovakian Financial Administration to facilitate communication with citizens.

Despite the emphasis to improve the service quality to citizens, it is to be noted that very often the AI is also introduced to not only make the service more accessible or easier for citizens, AI also aims to reduce the administrative burden for the administration itself as it lessens the workload of the staff members. Whereas in some cases the Chatbots seem to be introduced as a pure quality improvement, in several cases the main goal of the AI systems is to either automate or lessen the workload of civil servants, highlighting the strong prevalence of the efficiency values even in AI systems aiming to improve the service quality to citizens. Other use cases aiming to achieve service-related public values are diverse in scope and include many forms of making existing public services more accessible, in particular to citizens with disabilities, by enabling automatic subtitles on public and internal videos of the Finnish Tax Administration, allowing an AI-based interpreting service for deaf communicating with the Flemish Agency for Persons with Disabilities, automatic translation services such as on the Official Gazette of Estonia to English to support foreign businesses or provides advice to businesses such as an AI system that provides advice on the chances of success for a craftsman based on a given location used in France.

The use of Artificial Intelligence in public administrations to better connect with citizens through enhanced deliberation, participation, and other goals more linked with citizen participation are very rarely mentioned at all. Only in a minor number of cases, AI was connected with the engagement public values, namely only 19 out of the 549 cases. One such example is the AI system *The Dublin Beat* that analyses citizen opinions in the Dublin region to provide an overview of their most pressing concerns. The tool is based on a combination of both natural language processing and machine learning to categorize the unstructured tweets of citizens, providing an overview of key issues such as how people feel about environmental issues, cultural events or city region developments expressed on the online media (Kirchner, 2020).

Another example of an AI use case which aims to support democracy is the speech recognition system in place in the Estonian Parliament, capable of transcribing the parliamentary sessions taking place in the parliament called HANS (Plantera, 2019). This AI system has been put in use as an effort to make the work of the stenographers more effective as it significantly speeds up the transcription work previously done by the four stenographers (Plantera, 2019). Next to the expected economic gains, the project has been linked strongly with enhancing the transparency of the democratic system of Estonia. The transcriptions made by HANS are planned to be released in machine-readable open data format, so that they are suitable for additional data analysis or for use in other information systems (Plantera, 2019). Next to the parliament, there are expectations that the same solution might be used in other public sector organizations as well, increasing the efficiency of transcription processes and allowing higher degrees of transparency (Pau, 2020).

In summary, the following graphic provides an overview of finding 2 – the driving public values in the AI use cases.

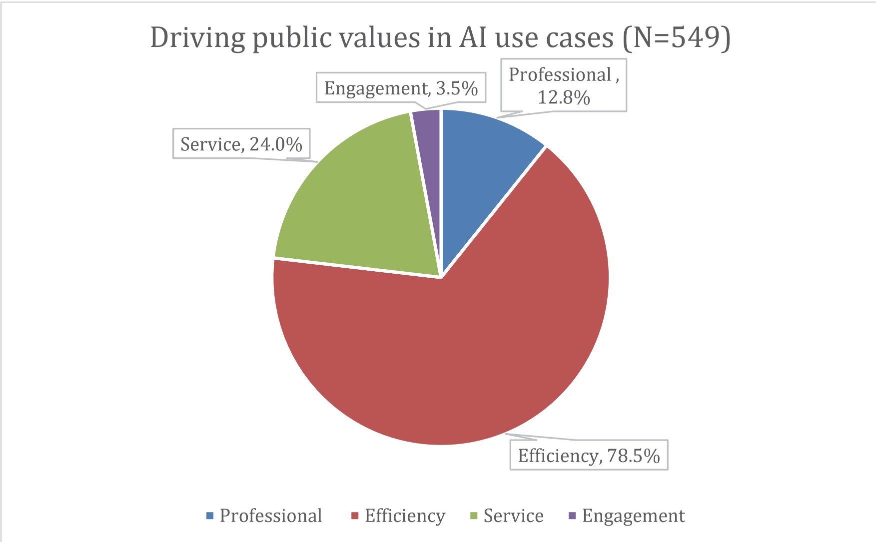

Figure 2: Driving public values in AI use cases

Risks of public value destruction through AI

Despite the positive public value drivers underpinning the various AI use cases in the public sector, there are several key considerations to be held that emerge from either tension between the different objectives the AI initiatives aims to achieve or due to the potential risks that deploying AI-based public sector innovation holds (Mikalef *et al.*, 2022). Whereas this overview does not hold all the potential tensions and trade-offs which may occur during the development and deployment of AI (Madan and Ashok, 2022), several considerations did stand out.

The first risk comes from the prevalence of many of the AI initiatives to support efficiency-related goals. As previous work on e-Government showed is that efficiency values dominate not only the expected gains of digitalisation of the public sector, when in conflict or tension with other important public values, public managers tend to value the efficiency-related values more strongly than others. With the use of AI however, a too strong emphasis on reducing costs or being more efficient could lead to illegal practices of data gathering, the lack of responsiveness towards citizens and not ensuring the AI systems work as they are supposed to (Rinta-Kahila *et al.*, 2021). Other risks of focusing too strongly as seeing AI technologies as a quick win for limiting costs through automation means that a wider picture of digital transformation through multiple stakeholders may get lost or additional costs needed to make the AI system run completely overlooked (Maragno *et al.*, 2022). It may also be the case that many AI-innovations will not see themselves adopted within the public administration if they do not have a strong efficiency-related focus. Some uses cases in the inventory are aware of these risks, such as the AI system in use in the city of Amsterdam, the Netherlands, tasked with tracking down people illegally renting out their homes via platforms, such as Airbnb (Volkskrant, 2020). However, there are risks to public value destruction, of which the city is already aware of (Amsterdam, 2020). Therefore, personal data such as birth, nationality and others are not included in the algorithm, aiming to limit prejudice of the algorithm to a certain demographic or increasing privacy concerns (Meijer, 2020).

In fact, these challenges may occur especially in the cases that aim to support both the professionalism and efficiency public values, namely 38 (out of the 70). These cases often revolve around fraud prevention due to the automatic verification, checks and analysis of data and documentation, aiming to both make the record-keeping of the administration more correct while at the same time making the fraud prevention processes more efficient and effective as well as minimizing the risk of misallocation of public funds. However, it remains controversial to assume that striving to achieve both these values may be done so successfully as some discontinued use cases already highlight (Sarah N Giest and Klievink, 2022; Simonofski *et al.*, 2022).

Secondly, there may be an overexcitement for the deployment of AI tools to support the quality and accessibility of public services. Whereas Chatbots and other AI-tools may indeed support the information provision to citizens, it may be an open question to which extent citizens may want to talk to a Chatbot rather than a person and in which scenarios (Aoki, 2020). This is particularly true when the introduction of new AI-enabled technologies also aims to relieve or automate tasks of staff members. Performance of Chatbots may also vary greatly (Wang, Zhang and Zhao, 2020) depending on the in-house resources of the organisation. Furthermore, there are questions to be raised to which extent new technological innovations may immediately resolve difficulties in citizen unwillingness to use e-services such as the lack of trust in government (de Walle *et al.*, 2018).

Thirdly, despite the potential and interest to use smart technologies in such ways to facilitate inclusion and participation of citizens in public-sector decision making processes (Criado and Gil-Garcia, 2019), the analysis of the AI use cases suggest that the role of AI deployed by public administrations does not necessarily aim to improve engagement and citizen participation. While the intent of the AI system may be to make public administrations more responsive and accepting of citizen needs, it is, in the end, not the citizens who are meaningful participating in policy processes, but merely their online data is passively used without additional explanations and often without their knowledge and consent (Cardullo and Kitchin, 2019).

Lastly, in some cases, public values are not explicitly mentioned and the underlying goal of the initiative risks to be self-referential, with the data analysis or the development of the system being the aim, with the expectation that 'something' will come out of it and provide patterns and indications for further research or policy action, doing innovation for the sake of innovation (Meijer and Thaens, 2020). In that respect, several of the AI use cases aimed to create some form of dashboards where AI-based analysis could be conducted with or where the results of such analysis could be found. It is, however, often unclear how the creation of these dashboards link with the actual organisational workflows, how it is supposed to change the work of the organisation, or towards which aims the dashboard is supposed to be supportive. This highlight a disconnect between the effective adoption and implementation and the real public service transformation that could be generated from the insights emerging from the use of AI systems.

This risk is reinforced when the development of the AI systems is completely outsourced by private organisations, and it is not aways clear what the contribution of public organisations is, or whether they play an active role in the public value creation when the system is put in active used. There is a risk that public administrations only act as a funding or sparring partner, rather than actively involved in using these developed systems themself. While there is public value to be created during co-creation and co-design (Crosby, 't Hart and Torfing, 2017; Rösler *et al.*, 2021), leaving non-governmental organisations the main actors for the development and the implementation of the AI systems may lead to further accountability issues or the privatisation of public services later. For instance, several cases in the inventory focus on energy services, waste management and the water supply. Whilst considered public services or supervised by ministries of their countries, these often are in fact already private services due to historical outsourcing.

Concluding remarks:

The analysis of the findings shows a high heterogeneity of AI use across Member States in the EU and a still unclear understanding of the public value that is effectively created. In particular, despite the strong potential of AI to transform public services and make them more citizen-oriented (Dwivedi *et al.*, 2019; Veale and Brass, 2019), public administrations are predominantly applying AI technology to produce economic value. However, while AI systems may contribute to the improvement of higher-level public values, such as inclusiveness in terms of enhancing outreach and improving user satisfaction, they rarely involve citizens directly in their design or implementation.

Nevertheless, it seems that there is a gap between the transformative potential to generate public value that AI technologies promise and the observable adoption and use of AI. This has implications for the value-orientation of the initiatives under investigation, which are to a great extent focusing their attention on increasing performance (efficiency and effectiveness) by generating economic and administrative value, as seen in our analysis. The evidence shows instead a less prevalent – direct - focus on the citizen and societal values, that when present are driven by a greater emphasis on other dimensions and value drivers, such as openness and transparency, trust and legitimacy and also inclusiveness and diversity. This calls for further research through in-depth case studies to explore more in detail these dimensions of analysis as well as a further empirical application of the framework suggested. A specific attention should also be given to AI initiatives implemented at the local and municipal levels, also considering the diverse values that are associated to different sectoral policy domains.

Future research should therefore further elaborate on the framework and may infer theoretical implications from the findings gathered. For this purpose, with our paper we developed a baseline for the use of AI in public services which might serve as a future research framework or even as the basis for future benchmarking. However, a robust methodology to assess social and economic impacts of AI in public services is still strongly required, and in our opinion, it should build on a public value perspective that can benefit of the analysis provided in this paper to categorize potential benefits, while also considering risks and possible negative side-effects that could lead to value destruction if not well assessed and/or anticipated.

The results of our analysis provide thus an important contribution to advance knowledge in the field of AI-enabled innovation in the public sector, that we consider as a form of ICT-enabled innovation to be addressed from a multidisciplinary perspective. In particular, the categories of analysis proposed and the underlying framework for public value assessment suggested, are suitable to provide the basis for additional comparative analysis. The current findings provide insights for future evaluations of the functional use of AI in public services stemming from the insights resulting from the exploratory approach we have taken. In this respect, our findings confirm the growing interest on the use of AI in the public sector to redesign internal processes, enhance policy-making mechanisms and improve public services delivery – even though this is clearly still an emerging practice among public sector organizations. In line with the search for 'best practices'' which is started at both academic and policy levels, it becomes clear from our analysis that there is a strong need to learn from in depth case studies and to identify the key dimensions and barriers to be overcome, transfer and potentially replicate success stories across the public sector. This includes not only the potential for 'scale-up', but also the 'scale deep' and the 'scale-out' of initiatives, beyond the 'ever-piloting' paradox that is instead often limiting adoption of AI, and ICT-enabled innovation in general.

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Publication X

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Towards a Systematic Understanding on the Challenges of Public Procurement of Artificial Intelligence in the Public Sector

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Abstract

There is increased interest amongst governments and public sector organizations about how to best integrate artificial intelligence into their day-to-day business processes. Yet, a large majority of technical know-how is concentrated outside of the governmental sector, many governmental organizations are likely to rely on public procurement for their AI systems. Thus, there is a clear need for new insight into the process of AI procurement, challenges that may be encountered, and guidelines on how to potentially overcome such challenges. This chapter aims to make an initial contribution of such insight. Methodologically, this chapter presents a multiple case study of four European countries (Estonia, Netherlands, Serbia, and the United Kingdom) who have drafted guidelines and recommendations for how to procure AI in the public sector. As a result of this research, it is possible to provide an overview of challenges that may be encountered during the procurement of AI in the public sector and potential solutions for the public sector overcome such challenges.

Keywords: Artificial Intelligence, Public Sector, Procurement, Digital Government, Challenges

1. Introduction

Artificial Intelligence (AI), can be understood as ”systems designed by humans that, given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data and deciding the best action(s) to take (according to pre-defined parameters) to achieve the given goal.” (HLEG, 2019). AI is studied and applied across sectors, contexts, and domains; it has become ingrained within our societies with its influence likely only to grow as AI technologies improve. The public sector is no exception. In the public sector, it is hoped that the usage of AI can increase governmental effectiveness and efficiency, enable new forms of public services and mechanisms for delivery, assist evidence-based policy making, and play a role in the ’transformation’ of the public sector (Berryhill et al., 2019). This is especially true in Europe, where large amounts of effort have been devoted to understanding how AI can be used in the delivery of public services Misuraca, Van Noordt, et al., 2020; van Noordt and Misuraca, 2022 and where one of the most ambitious regulatory approaches to AI is currently being developed Dempsey et al., 2022. Aiming to understand the impact that AI may have in or on the public sector, scholars of digital government and public administration have devoted a large amount of attention to the issue´. However, one area of research that remains under explored is the public sector procurement of AI. This is unfortunate as procurement will likely remain a key method for public sector organizations to develop and implement AI technologies as governments aim to access the AI capacity held within private sector companies. However, procurement is hard, especially when it comes to procuring AI systems. It is for this reason that a report from the House of Lords Select Committee on Artificial Intelligence noted that:

‘*Most of GovTech is about procurement. . . getting procurement rules right is one of the most important parts of driving improvements in technology. . . [and] that [procurement] is a huge part of driving digital as a whole, including the take-up of AI*`(House of Lords, 2018). This raises a clear question of how can governments ”get it right” when procuring AI? One potential way would be through the adoption of well developed, targeted, and responsible public procurement methods, strategies, and guidelines. While many governments do have large amounts of experience with procurement, including the procurement of digital technologies, procuring AI appears to present new and unique challenges. This represents a clear gap in our knowledge. On the one hand, procuring AI is becoming increasingly important. On the other, there is still limited research on what guidelines and strategies could look like and how they could be enacted to improve the AI procurement process.

This chapter aims to address this gap. It does so by, firstly, exploring what challenges may be encountered during the procurement of AI in the public sector and, secondly, by identifying potential guidelines or strategies that may help to overcome such challenges. The research is guided primarily by the following two research questions:

- What are the key challenges associated with the public procurement of AI?
- What are the commonly occurring strategies, recommendations, and guidelines to overcome such challenges?

To answer these questions, the study is empirically structured as a qualitative, descriptive, exploratory, and comparative multi-case study was conducted. The four countries selected for this study were Estonia, Netherlands, Serbia, and the United Kingdom. These four countries represented the four countries with clearly developed and conceptualized guidelines to better procure AI as well as for overcoming challenges that public sector organizations may encounter during the procurement of AI.

As a result of this research three core contributions are made. First, the chapter helps to conceptualize the concept of procurement of AI in the public sector. Second, the chapter identifies commonly occurring challenges during the process of procuring AI in the public sector. Third, the chapter presents solutions and approaches that have been proposed by public sector organizations for overcoming or preventing these challenges. Taken in totality, these contributions develop a strong foundation for future research on AI in the public sector, particularly research utilizing a lens based on procurement or challenges.

To reach these contributions, this chapter proceeds by offering a short conceptual overview on public sector procurement, the use of AI in the public sector, andthe challenges of procuring AI in the public sector. Following this, the methodology is presented together with the empirical evidence sources used and the mechanism of data analysis. This is followed by a short overview of each of the selected case countries, the results of the analysis, and a discussion of the findings. The chapter concludes by elucidating on the answers to the research questions, offering future directions for research, and offering initial policy and managerial insights and recommendations.

2. Background Literature

Public Sector Procurement

It can be said that there are at least three primary phases of procurement: feasibility assessment, implementation and organization of procurement, and monitoring and evaluation of performance (Brown and Potoski, 2003). Within this tri-phasic procurement process, previous research has identified a number of factors that seem to play a role with why a procurement may fail or succeed.

One of the most relevant factors is that of contract-management capacity (Brown and Potoski, 2003); the likelihood that a procurement is successful is highly dependent on how well the organization is able to manage the process. Second, the identification and formulation of necessary and relevant technical requirements before a procurement takes place (Edler et al., 2006; Georghiou et al., 2014). Third, market knowledge, it must be understood what the current market is actually able to produce; the creation of unrealistic requirements, or an over/underestimation of the current market will lead to potential failure (Edler et al., 2006; Mulligan and Bamberger, 2019). Fourth, (Edquist et al., 2000) highlights additional factors that influence the chance a procurement is successful: timing, technical competence inside the procuring organization, and broader organizational competencies. Finally, the organization must have a high degree of technical knowledge, or, if they do not have this capacity inside their own organization, must be able to coordinate the attainment of this knowledge (Edler et al., 2006; Edquist et al., 2000).

In the context of AI, this implies that governments must:

- have the ability to successfully manage AI procurement contracts,
- have the relevant technological knowledge and in-house capacities,
- be aware of the current market abilities and relevant state-of-the-art, and
- have an in-depth understanding of their own IT infrastructure, data, and capabilities.

However, as AI expertise in the public sector is scarce (Wirtz et al., 2019), administrations often have to collaborate to get AI capabilities (van Noordt and Misuraca, 2020), and data governance regimes may be lacking (Janssen et al., 2020), public procurement of AI will likely prove challenging for public sector organizations, especially without additional guidance.

Artificial Intelligence in the Public Sector

Inside the public sector, AI is applied in a wide variety of ways. For example, researchers have explored AI use cases such as: chatbots or virtual assistants (Aoki, 2020; van Noordt and Misuraca, 2019), natural language processing (Agarwal, 2018), food safety (McBride et al., 2019), or automated decision making (Wihlborg et al., 2016). This is not a complete nor comprehensive list, but it does demonstrate that there are a number of different ways that AI is currently being used in the public sector. It is also likely the case that, as AI technology develops, the number of use cases and its influence in, on, and for governments will only grow. What is clear, however, is that at least currently AI applications rarely replace governments, but rather augment and improve processes, for example by improving internal efficiency, improving decision making, or improving interactions between governments and citizens.

While research on AI often focuses on ”AI” broadly, data, or algorithms, infrastructure is also a core component for AI. In the above use cases, each one may, individually, be considered ”AI”, but each also will utilize different models or algorithms and require different data and infrastructure. As a quick example, A chatbot or NLP service may require large amounts of conversational data to train itself, whereas a computer vision-based service requires large amounts of visual training data. This data is held in different formats, and stored, gathered, and utilized using different technologies. Thus, as the use of AI increases inside the public sector, so too does the amount of infrastructure and technical capacity needed to effectively utilize AI. Due to this mashup of systems, algorithms, services, and infrastructure governments that heavily procure AI run the risk of creating an unmanageable hodgepodge of infrastructure and data.

Challenges of AI Procurement

The purpose of this section is to deal explicitly with the procurement of AI in the public sector, outline the potential challenges, discuss what makes the procurement of AI unique, and highlight some potential AI procurement best practices that have begun to emerge in the scholarly body of knowledge. This literature is limited to a handful of studies and scholars and is almost entirely based within legal studies; it has not yet widely expanded into the public administration, public management, or broader digital government areas of research.

One of the first challenges that appears during the public procurement of AI is that of data and the legal challenges that may arise as a result of using data in a machine learning service (Janssen et al., 2020). All machine learning algorithms require data to function, the question is, where does this data come from? In case the government is providing the data, they must ensure it is clear where the data can be held. Is it on their own servers, in a cloud, with the provider? The answer to this will depend based on the relevant regulations and legal requirements the procuring organization is subject to. It is also important to understand how a citizen’s data could be removed from the relevant dataset should they request their data be forgotten. If data used in the algorithm is, for example, textual in nature, e.g. emails or chats sent to the government, how is it ensured that any personal information is removed from this data (Harrison and Luna-Reyes, 2020).

A second challenge, also related to data, is that of data ownership and data sovereignty. If data is collected by a government, but then is used by a private sector company to train an algorithm, can the company sell this trained algorithm to other countries, or can the procuring organization retain complete ownership over the data? This issue works in the reverse as well, in the case that data is coming from the private sector organization (Campion et al., 2020).

The potential for bias and discrimination in AI is a third clear challenge. It is apparent that many machine learning algorithms and tools exhibit human bias and discrimination (Caliskan et al., 2017) and these biases can have real impact if left to their own devices in the public sector. These issues have already materialized when algorithms are used in the public sector for services such as criminal sentencing (Washington, 2018) or predictive policing (Benbouzid, 2019). Furthermore, there needs to be an understanding on who bears responsibility for any potential bias or discriminatory algorithmic decisions. Is it the AI itself? Is it the government? The private sector? Such issues must be covered in either legal regulations, or via the procurement process itself. Some initial initiatives to address these issues have already begun to emerge. For example, both the OECD and the EU have drafted and released guidelines to address ethical creation and use of AI, so too has the council of Europe drafted initial guidelines for procuring AI systems that respect human rights.

A fourth issue associated with public procurement of AI is that of trade secrecy and intellectual property rights, which can effect algorithmic transparency (Brauneis and Goodman, 2018; Mulligan and Bamberger, 2019). For example, a purchased AI solution may be used by different organizations, and, in this case, the provider of the service likely desires to protect their product, algorithm, and the data it uses. This could limit the government from providing this information to any concerned or effected stakeholders.

A fifth issue is that of transparency; one of the best ways to increase transparency appears to be through procurement and regulatory guidelines. As highlighted by Brauneis Goodman, 2018, transparency can be increased by placing importance on “contract language requiring provision and permitting of disclosure of records” therefore “placing the burden on the contractor to identify and mark specific passages in a document as trade secrets” and subsequently “[linking] disclosure provisions to demands that records be produced to the government” (p.164-165).

Finally, it is necessary that the procuring organization has a clear understanding about how the specific machine learning model works. In their study, Brauneis Goodman, (2018) sent records requests to forty-two agencies about six different algorithmic programs in twenty three states; only one respondent could provide information about the algorithm (Mulligan and Bamberger, 2019). To some extent, this is understandable. If a government organization is procuring AI they may not have the capability internally to understand the solution. However, it is also imperative that algorithms are developed in an ethical manner, and the only way to ensure this, is through the appropriate procurement measures.

3. Methodology

Methodologically, this chapter utilizes a descriptive and exploratory multi-case study (Yin, 2013) approach to explore the AI procurement guidelines in four European countries: Estonia, Netherlands, Serbia, and the United Kingdom. For case selection, this study focused on the European context and looked for countries that had made explicit steps

at developing, implementing, or trialling guidelines for the procurement of AI in public sector organizations. After this initial review, only the aforementioned four countries had clearly identifiable guidelines related to the procurement of AI in the public sector. Though four countries is not a large sample size, due to the relative newness of the procurement of AI in the public sector, this initial exploration of critical cases is relevant and useful.
Empirically, a number of evidence sources were used to ensure the triangulation of the findings and thereby improve the internal validity of the study. The primary documents analysed during the desk research were the official AI strategies for each country (this exists in three out of 4 countries, the United Kingdom does not have an official "AI Strategy", but rather a policy paper) and, in the case of Estonia and the United Kingdom, existing and relevant AI procurement guidelines. Other documents analysed included training seminars recorded and published to YouTube, magazine articles, newspaper articles, and governmental hearings or reports.

The desk research was followed by a total of nine-semi structured interviews (3 in Estonia, 1 in the Netherlands, 4 in Serbia, and 1 in the United Kingdom). The nine semi-structured interviews were conducted with the leaders and users of the relevant AI procurement initiatives; interviewees have been anonymized and given a code based on their interview number and the country's guidelines they were involved with. Interviewees were selected due to their direct role in developing their specific country's guidelines for the procurement of AI in the public sector. Though the number of interviewees is low, those interviewed were experts on not only the guidelines, but also the motivation and reasoning behind them.

All conducted interviews were done virtually by the researchers behind this chapter, lasted up to 45 minutes, were transcribed, and then coded and analysed using conventional content analysis (Birks and Mills, 2015; Hsieh and Shannon, 2005). The interview questions all aimed to address different aspects of the AI procurement process, such as: internal organizational capacity, the procurement process, existing guidelines or best practices, AI development strategies, and any encountered barriers to AI adoption. The interviews were conducted after the initial document and textual based desk research and served as a way to get insight about the behind-the-scenes processes associated with the development or ideation of AI procurement guidelines.

As with all research, there is the potential for limitations and weaknesses, thus it must be highlighted that this research offers only a preliminary view of the challenges faced during the public procurement of AI as many of the guidelines studied are still currently under development or in a testing phase. One respondent, NL.PS1, noted that in the Netherlands there were difficulties in assessing the usability of the created guidelines due to a lack of potential cases that they could be validated against. A second potential weakness is similarly related: there is a small bias in the analysed cases as they represent the most developed countries. How other administrations, with less experience, may address similar and/or other public procurement of AI challenges remains unknown; though there is likely to be significant overlap, it is not possible to make a strong statement to this effect, slightly limiting the external applicability of the research.

4. Case Overview

Estonia

Starting in 2016, Estonia began to develop a comprehensive strategic and regulatory approach to the adoption and implementation of AI in the public sector. These efforts were led and coordinated by the Estonian Ministry of Economic Affairs and Communication (MKM). In 2018, a task force was announced that was composed of AI experts, lawyers, and policy makers who were given the responsibility of developing an Estonia AI strategy. This strategy was finished and approved in 2019 and focused on four primary areas: advancing the uptake of AI in the public sector, advancing the uptake of AI in the private sector, developing AI RD and education, and developing a legal environment for the uptake of AI (Riigikantselei and MKM, 2019).

To help address a perceived general lack of knowledge and experience about best practices for AI procurement in the Estonian public sector, the chief data officer has created a number of different guidelines and tools for improving and aiding public sector officials with their procurements (EE.PS1, 2020; EE.PS2, 2020). These include: A questionnaire to decide if AI is the correct technology for a specific project; instruction materials with instructions, recommendations, and best practices for AI projects in the public sector; a reusable structure and template for AI procurements; an overview document for public servants about key terms and concepts in AI; data impact assessments; and a number of training presentations and videos about different AI projects (MKM, 2020; EE.PS1-3, 2020).

Netherlands

In the Netherlands, Amsterdam has developed AI procurement guidelines to assist with the responsible and democratic use and development of AI technologies within the city (NL.PS1, 2020) and these are being evaluated for use at all administrative levels across the country. The Association of Dutch Municipalities has also made the guidelines available for all municipalities to use. These guidelines consist of nine different articles that describe the various terms and conditions that AI systems should adhere to when they are procured by the municipality. These include transparency requirements, data ownership and governance requirements, AI system quality, risk management and maintenance. The guidelines are still in the testing phase, as the city aims to understand how different stakeholders, such as other municipalities, civil servants, smaller and bigger companies view and evaluate these guidelines (Amsterdam City, 2020).

The procurement guidelines should be followed whenever a contractor provides an algorithm for decision making, decision support, enforcement, fraud investigations or a system to be used on the staff on the municipality. A key aspect is the requirement for AI to be transparent in three different ways: procedural, technical and explainable (Amsterdam City, 2020). This requires the contractor to document and describe the non-technical, core functioning of algorithm, the technical quality and operation such as the source code, and explainability of case by case outcomes, respectively. At all times should decisions with or by AI be explainable, as per requirement of Dutch public law.

Serbia

The Serbian government has released their strategy regarding the Development of AI in their country for the period 2020-2025. In this document, public procurement has been regarded as an important element to stimulate AI within Serbia. Public procurement is seen in the strategy as a tool to create market opportunities for start-ups and as an opportunity for the public sector to modernize public services (RS.PS1, 2020). The lack of a framework for the use of public procurement for innovative technologies such as AI is regarded as one of the key issues limiting the development of AI adoption in the Serbian public sector (RS.PS1, 2020). Hence, the strategy mentions the need to adopt public procurement regulations, and particularly to regulate issues regarding data ownership and to regulate algorithmic bias (Government of Serbia,2019). In this respect, it is mentioned that public procurement contracts should include the obligation to assign data to the state and to define the structure, form, and format of the submitted data.

UK

The government of the United Kingdom partnered with the World Economic Forum to draft guidelines for AI procurement in the public sector. These guidelines specifically address challenges that public sector organizations may face during the public procurement of AI based solutions. Public procurement is regarded as the primary mechanism to facilitate the adoption of AI in the government (UK.PS1, 2021), which may be done to improve public sector delivery, reduce costs, improve effectiveness, or reduce administrative burden (Office for AI et al., 2020; World Economic Forum, 2020). In these guidelines, AI is understood as the use of digital technology to create systems that conduct intelligent tasks, but the document itself primarily refers to machine learning. Though the guidelines focus primarily on machine learning, they also acknowledge that there are fundamental differences between different AI-based systems and offers specific guidance for different AI use cases at different stages of readiness. The guidelines provide a number of considerations during various stages of the AI procurement process. These guidelines make it clear that there is a pre-procurement process, which starts by assessing whether or not AI is truly needed and whether or not the relevant data or skillsets exist to develop and evaluate an AI system (Office for AI et al., 2020). Specific guidance is offered to assess whether or not an AI system is or is not needed. Further, the guidelines highlight the need to ensure transparency and explainability of AI system in the procurement, as this ensures future understandability of the system, and reduces the potential of vendor lock-in. The guidelines also highlight the importance of testing and evaluating AI systems, specifically by using data and impact assessments throughout the entire development process, from ideation through to implementation.

5. Results and Discussion

While many governments do have experience with procurement, during this research interviewees from all four countries agreed that procuring AI was different, and that because of this there was a clear need for new guidelines. A great example of this comes from UK-PS1 who noted that they saw two reasons why procuring AI was different:
'*... when you procure AI technologies you also, sometimes, make policy decisions. You basically are outsourcing, somewhat, policy decisions' and furthermore that, 'we thought about the public procurement of AI as a policy tool to drive innovation and regulation'* (UK-PS1, 2021).

The importance of using procurement as a policy tool to drive innovation and regulation has also been mentioned in Serbia and the Netherlands. This brings us to the first important finding of this paper: **there is a conceptual difference between traditional procurements in the public sector and the procurement of AI in the public sector.** While each of the countries selected had guidelines and approaches for AI procurement, the motivational reason behind them slightly differed. For example, in the Netherlands and the UK it was clear that AI procurement emphasis was given to

viewing procurement as a policy tool, whereas in Serbia and Estonia AI procurement was emphasized as the means to stimulate and develop the AI ecosystem and private sector. Interestingly, in Estonia, Netherlands, and the United Kingdom interviewees suggested that the private sector, especially SMEs, were responsive and appreciative of the development of AI procurement guidelines as it helped to improve procurement clarity, relevance, and alignment with the market. On the challenges of procuring AI in the public sector, during this research, 14 key challenges faced during the procurement of AI in the public sector were identified and triangulated.
These challenges can be subdivided into four categories:

- **Procurement Process Challenges:** market knowledge, trade secrecy, service needs, structure
- **Data Challenges:** data availability, data ownership, data governance, data infrastructure
- **AI-Model Challenges:** ai system quality, ai transparency, ai bias
- **Organizational Capacity Challenges:** technical capacity, organizational capacity, individual capacities

To overcome these fourteen challenges, a total of 22 potential strategies were identified during this research. These solutions are discussed below, but an in-depth overview of the challenges, explanations, solutions, locations within the procurement process.

While, not all challenges or solutions identified were unique to the procurement of AI, more were than were not. In any case, it is useful to provide a systematic overview of all challenges that may be encountered during the procurement of AI in the public sector. Furthermore, it was possible to identify currently proposed solutions for addressing these challenges from the guidelines of the studied countries. This research cannot make a claim on whether or not such solutions work or not, only that these are what the identified countries dealing with the procurement of AI are currently suggesting in their procurement guidelines.

Procurement process challenges

The first group of challenges identified were those specific to the procurement process itself. As a starting point, it must be decided whether AI is actually needed for a specific problem as AI should not be applied just for the sake of using AI. To help public sector organizations overcome this problem checklists and guidelines have been prepared that allow for an organisation to assess whether an AI-based system should be procured; these checklists exist both in Estonia and the United Kingdom.

A second challenge is having an understanding of the market; this is critical for the success of a procurement. Addressing this issue, EE-PS1 noted during an interview that in Estonia there were problems with procurement from the public sector and the market let them know. However, while there were challenges with the public procurement of AI, 'it's not AI specific, a lot of procurement of anything IT is quite crappy anyways, right. That's a problem in itself' (EE-PS1, 2020). Yet, even so, the interviewee continued on to note that after the chief data officer had 'come up with an instruction manual or a guidance paper about how to procure these things' and that since then, they 'hear from the market, [that] it has gotten better' (EE-PS1, 2020). Similar sentiment was offered by UK-PS1, who noted that there 'was a very positive narrative from the private sector' and that the new guidelines 'made it easier for the private sector to reply or participate in procurement' (UK-PS1, 2021) as well as NL-PS1, who stated that companies found the produced guidelines 'quite logical and reasonable' (NL-PS1, 2021).

For trade secrecy challenges, it is important to ensure that government organizations are not stuck in a situation where they are not able to share relevant information about how a specific algorithm or AI-system functions if requested. In the guidelines from the United Kingdom and the Netherlands specific guidance is given on how to ensure sufficient documentation and transparency of AI systems. An additional way to do this, as highlighted by (Brauneis and Goodman, 2018) is to place importance on 'contract language requiring provision and permitting of disclosure of records' therefore 'placing the burden on the contractor to identify and mark specific passages in a document as trade secrets' and subsequently '[linking] disclosure provisions to demands that records be produced to the government' (p.164-165).

Finally, there is the challenge of procurement structure. In Estonia, the chief data officer has created a standardized template with accompanying questionnaires that can be used by organizations to aid them in the procurement process. Interviewees EE-PS2 and EE-PS3 both noted that this guidance and structure was helpful for their organizations in the procurement process. Such templates and structured documents were not readily apparent in the other studied countries.

An overview of these challenges, and some solutions, can be found in the Table below:

Table 1 Procurement Process Challenges

Challenge	**Explanation**	**Procurement process stage**	**Solutions**	**Source(s)**
		Procurement Process Challenges		
Market knowledge	There is knowledge about the state-of-the-art and what currently is or is not possible in the market, as well as correct and relevant pricing	Feasibility assessment	1. Engage in market research to understand the state-of-the-art and whether or not a specific project is feasible.	Estonia, United Kingdom
Trade secrecy	There is an understanding about who owns the intellectual property of the procured system.	Implementation and organization of procurement	1. Include specific regulations within the procurement on trade secrecy and intellectual property rights. 2. Ensure that proper documentation is provided and mandated in procurement documents.	Netherlands, United Kingdom

Service needs	AI is the best solution for the specific problem	Feasibility assessment, monitoring and evaluation of performance	1. Engage in a pre-procurement process to check whether or not AI is the best solution for a specific problem	Estonia, Netherlands, Serbia, United Kingdom,
Structure	There is a clear structure to the AI procurement that enables the suppliers to clearly understand what is needed and what the requirements are	Implementation and organization of procurement	1. Create standard procurement templates to ensure consistency and validity of AI procurements.	Estonia

Data Challenges

The second group of challenges are those related to data, namely its availability, governance, ownership, and infrastructure. In all four of the countries studied, the role of data in AI procurement was given prominence. For example, in Serbia, RS-PS2 noted that there needed to be clear guidelines on how to give data away in an organized way and how such data should be stored, arguing that data infrastructure must be developed before engaging in AI procurement. Additionally, in the Serbian AI strategy, it is noted that 'public procurements and contracts must contain. . . the provider's obligation to assign [data] to state authorities' (Government of Serbia, 2019). Thus, when it comes to data governance and data ownership, specific measures may help in to ensure that there are proper regulations and governance mechanisms in place for data consumed or generated by AI-systems. Similar arguments existed in all countries studied. Regarding data availability, there are two separate aspects at play. First, whether the data needed for a specific AI-system actually exists. To this end, the United Kingdom guidelines strongly recommended to assess the data quality and availability prior to any tender as to understand possible issues of the data available for the procured AI system. In Estonia organizations can engage in deep dive sessions with the chief data officer and private sector experts to explore the organization's available data and potential AI use cases. The second aspect related to data availability is ensuring that sample data is available and provided during the procurement process. This aspect was highlighted as being important by interviewees from the United Kingdom and Estonia.

Table 2 Data Challenges

Challenge	**Explanation**	**Procurement process stage**	**Solutions**	**Source(s)**
Data Challenges				
Data availability	Making the data required for the AI	Feasibility assessment	1. Conducting a data availability assessment	Estonia, United

	development available, accessible, or obtainable		prior to the procurement process 2. Ensuring data access, storage and consent before the procurement	Kingdom
Data ownership	Understanding who owns which data is used or created by the AI system	Implementation and organization of procurement	1. Ensure that the procurement has specific language that data provided by the public administration, or collected in the context of procurement, remains with the administration.	Estonia, Netherlands, Serbia United Kingdom
Data governance	Having the necessary governance and legal mechanisms are in place for sharing, collecting, and disseminating data	Feasibility assessment	1. Ensure that contractor has followed regulation and standards during the collection of their data as well as storage.	Estonia, Netherlands, Serbia, United Kingdom
Data infrastructure	Understanding the necessary infrastructure and its location for a specific AI project (e.g. Own premises, in the cloud, with provider)	Feasibility assessment	1. Systematically analyse the current infrastructural capabilities of your organization and make it clear within the procurement.	Estonia, Serbia, United Kingdom

AI-model challenges

The third grouping of challenges are those related to the AI-model or system itself and concern the quality, transparency, and bias of the system. About transparency and bias of AI-systems, all four countries made explicit commitment to the procurement of transparent, ethical, and unbiased AI. As has been mentioned previously in this chapter, there are several international initiatives that layout clear guidelines and mechanisms to ensure this, such as the OECD's principles on Artificial Intelligence of the European Union's Ethics Guidelines for Trustworthy AI. Within the procurement guidelines studied for this chapter, only the United Kingdom and the Netherlands had their own guidelines in place for how this was to be done. Only in Estonia and Serbia were mentions to the international guidelines included. When it comes to ensuring ethical and bias free AI procurement, several solutions have been suggested. For example, there are checklists, tools, and reviews that should help to check for bias and ethical issues in AI systems. It is also possible to require clear documentation about how the algorithm itself works, how decisions are made, what data are used for making such decisions, requiring explainability and interpretability in the technical description of the procurement documents, requiring contractors to provide and confirm their compatibility with specific guidelines, and utilizing iterative assessments of utilized AI systems (Berryhill et al., 2019; Brauneis and Goodman, 2018; Mulligan and Bamberger, 2019).

Table 3 AI-model challenges

Challenge	**Explanation**	**Procurement process stage**	**Solutions**	**Source(s)**
		AI-model Challenges		
AI system quality	The finished system/model is of high quality and in line with legal regulations over a longer period of time.	Implementation and organization of procurement , Monitoring and evaluation of performance	1. Apply risk management strategy to identify and mitigate risks 2. Ensure maintenance (over a period of time) is contractually obligatory	Netherlands, United Kingdom
AI transparency	The AI system is transparent and explainable, potentially for an audit if deemed necessary.	Implementation and organization of procurement, monitoring and evaluation of performance	1. Including technical, procedural and explainability as mandatory requirements 2. Explainability and interpretability of algorithms as a design criteria 3. Require clear documentation about the functionality of the AI-system, the data used, and how it works (at a minimum)	Estonia, Netherlands, United Kingdom,
AI bias	Potential bias of an AI system is mitigated as much as possible	Implementation and organization of procurement, monitoring and evaluation of	1. Conducting a data assessment to identify and address data bias 2. Measures have to be taken by contractor to	Estonia, Netherlands, United Kingdom,

		performance	ensure bias is limited. Iterative AI impact assessments at crucial decisions points should be conducted. 3. Obligatory documentation on compliance to non-discrimination, equal treatment and proportionality	

Organizational Challenges

The final category is that of organizational challenges, these are primarily associated with capacities at the managerial, technical, and individual levels. For AI procurements to be successful, it is important that an organization develops and maintains the ability to procure AI well. In the case of Serbia, all interviewees noted that there was currently little capacity for procuring AI as there is a general lack of expertise. To counteract this, they have proposed to establish a government-academic collaborative institute to aid the government in future AI procurement. Similarly, in Estonia, the private sector and the chief data officer have worked with different organizations directly to improve understanding of AI, organized educational programs, and provided clear documentation to common questions and problems. Across all countries studied, it was noted that there was a clear need to improve the AI and technological capacity of organizations. This can be done by encouraging participation and availability of AI programs, as well by making IT experts available across organizations. For example, in the United Kingdom it has been noted that if there is missing capacity: '*you should seek [assistance] from elsewhere in your organization or relevant professional network.And make the consultation and collaboration with appropriate stakeholders a priority'* (Office for AI et al., 2020).

An overview of these challenges can be found in the Table below:

Table 4 Organizational challenges

Challenge	**Explanation**	**Procurement process stage**	**Solutions**	**Source(s)**
		Organizational capacity challenges		
Technical capacity	The organization has the necessary technical capacities to implement and procure an AI-based system	Feasibility assessment, implementation and organization of procurement	1. Encourage participation in and arrange educational courses on AI. 2. Consult with governmental experts in other organizations to develop an initial understanding on	Estonia, United Kingdom, Serbia

			AI.	
Organizational capacity	The organization has the necessary organizational capacity to plan and implement an AI-based system	Feasibility assessment, implementation and organization of procurement	1. Develop clear guidelines that specify the key challenges and risks with public procurement of AI-based systems. 2. Provide guidance and best practices for AI procurement, for example by providing templates or sample procurements	Estonia, United Kingdom, Netherlands, Serbia
Individual capacities	The organization has employees who possess the necessary capacities to manage, procure, and/or implement the public procurement of AI-based systems	Feasibility assessment, implementation and organization of procurement	1. Encourage participation in and arrange educational courses on AI.	Estonia

6. Conclusion

This chapter drew on the experiences in drafting guidelines for the procurement of AI in the public sector from Estonia, Netherlands, Serbia, and the United Kingdom. In doing so, it was possible to make a number of interesting contributions to the current knowledge, both practitioner and academic, on the procurement of AI in the public sector. The first contribution is related to conceptualizing the concept of the procurement of AI in the public sector. The second major contribution is related to the elucidation of 14 commonly occurring challenges related to the procurement of AI solutions in the public sector. These challenges were further able to be categorized into procurement process challenges, data challenges, AI-model challenges, and organizational capacity challenges. The third contribution is in identifying commonly occurring proposed solutions in currently existing public sector AI procurement guidelines to overcome these identified challenges. In total, 22 potential strategies have been identified.

This initial work should serve as a strong foundation for any public sector organization interested in developing their own AI procurement guidelines. For scholars, this work represents one of the first attempts to identify and categorize the challenges and potential solutions for procurement of AI in the public sector. Thus, this chapter is likely to be of interest for those studying procurement and the public sector. While this research has provided a strong foundation on the procurement of AI in the public sector, future research is still needed on the topic. In the course of this research it became clear that there is a wide breadth given between governments about what is considered AI and what is not.

Further clarification about this should be sought in future research on the topic of public procurement of AI. Similarly, in this study it became clear that guidelines were just that, guidelines, there was often no obligation to use or implement them. In this way the guidelines may well help procurements to be successful, e.g. by providing guidance on how to write procurements better, but does not necessarily guarantee the relevant regulations and safeguards for ethical and unbiased AI are taken into account. While guidelines are apparently important for the public procurement of AI, there are a number of other important and relevant issues that must be explored. These aspects include how can AI be integrated into traditionally existing legacy infrastructural systems, how to address the legal and regulatory challenges associated with AI, how do environmental and cultural aspects influence the adoption of AI, how does context influence the ethical implications of AI. Outside of these concerns, there is also a need to further explore how to develop the relevant organizational capacities and culture needed to ensure successful public procurement of AI. In other words, there is a clear need for extensive and comprehensive research within the domain of public administration and management on the subject of public procurement of AI. It is certain that AI is here to stay in the public sector and that procurement will play an increasingly important role in the adoption of AI amongst public sector organizations. In effect, this also raises both the prominence and the need for scholars and experts to conduct research on this emerging area of inquiry. It is critical that scholars and governments alike to collaborate and cooperate to make a conscious effort toward generating research and knowledge about the required administrative and organizational capacities needed for the successful public procurement of AI, that procurements can be conducted successfully, that guidelines exist for this process, and that the public procurement of AI is used to generate a positive impact and public value for society.

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Annex - List of Interviewees

EE.PS1 – Senior government IT advisor.

EE.PS2 – Ministerial Chief Information Officer.

EE.PS3 – Private sector manager involved in organizing ministerial data dives.

NL.PS1 – Senior ranking official involved with creation of Amsterdam's AI guidelines.

RS.PS1 – Senior ranking governmental advisor on public sector reform.

RS.PS2 – Official involved in the creation of Serbia's AI strategy.

RS.PS3 – Senior official in Prime Minister's office's IT team.

RS.PS4 – Senior official in Prime Minister's office's IT team.

UK.PS1 – Senior consultant in UK's AI Procurement guidelines team.

Publication XI

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The challenges of AI implementation in the public sector. An in-depth case studies analysis

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ABSTRACT

Time is now mature for researching AI implementation in the public sector, creating knowledge from real-life settings. The current paper goes in this direction, aiming to explore the challenges public organizations face in implementing AI. The research has been conducted through eight in-depth case studies of AI solutions. As a theoretical background, we relied on a framework proposed by Wirtz et al. [36] that identified four classes of challenges: AI Society, AI Ethics, AI Law and Regulations, and AI Technology Implementation. Our results first confirm the importance of the four classes of challenges. Second, they highlight the need to add a fifth class of challenges, i.e., AI Organizational change. In fact, public organizations are facing important challenges in settling AI solutions in daily operations, practices, tasks, etc. Finally, the five classes have been discussed, including more detailed insights extracted from the coding of the cases.

CCS CONCEPTS

• **Artificial Intelligence**; • **Public Sector**; • **Challenge**;

KEYWORDS

Artificial Intelligence, Public Sector, Organizational Change, Challenges

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1 INTRODUCTION

With the exponential increase availability of data, easier access to computational power and new techniques, the widespread use of AI is now advancing in all industries. The whole society is aware that AI has the potential to disrupt and is already disrupting almost all industries [26]. The public sector is not excluded by this disruptive change, while, on the opposite, it might become one of the sectors where AI can have a significant impact by improving internal operations, decision-making, public services, and trust in government, amongst others [31].

Recent studies show that AI adoption and deployment are becoming more prevalent in public settings [2, 17]. The growing number of use cases, thus the growth in the usage of AI in the public sector, is also fostered by a clear policy direction, especially in Europe [21, 23]. More particularly, the European Commission recently released a proposal to regulate AI use in all sectors, the so-called Artificial Intelligent ACT [25]. Despite this potential, the adoption and deployment of AI in public organizations face difficulties and barriers [15, 32]. Some public organizations have succeeded with AI pilots but struggle to scale them across the organization [17]. Moreover, research shows that little is known about the extent of these barriers within public administrations and how they influence the use of AI in public organizations [2, 17, 37].

This paper goes in this direction, exploring the use of AI in the public sector by answering the following research question: What challenges are public organizations facing when implementing AI?

As a theoretical background, we rely on the four classes of challenges proposed by Wirtz et al. [36]. This framework focuses specifically on AI-related challenges within the public sector and encompasses a broad range of potential factors beyond technical hurdles. Despite its academic relevance and recognition, to our knowledge, it was never tested by scholars on real-life cases. Building on this framework, we aim at detailing and refining it with on-field insights from eight in-depth case studies of public organizations that are implementing AI solutions. By doing so, we seek to enhance our understanding of the obstacles involved in deploying AI technology in the public sector through concrete examples.

2 LITERATURE REVIEW AND THEORETICAL BACKGROUND

Applications using AI in public settings appeared over a decade ago [29]. However, only recently, the topic (re)gained momentum [5] due to the perceived novelty and the possibility of technology in tackling societal challenges and improving the efficiency and effectiveness of public organizations.

Several studies show that public organizations are adopting AI solutions (see, for example, [1, 20, 36]) in several domains which are not often alike, such as surveillance, law enforcement and service delivery [38]. Those AI solutions are not only pilots developed in testing environments but also already deployed solutions in daily operations [20, 21]. For instance, a study from the European Commission (2021) identified 686 use cases of AI in the public sector

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[32]; another study instead selected 215 cases worldwide [15]. These simple numbers hint at the large impact that AI is having and will have in the future on the public sector, as some exploratory case studies have also suggested [7, 22].

The integration of AI in the management and delivery of public services, has the potential to provide, and in some cases is already providing, large benefits to public organizations and their users, i.e., citizens and firms. Benefits vary from internal efficiency to effectiveness in service delivery or policymaking [17]. For example, scholars identified efficiency benefits derived mainly from task automation and staff empowerment through the recommendations of AI systems [18]. Other scholars highlight the value of AI on the policy process: it can enable faster and more accurate identification of the issues, better predictions of the effect of potential policy solutions and a more effective feedback loop after deploying new policies [10]. Finally, public service delivery can benefit from AI solutions through more personalized and effective services, such as chatbots, but also proactivity in service delivery diminishes the administrative burden for citizens and firms [3, 12].

Surprisingly, this clear movement from a policy and practitioner perspective is not mirrored by the attention of the scientific community [11]. Academia was seriously lagging in publications a few years ago [30]. Nowadays, the body of knowledge, as well as research interests, has started expanding. For example, in 2021, three literature reviews in the topic were published in academic journals [16, 37, 38].

However, there is still a gap to fill and a discrepancy between literature and practice. Research on AI is mainly theoretical; it debates principles, potential challenges and risks, lacking empirical insights [13]. This leaves a gap in on-field research that starts from and theorizes empirical evidence and concrete practices [31]. This is even more important nowadays, where AI is more widely implemented in public settings. Hence there is a need to take a step forward in the research going beyond pilots and supporting public administrations in the implementation phase [21]. In this direction, a recent publication highlights how the implementation is one of the most critical steps that make AI less widespread than it could be in public settings [34]. Other studies highlight how, when implemented, AI is changing the role and duties of bureaucrats, bringing a relevant set of challenges for public administrations [7, 14].

This paper is making a step in this direction, trying to move research closer to practice and derive research from existing practices on a specific topic related to AI implementation i.e., the challenges AI is bringing to public organizations.

The focus on the challenges has been selected because there are already several research articles mainly addressing this topic from a theoretical point of view (see, for example, [1, 5, 36]). All these studies start from the clear assumption that adopting AI in the public sector differs from the adoption of ‘standard’ digital technologies. Several authors include some insights that can be related to public sector challenges. For example, Mikalef et al., [19] highlight the importance and the need for funding and incentives and pressure from the government. Ahn and Chen [2] highlight the importance of training and education on AI. Bruijn, Warnier, & Janssen, [4] listed a series of challenges for making AI more explainable since any AI-based will be more acceptable if it could be explained to the users. These challenges go beyond merely technical explanations of how the AI system works but also include the management of the dynamic environment that changes over time in which these AI solutions operate and the acceptance and management of machine biases.

Among those studies, the first and the most complete one, that aims at embracing and categorizing all the challenges has been published by Wirtz et al., in 2019 [36]. The authors identify four main classes of challenges related to AI in the public sector:

- **Societal challenges.** This class of challenges includes the issues related to social acceptance of AI, like citizens’ trust or employees’ fear of workforce substitution.
- **Ethical challenges**. This class embeds all the challenges related to AI ethics, like discrimination or machine value judgments.
- **Regulatory challenges.** This class of challenges focuses on legal and law issues, above all, privacy or accountability.
- **Technological challenges.** This class of challenges comprises the issues related to the implementation of AI, like data and system integration.

The framework presented in this study is considered to be among the initial and extensive frameworks addressing the challenges associated with AI implementation within the public sector. It has gained notable recognition within existing literature due largely to its thorough examination of potential obstacles and general applicability across diverse contexts. In addition, it is one of the few frameworks tailored specifically to AI in the public sector. Despite the relevance of this framework, to our knowledge, it has never been tested with empirical evidence, leaving an open question about its empirical validity ad robustness. Finally, the framework was published in 2019, hence considering that AI technology has rapidly evolved, a few new challenges might have arisen, especially considering that now there are public administrations are using AI in daily operations, while in 2019 the debate was more focused on exploring the potential usages and try to use A with pilot solutions [21].

For these reasons, in collecting the evidence from the case studies, we started with these four classes of challenges. The study aims at detailing the challenges with concrete, on-field insights and evaluating (i) if those challenges properly mirror the challenges a public organization is facing, (ii) if something is missing in the current framework and (iii) which more detailed insights can be drawn from our cases on those classes of challenges.

3 METHODOLOGY

3.1 Case selection

Case studies were selected from a large database published by the Joint Research Centre of the European Commission [32][1]. To our knowledge, the database represents the larger and more complete source of information at disposal for the research community. The source of information is limited to European countries; hence we focus on those cases. This choice allows a higher homogeneity in the policy background (see the aforementioned Coordinated Plan) and the legislative boundaries (above all, the European General

[1]The database is available at the following link: https://data.jrc.ec.europa.eu/dataset/7342ea15-fd4f-4184-9603-98bd87d8239a

Data Protection Regulation (EU GDPR)), contextual elements that strongly influence the implementation challenges.

The analyzed cases have been selected following a pragmatic approach. The important selection criteria that have been applied are:

(i) The inclusion of cases with a different level of maturity in the implementation status, from pilots to already deployed cases. This criterion has been included for having the possibility to evaluate the challenges in the deployment cycle of the AI solution.
(ii) The inclusion of cases using different AI techniques to ensure the validity of the results in the context of AI adoption, with no specific focus on a subset of AI techniques.
(iii) The inclusion of only one case per country in order to limit as much as possible the influence of national factors (national strategies and policies, funding programs, etc.) on our findings.

These figures are data already available in the original database. Considering the selection criteria, the cases have been selected as follows. First, we started by identifying the potentially relevant cases with already several detailed information available on the web, considering that the original database already included a link pointing to a website with information on the case. Second, we reduced the list to include only the cases where the contact details of at least one person working on the project were available. Third, only the cases where at least one interview could have been included. Overall, eight in-depth case studies have been analyzed.

Given the nature of the study, this pragmatic approach has been considered appropriate. The study does not aim at assessing best practices or practices with specific, peculiar characteristics, but on the opposite, it aims at gathering insights from common, real-life cases that faced and are facing implementation challenges.

The description of those cases has already been published in a dedicated report [32]. However, the report deals with those cases mainly from a policy angle, leaving room for theorizing the insights collected and linking them to the existing body of literature. The descriptive information of the cases is reported in Table 1.

3.2 Data collection[2]

Data were collected through multiple data sources. The primary data consisted of 10 semi-structured interviews with eight different informants. The interviews were conducted online between October 2021 and December 2022. Interviewees including the project managers responsible for the implementation of the project. In most of the cases, the project managers were public managers working within the administration; only for case 2 and case 6 the project managers were professors at public universities, as the implementation was outsourced to a technical university.

The interviews followed a pre-designed protocol with a semi-structured approach. First, the interviews relied on questions focusing on a brief description of the project and its main objective. Second, they deepened their understanding of the challenges and how they dealt with them. In the first place, no specific class of challenges has been mentioned, allowing the interviewee to frame the narrative at their convenience. If necessary, follow-up questions were asked touching upon the specific points from the existing literature.

The interviews have been conducted by the first two authors to avoid as much as possible interpretation biases. Moreover, they have been recorded and transcribed. The interviews were complemented with wide-ranging archival data. For example, the authors analyzed the project's web page – if available – and at least one news article describing it. This was also possible given the nature of the original database of cases that, for each case, identified at least a news article.

3.3 Data analysis

Within- and cross-case analyses were performed, building theory from multiple cases [6]. First, we defined the theoretical model and the subsequent coding scheme building on the four classes of challenges proposed by Wirtz et al. [36]. Next, we coded all the information collected, assigning them to one of the classes, if possible. Then, the two authors independently moved to a subclassing search, using replication logic across cases, and identifying subcategories considering, when applicable, the existing academic knowledge. These initial relationships were then refined via replication logic – frequently revising each case to compare and verify the occurrence of specific constructs, relationships, and logic [27].

Once the cross-case analysis was underway, the authors cycled among the emergent theory, case data and literature to further refine the construct definitions, abstraction levels, and theoretical relationships. The cycles continued until a strong match between the cases and emergent theory was achieved. Once it reached a certain degree of saturation, the authors were able to compile and relate the construct with the challenges proposed by Wirtz et al. [36] and verify the need for new classes of challenges.

4 RESULTS

The narrative of the results section follows the four classes of challenges proposed by Wirtz et al. [36] and finally proposes a new class, AI Organizational and Cultural Change, explaining the reasons behind this choice. Moreover, results highlight a relevant difference in the challenges for piloting a new solution and implementing it in daily routines. Hence, this distinction has been made. Table 2 reports a synthesis of the main insights from the cases. Finally, for each class of challenges, we draw one proposition distilling the main theoretical insights derived from the cases analyzed.

4.1 AI technology implementation

The availability of data is always key for the development of an AI solution; this has been recognized by all the cases analyzed. However, the need for data and the complexity of obtaining them depend strongly on the project's characteristics. Hence, we observed that there is not a clear and unique challenge to data quantity and quality but a series of possible challenges that depend on project's nature. There are, for example, projects where the data collection is one of the main and most critical tasks. For example, the AI developer of case 5 reports:

> "We asked employees that we can call 'neighborhood watch' to drive around the city a few times a week for a period of 3-4 months to collect the video data.

[2]Further information on the methodological approach is available upon request.

Table 1: Description of case studies

#	Description	Status	AI Classification [28]
Case 1	A digital platform that provides an automated assessment of how a selected company is more likely to commit fraud than others.	In production	Machine Learning, Automated Reasoning
Case 2	An AI system in border control points that help with the selection of the travelers to test upon arrival. The purpose was to effectively allocate the scarce Polymerase Chain Reaction tests within the summer tourism season.	Not in use anymore	Machine Learning, Planning and Scheduling
Case 3	Installation of sound meters installed and development of an application for citizens to report noise in the street. The results will allow proper corrective actions, also through nudging.	In production	Audio processing, Machine Learning
Case 4	AI system that operates on top of the results of the different OCR (Optical Character Recognition) used over the years for digitizing historical newspapers and books. The system aims at improving the quality of the result, identifying and correcting mistakes.	Implemented	Computer Vision, Natural Language Processing
Case 5	AI solution to detect garbage. The AI solution automatically identifies trash on the street and shares this with the garbage management services of the city to act and solve the issue.	Not in use anymore	Computer Vision, Machine Learning
Case 6	AI system used to assist consultants with unemployment by providing insights predicting the chances of their client – an unemployed person - getting a new job.	In production	Machine Learning. Automated Reasoning
Case 7	The AI system is based on understanding speech and transforming it into text. It is used to provide subtitles on all the videos and is part of a wider initiative within the administration to use Speech-to-Text technologies in various use cases.	In production	Audio Processing, Machine Learning
Case 8	AI system used to estimate the income of Small and Medium Enterprises as well as of self-employed individuals who have decided to pay their taxes by module rather than defining an exact amount of income.	Proof of concept	Automated Reasoning, Optimization

Note. Proof of concept = the idea is to be refined and experimented. In production = the solution has already been tested and is now in production for using it in daily operations. Implemented = the solution is already in use by the administration. Not in use anymore = the solution has been dismissed (either after the pilot phase or after using it for a while). For more details on the classification, please refer to the full report [32].

Note2. The status refers to the situation at the date of the interviews, i.e. between October 2021 and December 2022.

> Those are people hired by the municipality who usually already go around the city to see what is going watch."

A similar situation for case 2, where the developer stated:

> "A lot of effort was put in designing the form that passengers had to fill in prior to their arrival to the country in order to have the needed amount of data without collecting sensitive, prohibited information"

Something similar has also been detected in case 3, where there was a need for data on the noises. Even though the cases are completely different, they are comparable in the importance of collecting new data for training the system. In other cases, the situation was quite different, and the provision of data was not one of the key issues. For example, for cases 6 and 8, the issue was more related to the selection of the proper data to continuously train the system over time and create the scores. Apart from the element related to data, it was interesting to note that technicalities in developing the source code were not identified as critical in any of the cases. Either because the public organization relied on external suppliers or because this has not been viewed as a difficult challenge to solve.

The last important element to mention among the technical challenges is interoperability. Again, cases confirm that it is key, especially when the project is moving beyond the pilot phase. The emblematic example in this direction is case 3, as mentioned by the interviewee:

> "At the start of the project, there was no municipal data platform, and there would have been a risk that the project would be then too reliant on this contractor. Now, this risk has been avoided, and a project is ongoing to integrate the noise data into a larger smart city data platform. Naturally, the development

Table 2: Insights from the cases on AI challenges

Class of challenges	Piloting	Implementing
AI Technology implementation	•Data gathering is necessary, as a large amount of non-biased data is required for training the system •Proper procurement process is needed to ensure a trustworthy AI system	•Data gathering remains critical for continuous training of the model and avoiding system degradation •Interoperability becomes key for an easier continuous training process
AI Society	•Transparency of operations and algorithms is key to ensure trustworthy AI development	•Citizens' acceptance and trust in the system are to be fostered
AI Ethics	•Ethical questions are to be posed since the first piloting phase to ensure fairness, and non-discrimination	•Mitigation measures are to be designed and implemented to limit ethical risks
AI Law and Regulations	•GDPR compliance is an important challenge in terms privacy issue for AI applications that process personal data •Beyond mere compliance, internal regulations and shared principles are to be defined	•Compliance is to be continuously checked and revised
AI Organizational and cultural change	•Domain-knowledge is extremely important for training the system, particularly in terms of explainability	•New processes and procedures are to be designed to ensure a proper – trustworthy – use of the AI solution •Permanent human supervision and domain experts' involvement is key to maintaining the system and avoiding its degradation

> of a dedicated platform for noise data could have been avoided if the municipality would have had this infrastructure already in place before the project was initiated."

It is worth mentioning that the need for proper IT equipment was not identified as one of the main factors influencing the project: overall, the cases reported the presence of equipment with enough quality to implement the AI system.

Wirtz et al. [36] included among the technology implementation also challenges about financial feasibility. Besides the importance of having proper funds and some choices that have been done due to financial constraints, we did not observe any new and interesting financial issues in the analyzed cases. Dedicated funds were always allocated to the project, often coming from regional or national programs. An interesting element that can be related to funding but not solely is the selection of the proper partner or suppliers for developing the AI solution. The relationship with suppliers was extremely varied among the cases. From cases almost completely externalizing the technical development (e.g., case 7) to cases having the whole development in-house (e.g., case 5). Moreover, relations with university departments have often been seen as a good opportunity for innovating (e.g., case 6).

Proposition 1. Technology implementation challenges vary significantly among cases; each case highlighted different challenges to face. This strongly depends on the features and the needs of the AI project as well as the previous IT equipment available.

4.2 AI Law and regulations

This class of challenges is led by privacy issues related to GDPR compliance. Nevertheless, this was not the case in the use cases analyzed as some of them did not report any issue in this direction. For instance, the interviewee of Case 2 reported:

> "During the design of the information form, discussions with lawyers were held to ensure that which questions were legally allowed to be asked, but also which questions were ethically allowed. In doing so, considerable trade-offs were made in ensuring a balance between privacy and the capability in assessing individual risks. For instance, a question that could be very helpful in assessing the risk of infection would have been occupation – but this was considered too invasive and thus excluded. As a result, only fairly course information about travelers was asked."

Also, the interviewee for Case 6 reported some GDPR-related challenges:

> "An analysis has been conducted by the legal department to make sure the system is GDPR compliant. One of the consequences of this review is the persons registering as unemployed must give their agreement to their data being used and also for the purpose of the risk model to make a more targeted service and recommendation. There are also limitations to which data may be used by the system, as it is not possible for our organization to gain some sensitive datasets such as medical information."

In addition, transparency and accountability were important elements for some of the cases. For example, the interviewee of case 1 declared:

> "From the beginning of the use of AI, transparency and explainability has been a key focal point – although

> this is also required by law to be transparent to a certain extent. Hence a framework has been built to ensure the transparent, responsible, and accurate use of Machine Learning in the public sector. To this end, an observability expandability component was developed in the first iteration of the platform, to ensured that all business events occurring within the platform are logged, allowing traceability of all the changes in data leading to decisions in case of court cases."

Moreover, transparency towards citizens was a key driver also for case 5, as reported:

> "There is strong documentation and registration of the AI system available online on the public to allow strong transparency of what is going on in the project, but also to provide information to citizens and to invite comments. We consider having high transparency and being easily approachable as a government organization about what AI is being developed and what it is used as one of the main ways to mitigate potential ethical risks."

In general, from a regulatory perspective, the cases show the importance of going beyond a mere law compliance.
Proposition 2. All the cases about AI law and regulations show the importance of going beyond mere law compliance. Ad-hoc regulations or ethical principles have been designed and applied to ensure the proper use of AI.

4.3 AI society

Interesting insights were collected on the effects of those systems on society and, more specifically, on the citizens and firms directly or indirectly affected by the systems. However, this has been a case-by-case analysis, given each case's peculiarities and different users.

In general, it is interesting to note that the concept of 'fear' was never mentioned in any of the cases. Neither related to the fear of overcontrol by the organization nor the fear of job replacement by employees. This testifies that, at this stage, when moving to practice and practical cases, these elements are not present, probably also because they were addressed a priori by the organization before starting the project.

Some projects are affected by pressure from outside and demand for changing the status quo. For example, case 3 needs to solve a noise issue that citizens have been complaining about for a period of time. However, it is interesting to note that the same cases are facing an issue of acceptance of the solution by the citizens.

As described by the interviewee of case 3:

> "Some have expressed skeptical remarks towards the initiative, as they did not understand why an app is needed to notify regarding noise disturbances, as the same people have been calling the police for numerous years regarding the issue – in their perspective to no avail. To this end, they find it rather dismissive that now they are taken seriously only because of the app."

Another example of mistrust, even with completely different evidence, has been reported by the interviewee of case 2:

> "Some blogs online were spreading misinformation to travelers that if you want to avoid being tested, you had to put your city to xxx in the form. Following this rumor, a lot of travelers from that city came up in the data independently from their real nationality. Such data anomalies are to be expected with using AI, but it also showed that people try to game AI systems which could lead to unexpected data inputs following its deployment"

Finally, citizens' acceptance and trust in government need to be monitored and ensured. As mentioned by the interviewee of case 5:

> "There are limitations in placing cameras everywhere in the city, as it has significant implications to the privacy and feeling of safety of citizens. The city does have other cars with cameras already driving around, such as cars doing parking scans, which theoretically could have been used for the training of the system. However, these cars were not used as these cameras have a different purpose and we risk a situation like the 'big brother'."

Proposition 3. Societal challenges are mainly based on citizens' acceptance of and trust in the new AI solution. AI systems risk not being trusted by the citizens and consequently increase a general mistrust in government.

4.4 AI Ethics

Without a doubt, ethics is one of the biggest challenges that affect AI implementation in the public sector, even more than in the private one. Each analyzed country wondered about ethical dilemmas and identified proper mitigation measures to limit the risks.

Some of the analyzed cases defined specific guidelines or checklists for every AI solution to ensure ethical compliance. This is the case, for example of case 7:

> "We have ethical principles which were drafted around 2019. Each AI solution must check each of the principles before it gets developed, but also after development to ensure that it still aligns with the principles defined at the start. Each of the principles is accompanied by specific questions that have to be answered with regard to the specific AI solution."

Several mitigation measures have been used to avoid or limit ethical risks. Human oversight and discretion were put at the center as one of the measures for limiting the risk. In fact, in all the cases, AI solutions were not taken any decision, but they were limited to suggestion and support, always with human oversight. As a result, risky systems like the scoring for unemployed people in case 6 and systems like case 7 dealing with subtitling humans can intervene and modify the results.

Moreover, ethics relates to all the other challenges: almost all the aforementioned challenges might be traced back to ethical challenges or dilemmas. For example, ethical questions affect the technological development for societal acceptance, as in the example of the cameras of case 5. For this reason, as better explained in the discussion section, we propose a new framework that poses ethical challenges like the umbrella ones, diagonal to all the others. **Proposition 4**. Ethical challenges are the biggest challenges in developing and using AI to ensure proper, trustworthy use of the AI solution. Moreover, almost all the challenges reported by the cases can be traced back to ethical dilemmas.

4.5 Organizational and cultural change

Coding the results, a new class of challenges emerged: the organizational one. Some not exhaustive elements and insights related to this class have been addressed and included by [36] in the other classes of challenges. For example, something related to skills has been included in the class 'AI technology' implementation or elements on workforce transformation in 'AI Society'. However, our cases showed that the relevance of the organizational elements deserves specific attention and a dedicated class of challenges. This confirms a research trend already in place on the organizational effects of digital transformation (see, for example, [24, 33]) and highlights that the discussion on organizational change is still relevant when applied to AI introduction.

Several organizational challenges influenced all the analyzed cases. In many cases, the introduction of AI required allocating different and new tasks to domain specialists for training, maintaining and controlling the system. For example, the interviewee of case 5 declared:

> "During the development, there were some people from the garbage collection department who were keen on helping. They were identifying and classifying the garbage from the images. For us, it was extremely important to have this domain expertise involved during the creation of the AI system, as we based our data on experts and we ensured we were accurately classifying the trash."

Also, the interviewee of case 6 insisted on the importance of domain experts, especially for the maintenance and refinement of the algorithm. They declared:

> "Every quarter, the model is retrained to ensure the accuracy. For doing it, consultants [i.e., domain specialists] are involved. A good understanding of the domain expertise is really crucial to make sure that the information provided by the model is useful and actionable. Ideally, the maintenance should be done by a labor economist who also has data science expertise, but of course, this is not possible."

Not only domain specialists but also technical, data scientists were relevant for the deployment of the system. It is interesting to note that in some cases, the development of the system was subordinated, hiring data scientists. For example, the interviewee of case 4 stated:

> "The project follows a proof of concept done a few years earlier but that wasn't scaled up at that time due to a lack of resources. Thanks to parental leave, resources were made available to hire an additional IT expert. This was fundamental for overcoming a lack of expertise and starting working on the project."

I general, all cases partially relied on external suppliers or partners, while at least one internal person with data science skills was involved in supporting the development.

Changes that go beyond the single project have also been identified. For instance, in case 5, the municipality has a dedicated data science team that is different from the IT departments. Similarly, case 1 created a data science team that is now dealing with about 30 AI models and solutions.

Not only tasks and organizational structures but also processes have been affected by AI introduction. This has been clearly stated by the interviewee of case 2:

> "AI is only half of the story. The governance system surrounding the system strongly defines its success. In fact, the use of AI in this challenge was not solely an AI problem, but an operational and logistic challenge as well."

Proposition 5. Organizational and cultural challenges play a significant role, especially when AI systems are in use in daily operations. New approaches and ways of working with the machine need to be implemented mainly through different task allocations and the acquisition of a novel set of technical and non-technical skills.

5 DISCUSSION

The research first confirms and assesses the classes of challenges proposed by Wirtz et al. [36]. Results first show that the challenges related to AI implementation in the public sector can be led back to those classes of challenges. This is the first important contribution of the study, as, to our knowledge, this study is the first attempt to apply the well-known framework proposed by Wirtz et al. [36]. However, as the case studies also highlight, there is variance in terms of the occurrence and relevance of the different challenges, as they do not all apply in each of the cases or in similar severity. This highlights the context-specific requirements and sensitivity of using AI in a government context.

In coding the interviews and applying the framework, we challenged the existing framework proposed by Wirtz et al. [36], and we introduced a new one, as reported in Figure 1. First, we shift the 'AI Ethic' challenge, in our framework called 'AI trustworthiness' to a different level. As the interviewees explained, ensuring a trustworthy usage of AI is at the core of each AI development and affects the way public administrations' approach all the other challenges. Ensuring an ethical, non-discriminatory, and trustworthy use of AI requires measures that affect organizational, regulatory, technological, and societal aspects (Proposition 4). As suggested by the High-Level Group on Artificial Intelligence, all the elements related to fair and non-discriminatory use of AI are considered under the umbrella concept of 'trustworthiness' [9]. Thus, our finding suggests introducing the 'AI trustworthiness' set of challenges as an umbrella challenge that cuts across and affects all the other challenges. Trustworthy use of digital systems is probably one of the most innovative elements that characterize AI, especially in the public sector, where, given its nature, algorithmic transparency is key [8] and unfair and discriminatory behaviors are unacceptable [35]. Although literature in this area is still scarce [13], de Bruijn, Warnier, & Janssen [4] provide some hints on how to deal with the need for explainable algorithms. Our cases first confirm that ethical

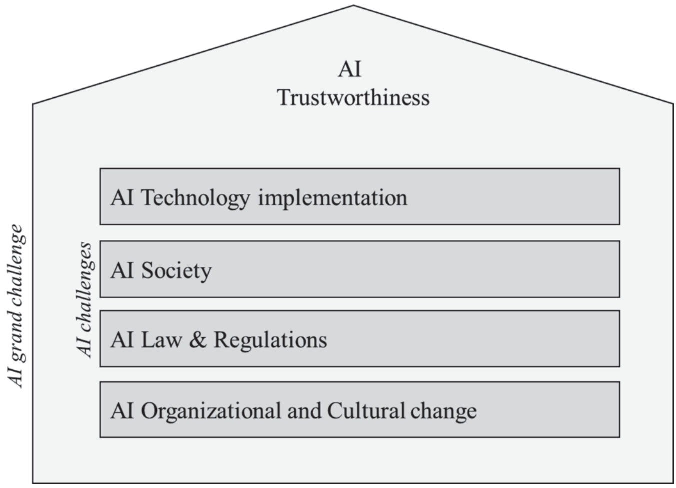

Figure 1: AI challenges in the public sector

dilemmas are at the center of AI development, and a few of the analyzed cases are also settling procedures at the organizational level to ensure a common and equal procedure for ensuring ethical compliance.

Second, a fifth class of challenges was missing and deserved higher attention: AI Organizational and Cultural Change. This is a new, novel proposal in the academic debate on AI implementation, as it subtends elements that have barely been considered and rarely clearly highlighted as key pillars. The advent of the organizational class of challenges might be explained by the rapid change in the situation since 2019 (i.e., when the paper by Wirtz et al. [36] was published). We are assisting in shifting from a sporadic deployment of AI solutions to a more mature technology that now requires a more structured approach for its introduction [21]. Due to this shift, public organizations are facing challenges in identifying the proper tasks, processes, and structures for introducing and using the new technology (Proposition 5). This type of transformation is extremely complex in public settings [33], and our insights confirm the importance of dynamic and innovative organizations, as also reported by Mikalef et al [19].

Moreover, AI differs from standard technologies as it does not follow simple if-then logic, while on the opposite, it can be considered as a new class of agents in the organizations that needs to be trained but also that can make mistakes [26]. In fact, algorithms are biased, and in certain cases, they might make mistakes and lead to wrong decisions – as humans might do. This characteristic of AI has some important organizational consequences. IAs also reported by de Bruijn, Warnier, & Janssen [4], these characteristics of AI go beyond merely technical challenges but brings the need for a new, dynamic environment characterized by a diffuse acceptance of machine biases. As also reported by our cases, for working in an environment with these characteristics, public organizations should be properly structured in terms of procedures, roles, rules, tasks, etc. Hence, a whole class of organizational challenges needs to be considered by researchers, practitioners, and policymakers. This evidence confirms and enlarges recent findings that highlight the importance of bureaucrat in training the algorithm, hence, the need to introduce new tasks and duties for public servants [7, 14].

While organizational and cultural challenges have been identified as extremely relevant, and AI trustworthiness has been identified as an umbrella challenge, all the other classes identified by Wirtz et al. [36] remain relevant and reflect the empirical data collected (Proposition 1, Proposition 2 and Proposition 3).

The third novelty of our framework is the introduction of the distinction between the piloting and the deployment phases. While the class of challenges is the same, there is an evident difference in the approach and barriers in the two phases. Piloting an AI solution requires the creation of the proper condition for AI to be tested and to grow, such as the creation of a proper, large, and non-biased database, a testing process for ensuring trustworthiness, and a proper procurement process that ensures explainability. On the other hand, the approach to effectively introducing an AI system into daily routines is completely different. For example, maintenance is a heavy and time-consuming process, as the system needs to be continuously retrained and improved to avoid its degradation. Moreover, a general awareness of AI is needed, as the AI system can fail, and public servants need to properly interpret the results and act to challenge the system when necessary. A complete overview of the different challenges is reported in Table 2.

6 CONCLUSIONS AND FUTURE RESEARCH

Through eight in-depth case studies, the current research offers some novel, on-field insights on how AI is developed and implemented in public settings building on the framework proposed by Wirtz et al. [36] that dived the challenges into four classes. Our results challenge the existing model, confirm the applicability of the challenges in real-life contexts but also add novel elements to it, and (i) highlight the need to add a new class of challenges, the organizational one, (ii) consider AI ethics and trustworthiness as an umbrella challenge that cut across all the others, (iii) include a clear distinction between the piloting and deployment phase, where different challenges apply. Finally, the study offers some details on the main challenges faced by the cases analyzed.

In addition, the results enrich the current body of knowledge, which is missing some concrete, on-field contribution that creates knowledge starting from real-life settings, and opens several paths for further research. First, scholars could start considering AI not only as an innovation topic but also as a transformation one. In other words, scholars could consider two paths of research on AI: the innovation path exploring innovative, unknown possibilities that AI can bring to the public sector and the transformation path, looking at how current, mature AI solutions are transforming and need to transform the public sector.

Overall, our research aims at shedding light on this second path. However, the study is not exempt from several limitations: given the limited number of cases analyzed, the insights need to be confirmed by further research, both qualitative for better detail of the list of challenges towards a comprehensive and saturated list and quantitative for testing the magnitude of those challenges.

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