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A Public Values Perspective on the Application of Artificial Intelligence in Government Practices: A Synthesis of Case Studies

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A public values perspective on the application of Artificial Intelligence in government practices:

A synthesis of case studies

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ABSTRACT

The use of Artificial Intelligence (AI) by governments represents a radical transformation of governance, which has the potential for a lean government to provide personalised services that are efficient and cost-effective. This represents the next frontier of Digital-era governance (DEG), which is an extension of the traditional bureaucratic model representing digital manifestations of instrumental rationality. However, the use of AI also introduces new risks and ethical challenges (such as biased data, fairness, transparency, the surveillance state, and citizen behavioural control) that need to be addressed by governments. This chapter critiques DEG enabled by AI. The authors argue for adopting a public values perspective for managing AI ethical dilemmas. Through a cross-case analysis of 30 government AI implementations, four primary AI use cases are outlined. Furthermore, a conceptual model is developed that identifies relationships between AI ethical principles and public values as drivers of AI adoption by citizens. Finally, six propositions are outlined for future research.

Keywords: AI ethics, AI use case, AI adoption, digital-era governance model, public sector, public value management, new public management, qualitative synthesis

INTRODUCTION

The first wave of technological innovation in governments focussed on digitising back-office operations with the goals of efficiency and cost savings inspired by the New Public Management (NPM) reforms of the 1980s. NPM was driven by the neo-liberal agenda and critique of large bureaucratic structures associated with red tape and cumbersome processes (Bernier et al., 2015; Kamarck, 2004). However, technology took a backseat and was considered simply a tool for achieving managerialism. Succeeding this initial technology implementation which has had mixed results in meeting its innovation goals (Hung et al., 2006), the second wave driven by Artificial Intelligence (AI), however, is transforming the roles and functions of government. Often referred to as the next frontier of digital-era governance (DEG) (Dunleavy et al., 2006), this technologically centred model of governance enabled by AI has the potential for a lean government providing personalised services that are efficient and cost-effective. The use of AI also introduces new risks and ethical challenges such as biased data, fairness, transparency, the surveillance state, and citizen behavioural control (Ashok et al., 2022; Saura et al., 2021A; Ashok, 2018). Maintaining citizen trust and legitimacy of AI-driven governmental services and processes is vital more than ever for sustaining democratic processes (Janssen & van den Hoven, 2015).

The concept of AI, introduced by John McCarthy in 1956, is aimed at developing intelligent machines that can emulate human cognition autonomously (von Krogh, 2018; Washington, 2006). Following an enthusiastic start, progress stalled due to technical limitations; AI was limited to expert systems with specific applications (Haenlein & Kaplan, 2019). At the beginning of the 21st century, with advances in processing speeds and storage, and decreasing computational costs, interest in AI grew exponentially (Haenlein & Kaplan, 2019; von Krogh, 2018). Brynjolfsson and McAfee (2014, p. 7) claim this renewed interest as the "second machine age" where machines are taking over cognitive human tasks.

Dwivedi et al. (2021) discuss the terminological challenges associated with defining AI. The meaning of artificial vs natural is derived from the epistemological assumptions of objectivist or constructivist ideas and scientists and philosophers still do not have a good grasp of what intelligence entails (Ibid.). Following Dwivedi et al. (2021, p. 24) "institutional hybrid" approach, AI for this chapter is defined as emerging technologies that enable machines to "learn, adapt, be creative and solve problems" autonomously (Rosa et al., 2016, p. 6). Scholars (Raisch & Krakowski, 2020; Sousa et al., 2019; von Krogh, 2018) generally agree on the three components of AI: input, often big data; task processing algorithms; and output, either digital or physical.

The primary applications of AI in government are process automation, virtual agents, predictive analytics, resource management, and threat intelligence and security (Ojo et al., 2019; Wirtz et al., 2018). The associated benefits include efficiencies, accelerated processing of cases, workforce redistribution to productive tasks, and enhancing satisfaction and trust in public authorities (Susar & Aquaro, 2019; Wirtz & Müller, 2018). AI represents radical innovation transforming internal organisational structures and introducing new governance models (Ashok et al., 2016). However, the use of AI for making policy decisions is accompanied by ethical dilemmas of fairness, transparency of black-box algorithms, privacy concerns, and respect for human rights (Ashok et al., 2022; Ribeiro-Navarrete et al., 2021; Wirtz et al., 2018). Kuziemski and Misuraca (2020) and Helbing et al. (2019) discuss externalities from the use of AI leading to the detriment of human dignity and well-being such as mass surveillance, profiling, and nudging for incentivising compliance with government direction akin to programming citizens. Mehr et al. (2017) caution AI should not be used solely for its innovation potential but adapted towards a broader social development goal. Citizens expect responsive governments able to meet their personalised needs with the adoption of AI-driven governmental services. The level of trust and legitimacy of government determines expectations of privacy and a fair, equitable, and secure outcome. Erosion of this trust with mismanagement of ethical issues undermines democratic institutions and impacts adoption.

The ethical design of digital technologies is a contemporaneous issue debated in academia and policy (Saura et al., 2021A). The use of AI further intensifies this debate especially in terms of biased data having a detrimental effect on its trustworthiness (Janssen et al., 2020) and consequently marginalising already most at-risk populations. AI has also been discussed from the perspective of maintaining power and control than as an agent for societal advancement (Crawford, 2021). Motivated by these growing concerns, governments and technology companies have published several ethical guidelines for the development of AI solutions. Floridi and Cowls (2019, pp. 6-8) conducted a comparative analysis of leading AI ethical frameworks and developed five AI principles: 'beneficence', 'non-maleficence', 'autonomy', 'justice', and 'explicability'. Jobin et al. (2019)'s analysis of global AI guidelines shows a convergence of these high-level AI principles but divergence on interpretation and application. There is still a large gap in the literature on how to use these macro-level principles during the design and implementation of AI. Ashok et al. (2022) discuss AI ethical impact analysis, balancing AI ethical considerations with societal impact, a critical topic of research and currently a significant gap in literature and policy. In the context of the government's use of AI, these ethical principles need to be front and centre towards balancing societal goals against economic and political objectives.

The literature on the use of AI within governments and its transformation has received far less attention than the role of government as a regulator of these technologies (Kuziemski & Misuraca, 2020; Valle-Cruz et al., 2019). Wirtz et al. (2018)'s literature review of AI in the public sector shows scarce research on AI applications and challenges. The factors affecting AI adoption in governments have not been tested (Valle-Cruz et al., 2019). Scholars (Alsheibani et al., 2018; Jankin et al., 2018; Misuraca et al., 2020) have called for research to understand the adoption of AI-driven government services.

In light of these literature gaps, this chapter explores AI use in governments and argues for an adoption model balancing broader public interests against the ethical risks of AI. The chapter seeks to explore two research questions:

RQ1: How is AI being used in governments?

RQ2: What are the factors that impact citizen adoption of AI-driven governmental services?

The next section critiques public administration paradigms and argues for adopting a Public Values Management (PVM) perspective for exploring the use of AI in governments. This is followed by a review of technology adoption models providing a theoretical basis for exploring citizen adoption of AI-driven governmental services. There is scant empirical evidence on how AI is being implemented in governments (Mikalef et al., 2019). Thus, the authors adopt a cross-case analysis method and through a systematic literature review identify thirty cases. A typology of AI use cases is developed and explicate the balance between AI ethics principles and public values as drivers of adoption by citizens. The resulting conceptual model extends the literature on the current technology adoption models within the context of AI in governments. The model also has practical implications providing a framework for exploring benefits and risks from the use of AI towards achieving citizen adoption.

LITERATURE REVIEW

Public Administration Paradigms

Weber's ideal-type bureaucracy, an embodiment of "techno-scientific" logic separating bureaucrats from political questions of morality and obtaining legitimacy through established laws of the land, assumed a dominant position in the twentieth century as the appropriate organisational design for managing modern and complex capitalist societies (Chris & Susan, 2018, p. 192; Courpasson & Clegg, 2016). Bureaucracy came to be seen as means of maintaining control over the masses and critiqued for elite bureaucrats assuming increasing decision-making power distancing citizens from democratic processes (Chris & Susan, 2018, p. 192). Such neo-liberal ideas garnered mainstream support in the 1970s with stagflation and oil crisis seen as failures of Keynesian policies. The popular discourse moved towards liberating individual entrepreneurial freedoms and limiting the role of the state as an "institutional framework … [to] guarantee … integrity of money … set up military, defence, legal structures … secure private property rights … functioning of markets" (Harvey, 2007, p. 2).

Neo-liberalism propagated decentralisation in public administration emboldened by the dominant discourse of market control as the superior form of organising evident from private sector success (Christensen et al., 2007; Hartley et al., 2013). This perception of antiquated hierarchical government structures characterised by inertia and red tape has persisted in practice and scholarship to this date (Perry & Rainey, 1988; Rainey & Bozeman, 2000).

A confluence of neo-liberalism and economic climate led to the set of reforms categorised under NPM beginning in the 1980s with successful political campaigns in the UK, US, and Canada highly critical of governmental bureaucracy (Bernier et al., 2015; Kamarck, 2004). However, following the limited success of NPM and concurrently technology assuming the dominant role of a social actor, two new paradigms are emerging, Public Value Management (PVM) and Digital-era Governance (DEG) (De Vries & Nemec, 2013; Dunleavy et al., 2006; Hood, 1991).

New Public Management (NPM)

NPM became the dominant public administration paradigm in the 1980s seen as a pragmatic synthesis of operating principles borrowed from private sector successes. The three main themes of NPM are "disaggregation" through splitting up of large governmental hierarchies, "competition" adopting marketisation of public services, and "incentivization" through empowering employees and rewarding performance-based management (Dunleavy et al., 2006, p. 470). The American reform movement by Osborne and Gaebler (1992) argued for downsizing public services by focussing on policy development and marketizing service delivery functions while Hood (1991, 1995) in the European context argued for improving the quality of public service delivery by adopting management practices but maintaining the central role of the government. These reforms introduced quasi-markets, managerialism, and performance management metrics (Hartley et al., 2013; Torfing, 2019).

Hood (1991) synthesises NPM critique in four main categories. First, the strong institutional character of the governments resisted cultural change from NPM. Parker (2000)'s examination of Australian public sector organizations supports this view. Notwithstanding a central mandate to adopt NPM, these agencies were resilient and continued to emphasise values of hierarchical and bureaucratic culture. Christensen et al. (2007) argue the inherent multifunctional conflict regarded as a systemic defect in NPM and resolved through disaggregation and marketisation principles is instead a core organisational trait in public administration that cannot be eliminated. Ashok et al. (2021) show organisational inertia driven by bureaucracy negatively impacts knowledge management practices adoption in UAE public sector despite a national agenda towards innovation and knowledge economy.

Second, public administration scholars (Bryhinets et al., 2020; Dunleavy et al., 2006; Rainey & Bozeman, 2000; Torfing, 2019) concur NPM was politically motivated than based on empirical evidence and has failed to deliver on its promises of reinvention. Dunleavy et al. (2006) argue NPM's performance and disaggregation principles damaged public service ethos and reduced citizens' engagement with government. Skålén (2004, p. 251) empirical research in Sweden contradicts NPM claims of performance-based pay summarising ''NPM creates heterogeneous, conflicting and fluid organizational identities, rather than the uniform and stable business identity it is supposed to." NPM led to unintentional consequences of "overbidding" and "free-riding" problems (Hartley et al., 2013, p. 823).

Third, NPM marketisation principles have been critiqued for the implicit assumption of the superiority of market control. Scholars argue pursuit of efficiency initially seen as means towards social goals became ends in themselves (Bannister & Connolly, 2014; Dunleavy et al., 2006; Harvey, 2007). Performance management goals compelled public managers to focus on specific short-term institutional goals while ignoring the broader vision of public service (Bryhinets et al., 2020).

Fourth, Hood (1991, p. 9) argues NPM's claims of "universality" were unfounded with different administrative values having varied implications on the administrative culture. NPM's focus on economic values has been detrimental to the pursuit of external societal goals with public administration becoming internally focused.

The first two critiques on the incongruity and adverse effects of applying market control principles to governments have led to a reversal of NPM changes since early 2000 (Dunleavy et al., 2006). The disaggregated agencies have been consolidated into coherent government-wide processes, however, performance management, marketisation, and incentivisation persist (Ibid.). The first wave of information technology (IT) implementations within the governments was driven by NPM principles of efficiency and cost savings (Cordella & Bonina, 2012). These projects failed to consider the critical importance of technology and its role in transformational change of governments and society at large, the narrative was centred on technology as a tool enabling managerial values (Dunleavy et al., 2006; Ashok, 2018). Ojo et al. (2019) contend NPM even worked against the digital transformation of government through outsourcing and failure of large IT implementations. With the current wave of digital transformation through AI, technology needs to be central and hence, a new paradigm of DEG is emerging.

Following the critiques on the NPM discourse of serving society exclusively through economic goals (Dunleavy et al., 2006) and the proliferation of AI inducing ethical dilemmas, the paradigm of PVM is emerging.

Digital-era Governance (DEG)

DEG encompasses "complex…changes, which have IT…at their centre, …[and] spread…in many more dimensions simultaneously than was the case with previous IT influences" (Dunleavy et al., 2006, p. 478). The vision of DEG is a lean and smarter state administration driven by big data and advanced analytics (Andrews, 2018). DEG represents a transformation change often described as the second wave of technological development and takes a step further from e-government in locating human-machine interactions at the core of government service delivery; citizens and private agents are governed through co-producing big data and machine interactions (Williamson, 2014).

Dunleavy et al. (2006, p. 480) discuss three primary themes of DEG: "reintegration", "needs-based holism", and "digitalization changes". First, reintegration encompasses consolidating distinct agencies created as a result of the disaggregation agenda of NPM and the establishment of central shared services for the efficient and effective government (Ojo et al., 2019). Second, needs-based holism characterises transformational change between government and citizens through end-to-end reengineering, digital citizen engagement, crowdsourcing of policy ideas, and concepts like agile government (Ibid.). Third, integrating the other two themes is digitalisation change referring to the global trend towards open government and transparency (Ibid.). Paradoxically, quantification of citizen transactions and surveillance without checks leads to a manifestation of Orwell's fictional big brother state (Chris & Susan, 2018; Kuziemski & Misuraca, 2020).

Chris and Susan (2018) argue DEG draws a parallel to Weber's bureaucracy with digital manifestations of efficiency, objectivity, and rationality. Efficiency and cost savings remain the key objectives for the implementation of AI in government (Misuraca et al., 2020). Algorithms have assumed the role of bureaucratic experts representing objectivity by distancing humans from the decision-making process and representing "instrumental rationality in the public sphere" (Dunn & Miller, 2007, p. 353). Similarly, big data represents the ontological assumption of realism capturing the world the way it exists without human subjectivity and engenders legitimacy through data and algorithmic neutrality (Chris & Susan, 2018). With the proliferation of digital technologies, citizens can disseminate information and cultivate their realities weakening the formal rationality and legal dominance of administration, most apparent in fake news, nationalistic campaigns, conspiracy theories, etc. This represents a "control crisis" requiring experts' intervention, where a centralised hierarchy is achieved through a distributed "bureaucracy at distance" (Chris & Susan, 2018, p. 206). Thus, DEG represents an "institutional matrix" consisting of humans, algorithms, data collection devices, and surveillance representing Weber's "techno-scientific" logic through rule-based rationality (Chris & Susan, 2018, p. 207).

Public Value Management (PVM)

The debates on public values grew out of the critique of NPM's claims of being universal in its application. Hood (1991, p. 11) argues governmental strategy is fundamentally dependent on administrative values and discusses three core values as: "…'sigma'…relates to economy and parsimony, 'theta'…relates to honesty and fairness, and 'lambda'…relates to security and resilience." NPM in principle only represents "sigma" values of "cost-cutting, efficiency, and performance management" (Ibid.) and fails to satisfy universality assumptions.

Bannister and Connolly (2014, p. 120) define values as "a mode of behaviour, either a way of doing things or an attribute of a way of doing things, that is held to be right." In the context of technological change in public administration, values ascribe public servants behavioural intention towards goals that "citizens … consider … to be right" (Ibid.). This definition concurs with Schein (1992)'s conceptualisation of values as basic underlying assumptions that drive acceptable norms and are the primary source of motivation and coordination of organizational activity (Daher, 2016; Gregory et al., 2009). Pant and Lachman (1998, p. 197) refer to these as core values that exert "high consensus and high control."

PVM was forwarded by Moore (1995) who popularised the strategic triangle as a pragmatic model for public managers to undertake strategy development. The strategic triangle encompasses public value, legitimacy and support, and the development of operational capabilities (Moore, 1994 1995). The key tenant of PVM is public value creation through government programs and services (Bryhinets et al., 2020; Karkin et al., 2018). As opposed to the NPM tenants of delivering public goods by the most efficient means (Hartley et al., 2016), public values are pluralistic over and above economic values. PVM is derived through democratic processes engendering legitimacy and clearly understanding the public interest and the overall public sphere (Andrews, 2018; Ranerup & Henriksen, 2019). With strategy derived from public values, the operational capacity building turns towards long-term outcomes, public managers shift from results orientation to stakeholder interactions and co-production with citizens (Bryhinets et al., 2020; Karkin et al., 2018; Panagiotopoulos et al., 2019).

In the contemporary e-government literature, PVM is discussed as a new paradigm that can address the challenges of governmental reforms centred on digital technologies (Cordella & Bonina, 2012). Ranerup and Henriksen (2019) contend technology is not only an enabler of value creation but also a mode for engaging citizens. PVM provides an appropriate democratic process for resolving ethical dilemmas with the implementation of AI in the public sector (Andrews, 2018; Panagiotopoulos et al., 2019). PVM orientation helps public managers to ensure the maximisation of aggregate values of all services delivered together (Panagiotopoulos et al., 2019).

Bannister and Connolly (2014, p. 123) adapt Hood (1991)'s taxonomy to analyse the impact of technology on public administration and propose three core values as "duty", "service", and "social". Duty orientation aligns with Hood (1991)'s sigma values adopting a "broader view incorporating non-financial aspects [of public administration]", service orientation falls within lambda values "covering responsibility … to provide good service to customers" and social orientation corresponds to theta values but also incorporate "wider, quasi-political view … [of] social goals" (Ibid.).

Dunn and Miller (2007, p. 353) argue instrumental rationality is embedded in both NPM and Weber's bureaucracy with the main goal of "control of human and material nature on the basis of knowledge." This deduction can be expended to DEG in the form of digital Weberianism where the role of scientific, professional, and technocrat's expertise is being assumed by algorithms (Chris & Susan, 2018). From a critical theory perspective, there is a large gap in the theory and practice of public administration on the "emancipatory" rationality concerned with "critical self-reflection and creation of institutions through moral discourse and ethical reflection" (Dunn & Miller, 2007, p. 354). In addition, ethical dilemmas introduced with the implementation of AI in government further strengthen the need for assuming "emancipatory" rationality in both research and practice. PVM provides an opportunity for such ethical discussions and offers a complementary perspective to DEG in light of AI implementations.

Technology Adoption

Technology adoption models use theories from informatics, sociology, and psychology, and explain potential users' intention to use new digital technology, (Chatterjee & Bhattacharjee, 2020; Williams et al., 2009). Venkatesh et al. (2003) synthesised eight leading technology adoption theories into a UTAUT model that has received wide acceptance and application in research. UTAUT suggests four exogenous constructs as determinants of behavioural intention to adopt a technology, "performance expectancy, effort expectancy, social influence and facilitating conditions" (Venkatesh et al., 2003, p. 447). This model has been used as a theoretical lens to study the adoption of AI such as Chatterjee and Bhattacharjee (2020), Fan et al. (2018), Gao et al. (2015), Wang et al. (2014), Adapa et al. (2017). In many studies, UTAUT has been expanded by adding additional variables such as trust, perceived enjoyment, and personal innovativeness (Chong, 2013). Venkatesh et al. (2012, p. 160) extend UTAUT to UTAUT2 by adding consumer-specific constructs to further incorporate end consumer context. Most recently, Dwivedi et al. (2020, p. 14) performed a meta-analysis of UTAUT usage and further outline a meta-UTAUT model adding attitude as a mediator and several other constructs such as “compatibility, perceived information security, perceived social pressure, perceived innovativeness in IT, resistance to change, perceived enjoyment”.

Kim et al. (2007) argue traditional technology adoption models are internally focussed on organisational users with desired outcomes of efficiency. Externally focussed models like UTAUT2 and meta-UTAUT are consumer focussed with profit motive outcomes. Literature on e-government adoption using such models propagates bias towards managerial and economic outcomes driven by NPM tenants (Cordella & Bonina, 2012) and continues to be driving AI implementations. Misuraca et al. (2020) review of 85 AI implementations in the European public sector shows 70% were driven by performance and efficiency goals, with only 30% being focussed on making the government open and none on public values. As well, the expected benefits in 56.5% are internally motivated towards organisational performance and only 27.1% towards social values (Ibid.). Reis et al. (2019) discuss current AI models are heavily skewed towards private sector needs and lack consideration of public values. Furthermore, the discourse on the role of government in directing AI development is divided between the US pursuing a private-sector led agenda and UK and EU propagating a public-private partnership approach (Reis et al., 2019). In either case, there is a concern that lack of public administration scholarship and consideration of public values will once again create conditions whereby the government adopts private sector models with disappointing results similar to NPM-era IT projects.

With the implementation of AI, technological change is growing in complexity. Governments need to build mechanisms able to examine the value judgements behind a decision made by AI (Susar & Aquaro, 2019) and the public value perspective provides one such mechanism. However, there is limited research on exploring the technology adoption from a PVM perspective (Andrews, 2018; Cordella & Bonina, 2012; Karkin et al., 2018; Moore, 2014). Political reform agendas discuss the critical role of technology as a driver of governmental innovation but lack any discussion on the relationship between technology and public values (Bannister & Connolly, 2014). Thus, with ethical dilemmas associated with AI implementation as enumerated by AI principles and the evolving DEG paradigm at the risk of becoming a digital version of Weber’s bureaucracy, this chapter aims to develop an AI adoption model that incorporates public values at its core.

CROSS-CASE ANALYSIS

The objective of this chapter was two-fold. First, develop a typology of the use of AI in governments. Second, enumerate the factors that impact citizen adoption of AI-driven governmental services drawing on public administration and technology adoption theories. To achieve these objectives, the authors undertake a case study synthesis approach exploring the phenomenon of AI implementations within governments. Given the scarcity of empirical studies on AI implementations, secondary case studies are used to achieve theoretical saturation on AI use and determinants of adoption. Khan and VanWynsberghe (2008) argue cross-case analysis assist with identifying commonalities and differences in the phenomenon and contributes towards conditional generalisations. Stake (2006, p. 6) discuss themes identified through cross-case analysis that can be used to make assertions about the “quintain”, the phenomenon or object being studied. In the current analysis, this is an AI-enabled governmental service or process. As well as cross-case comparisons can support the identification of clusters sharing certain configurations and help build typologies of the phenomenon (Khan & VanWynsberghe, 2008). Denzin (2001) suggest identifying essential elements and components of a phenomenon across multiple cases. These essential elements when clustered within a social context can assist with developing typologies.

Using a sample of 30 representative case studies of AI application in governments (Table 1), qualitative synthesis is conducted to identify AI use cases and determinants of AI adoption.

Methodology

The chapter follows the widely used ‘Preferred Reporting Items for Systematic Reviews and Meta-Analyses’ (PRISMA) (Moher et al., 2009) methodology to conduct a systematic review and qualitative synthesis of the case studies. The public sector innovation case study archive maintained by OPSI (2020) was used that includes details on 396 cases of public sector innovation (as of March 2021). Using the search terms “artificial intelligence”, “big data”, and “machine learning”, 70 cases were identified for a full-text review. Twenty cases were finally selected for coding after excluding ones that did not involve AI or government context. In addition, through Google Scholar search and following the same exclusion criteria, ten more relevant cases were identified from UNESCAP and Google (2019), Forum (2020), and Berryhill et al. (2019). A range of data was collected for the final 30 cases using desk research to enable triangulation and build the external validity of the findings. These sources included case descriptions published on the case archive databases, government reports, presentations, blogs, news releases, media documents, and website archives.

Qualitative synthesis was conducted using template analysis to identify themes and cluster constituent themes across cases (King, 2004). Data analysis was conducted in three steps as described below. The unit of analysis was the AI-enabled governmental service or an internal process.

In step one, a priori template was developed from the literature that included public values (derived from Bannister and Connolly, 2014) and AI principles (derived from Floridi & Cowls, 2019). In step two, the cases were coded in NVivo identifying the AI use case, objectives, expected outcomes in terms of public values, consideration for AI principle(s), and lessons learned. The resulting themes were organised into constituent and global themes. The final template was developed following a few rounds of reflection and re-organising themes. In step three, results were summarised, and a novel Public Value-based Adoption Model and corresponding propositions were developed.

Results

The case studies are summarised in Table 1. Four themes of AI use are identified. First, compliance involves the use of AI for ensuring citizens, private actors, and governmental agencies abide by the rules and regulations of the land. Second, organisational management involves the use of AI for government administration and internal processes. Third, public service delivery involves the use of AI for delivering public services to a range of stakeholders. Fourth, regulatory functions involve the use of AI for research and policy development. Table 2 shows the definitions and related codes.

Figure 1 shows cases by AI use case. The highest percentage of AI use cases relate to public services delivery at 47% followed by 30% for regulatory functions, 23% for compliance, and 13% for organisational management. Some cases relate to more than one use case and percentages are not exclusive.

Table 1. Case studies summary

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
1	Annie™ MOORE (Matching and Outcome Optimization for Refugee Empowerment): ML and optimization methods to recommend optimal placements of refugees (OPSI, 2020)	US	Public services delivery	Service Social	Autonomy Beneficence Non-maleficence

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
2	AuroraAI: personalised AI-driven services for citizens and businesses (Berryhill et al., 2019)	Finland	Public services delivery	Service Social	Beneficence
3	City of Things: development of a smart city (OPSI, 2020)	Belgium	Public services delivery	Social	Beneficence
4	Queensland Land Use Mapping Program (QLUMP): ML and computer vision to automatically map and classify land use features in satellite imagery (OPSI, 2020)	Australia	Public services delivery	Service Social	Explicability
5	MyService: a digital solution enabled by AI/ML to improve veterans' experience when accessing health care (OPSI, 2020)	Australia	Public services delivery	Service	N/A*
6	R2D3: active-waiting robot to at the reception desk of the Department's Home for Disabled Persons (OPSI, 2020)	France	Public services delivery	Service	Beneficence
7	Services Guide: a digital catalogue that centralizes all information regarding public services and Jaque, a virtual clerk based on AI (OPSI, 2020)	Brazil	Public services delivery	Duty Service	Explicability
9	TradeMarker: AI-enabled system for detecting similar trademarks (UNESCAP & Google, 2019)	Israel	Public services delivery	Service	Autonomy
9	UNA: a virtual assistant (OPSI, 2020)	Latvia	Public services delivery	Service	Explicability
10	Aylesbury Vale District Council (AVDC): AI-powered voice control (OPSI, 2020)	UK	Public services delivery	Service	Explicability
11	The Work: a service that recommends jobs without the need to conduct individual searches (OPSI, 2020)	Korea	Public services delivery	Service Social	Explicability
12	Insights.US: a tool that helps governments and cities obtain insights directly from their stakeholders (OPSI, 2020)	Israel	Public services delivery Regulatory functions	Duty Service	N/A*
13	Converlens: digitally-enabled community engagement in policy and programme design (OPSI, 2020)	Australia	Public services delivery Regulatory functions	Duty Service	Autonomy Explicability

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
14	Farming the Future: AI in the agricultural sector for sowing advisory and commodity price forecasting (UNESCAP & Google, 2019)	India	Public services delivery Regulatory functions	Service Social	Explicability
15	Better Reykjavik: a crowdsourcing platform for solutions to urban challenges, agenda-setting, participatory budgeting, and policymaking (OPSI, 2020)	Iceland	Regulatory functions	Duty	Beneficence
16	Bomb in a box: use of AI for risk-based reviews of air cargo records (Berryhill et al., 2019)	Canada	Regulatory functions	Service	Explicability
17	CitizenLab: a platform to automatically classify and analyse thousands of contributions collected on citizen participation platforms. (Berryhill et al., 2019)	Belgium	Regulatory functions	Duty	Autonomy Explicability
18	Department for Business, Energy & Industrial Strategy: technological solution to help analyse the cumulative effect of different regulations on business (Forum, 2020)	UK	Regulatory functions	Service	Explicability
19	UK Food Standards Agency: the predictive capability to mitigate against food safety risks (Forum, 2020)	UK	Regulatory functions	Service	Explicability
20	Policing: ML within a policing context for human trafficking mapping; crime ‘solvability’ estimates; misclassified crime detection; missing person anticipation; geospatial predictive mapping (UNESCAP & Google, 2019)	Unknown	Compliance Regulatory functions	Service	Autonomy Explicability Justice
21	AELOUS: a mid-altitude airborne maritime sensor platform (OPSI, 2020)	Ireland	Compliance	Service	Explicability
22	Fraud detection in social security payments (UNESCAP & Google, 2019)	Australia	Compliance	Justice	Explicability
23	Counterfeit drug detection using Blockchain and AI (OPSI, 2020)	Mongolia	Compliance	Social	Beneficence
24	Serenata de Amor: AI for financial transparency finding misuse of public money by congress members (UNESCAP & Google, 2019)	Brazil	Compliance	Duty Service	Explicability

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
25	Statement of Interests and Assets system (DIP): monitoring assets and potential conflicts of interest of officials through business intelligence (OPSI, 2020)	Chile	Compliance	Duty Service	N/A*
26	Slavery from Space: satellite remote sensing data with ML algorithms to detect slavery and monitor antislavery intervention (OPSI, 2020)	UK	Compliance	Social	Beneficence
27	Text analysis: help several government institutions in streamlining and automating their processes, conducting document management audit, removing personal information from nearly 80,000 expired court sentences (OPSI, 2020)	Estonia	Organisational management	Service	N/A*
28	Big Data Analysis for HR efficiency improvement: improve efficiency, develop organisational capacity, improve effectiveness and efficiency, and staff satisfaction. (OPSI, 2020)	Slovenia	Organisational management	Service	Non-maleficence
29	Emergency services forecasting: inform sophisticated machine learning forecasts of hazard probabilities (e.g. flood, cyclone, fire, road crash, rescue, etc.) and evolving exposures (e.g. people, assets) over the coming 10 years (OPSI, 2020)	Australia	Organisational management	Service	Explicability
30	R&D Platform for Investment and Evaluation (“R&D PIE”): provides an evidence-based policy platform to monitor, analyse and manage technologies, talents, and regulatory issues via the PIE model (OPSI, 2020)	Korea	Organisational management	Service	Explicability

* The case descriptions did not outline any specific considerations of risks that can be coded for AI principles.

Table 2. AI use case definitions and related codes from thematic analysis

AI use case	Definition	Codes
Compliance	AI is used for activities related to ensuring citizens, private actors and other governmental agencies adhere to the legislated rules and regulations.	Monitoring and surveillance, fraud detection, counterfeit drug detection, policing, slavery, auditing

AI use case	Definition	Codes
Organisational management	AI is used for activities related to the management of internal organisational processes and resources	Streamlining processes, efficiency improvement, budgeting, resource and demand forecasting towards business planning
Public service delivery	AI is used for the delivery of public services to citizens, businesses, and other governmental/NGO bodies.	Refugee resettlement, job recommendations, public engagements, agricultural advisory, land use, administrative claims processing, operations of public service centres, digital catalogue and virtual assistant, trademark registration
Regulatory functions	AI used for activities related to policy development and research	Crowdsourcing, risk-based oversight, predictive regulation, forecasting

Figure 1. Cases by AI use case

Figure 2 shows the cases by country. The sample is global with the largest number of cases from Australia (17%) and the UK (13%).

Figure 2. Cases by Country

Table 3 shows the definitions and codes of public values and AI principles identified from the literature and supported by the cases. A map of public values and AI principles by AI use case is shown in Figure 3. The percentages represent the number of cases that mention a particular public value or AI principle by use case; a case may mention more than one public value or AI principal and hence, the percentages are not exclusive.

Where black cells represent cited in more than 2/3rd cases, grey cells show cited between 1/3rd and 2/3rd cases, and light grey cells indicate less than 1/3rd cases. For cases related to compliance, 71% mention service followed by 29% for duty and social. Service is the only public value for all cases related to organisational management. For cases related to public services delivery, 93% mention service followed by 43% social and 21% duty. For cases related to regulatory functions, 78% mention service followed by 44% duty and 11% social.

In terms of AI principles, compliance use cases identify considerations for explicability in 43%, beneficence and justice in 29%, autonomy in 14% cases, and none consider non-maleficence. For organisational management, 50% of cases identify explicability, 25% non-maleficence, and none for autonomy, beneficence, and justice. For public services, 50% identify explicability, 29% beneficence, 21% autonomy, 7% non-maleficence, and none for justice. For regulatory functions, 78% identify explicability, 44% autonomy, 11% beneficence and justice, and none for non-maleficence.

Table 3. Public values and AI principles definitions and codes

Constructs	Measures and definitions	Codes
Public Values (Bannister & Connolly, 2014, pp. Table 2, 123)	Duty orientation: "responsibility to the citizen, politicians, efficient use of public funds, integrity and honesty, democratic will"	Citizen participation, citizen needs, dialogue on the public sphere, inclusive and responsive engagement, government transparency
	Service orientation: "responsiveness, effectiveness, efficiency, transparency"	Streamline processes, resources, and budgets, effectiveness, quality, better planning, efficiency, reducing time, service experience
	Social orientation: "inclusiveness, justice, fairness, equality, respect for citizens, accountability"	Community development, quality of life, access to employment, elimination of counterfeit drugs, environmental concerns, humanitarian efforts, social value
AI Principles (Floridi & Cowls, 2019, pp. 6-8)	Non-maleficence: "do no harm and avoid misuse of privacy and security"	Data privacy, data security, the confidentiality of personal data
	Autonomy: "the power to decide"	Augmenting decision making, free up time for humans to make crucial value judgements
	Explicability: "the knowledge of how AI works and who to hold responsible for its outcomes"	Quality of data, accuracy, explainable AI, trust and awareness, transparency
	Beneficence: "promoting well-being, preserving dignity, and sustaining the planet"	Community development, wellbeing, happiness, quality of life, save lives, inform liberation
	Justice: "the quality of being fair and eliminating discrimination ensuring equal access to the benefits of AI"	Protect vulnerable populations, social biases in machine learning

Figure 3. Public values and AI principles by AI use type

The success criteria and lessons learned were coded into two global themes of external and internal. As the objective of this analysis is citizen adoption, the chapter focuses on the external theme. Three constituent themes were identified under external as shown in Table 4. First, the dominant external theme relates to co-design practices and public-private partnerships. 73% of the cases report a collaborative design process involving citizens and businesses and encouraging public-private collaborations as key to successful adoption. Second, 17% of the cases report communication of benefits vital in successful take-up. Third, 13% report product design as a relevant determinant of higher adoption and discuss simple intuitive design and adaptability of the applications.

Table 4. Externally focussed success criteria and related codes

Global theme	Constituent themes	Codes	Percentage of cases
External	Market the benefits	Communication and promotion of benefits, manage expectations, market the project to citizens, clients understand the benefits	17%

	User interface	Attractive design, lightweight, intuitive to use, make apps interesting to use, human-centred design, design thinking	13%
	Co-design with citizens and stakeholders	Co-design and feedback cycle between all users and stakeholders, consulting process with citizens and businesses, understanding of target users, results of citizen work are used, engagement from different stakeholders, co-creation, bottom- approaches, public-private collaborations, civic volunteers, connecting local knowledge and experience to machine learning, citizen-science platform, social acceptability	73%

DISCUSSION

For the first research question on how AI is being used in government, the cross-case analysis identifies four AI use cases: compliance, regulatory functions, public service delivery, and organisational management. All four use cases support literature regarding the transformational impact of AI, its embedded instrumental rationality, and corresponding ethical dilemmas.

Figure 3 shows service is the dominant public value irrespective of AI use case. This concurs with the literature that NPM values of efficiency and cost savings are still driving the majority of AI implementations in government. The use case of public service delivery show social is the second-ranked public value explicating support for external orientation geared towards customer satisfaction and societal reforms. In these cases, AI has been delegated the role of a public agent interacting with citizens and businesses. For fully automated solutions, such as Aylesbury Vale District Council's AI-powered voice control, citizen-government interactions become citizen-AI interactions. The self-learning capabilities of AI risk divergence from its original design towards unexpected influence on citizens' choices. When AI is used for decision augmentation, such as US' Annie™ MOORE on refugee settlement, employees increasingly rely on options suggested by AI which might have a detrimental effect on human learning and knowledge (Berente et al., 2021). AI becomes a salient techno-rational actor learning and influencing public decisions.

The use case of organisational management is internally oriented towards achieving service-oriented values. AI is being used for automating and/or augmenting processes, such as Estonia's text analysis, or directing and evaluating humans, such as Solvenia's HR application. As opposed to expert systems whereby human know-how was embedded as business rules, AI-driven systems incorporate the extreme form of rationality using autonomous learning and correlational knowledge lacking contextual considerations. This is most visibly evident in the regulatory use cases where predictive modelling is used for policy development, such as the UK's predictive solution on the effect of regulations on business. The regulatory functions show duty as the second-ranked public value explicating an internal motive consistent with the ethos of public service to increase transparency and ensure democratic processes for policy development. The use of AI in these use cases have the biggest potential impact on society with policy determining the future of citizens lives and which interventions take precedence. Compliance shows an equal balance of duty and social values explicating the balance between both internal and external goals.

The results also support DEG themes outlined in the literature. The reintegration, needs-based holism, and digitising change themes of DEG (Dunleavy et al., 2006, p. 480) are reflected in Finland's National AI Strategy. This strategy document summarised "developing new operating models to shift from organisation-based activities to systems-wide approaches"; "improve the interoperability of government data, and open up this data to fuel innovation in all sectors"; " public discussion on AI ethics"; and "break down silos within … public services" (Berryhill et al., 2019, pp. 144-148). The specific case of AuroraAI within this national strategy holistically integrates public services from different agencies around three life events: "moving away from study, remaining in the labour market, and family wellbeing after a divorce"

(Ibid.). The Services Guide case from Brazil provides another example of DEG themes of reintegration and digitising change by integrating scattered information on public services as an open data digital catalogue and the use of AI as a virtual clerk.

Several cases exemplify the needs-based holism theme of DEG. For example, Belgium's CitizenLab platform uses natural language processing (NLP) and ML to automatically classify thousands of citizen contributions. Similarly, Australia's Converlens assists public servants to manage community engagement using NLP and ML. Australia's use of AI for fraud detection in social security payments, and the use of ML in policing for mapping human trafficking, crime detection, missing person anticipation, and geospatial predictive mapping. The counterfeit drug detection case from Mongolia exemplifies needs-based holism and digitalising change themes. The use of blockchain as an immutable ledger among all stockholders in the supply chain ensures an easy track and trace of counterfeit drugs in real-time.

The four AI use cases explicate the need for a broader public values perspective for exploring AI adoption. Drawing on the consumer choice theory, Kim et al. (2007) developed a Value-based Adoption Model (VAM) that hypothesises perceived value, measured through benefits and sacrifices, as a determinant of adoption intention. VAM has been used extensively to explain the adoption of several AI-based technologies (Hsu & Lin, 2016; Kim et al., 2017; Lau et al., 2019; Yu et al., 2019). Sohn and Kwon (2020) analysis of consumer acceptance of AI-based intelligent products shows VAM performed better than UTAUT in modelling user acceptance. Thus, the authors postulate perceived value of an AI-driven governmental service from a citizen's perspective is measured through public values (a proxy for benefits) and consideration of AI principles (a proxy for sacrifices). The unit of measurement, AI-driven governmental service, is postulated to include uses cases across compliance, regulatory functions, public services delivery, and organisational management in the sense they relate to citizen's perceptions of value generation through consumption of public services, ensuring safety and well-being, or efficient use of public funds. Hence, for the second research question regarding factors influencing citizen adoption of AI-driven governmental services, first two propositions are stated as:

P1: The citizen perception of perceived value associated with AI-driven governmental service is a key determinant of adoption intention.

P2: Public values related to service, social, and duty affects the perceived value of AI-driven governmental services.

In terms of AI principles, explicability is dominant regardless of the AI use case. The focus on explicability-related concerns, such as transparency, accuracy, trust, and explainability, align with the dominant service value. A surprising finding is a low percentage for non-maleficence related concerns, especially those relating to data privacy and security. Literature, policy, and media focus extensively on these concerns especially concerning the proliferation of big data (Ribeiro-Navarrete et al., 2021; Saura et al., 2021B). Similarly, justice-related concerns such as discrimination from biased data, equal rights, etc. are also low in the sample. For the public services delivery use type, beneficence considerations are high aligning with social values and reflecting the outward focus. Similarly, for regulatory functions, autonomy considerations are higher reflecting an internal focus on preserving public service jobs and using AI in an augmentation capacity.

This analysis supports the PVM discussion that suggests value orientation that is internally focussed will drive risk mitigation towards accuracy and explainability of data. Hence, this diminishes the considerations for externally focussed societal risks of privacy, discrimination, and justice. The third proposition is stated as:

P3: The citizen perception of risk mitigation related to AI implementation expressed in terms of AI principles affects the perceived value of AI-driven governmental services.

Deducing from the success criterion themes three constructs are identified. First, perceived citizen collaboration is identified as a key determinant of adoption intention. When citizens perceive a strong collaborative process was followed and their needs were considered as evidence of democratic involvement, adoption of such public services will be higher. Second, the "effort expectancy" construct from the UTAUT model (Venkatesh et al., 2003, p. 450) is identified representing the theme of an attractive, intuitive, and adaptive user interface. Third, the "perceived usefulness" construct from the TAM model (Davis, 1989, p.

320) is identified as a measure of the theme around communication of benefits. Hence, three final propositions are stated as:

P4: Perceived collaborative process moderates the relationship between perceived value and adoption intention.

P5: Effort expectancy moderates the relationship between AI principles and perceived value.

P6: Perceived usefulness moderates the relationship between public values and perceived value.

To test these propositions, a Public Values-based Adoption Model is developed as shown in Figure 4.

The definitions of public value and AI principles constructs are derived from literature and case analysis as shown in Table 3. Furthermore, perceived value is defined as the "overall evaluation of the user regarding the benefit and cost of using" an AI-based public service (Kim et al., 2017, p. 1153). Adoption intention is defined as "a desire to use" the new AI-based public service compared to e-government or paper-based alternative (Kim et al., 2017, p. 1153). Effort expectancy is defined as "the degree of ease associated with the use of [AI based public service]" (Venkatesh et al., 2003, p. 450). Perceived usefulness is defined as "the degree to which [citizens] believe an [AI driven public service] would enhance" personal and societal goals (Davis, 1989, p. 320). Perceived collaboration is defined as an overall evaluation of the level of collaboration between the public sector, citizens, and private sector when developing the AI-based public service.

Figure 4: Public Value-based Adoption Model

CONCLUSION

In this chapter, the authors aimed to explore the use of AI within governments with a specific focus on the variety of uses and the corresponding citizen adoption. Much of modern government administration has been heavily influenced by the NPM reforms of the 1980s adopting private sector managerial ideas and marketisation of services. With the failures of NPM in bringing forth any meaningful change and the socio-technical transformation of society through AI, DEG is emerging as a new paradigm of governance. However, as much as DEG is hailed as the technological transformation of public administration, the implementation of AI in government introduces several risks.

Following a review of multidisciplinary literature on public administration, AI, and technology adoption, the chapter highlights a critical gap in the use and implementation of AI in government and scant empirical evidence on the determinants of citizen adoption. Furthermore, the majority of technology adoption models focus on internal efficiency and discount the consideration of societal and public values. As a result, AI adoption is being motivated through the efficiency and cost savings ethos (Misuraca et al., 2020) of the NPM-era. Thus, the chapter argues for the adoption of a public values perspective whereby the outcomes of the use of AI are not only related to service values but also incorporate duty and social related values.

In response to these gaps, the authors performed a systematic review of AI implementation cases in government and selected 30 cases for cross-case analysis. Using a range of data sources, the authors conducted a qualitative synthesis and identified four major AI use cases in government: compliance, organisational management, public service delivery, and regulatory functions. Drawing on technology adoption and public administration literature, the authors postulate the primary determinant of AI adoption intention by citizens is the perceived value of the services. Public values are postulated as a proxy for benefits affecting the perceived value. The management of AI principles is postulated as risk mitigation affecting the perceived value. Furthermore, the authors postulate that perceived collaboration moderates the relationship between perceived value and adoption intention, effort expectancy moderates the relationship between AI principles and perceived value, and perceived usefulness moderates the relationship between public values and perceived value. A public values-based adoption model is developed to test these propositions.

Theoretical implications

This chapter contributes to both public administration and technology adoption literature. Three primary theoretical contributions are highlighted. First, the chapter develops a new typology of AI use in government. This typology highlights the commonalities and differences between AI implementations and their transformational effect on internal processes or government-citizen interactions. Second, the chapter develops a new AI adoption model in the government context. The new model extends the technology adoption literature within the context of AI use in government. The model can be extended to other contexts through future qualitative research and model testing. Third, the chapter addresses the literature gap on using a public values-based perspective to explore the phenomenon of AI use within governments. The authors postulate viewing the benefits of AI in terms of public values, over and above economic measures, is one way of balancing risks associated with the AI principles.

Practical implications

The practical contribution of this chapter includes both policy and operational implications. First, the typology of AI use cases can be used by policymakers considering regulations on the use of AI within governments. For example, Figure 3 provides a conceptual map of AI principles and public values mapped to each of the AI use cases. Even though limited in terms of generalisability with the small sample size, it provides a starting point on the current state of benefits versus risk considerations in AI implementation projects. A policy intervention towards the desired outcome from AI can then be designed and implemented. Second, citizen adoption is the ultimate measure of the success of AI-driven governmental service. It ensures continued trust and legitimacy in the governmental agency and its actions. The conceptual model with a broader public values perspective will help public managers implementing AI to enumerate and explore the balance between benefits (public values) and risks (AI principles) in terms of achieving a maximised perceived value by the citizens.

Limitations and future research

There are two key limitations of this research. First, the data used for the cross-case analysis is limited to secondary published records and documents. The published data might be biased towards highlighting successes and the politically positive view of such implementations. Second, although, the sample of 30 cases achieved theoretical saturation, the findings are limited in terms of inferences of relationships between the constructs and hence its generalisability.

Thus, three future research agendas are suggested. First, collecting primary data through interviews and in-depth case analysis to increase the external validity of the propositions. Second, testing the propositions and the model using mixed-method and quantitative techniques. Third, comparing the proposed Public Values-based Adoption Model results against UTAUT and TAM to determine which model performs better in modelling users' acceptance of AI-driven governmental services.

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KEY TERMS AND DEFINITIONS

Artificial Intelligence (AI): A cluster of digital technologies that enable machines to learn and solve cognitive problems autonomously without human intervention.

AI for Compliance: AI is used for governmental activities to ensure citizens, private actors, and other governmental agencies adhere to the legislated rules and regulations.

AI for Organisational Management: AI is used for activities related to the management of internal governmental processes and resources.

AI for Public Service Delivery: AI is used for the delivery of public services to citizens, businesses, and other governmental/NGO bodies.

AI for Regulatory Functions: AI is used for activities related to policy development and research.

Digital-era Governance: An emerging public administration paradigm that situates technology at the centre of governmental processes and advocates for a lean and data-driven governance model.

Public Value Management: The government's organisational values and processes are geared towards achieving duty, service, and social-oriented goals that citizens regard as pertinent.

New Public Management: Public administration reforms of the 1980s that propagated adoption of private sector organisational management practices in public sector organisations. These included quasi-markets, managerialism, employee empowerment, public entrepreneurialism, and performance management practices.