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RESEARCH ARTICLE

A value-chain perspective of artificial intelligence in public services

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Abstract

The advent of generative Artificial Intelligence (AI), popularized through ChatGPT and other similar platforms, has in recent years become a focal point for governments' ambitions to enhance the quality of public services and policy. Whilst governments have been using technological systems and platform for decades, such as big data analytics and automated decision-making, recent developments in generative AI, and its perceived capability of simulating human thought, is accompanied by both opportunity and risk. AI is not only significant for the future delivery public services, it also constitutes a challenge to how we define and prioritize public value. This article uses a 'value-chain approach' to explore and summarize the immediate experiences of the use of AI in public service contexts, and highlights some of the hurdles and challenges associated with the adoption of this technology. While value-chain approaches are traditionally associated with identifying sequences in a (commercial) production (manufacturing) process - as an analytical tool to realize desired outcomes - recent literature has successfully applied this approach to public service contexts, including in relation to digital service delivery and public policymaking. This article provides an opportunity to reflect on some of the promises and pitfalls associated with this technology, as well as presenting some elements for better diagnostic tools used for forecasting and evaluating digital platforms and systems utilizing generative AI in a more systematic manner. This includes value issues associated with data quality, intellectual property, surveillance, privacy, and transparency. The article also highlights issues around trade-offs between different values, and in doing so, argues that assessing the interlinked relationship between values and digital services are key to understanding the future nature of public service delivery.

Keywords Artificial intelligence · Value-chain · Public service · Digital service delivery

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1 Introduction

Since the release of the first version of Chat GPT in late 2022, governments from across the world have rushed to make investments in generative Artificial Intelligence (AI) (Salah et al., 2026). The promise of technological systems and platforms replicating human senses and functions has generated technological hype in the public sector like the ones we witnessed with Internet of Things, quantum computing and blockchain technologies. Propelled by online news and the financial incentives of those involved in promoting innovation and entrepreneurship, new technological innovations are promoted as game changers in the economy and society (Funk, 2019). AI has become a symbol for a more productive, accurate and resource efficient public administration driven by technology (Mergel et al., 2024). However, unlike previous waves of technological innovation, the AI trend has quickly generated detractors with concerns raised about the efficacy of algorithms. Ethical concerns have been raised by academics (Bannister & Connolly, 2020), and by both national governments (van Noordt & Misuraca, 2022) and transnational organisations (OECD, 2019; European Union, 2024). Discourse around the prospects and challenges/risks are established narratives of new technologies in government (Gasco-Hernandez & Valle-Cruz, 2025). Amongst the promises made, are service enhancements (Chen et al., 2024), increased accessibility and personalized services to citizens((Medaglia et al., 2023), and higher productivity (Zuiderwijk et al., 2021). Among the pitfalls are issues around data quality and accuracy (Boyd & Crawford, 2012); privacy and surveillance (Zuboff, 2019; Manheim & Kaplan, 2019); bias (Favaretto et al., 2019; Kordzadeh & Ghasemaghaei, 2022); accountability (Shah, 2018) and transparency (Bannister & Connolly, 2020). While these challenges and risks could be controlled and mitigated by national and regional regulatory bodies, modern networked practices with cloud services are reducing national governing and regulatory capability. Rather than repeating the dichotomous and normative promises-versus-pitfalls narrative, this article takes a *value-chain approach* to understanding AI in public services and policy. Here, the deployment of AI platforms and practices are assessed through the lens of 'public service value' (Box, 2014) as a vehicle to aid understanding and to highlight both the benefits and challenges offered by technological innovation. The research question we pose is: *how are values in public services enhanced and challenged with a public value chain approach?*

Our value chain approach allows us to break down the production process into a series of interlinked activities, and in doing so it becomes easier to identify where value is created, who derives this value, and if links in the chain are not performing adequately, creating problems, or hindering the creation of value. The value chain approach also alerts us to the challenges of all-encompassing attempts to regulate and govern AI practices in the public sector.

Following this introduction, we define and juxtapose the concepts of AI as they relate to public services and policy and seek to align them to our research objective. Section three, then presents our analytical lens of the value-chain as a tool for distinguishing between the different stages of AI use. In section four, we apply the value-chain as a 'roadmap' for reviewing the extant literature, and finally, in section five, we discuss our review in light of our research objective.

2 Artificial intelligence and public services

AI is one of those hyped all-encompassing concepts that tells us more about future promises than what can actually be achieved in practice (Floridi, 2024), and the public sector has been here before, in relation to the technological promises of 'big data' and 'smart cities' for example. By definition, these emerging technologies are disruptive and create situations where the full individual and societal impacts and consequences cannot be known. The most recent published literature on AI in public services reveal a focus on conceptual issues, such as the perceived nature of the technology and potential challenges, with a lack of attention paid to actual empirical studies of the phenomenon (Medaglia et al., 2023).

Importantly, any discussion about AI in public services must have as a starting point a recognition that there is not a consensus on what constitutes AI, and what does not. The borderline between previous automated systems and new generative AI systems is not clear-cut. This is emphasized in a recent OECD report:

> An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment. (OECD, 2024, n.d.)

Without entering a philosophical discussion about what constitutes intelligence and whether machines will be able to replicate human cognitive functions partly or fully, we can identify some commonly occurring narratives around the use of AI in public services. First, the current and future opportunities embedded in AI is not a rupture in our history, but part of the digital government trajectory which has swept the world since the 1950s (Oravec, 2019; Henman, 2020). Associated technologies, such as voice recognition, decision-making support systems and bots have been around for decades. Many of the pros and cons attributed to generative AI, such as, for example, autonomous decision-making, have been debated in both academic and policy circles for decades (Zhuang et al., 2017). What makes the current discourse different is that new AI technologies are assumed not to follow a pre-programmed conditional sequence of orders (*if-then*) but also include machine learning, neural network, and large language models (LLMs, which approximate the alleged more advanced cognitive functionalities). This includes foundation models (general purpose systems using raw data), probabilistic outputs (answers based on statistical likelihood), and emergent capabilities where the 'skills' of machines or systems are being spontaneously upscaled because of the algorithmic training process. Unlike the more elementary forms of AI, recent models have (based on algorithms) the capacity to perform much more complex functions replacing not only acquired skills, but also to autonomously reproduce human sense-making. Or to put it differently, moving from *generative AI* (producing content) to making multi-step decisions and reasoning with other agents, which is being labelled *agentic AI*. While the list of challenges and risks is long (as set out below), the potential value of autonomous and machine learning systems ultimately replacing human cognitive functions come with several benefits. Among them we find more accurate and less biased decisions, enhanced efficiency, cost savings, reduced corruption, replacement of human resources and improved analysis of policy (Valle-Cruz et al., 2019). Also, based on past experiences from less advanced automated decision-making technologies, such as, the Australian Robodebt system or the British Post Office system (Christie, 2020), certain challenges can be predicted and expected. Unlike the previous diffusion of digital technologies in public services, the attention given to risks and challenges can be observed from the outset. This in turn, has generated policy initiatives seeking to manage AI through regulation and ethics. To date, these measures have typically focussed on 'soft' instruments which seek to increase awareness, improve data quality, establish ethical AI principles and assurance frameworks, often envisaging that the AI industry will develop technical standards and assurance frameworks to overcome the perceived various challenges and risks (van Noordt et al., 2024). It is also important to recognise that the roll out of AI in public services is very 'context' specific and is shaped by norms and expectations surrounding nature and value of public services and policy, the technology should not be divorced from the context in which it is being deployed. Whilst public management commentators have been arguing that we are entering a more 'relational' and 'citizen-centred' phase of public service delivery, the harsh reality of managerialist and controlling reasoning still prevails in most industrialized democracies (Clarke & Newman, 2025). Unsurprisingly, the implementation of AI has been shaped by this context and has mainly been applied as a tool to solve structural issues within areas such as sustainability, public services and transport, and to a lesser extent in education and health care (Sharma et al., 2020; De Souza et al., 2020). In other countries, Ai has been utilized for the purposes of surveillance and control, with perhaps the Chinese system of social credits being the most notable example Kostka & Bogs (2026).

3 The value-chain approach

Although the Value-Chain Approach has traditionally been associated with the commercial sector, there are numerous examples of its application in relation to public service value chains (Heintzman & Marson, 2005), and the approach has become increasingly popular for public service strategy, albeit with a very narrow focus on sectors or functions (Cardoso et al., 2022). The public service variant of the value-chain goes beyond conceptualizing value as producer and/or consumer benefit, and considers other forms of value, such as societal good. Additionally, the public service-oriented value-chain can be seen to follow a 'public service logic' (Osborne et al., 2022). This 'logic' implies that there are multiple types of value which are created at multiple points in the value-chain and that this process is a co-creating process which engages multiple actors in the process and where each actor can function as both a supplier and an end-user (Sienkiewicz-Małyjurek and Szymczak, 2024). The value chain approach is a simple model that identifies a series of essential sequential steps in the creation and delivery of a good or service. In the commercial sector this approach is usually associated with satisfying consumer demand, and thereby creating value, whereas in a governmental context it can be applied to stages of policy formulation and service delivery implementation, and through doing so creates public value. Furthermore, it is essential to address that the value we are discussing in this article is referring to what the academic literature is referring to as public value rather than the process where ideas and materials are turned into products or services which can be commercialized and traded in a marketplace (Porter, 1985). Notwithstanding being a contested concept, we will in the remainder define public value as three dimensions which citizens value: services, outcomes and trust (Kelly et al., 2002). Our point is that the dimensions of values can be identified at different stages or steps of a process. These steps are illustrated in Fig. 1 and compare the generic value chain with that applicable to public services.

Such models are simple interpretations of real life and should be seen as basic heuristic devices to help understand complex societal situations. They are particularly useful in that they can help identify different actors, actions, and activities in different stages in the chain, and from there it is possible to explore their motivations and other vested interests. In this respect, the value-chain is not a neutral process (Mayer et al., 2017). The value-chain can also be reconstructed around a technological system, in this case AI. In such cases, the value-chain extracts societal and/or individual value from processes associated with collecting, processing, and using information to deliver better policy and services (Curry, 2016). In the specific case of AI, the enhancement of values is probably more perceived in terms of better services, while we are more likely to witness negative impacts on outcome and trust in light of the new technological promises. A simple linear version of the value chain associated with AI is incorporated into Fig. 1.

However, what is unique about the AI value chain is that it is too simplistic to present it as a linear model. Both Janssen et al. (2022) and Pahune et al. (2025) are addressing similar issues around values and generative AI with a special attention to governance, and more precisely data governance through different steps of life cycles of data. While they make a valuable contribution to literature, we do not agree that

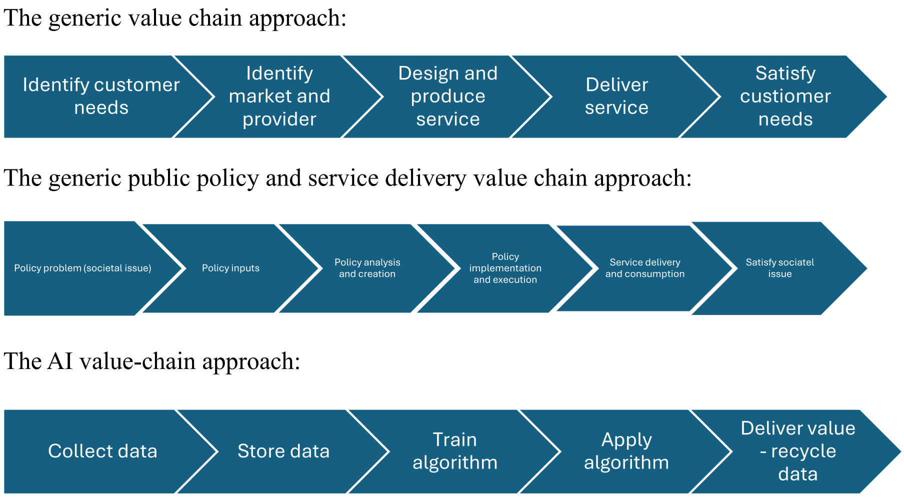
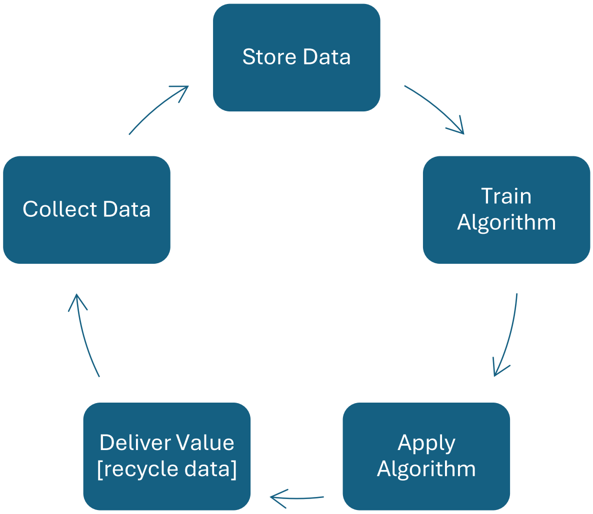


Fig. 1 The value-chain approach

Fig. 2 The AI value-chain approach



you can reduce the steps to life-cycles with a well-defined beginning and an end. The crucial difference between previous digital technologies and generative AI is that there is a value output from any step in the generative AI process is recycled and goes back into the chain contributing to new data or to the calibration of the algorithm. With AI, data is constantly recycled in a continuous learning process (Fischer & Piskorz-Ryń, 2021). In this respect, the AI value chain is better illustrated as a cyclical process and not a linear one as presented in Fig. 2. Conceptualizing it in this way allows us to highlight the way data process and actors are interrelated and integrated, and how this affects values. Within this cyclical process there are 5 stages in the cycle.

3.1 Value-chain step 1: Data collection

3.1.1 Quality of data

The data collection phase is pivotal for attaining positive outcomes via the use of AI. For both public services and policy, different data sets are likely to have several different stakeholders involved in the collection process and are likely to have been created for fundamentally different initial purposes. First, there are existing historical administrative data sets, stored and maintained by public authorities for economic and social purposes, these would include, for example, census data, tax records, welfare benefits and health data. This data often incorporates unique personal identifiers, such as tax or social insurance identity numbers. It is regularly updated, compulsory and covers (in principle) all residents within a specific jurisdiction. Second, there is data that has been voluntarily shared by individual data subjects, for example through transactions with public authorities, such as for library cards, drivers' licenses and building permits (etc.). This would include digital transactions for making purchases, the tracking of electronic building entry, vehicle and information systems, and social media activity. Third, there is data collected by non-public agents which have been surrendered to public authorities voluntarily (or non-voluntarily). This includes, for example, data from banks and financial institutions, insurance companies, or car mechanics conducting vehicle maintenance checks. It also includes services where private or not-for-profit contractors/operators deliver services to citizens, such as day-care, health and social services (etc.). Finally, there are datasets where a public sector agent has procured data collected and collaged by a private actor, which is then repurposed for public service use. An example here would be local governments procuring location data from telecom providers with the aim of, for example, public transport demand modelling, or tracing mobility during a pandemic. Combined, these data sets contribute to the creation of public value via AI, but their origins mean that they are fundamentally quite different.

There are very high expectations about the accuracy and completeness of data derived from the first two data categories noted above. Tax records, election registers, health records, and passport identities are largely assumed to very accurate with only limited numbers of inaccuracies. Their completeness, integrity and accuracy make them important building blocks for AI processes.

The latter two data sources are not compelled to be as accurate and are much more likely to have omissions and errors. Here there could be data quality issues, such as duplicate data, inconsistent data, missing data, and incorrect data (Janssen et al., 2022; Gong et al., 2023). Moreover, in relation to social media data sources, there are few incentives for private sector actors to value quality and fairness, and they may change both sampling and algorithmic processes if it is deemed more lucrative to do so. Indeed, many AI systems often distort data by 'ruminating' it as the data subjects are making decisions based on recommendations suggested by algorithms, which in turn is based on historical data. An example of this practice is when users are suggested choices based on automated algorithms often linked to historically obsolete data ('*longitudinal data fallacy*') (McAllister, 2018). There is also a tendency for sampling bias as certain features of the data are collected more readily than others, thereby contributing to issues about the quality of the data contributed by the data subjects (Haklay, 2010).

3.1.2 Biased data

A variety of biases arise from the data collection side of AI value chains. These include, among others, biases in measurement, representation, aggregation, and sampling (Ntoutsi et al., 2020).

In relation to representation and selection, it is well understood that there are inequalities in use of and access to digital technologies by data subjects, which in turn creates a bias in automated processes (Alon-Barkat & Busuioc, 2023). This is evidenced by numerous studies of users of emerging technologies and highlights the skills required to master new technological platforms, as well as physical access, such as access to broadband and the Internet (DiMaggio et al., 2001; DiMaggio & Hargittai, 2001). Certain demographic factors, such as age and wealth, are affecting the representation of the data. Age is often argued to be the most important demographic factor (v. Deursen et al., 2015; Friemel, 2016) with older age groups often absent in attempts to retrieve representative digital data for policy analysis. This age bias does not mean younger users' usage of technology is more valid or representative of the population. Many younger users have limitations in how they use new digital technologies and lack both the skill and capacity to be fully 'native' (Bennett & Maton, 2010; Kirschner & De Bruyckere, 2017). Also, despite a massive proliferation of mobile devices there are still huge socio-economic inequalities evident in many countries (Dodel, 2024), which again impacts certain groups' access to, and use of, this technology. These inequalities and biases are reflected in the use - the 'individual production' of data - the individual production of content and the 'digital footprints' which are to be harvested for analytical purposes (Hargittai, 2007). Finally, in relation to commercial actors and their data collection methods, it is argued that they are usually not interested in capturing the views and behaviour of less prosperous socio-economic groups as they do not represent attractive customer groups, and these groups may be of considerable interest to public policymakers and services (Neumann et al., 2024).

In terms of aggregation biases, there is a wide-spread belief that AI is going to revolutionize processes associated with undertaking research and predicting human behaviour (González-Bailón, 2013; Janssen & Kuk, 2016). With enough data the numbers will '*speak for themselves*' and if totalities can be analyzed then there is no need for theories, frameworks, and models (v.d. Voort et al., 2019). But data does not speak for itself - 'someone' is always formulating the questions, organizing the material, conducting the analysis, and interpreting the results. As expressed in the classical aphorism regarding research methods – 'correlation is not causation'. Big data needs to be supplemented with small data (Kitchin, 2014) and basic social science. Another aspect of the representation bias is when values become conflated with preferences. There is never a single value dominating any society, but with AI most preferences, but an aggregated composite of the data subjects' preferences can easily become interpreted as the dominant value, which in turn may be used for policymaking (Baum, 2024).

3.1.3 Privacy and consent

Although privacy constitutes prominent challenge at the usage stage of AI value chain (see for example Andreotta et al., 2022 for a discussion of privacy issues and consent), the data collection phase exhibits a variety of challenges pertaining to the privacy of data subjects. Given the multitude of data sources large quantities of data are being routinely collected without informed consent, although the GDPR under the EU provides a global minimum standard for informed consent of personal data (Breen et al., 2020). This issue is not unique to AI and historically dates to the early use of computers in the public sector. Still, there are substantial risks associated with the 'over-collection' of data causing potential risks in terms of data breaches and the (re)identification and profiling of individual citizens at a later stage in the value chain. This has been previously observed in the case of video surveillance cameras (Webster, 2009; Björklund & Svenonius, 2013). However, unlike other forms of technologically enabled practices in modern society, the contemporary privacy paradigm of 'privacy self-management' (Solove, 2013) or 'notice-and-consent' is unattainable in an AI context given the multitude of sensory devices, multiple sources for data collection and indefinite possibilities for future data processes. So, while it is possible to notify citizens about some of the sources for data collection, for example by using 'surveillance cameras in operation' signage, it is difficult to envision a public sector context where individuals would, or could, give informed consent to the vast array of data being collected by different devices and platforms, not to mention the repurposing and reuse of data sets. In this respect, some of these new devices and platforms, including the IoT and the data processes they allow, appear to be at odds with basic data protection principles enshrined in European and national data protection legislation (Maple, 2017; Loideain, 2019). The privacy risks associated with data usage are revisited in Sect. 4.3.

3.2 Value chain step 2: Data storage

3.2.1 Security

Problems associated with data security are exaggerated by increased volumes of data and can be evidenced by the increasing frequency of large-scale data breaches, as well as the use of remote cloud storage (Singh et al., 2016; Kumar & Goyal, 2019; Yang et al., 2020). Challenges relating to securing data that is resilient to tampering, malicious insiders, data loss, system failure, and data breaches are magnified in the big data context (Ismagilova et al., 2022). Arguably, one of the most important challenges is how to identify, isolate and protect sensitive personal information in heterogenous data sets (Elmaghraby & Losavio, 2014). The widespread use of cloud computing, although not strictly a perquisite for AI, has amplified this concern. What data should be placed in clouds, and how should the public sector procure cloud services (Gleeson & Walden, 2016)?

3.2.2 Access and transparency

Any discussion about access to stored data is also a discussion about the relationship between, and status of, the public and private sector organizations involved in storing and protecting data for AI purposes. The ultimate responsibility for collecting and storing data is likely to be shared between public sector actors (local governments, government agencies, utility providers, law enforcement agents, and other public service providers, etc.) and several private actors (social media companies, financial institutions, data brokers, cloud providers and telecoms companies, etc.). To realize the purported benefits of AI there needs to be strong relationships between these actors and efficient technical data exchange between the organizations and technological platforms and data sources involved (Johnson et al., 2017; Herzog, 2021). These practices raise several issues - about the ability to combine heterogenous data sets whilst ensuring data quality and integrity (Dasu, 2013; Bertino et al., 2019). Furthermore, questions are being asked about whether the sharing of public service data with private companies implies that the public sector organization renounces its responsibility for future breaches and ethical standards (Yang & Maxwell, 2011) and whether norms and practices in private sector companies in this area matches the standards of the public sector (Campion et al., 2022).

There are also issues whether a private organization, whose data sets have emerged from public service sources, can deny others access to them, claim copyright, commercialize it and sell it back to the public sector. Some of these issues touch upon the global movement for 'open government data' in which there is an underlying assumption that increased access to government data by default is a 'good thing' and will provide for greater transparency, better data use and commercial opportunity. As Janssen et al., (2022) argue, there are several myths concerning the potential to create public value from making government data accessible. Most important, data containing sensitive information is not suitable for general publication as it not only violates basic data protection principles but can also be harmful for individual citizens if they are made public, for example in relation to protected identities, health, financial and lifestyle information.

3.3 Value chain step 3: Training the algorithm

3.3.1 Transparency

Precise prediction and the reliability of the algorithms represent the 'holy grail' of AI. However, to be successful, the algorithm needs to be fed ('trained') with not only large quantities of relevant and accurate data but also being devised clear objectives. This is one of the key challenges of AI in the public sector. First, when designing an algorithm, the computer and/or data scientists and their organizations retain the privilege of formulating the purpose of the data process. Algorithms are part of wider socio-technical assemblages (Kitchin, 2014) and construct, reinstate and devise regimes of power and knowledge (Kushner, 2021). In other words, the process of devising algorithms can be expected to reinforce subtle institutional and historical biases reflecting the context in which the actors are operating. These negative sides of the learning element are perpetuated by the absence and dearth of feedback mechanisms. From a public sector perspective, we have observed (at least) two types of issues. First, that data flow between the private and the public sector adhering to different institutional logics where commercial actors are driven by a commercial logic while a service (or a compliance) orientated logic can be observed among public service providers, As in much of the digitalization of government, the outsourcing of the design of digital systems has resulted in a more consumerist agenda reliant on and aligned with algorithms producing predictions about consumer behaviour (Löfgren, 2020).

Second, there is a mushrooming academic literature and empirical research highlighting the ways in which algorithms create unanticipated and biased outcomes particularly in policing (Meijer et al., 2021). High profile examples of algorithmic bias in the law-and-order arena alone include racial bias embedded in facial recognition software in policing (Janssen & Kuk, 2016), bias targeting the 'usual suspects' in predictive policing applications (Meijer & Wessels, 2019), and in algorithms assessing an individual's risk of reoffending (Andrews, 2018).

While biases are inevitable, the lack of transparency regarding the design process is something which has been highlighted not only in academic literature, but also in proposals to ethical guidelines and risk assurance frameworks (Coglianese & Lehr, 2019).

3.4 Value chain step 4: Data analysis and usage

3.4.1 Lack of standards

At the analysis stage of the value chain there is an array of issues relating to the different technical, organizational, semantic, and legal standards of the organizations and technologies involved. The core premise of AI in government is that different and often disparate data sets can be combined in new ways using algorithms to provide new insights and services. In government, this may include data relating to public transport flows, social media activities and sensory devices, which can be used to provide rich insights in current events. Despite this being one of the core premises of AI, and well-known to information system scholars (Novakouski & Lewis, 2012), the ability to combine diverse forms and sources of data is extremely challenging and often goes beyond the abilities of existing data integration technology (Sivarajah et al., 2017). This is not only a question of technical and semantic issues, but also a question of organizational, political, and legal differences pertaining to the use of different data sets. For example, in a public sector context, policies (and/or inadequate or missing policies) determine the possibility of achieving joint standards in information architecture, the possibility for using algorithms and for planning for consequences and impacts (Yang & Maxwell, 2011).

3.4.2 Intellectual property

In the final stage of the value chain there are several copyright issues involved with AI in the public sector. Many of these issues are not new, but pertain to existing legal disputes about copyrighting software, source code, algorithms, and databases (Smits & Borghuis, 2022). However, there are a couple of specific issues connected to AI. Firstly, the strength of data analytics in our space rests on the possibility to combine multiple data sets. Whilst the ownership of the raw data is normally undisputed with most jurisdictions seeing open data as a key to public values, the question of who owns and controls learning-based data sets is not always as clear (Marcowitz-Bitton, 2015). Governments operate with different types of licenses balancing open data policies and government ownership of intellectual property. Additionally, there is an issue whether private sector actors can commercialize data based on generative AI from the public sector for purposes not directly generating public values. This issue is aligned with the earlier discussion about open government data and the prospect of the sharing of government administrative and service data with non-government actors. It is also related to the broader issue of the ownership of personal data generated by digital platforms, where the data is clearly generated by users.

A reverse version of this argument is often raised in relation to the state's surveillance capacity and whether agencies of the state have the right to trawl through personal information imbedded in commercial data sets that have been created as part of a specific architecture of user generated data. Whilst most individuals appear to accept a trade-off between sharing personal data in exchange for free access to social media platforms, it remains possible to imagine some sort of redistribution mechanism for user-generated data (Smith et al., 2012).

3.4.3 Privacy and surveillance

Although the protection of individual privacy is pronounced throughout the value chain of AI, it is perhaps at the end of the value chain that the most prominent concerns arise. Proponents of freely collecting and analyzing personal data often encourage the myth that because big data is aggregated data, and big in the sense of containing large volumes, it is therefore by default anonymized. However, re-identification is recognized as constituting a genuine threat to individual privacy (Curzon et al., 2021) and is not technically difficult to achieve (Ohm, 2010) as exemplified in Stutzman et al. (2012). While unique identifiers, such as full names, may be erased from the data set, there are normally other unique identifiers, such as residency, workplace, age, shopping habits, etc., being sufficient to identify someone.

A second set of issues concerns repurpose of data which has been collected for a specific purpose. A core principle in most privacy and data-protection regulation is to inform the data subject about the purpose for which the data has been collected and to secure consent when asking individuals to share information with the organization collecting data. The whole point with AI in the public sector is to maximize the volume of data to increase the value of the data set. This raises issues about how to define 'public' and 'open' data, and how consent is observed, informed, and realized. Boyd and Crawford note in relation to the use of data: '*just because it is accessible does not make it ethical*' (2012:671). A prime example would be the use and reuse of social media data in public service contexts. Social media data is readily available, without prior permission, because consent for its use is embedded in service user agreements. This despite most social media data being personal data and consequently governed by data protection principles. Further to this, any use of data generated in social media raises questions about who will be accountable for service failures and data breaches.

3.4.4 Accountability

One of the more discussed issues when AI in the public sector is the lack of accountability when technology is used for decision-making whether giving advice (recommendations') or making administrative decisions (Adensamer et al., 2021). Contrary to manual processes in government where the relationships between official and citizens are codified through legislative sources and codes of conduct standards, where there is an expectation that decision-makers in the public sector are capable of explaining and justifying decisions, and where there is a chain of command with someone being ultimately responsible, the context is much more blurred whenever generative AI systems have replaced human decisionmakers. Why was this decision made, and who to blame when a machine is making the wrong decisions? Particularly in cases where human oversight is either weak or absent. Compared to some of the other issues in this paper, this is an area where we have empirical testimonies. Rather than being responsible, accountability refers to being called to account, that is, to answer for the actions. Something which cannot be delegated or transferred to another party. The problem is that it is difficult to ascertain the reasoning behind decisions made by a machine only partly inferring external decision rules, and even more opaque whether ‘bad’ decisions can be attributed to (human) individuals. The failures we have observed particularly cover social welfare (e.g., interventions in cases of overuse of social benefits) and the justice systems (e.g., biased or inaccurate profiling of demographic groups as part of crime prevention) (Yuan & Chen, 2025). The typical issues reported in this respect have been the lack of transparency (e.g., how did the algorithm end up with this decision?), human biases being transferred to the AI systems, and floating responsibilities between designers/developers, suppliers, administrative users and the political masters.

4 Concluding discussion

The value chain approach applied in this article illustrates that the challenges of AI in public sector contexts differ depending on the stage of the value chain. In this respect, it is a useful analytical tool which can be used to unpick some of the challenges ahead. Notably, issues around privacy are pronounced throughout the whole process and should be central to all discussions about extending the use of AI. Moreover, what this review also demonstrates is that the different concerns have little to do with technological maturity or technological capability. It is not just technology that causes concern, it is the naïve belief that technological advances are neutral and disregard political, social, and economic institutions and norms.

The application of the value chain to the use of AI in the public sector highlights the intimate intertwined relationship between commercial and public sector entities. The new digital sphere includes both hybrid data processes and the merging of values, processes, and institutions. The binary public-private divide no longer exists, and public service and policy outcomes are the result of the interaction of multiple organizations with competing motivations and values. The extent to which ‘value’ can be created for all parties without detriment to the other seems unlikely, given the challenges raised in this article. Furthermore, we have not touched upon the interrelationship between values including conflicts and trade-offs between them. Like other forms of emerging technologies within the public sector, there seems to be an almost generic conflict between enhancing efficiency and establishing guardrails to protect privacy and establish lines of accountability.

Interestingly, the value chain approach highlights a range of issues and challenges at every stage or link in the process, especially where the value chain relates to a governmental context. The challenges described in this article are not meant as an argument to reject the potential of AI. Rather, they point to the need for governance structures and risk assurance framework for managing AI in the public interest. The application of these platforms takes place in a highly fragmented space where public and private actors are assumed to collaborate and harvest value from the data, in order to deliver better public services and policy. To some extent this space is already well regulated, by data protection laws, intellectual property rights, impact assessments and data sharing protocols, However, there are some significant gaps in relation to responsibility and accountability. Rather than advocating more formal regulation of this new sphere, where the public and private sectors are intimately meshed, which may or may not be effective, attention could be focused on areas and practices which could be improved, which in turn could lead to more 'value' being extracted from big data whilst at the same time protecting and enhancing core public values. First, one of the underlying themes of this review is how both public and private sector actors interact in AI in the public sector, and that the two sectors are interdependent. While the technical challenges can be overcome, the real issues are how to deal with organizational differences, governance, and legal issues. Formal national and transnational regulation is slowly emerging but is still embryonic and predominantly characterized by 'soft' policy instruments (van Noordt et al., 2024) or constitutes a patchwork of different pieces of legislation covering different aspects. In this context, it is worth noting that overemphasising the technical side of generative AI may draw attention away from the bigger picture. Some of the challenges and risks reviewed are not solely attributed to technology but are embedded in existing structures and processes in government. Second, the discourse around AI needs to move beyond the speculative and technological determinist space of science fiction and into a discussion about the future of public services and policymaking. To date, most of the hyperbole around AI has created a fragmented race where individual government agencies implement AI systems and platforms with little attention paid to precautionary frameworks. This is more an issue of the maturity of the discourse as opposed to the maturity of the technology itself. It took eGovernment roughly ten years to abandon the utopian space in favour of a more 'sober', and perhaps more mundane, discussion about modern forms of public sector online service delivery. The argument here is not that AI is fatally flawed, rather that it needs to be understood in its institutional environment, alongside its impacts and consequences, if individual and societal value is to be realized. Such critical realism highlights the socio-technical integration of AI practices and how these are operationalized in a public sector context. In other words, the true value of AI cannot be solely understood in technical or commercial terms and is closely aligned to other organizational and institutional practices.

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