University of Reading

Making sense of AI benefits: a mixed-method study in Canadian public administration

Article

Published Version

Creative Commons: Attribution 4.0 (CC-BY)

Open Access

Madan, R. and Ashok, M. ORCID: https://orcid.org/0000-0002-9827-9104 (2025) Making sense of AI benefits: a mixed-method study in Canadian public administration. Information Systems Frontiers, 27. pp. 889-923. ISSN 1572-9419 doi: 10.1007/s10796-024-10475-0 Available at https://centaur.reading.ac.uk/115062/

It is advisable to refer to the publisher's version if you intend to cite from the work. See Guidance on citing.

To link to this article DOI: http://dx.doi.org/10.1007/s10796-024-10475-0

Publisher: Springer

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the End User Agreement.

www.reading.ac.uk/centaur

University of Reading

CentAUR

Central Archive at the University of Reading

Reading's research outputs online

Information Systems Frontiers
https://doi.org/10.1007/s10796-024-10475-0

Making Sense of AI Benefits: A Mixed-method Study in Canadian Public Administration

Rohit Madan[1] · Mona Ashok[2]

Accepted: 1 February 2024
© The Author(s) 2024

Abstract
Public administrators receive conflicting signals on the transformative benefits of Artificial Intelligence (AI) and the counternarratives of AI's ethical impacts on society and democracy. Against this backdrop, this paper explores the factors that affect the sensemaking of AI benefits in Canadian public administration. A mixed-method research design using PLS-SEM ($n = 272$) and interviews ($n = 38$) tests and explains the effect of institutional and consultant pressures on the perceived benefits of AI use. The quantitative study shows only service coercive pressures have a significant effect on perceived benefits of AI use and consultant pressures are significant in generating all institutional pressures. The qualitative study explains the results and highlights the underlying mechanisms. The key conclusion is that in the earlier stages of AI adoption, demand pull is the main driver rather than technology push. A processual sensemaking model is developed extending the theory on institutions and sensemaking. And several managerial implications are discussed.

Keywords Artificial Intelligence · Public administration · Sensemaking · Institutional theory · Institutional pressures

1 Introduction

Public administration is under immense pressure to deliver on service demands and political mandates while enduring austerity measures and systemic resource deficits (Hartley et al., 2013). The last two decades have witnessed several black swan events such as the global financial crisis, the COVID-19 pandemic, and the international conflict in Eastern Europe. Such events have further exasperated resource deficits and strengthen the call for the use of emerging technologies to meet such challenges (Eom & Lee, 2022; Mergel et al., 2023). Artificial Intelligence (AI) comprises a "cluster of digital technologies that enable machines to learn and solve cognitive problems autonomously without human intervention" (Madan & Ashok, 2022, p. 188). AI can accelerate digital government benefits in a myriad of ways. Canada's digital government strategy expounds that "Artificial intelligence (AI) technologies offer promise for improving how the Government of Canada serves Canadians" (Government of Canada, 2023). The benefits of using AI in public administration include improving efficiency and effectiveness, saving costs, automating case management, predicting and managing adverse events, and increasing service delivery, better citizen engagement, citizen centricity, and transparency (Kuziemski & Misuraca, 2020; Sousa et al., 2019). However, scholars have warned about the adverse effects of AI use on the environment and already at-risk population clusters (Ashok et al., 2022). Understanding the mechanisms and actors driving AI adoption in public administration is key to understanding how AI can be used for public value generation (Fatima et al., 2022; Wirtz et al., 2021).

The technology enactment framework (TEF) highlights the role of organisational forms and institutional arrangements in determining enacted technology (Fountain et al., 2001). At the micro level, organisational members engage in sensemaking to reduce ambiguity resulting from exogenous signals and institutional demands and develop shared meanings (Weick, 1995). Specifically with regards to AI, public administrators are bombarded with conflicting signals that

✉ Rohit Madan
r.madan@qub.ac.uk

Mona Ashok
m.ashok@henley.ac.uk

1 Queen's Business School, Queen's University Belfast, Riddel Hall, 185 Stranmillis Road, Belfast, Northern Ireland BT9 5EE, UK

2 G21, BISA, Henley Business School, University of Reading, Whiteknights Road, Reading RG6 6UD, UK

swing between the transformational aspects of AI-driven service delivery to counternarratives on job losses, political power grabs, surveillance, and citizen control. The socially constructed attitudes on the benefits of AI are then manifested in the adoption decision and the enacted technology. Against this backdrop, this paper explores the institutional factors and the mechanisms that affect the sensemaking of AI benefits in public administration.

The scholarship on AI adoption within the public sector, and specifically public administration, is still in its infancy and lacks empirical studies (Neumann et al., 2022; Zuiderwijk et al., 2021). A limited number of qualitative studies have explored AI adoption in the public sector identifying adoption determinants using qualitative methods (Campion et al., 2022; Neumann et al., 2022; Schaefer et al., 2021; Sun & Medaglia, 2019; van Noordt & Misuraca, 2022) or public organisation CIOs technological frames related to AI (Criado & Zarate-Alcarazo, 2022). Scant quantitative research has tested the effect of technological, organisational, and environmental factors and perceptions on adoption decisions (Ahn & Chen, 2022; Wang et al., 2020) or AI capabilities (Mikalef et al., 2021). However, the question of how perceptions or technological frames related to AI benefits are formed remains answered. More broadly, there are limited empirical studies in the management literature that explore the mechanisms that link the institutional environment at the macro level to sensemaking at the micro level (Ann Glynn & Watkiss, 2020; Kohtamäki et al., 2022).

The paper aims to address the above literature gaps by identifying and testing the effect of institutional factors on perception formation and uncovering underlying mechanisms that link institutions to sensemaking. The context for this research is Canadian public administration. We focus on two specific data-driven AI technologies: machine learning (ML) and natural language processing (NLP). These are among the most adopted AI technologies in the public administration context (European Commission, 2021). The two research questions are stated as:

RQ1: *What factors affect the perceived benefits of AI use in public administration?*
RQ2: *How do these factors affect the perceived benefits of AI use in public administration?*

The paper sheds light on the institutional pressures that are most significant in affecting the sensemaking of AI benefits within public administration. Through a mixed-method research design, a key contribution of the paper is a processual sensemaking model of AI innovation in public administration. The model expounds on the mechanisms and interactions between institutional pressures and exogenous factors that drive different stages of the AI innovation process. The paper adds to the institutional and sensemaking theory showcasing spatial mechanisms and temporality linking institutions at the macro level to sensemaking at the micro level. The model has implications for future research and testing in other technology innovation domains beyond AI.

The paper is organised as follows. First, a literature review of public administration is discussed followed by a discussion of institutional and sensemaking theory as theoretical frameworks for this research. This is followed by the development of hypotheses and discussion of the mixed-method research design, the quantitative study testing the hypotheses, and the qualitative study developing the sensemaking mechanisms. Finally, the discussion section provides a meta-analysis of the two studies, contributions, and limitations.

2 Literature Review

Public organisations have evolved through various reform movements discussed as public administration paradigms in the literature. Weber's ideal-type bureaucracy continues to be the fundamental building block of public organisations (Esmark, 2016). This traditional public administration model evolved in response to the modernisation enabled by capitalistic forces (Hood, 2000). Bureaucratic structures are characterised by hierarchal decision-making, rules and procedures, and specialised professionals distinct from political interests (Sager & Rosser, 2009).

The neo-liberalism wave of the late 1970s and 80 s witnessed the political stance in the Anglo-Saxon countries sway towards a hostile attitude towards bureaucracy. Bureaucracy came to be viewed as elitist, non-democratic, and evidence of failed Keynesian policies (Harvey, 2007). These reforms, known as the new public management (NPM), championed limiting the power of the state and brought forth drastic changes in the bureaucratic model. NPM was driven by the assumptions of market control as the most efficient organising principle and introduced "disaggregation", "competition", and "incentivisation" (Dunleavy et al., 2005, p. 470). These tenets were incongruent with the ethos of public service geared towards societal goals and the democratic pursuit of conflicting multi-stakeholder objectives (Christensen et al., 2007; Hood, 1991). The rapid trajectory of technological innovations and limited successes (De Vries & Nemec, 2013; Dunleavy et al., 2005; Hood, 1991) led to a downward spiral of NPM and the emergence of alternative reforms in the form of New Public Governance (NPG), Public Value Management (PVM), and Digital-era Governance (DEG).

The NPG paradigm is characterised by networked and collaborative governance structures. The partnerships between the public and private sector and citizens are not only means for delivering public services but also informing policy (Osborne, 2010). Its proponents argue society's wicked problems cannot be solved by a single governmental or political body and require open innovation, partnerships, and joined-up initiatives at all levels (Greve, 2015).

The PVM paradigm advocates for the triadic relationship between public values, legitimacy and support, and operational capabilities (Moore, 1995). Public values, analogous to business value, are generated through the public organisation's activities. Determination of these values through stakeholder engagements builds legitimacy and understanding of the public sphere (Andrews, 2019; Ranerup & Henriksen, 2019). The operational capabilities built on these public values shift the focus from primarily economic goals, as in NPM, to broader societal goals (Fatima et al., 2022).

NPM, NPG and PVM remain reticent on the use of technology with the implicit assumption that it's a critical tool for achieving the reform objectives. The DEG paradigm forwarded by Dunleavy et al., (2005, p. 480) advocates for the central role of technology in delivering public services around the themes of "reintegration", "needs-base holism", and "digitalisation change". In their later work, Margetts and Dunleavy (2013) argued for a second wave of DEG. This follows the austerity measures of the 2008 financial crisis with new technological innovations having both centralisation and decentralisation effects (Ibid.). Tan and Crompvoets (2022) discuss a more contemporary form of DEG with the adoption of emerging technologies such as AI, blockchain, etc. Scholars have argued bureaucracy is still persistent notwithstanding NPM and post-NPM reforms (Christensen & Lægreid, 2013; Esmark, 2016). Kernaghan et al. (2000) discuss the varying levels of bureaucracy in public organisations resulting from differing mandates. Keast et al. (2006) argue the failure of any single reform to deliver on complex policy problems requires decision-makers to select optimal mixes of state, market, and network approaches. Similarly, Lindquist (2022) argues each reform movement is associated with distinct values. These might be in tension but continue to persist at different levels. In all these narratives, the common thread is to infer DEG and the role of technology as enabling specific values rather than a distinct reform movement. The key themes for each of the reform movements and the related role of technology are summarised in Table 1.

The technology enactment framework argues that the institutional environment and organisational context shape how objective technological artefacts are adopted and used as enacted technology and dictate the outcomes from the use of technologies (Fountain et al., 2001). In a public administration context, this institutional environment comprises layers of overlapping changes introduced by NPM and post-NPM reforms. The persistence of historical context and effectiveness of reform is influenced by the interplay between the inertial forces and political motivation for change, all supported by technology as an enabler of these policy innovations. Thus, building on this perspective, AI innovation is a carrier of institutionalism and an enacted technology. In the next section, we introduce institutional and sensemaking theory and develop our hypotheses.

3 Theoretical Background and Hypotheses

The philosophy of technology discusses two contrasting views on technology and society, technological determinism and social shaping of technology (SCOT) (Poel, 2020). Technological determinism advocates that technological evolution is not significantly affected by human choice (Bijker, 2009). As the focal point of the analysis is a technological artefact, this perspective lacks the contextual dimension of institutional structures shown to be significant in several studies (Geels, 2020; Poel, 2020; Weerakkody et al., 2009). SCOT advocates an emergent perspective that contends technology is socially constructed and is a function of negotiations between relevant social groups and their technological frames (Bijker, 2009). SCOT perspective has also been critiqued for lacking consideration of the effect of social structures on the development of technological frames (Klein & Kleinman, 2002). SCOT ascribes undue emphasis on the group's agency ignoring historical contexts (Klein & Kleinman, 2002). Since the social groups operate and are part of institutional structures and existing power dynamics, scholars have advocated incorporating structural and institutional logic into SCOT (Klein & Kleinman, 2002; Mundkur & Venkatesh, 2009). We follow this thread to argue that the SCOT perspective is relevant for exploring AI development and implementation. However, for the pre-adoption stages, institutional logics are required to explain the dynamics between the social groups and the formation of their respective technological frames (Klein & Kleinman, 2002). These frames later serve as the contextual condition for SCOT once an adoption decision is made. Furthermore, sensemaking theory provides the theoretical lens to explain how technological frames of various social groups are formed in the first place (Jensen et al., 2009b). Thus, institutional pressures are the primary determinants of technological frames that dictate perceptions of the benefits of AI use. Furthermore, sensemaking helps explain the underlying mechanisms between institutional pressures and perception formation. Hence, this study draws on institutional theory and sensemaking theory as the basis of our conceptualisation as shown in Fig. 1. In the following subsections, we discuss the two theories and develop our hypotheses.

3.1 Institutional Theory

Christensen et al. (2007) discuss structural-instrumental and institutional approaches as two theoretical perspectives

Table 1 Public administration paradigms

Public administration paradigms	Key themes	Role of technology
New Public Management (NPM) (Hood, 1991, 1995; Osborne & Gaebler, 1992)	Disaggregation: • re-organisation of large public sector hierarchies into quasi-governmental agencies • separating policy from public service delivery Competition: • marketisation of public services • outsourcing • intra-governmental markets Incentivisation: • empowering employees, • performance management • managerialism	• Supporting NPM goals of efficiency and cost savings • Measuring and tracking performance • Enabling citizen/customer-centric service design • Examples: e-government services, performance dashboards, enterprise resource planning (ERP) systems, robotic process automation (RPA), blockchain technology
New Public Governance (NPG) (Osborne, 2010)	Network governance: • government as a platform • joined-up services • open innovation Public-private partnerships: • sharing risks and resources across the public and private sector Citizen engagement: • crowdsourcing • co-production and delivery of services	• Supporting communication networks and infrastructure for co-production and delivery of public services • Enabling joined-up services, government as a platform, and crowdsourcing • Examples: innovation labs, living labs, collaborative applications, digital and crowdsourcing platforms, open data initiatives, application programming interfaces (APIs), citizen reporting applications
Public Value Management (PVM) (Moore, 1995; Stoker, 2006)	Public values: • democratic determination of public interests and values Legitimacy and support: • political support for long-term outcomes rather than short-term performance metrics, • developing trust-based rather than performance-based systems Operational capabilities: • developing capabilities to deliver public values	• Supporting public value deliberations • Enabling large-scale engagement of citizens and the private sector • Examples: social media and citizen engagement platforms, textual and sentiment analysis

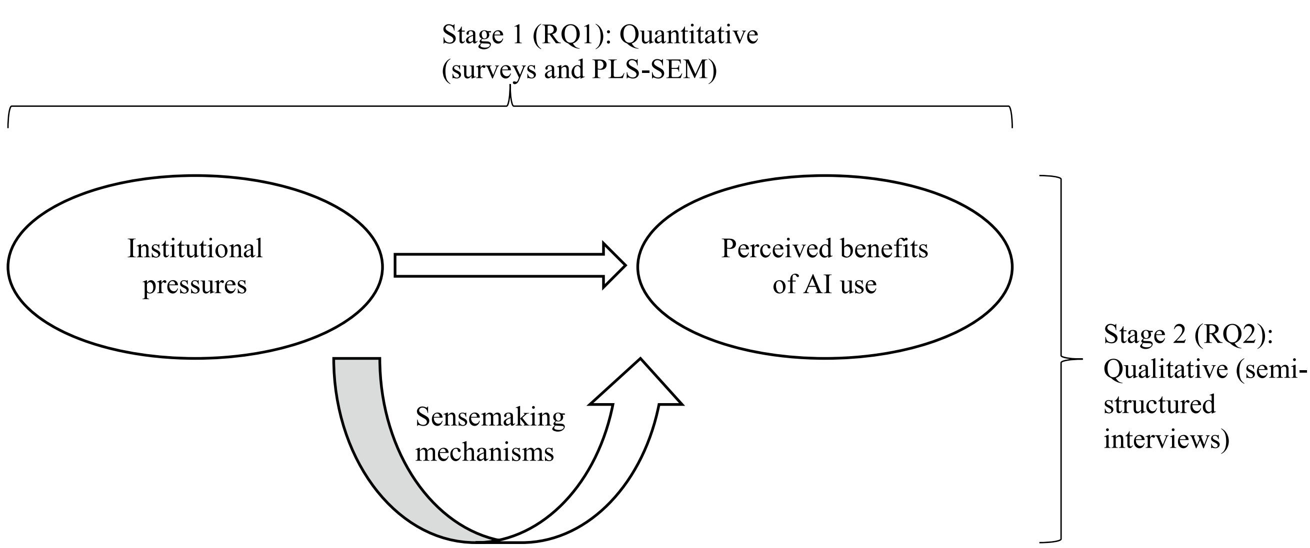

Fig. 1 Theoretical model

in the study of public organisations. The structural-instrumental perspective is based on the resource-based view of the firms forwarding the rational economic argument that strategic choices are driven by efficiency and effectiveness goals (Mignerat & Rivard, 2009). The institutional perspective is instead based on the “logic of appropriateness” whereby organisations operate within a social context and decisions are influenced by past experiences, reputational concerns, and conformance to the institutional environment (Christensen et al., 2007, p. 3). Oliver (1997) argues that even though the resource-based view and institutionalism are based on distinct assumptions, the institutional environment impacts resource configuration decisions. DiMaggio and Powell (1983) argue the pursuit of legitimacy within an institutional environment is the key driver for isomorphism. Isomorphism is even more prevalent in the public administration context alluding to strong institutional mechanisms (Frumkin & Galaskiewicz, 2004).

Zheng et al. (2013) demonstrate institutional pressures impact resource allocation for e-government adoption, mediated by top management commitment. Jun and Weare (2010) show institutional environment is more important than internal organisational pressures in e-government adoption by American municipalities. Weerakkody et al. (2016) demonstrate that digital-led service transformation in Oman's public sector was a strategic response to institutional pressures seeking legitimacy by conformance. Institutional theory has been extensively used to explain the drivers and barriers to technology adoption within the public administration context (Altayar, 2018; Pina et al., 2010; Savoldelli et al., 2014; Sherer et al., 2016).

Thus, for this research, we use institutional theory to argue that the sensemaking of AI benefits is influenced by the institutional environment of public administration. In the next section, we discuss the sensemaking theory.

3.2 Sensemaking Theory

Swanson and Ramiller (2004) build on Rogers's (2003) innovation initiation stages arguing for a more precise distinction between comprehension and adoption processes. During the comprehension process, organisational actors engage in sensemaking of the organising vision, a broad understanding of the technology and its benefits, and subsequently develop positive or negative attitudes. If the technology shows potential in the problem domain, active information is gathered to develop a supportive rationale and a business case. The established technology adoption models (such as the technology acceptance model, theory of reasoned action, UTAUT, etc.) test how perceptions, attitudes, and behaviours affect the adoption of technology. However, these models fail to explain how these perceptions are formed in the first place (Seligman, 2006). This pre-adoption reality framing plays a critical role in driving the adoption decision and the associated investments. Sensemaking can address this gap given the adoption process begins much earlier during the comprehension stage when perceptions and attitudes are formed (Seligman, 2006).

Maitlis and Christianson (2014, p. 67) define sensemaking as “a process, prompted by violated expectations, that involves attending to and bracketing cues in the environment, creating intersubjective meaning through cycles of interpretation and action, and thereby enacting a more ordered environment from which further cues can be drawn.” In the classical work, sensemaking is discussed as a retrospective process ascribing meaning to past events within the context of social structures and institutional frameworks (Weick et al., 2005). A future-oriented sensemaking perspective has also been prominent in the literature explaining mental processes in negotiating and creating probable future states, especially in a technological context (Elbanna & Linderoth, 2015; Goto, 2022; Luna-Reyes et al., 2021; Tan et al., 2020; Wang et al., 2019).

This paper adopts a prospective sensemaking perspective to explore how organisational members develop preferences regarding the use of AI within their organisations. Weick et al. (2005) caution against exaggerating the agency of organisational actors as rational and instead argue for an institutional perspective where actors have internalised institutional and organisational boundaries and are themselves carriers of institutionalism. Thus, actors enact the environment which might enable or constrain future action (Jensen et al., 2009a). Building on Fleming's (2019, p. 24) conception of “bounded automation”, the sensemaking process and the interpretation of the AI benefits are not only shaped by the innovation characteristics but also institutional pressures. Weber and Glynn (2006, p. 1640) identify three contextual mechanisms of priming, triggering, and editing operating between the institutional environment and sensemaking.

3.3 Hypotheses

The coercive, mimetic, and normative institutional isomorphic mechanisms (DiMaggio & Powell, 1983) are hypothesised as the primary institutional pressures that affect the sensemaking of AI benefits from its use within the public administration. Furthermore, consultant pressures are hypothesised as drivers of all three isomorphic pressures and directing affecting sensemaking. The output of this sensemaking process, the perceived benefits of AI use, is modelled as the dependent variable. The four predictor constructs are deduced from the institutional theory and the dependent variable is deduced from the sensemaking theory. Figure 2 shows the conceptual model.

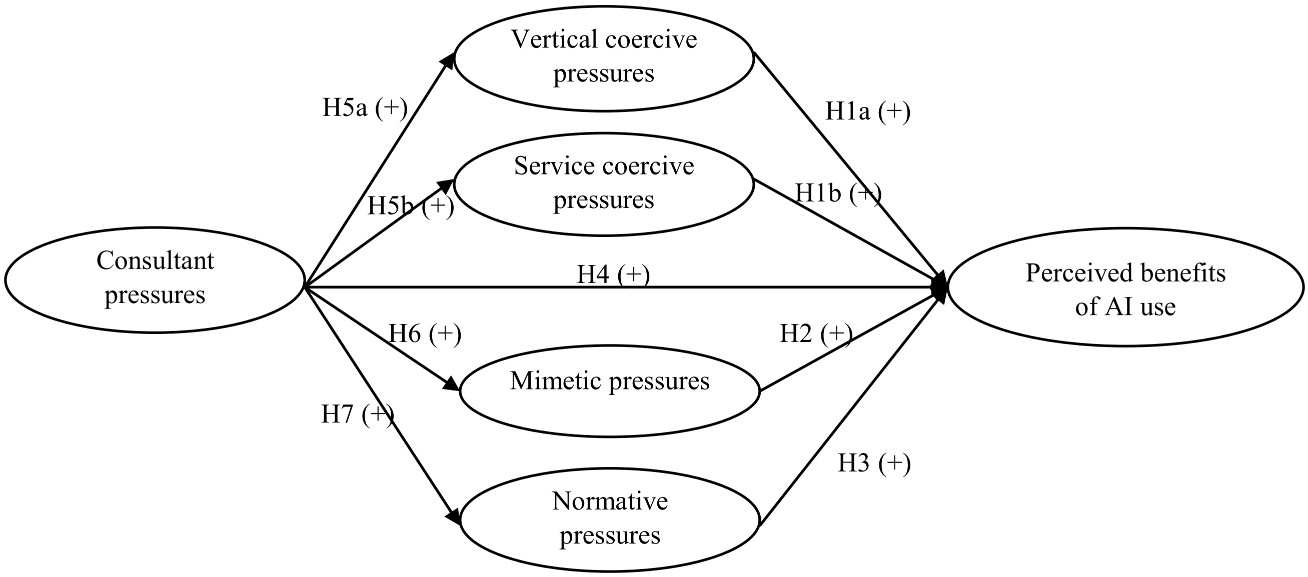

Fig. 2 Conceptual model

3.3.1 Coercive Pressures

Coercive pressures can be either formal or informal (DiMaggio & Powell, 1983). The formal pressures manifest in the form of political mandates and dependence of public administration on central governments for resources. The informal pressures manifest through the citizenry and might become formal pressures when endorsed by political leaders.

Political mandates for efficiency, innovation, and evidence-based decision-making fused with fiscal pressures compel public administration to seek newer technologies such as AI. Mergel (2018) discusses coercive pressures on public managers to adopt challenge.gov to support the political agenda of open innovation. Walker et al. (2011) find high-level government policies as key drivers of technological innovations within English local governments. The creation of digital departments in Canada and the UK is aimed at centralising digital-by-default agendas and leads to coercive pressures for digital government adoption (Eaves & Goldberg, 2017; Roy, 2017).

Another source of formal pressure results from political changes. Bernier et al. (2015) find majority governments, being stable, are associated with more innovation within the public sector. Election cycles and new political leadership might influence technology adoption. For example, Michael Bloomberg's appointment as New York City's mayor spearheaded several open innovation practices (Heimstädt & Reischauer, 2019).

Technology projects in the public sector encounter regular scrutiny from oversight bodies (Desouza et al., 2020). The threat of audits from these oversight bodies with the authority to reward or sanction specific innovations might exert coercive pressures for compliance with government mandates (Madan & Ashok, 2023; Walker, 2006). Research has shown a moderate effect of value-for-audit reports on organisational practices in the Canadian context; political intervention triggered by these audits has a more significant impact (Morin, 2008, 2014). Korac et al. (2017) find a negative influence of oversight bodies on managerial perceptions of innovation within the Australian local government.

Service coercive pressures are the informal pressures associated with the mandates of public administration to align with the demands and expectations of their citizens to remain relevant and legitimate. Citizens accustomed to digital and personalised services from the private sector have come to expect similar levels of service quality from public services (Chen et al., 2019; Wang et al., 2021). Research has shown a positive impact of citizen demands and public pressures on all types of innovation including technological (Berry & Berry, 1999; Hong et al., 2022; Korac et al., 2017; Walker, 2006; Walker et al., 2011).

Thus, vertical and service coercive pressures create demand for solutions triggering sensemaking to cast AI benefits in a positive or a negative light. Hence, we state our first two hypotheses as:

> ***H1a***: *Vertical coercive pressures positively affect the perceived benefits of AI use within the public administration.*
> ***H1b***: *Service coercive pressures positively affect the perceived benefits of AI use within the public administration.*

3.3.2 Mimetic Pressures

The need to imitate similar organisations when faced with uncertainty results in mimetic pressures (DiMaggio & Powell, 1983). Public administration witnesses frequent economic and demographical changes that create uncertainty and complexity. To resolve this uncertainty, organisations seek successful innovations implemented by their peers (Scott, 2013).

The environmental macro changes have been instrumental in public administration's digital transformation agenda seeking peer approaches and embracing digital government as a necessity (Eom & Lee, 2022; Janowski, 2015). Turner et al. (2022) research shows environmental shocks, such as the financial crisis, were drivers for South Korea's e-government progress. Citizen demographical changes have also been linked to the public sector's pursuit of innovative solutions and seeking peers' solutions (Richter, 2014; Suzuki et al., 2020).

Public administration is under pressure to adopt technological innovations that have been demonstrated to improve performance and better meet citizen demands under the omnipresent resource and fiscal pressures (Wang et al., 2021). Research has shown imitation pressures between governmental agencies affect the adoption of technological innovations, e.g. chatbots (Wang et al., 2020) and open innovation platforms (Mergel, 2018). Hong et al. (2022) show the existence of mimetic pressures in South Korean local administration imitating digital technology adoption of their peers. These pressures are further intensified by the public sector's fishbowl effect with persistent media and opposition scrutiny impelling imitation of successful innovations to demonstrate innovation and legitimacy for survival (Desouza et al., 2020).

Inspired by the quasi-market orientation of the NPM reforms, public administration organisations are also affected by the competitive pressures to showcase their legitimacy (Verhoest et al., 2007). The competition can be between agencies competing for funding, attracting and retaining citizens and businesses in their jurisdictions, or justifying their existence against privatisation. Korac et al. (2017) show service provider competition is an antecedent for innovation adoption in the local government. Competition between public agencies has been shown to impact technological innovations (Walker, 2006). Chen et al. (2019) case study research demonstrates political tournaments between local governmental agencies in China as a driver of AI adoption.

Thus, mimetic pressures compel public administration to showcase their legitimacy and build a reputation among their peers affecting perceptions of AI benefits. Hence, we state our third hypothesis as:

> ***H2***: *Mimetic pressures positively affect the perceived benefits of AI use within the public administration.*

3.3.3 Normative Pressures

DiMaggio and Powell (1983) argue normative pressures arise from professionalisation. They are a form of organisational learning through engagement with peer organisations and professional associations (Berry & Berry, 1999). These can also manifest as indirect pressures through organisational leaders engaging in their professional networks (Damanpour & Schneider, 2006) and influencing decision-making based on perceptions formed through these interactions.

In a local administration context, studies have shown learning from peers and networking in professional organisations are associated with innovation adoption (Korac et al., 2017) and differentiate high-innovation organisations from low-innovation counterparts (Walker et al., 2011). Similarly, McNeal et al. (2003) show legislative professionalisation and professional networks are associated with digital government adoption in the American states. Lee et al. (2011) test for factors associated with the level of e-government development among 131 countries and find support for organisational learning.

New public governance scholars forward network-based collaborative and open innovation strategies (Hartley et al., 2013; Provan & Lemaire, 2012; Sørensen & Torfing, 2011). These networks involving inter-agency or public-private collaborations provide fertile ground for learning and normative mechanisms to come into play. In their study of big data adoption at the US Social Security Administration, Krishnamurthy and Desouza (2014) find cross-agency collaboration and learning as critical. Similarly, Desouza (2014) in their study of public administration CIOs argues that cross-agency collaboration is crucial for big data projects.

Thus, engagement in professional associations and participation in inter-agency collaborations leads to normative pressures. These influence perceptions of the benefits of innovations when peer organisations share their successes. Hence, we state our fourth hypothesis as:

> ***H3***: *Normative pressures positively affect the perceived benefits of AI use within the public administration.*

3.3.4 Consultant Pressures

Saint-Martin's (1998) historical institutional analysis identifies the Glassco Commission of the 1960s as a pivotal moment in the Canadian political sphere. Consultants became influential actors within the government following the Commission's recommendations to develop managerial practices promoting efficiency and service delivery (Government of Canada, 1962). The widespread penetration of management consultants in all areas of policy and administration witnessed a further boost with the NPM reforms (Saint-Martin, 1998). Howlett and Migone (2014, p. 190) support this trend in their review of the expenditure of the Canadian government on management consultants and point to "symbiotic oligopoly-oligopsony relationships" referring to not only long-term multi-year contracts but also their oligopolistic nature consisting of a small number of large firms. Specifically, critical IT infrastructure was outsourced and key positions contracted out resulting in public administration losing expertise and tactical knowledge (Clarke, 2020). Momani (2013, p. 3) discusses this as a "hollowed out" state phenomenon with the propensity to seek management consultants for capacity and strategic advice. The lack of technological expertise has made public administration reliant on consultants to drive its digitilisation agenda (Collington, 2022). Galwa and Vogel (2021) shed light on the social identity constructed by consultants in a public administration context. The consultants themselves engage in sensemaking with the public administration clients co-creating reality regarding the use of AI. Hence, we state our fifth hypothesis as:

H4: Consultant pressures positively affect the perceived benefits of AI use within the public administration.

Consultants can influence political leadership through explicit sales pitches for adopting AI (Mignerat & Rivard, 2009). The consultants already managing the IT infrastructure are engaged for their expertise and up-to-date knowledge of the technological trends and can influence how AI is positioned as a solution to specific business needs (Stapper et al., 2020). Research has shown consultants play a role in legitimising decision choices by working with public managers and creating demand for their services by pitching co-created solutions to political leadership (Sturdy et al., 2022).

Capacity constraints and the ever-increasing complexity of policy problems have seen increasing use of consultants for facilitating citizen and stakeholder sessions or for conducting policy research and jurisdictional scans (Marciano). Research has shown consultant perceptions lead to different approaches to identifying citizen needs and subsequent policy interventions (Stapper et al., 2020). Thus, consultants impact which citizen needs are prioritised and put forward to leadership. Furthermore, lacking internal technological expertise, consultants can exploit public administration knowledge assets to highlight citizen needs that align with their profit agendas (Ylönen & Kuusela, 2019). Hence, we state our next two hypotheses as:

H5a: *Consultant pressures positively affect vertical coercive pressures for using AI within the public administration.*

H5b: *Consultant pressures positively affect service coercive pressures for using AI within the public administration.*

Consultants regard themselves as objective knowledge agents bringing in both public and private sector expertise (Lapsley & Oldfield, 2001). Consulting firms are associated with the diffusion of similar business practices and models through developing solutions using standardised templates (DiMaggio & Powell, 1983; Speers, 2007). The demonstration of peer successes in adopting AI might lead to positive perceptions and isomorphic pressures towards adoption. Consultants are keen to produce fast policies and standardise solutions in a local context (Stapper et al., 2020). Consultants have played a major role in advocating evidence-based policymaking as a means of reducing uncertainty and legitimising decisions (Ylönen & Kuusela, 2019). Thus, consultants act as institutional carriers of solutions highlighting their role in providing instrumental rationality (Scott, 2013). Hence, we state our eighth hypothesis as:

H6: *Consultant pressures positively affect mimetic pressures for using AI within the public administration.*

The consultants also influence adoption decisions by engaging with senior politicians and administrators through industry associations, professional training, and policy think tanks contributing to normative pressures (Mignerat & Rivard, 2009). In several policy spheres, there has been a fluid movement of people between consulting and political positions (Kipping, 2021). Consultants can act in the capacity of "linkages" between public administration and private sector expertise giving them the power to mediate knowledge flows and prioritise specific actors over others (Marciano, 2022). Hence, we state our last hypothesis as:

H7: *Consultant pressures positively affect normative pressures for using AI within the public administration.*

4 Research Methodology

We adopt an explanatory mixed-method research design to answer the two research questions (Creswell & Creswell, 2017). The study recognises a rich body of literature and strong theoretical frameworks already exist. However, the context of the research related to AI and public administration is novel and current literature lacks substantial empirical evidence (Alsheibani et al., 2018; Pencheva et al., 2018). Thus, a quantitative study followed by a qualitative study was considered appropriate (Venkatesh et al., 2013). The primary quantitative study informed the design of the focused qualitative study. The purpose of a mixed-method approach, in line with the research questions, was two-fold: completeness and expansion (Venkatesh et al., 2013). Mixed-method research can provide stronger inferences and compensate for the weaknesses of single quantitative or qualitative methods (Teddlie & Tashakkori, 2009).

As shown in Fig. 1, the quantitative study is based on a cross-sectional survey and tests the significance of institutional pressures, deduced from the literature, on the sense-making of AI benefits. The second qualitative study based on semi-structured interviews adds depth and richness to the results of the quantitative study. The qualitative study explores the underlying mechanisms that explain the results of the quantitative study. After the completion of the qualitative study, the results of the quantitative study were revisited and meta-inferences were developed through the process of "bridging" to highlight the temporal and spatial contextual mechanisms (Venkatesh et al., 2013, p. 39).

4.1 Sampling Strategy

4.1.1 Quantitative Study

The data for the cross-sectional survey was collected from the Canadian public administration at three levels: federal, provincial, and municipal. Canada has been at the forefront of AI research introducing the world's first national AI strategy in 2017 (CIFAR, 2020). The Canadian government's vision to be an AI leader, developing a rich local AI ecosystem and talent pool, and a history of pursuing technological innovations within the government makes Canadian public administration an appropriate sample to test our hypotheses. At these earlier stages of AI adoption, public administration across diverse jurisdictions and levels is at different stages of adoption and provides good variation in the data.

The data was collected using an online questionnaire designed in Qualtrics. Purposive sampling was used to identify key informants within the Canadian public administration who are involved in digital transformations. The criteria for informant selection aligns with Campbell's (1955) guidelines, informants were not only knowledgeable but also able to respond to the questions' specific context related to the meaning and adoption of AI. The respondent profiles included data scientists, business analysts, team leads, and managers and above. They were familiar with the implementation or use of AI within their organisation, either from a technical or a functional perspective, or were involved with IT strategy development within their organisations. In addition, technology consultants working as ad hoc employees in a technology context were also targeted.

The key respondents were identified and contacted through GCCollab,[1] LinkedIn, and emails gathered from open government directories. The data collection was conducted in April – June 2022 in two waves.[2] To improve the accuracy of the responses, invitations explained the context and any subsequent questions were addressed. Furthermore, the online questionnaire was designed to emphasise organisational-level responses. For consultants, the instructions specified response should be from the perspective of their current or recent public administration client. To minimise item ambiguity, key concepts were defined and examples were provided (such as AI types and example applications), statements were specific, and did not contain double-barrelled and complex wording (Tourangeau et al., 2012).

Table 2 shows the respondent sample demographic data. Out of the 386 responses that were complete, data was cleaned by removing flatline responses through visual examination. Cases with missing data greater than 5% were also removed. This resulted in 272 final usable responses representing a 30% response rate.[3] The sample represents a wide heterogeneous pool of expert respondents across three levels of government and different organisational sizes. The sample provides a good representation of the population and mitigates drawbacks associated with purposive sampling such as the generalisability of the results.

The missing data was 1.43% for only three variables, this was below the 5% threshold and was not concerning (Hair et al., 2016). Little's MCAR test was also conducted and was not significant ($p > 0.05$) concluding support for the null hypothesis that missing data is at random and not a concern (Little, 1988).

Since the data are cross-sectional and both dependent and independent variables were collected from the same respondents at the same time, there is a risk of common method bias (Podsakoff et al., 2003). Harmon one-factor test was conducted on the items comprising the constructs to check for common method bias. The results did not produce a single-factor solution, the maximum variance explained by one factor was 30.13% and below the 50% threshold. To check for non-response bias, we analysed variance on several variables, between complete and incomplete variables, and

[1] Government of Canada collaboration site restricted to Canadian public servants and academics: www.gccollab.ca

[2] Wave 1 was in April 2022 and wave 2 was from mid-May to mid-June 2022.

[3] The population size was determined as all Canadian federal government agencies at level 2 (departmental level), excluding defence; all Canadian provincial government ministries and agencies excluding law enforcement, health services, utilities; and all towns and cities with a population greater than 10,000. At least one informant at each of these organisations was targeted.

Table 2 Respondent Sample Demographic Data

Demographic characteristics		No. of respondents	% of total
Gender	Male	165	61%
	Female	104	38%
	Other	3	1%
Age	29 and under	18	6%
	30–39	62	23%
	40–49	86	32%
	50–59	82	30%
	60 and above	24	9%
Education	Diploma/ certificate or below	27	10%
	Bachelor's degree	82	30%
	Professional degree	23	8%
	Master's degree	116	43%
	Doctoral degree	24	9%
Position	Executive	19	7%
	Senior Director/Head of Department	22	8%
	Director	34	13%
	Senior Manager	41	15%
	Functional Manager/Project Manager	42	15%
	Team Lead	31	11%
	Consultant/ Advisor	34	13%
	Other (please specify)	49	18%
Level of government	National	150	55%
	Provincial	76	28%
	Municipal	46	17%
Organisation size	> 50	11	4%
	50–99	16	6%
	100–249	20	7%
	250–499	22	8%
	500–749	14	5%
	750–999	8	3%
	< 1000	181	67%

found no significant response bias. We also analysed the two waves of responses and found no significant difference. Finally, we analysed the duration of the response and did not find any significant difference.

4.1.2 Qualitative Study

In the qualitative study, 34 semi-structured interviews were conducted with 38 interviewees. All interviews were conducted virtually over MS Teams; 31 were one-on-one, one was a group interview of 3 participants, and two were group interviews of 2 participants each. The interviews were two-part and explored AI adoption and diffusion within the Canadian public administration. In the first part, the interviewees were asked about their opinions on the use of AI, its benefits, drivers, and the role of the institutional context. The results of the quantitative study were also explored to gather rich explanations. The interview guide for the first part of the interview is attached in Appendix D.

The interviewees represented a range of positions within the Canadian public administration at all levels of the government (federal: 42%, provincial: 39%, and municipal: 11%) and industry (8%). 32% of the interviewees were female. 39% of the interviewees were also participants in the quantitative study. The length of the interviews ranged from 30 – 170 min, the first part relevant to this paper ranged from 30–50% of the interview. Table 3 shows the participant profiles and the length of the interviews.

4.2 Operationalisation of Variables

To test the hypothesised model (Fig. 2), scales are adapted from the literature for five constructs: vertical coercive pressures, service coercive pressures, normative pressures,

Table 3 Interviewee profiles

Interview	Position	Gender	Level of the government/ industry	Length of the interview (in min)
I1	Assistant Deputy Minister and Corporate Chief Information Officer	Male	Provincial	80
I2	Internal Consultant	Male	Federal	66
I3	Digital Public Engagement Specialist	Female	Provincial	64
I4	Advisor to Chief Data Officer	Male	Federal	43
I5	Director of Internal Audit	Male	Federal	31
I6	Chief Technology Officer	Female	Industry	30
I7	Assistant Deputy Minister	Male	Provincial	58
I8	Director of Learning	Male	Federal	52
I9	Consultant and past civil servant	Female	Industry	55
I10	Executive Director/ Chief Executive Officer	Female	Provincial	45
I11	Director, Business Optimisation	Male	Provincial	61
I12	Director	Male	Provincial	51
I13	Data Scientist	Male	Federal	72
I14	Digital Information Strategist	Male	Provincial	54
I15	Director, AI	Male	Federal	56
I16	Director of Analytics	Female	Provincial	45
I17	Data Scientist	Male	Federal	54
I18	Chief Data Officer	Male	Federal	82
	Senior Data Analyst	Female	Federal	82
	Data Analyst	Male	Federal	82
I19	AI Analyst	Male	Municipal	52
I20	Vice President of Innovation	Male	Federal	52
I21	Senior Manager	Female	Provincial	53
	Senior Policy Advisor	Female	Provincial	53
I22	Chief Data Officer	Male	Federal	36
I23	Data Analyst	Male	Federal	40
I24	Director, Analytics & Innovation	Male	Municipal	62
	Team Lead, Information Analytics	Male	Municipal	62
I25	Chief Information Officer	Male	Municipal	50
I26	Senior Research Advisor (AI)	Male	Federal	60
I27	Consultant	Female	Industry	30
I28	Chief of Staff	Male	Federal	48
I29	Chief Information Officer	Female	Provincial	30
I30	Chief Information Officer	Female	Provincial	45
I31	Policy Analyst, Data and Digital Innovation	Female	Provincial	65
I32	Senior Data Scientist	Male	Federal	170
I33	Director, Digital and Analytics	Male	Provincial	50
I34	Director, Digital and Analytics	Male	Provincial	36

mimetic pressures, consultant pressures, and perceived benefits of AI use. The survey instrument for the study was pilot-tested (n = 34) in Jan-Mar 2022 to assess the quality, reliability, and construct validity. Following the results of the pilot, two questions were reworded, and one question was split into three for better clarity. The unit of analysis is the organisation. The constructs are measured on a 7-point Likert scale with 1 for strongly disagree and 7 for strongly agree. Appendix A provides a summary of the items used for each construct.

For the measurement of the dependent construct, perceived benefits of AI use, the respondents were asked to rate their agreement on statements related to AI benefits in terms of making better decisions, improving efficiency and speed, citizen engagement and service delivery, and reducing errors. Six items are used for this first-order reflective construct.

Vertical coercive pressure is a first-order reflective construct measured using three items that ask respondents whether political changes, political mandates, and oversight bodies drive the adoption of new technologies. The first-order reflective service coercive pressures construct is measured using two items that ask respondents whether citizen demands and expectations drive the adoption of new technologies. The first-order reflective mimetic pressures construct is measured using three items that respondents whether competition, economic changes, and citizen demographic changes drive the adoption of new technologies. The scale for normative pressures is a first-order reflective construct measured using three items that ask respondents about networking within the government and meeting with external stakeholders and the private sector. The scale for the consultant pressures is a single-item construct that asks respondents whether external consultants and advisors drive the adoption of new technologies.

Three organisational factors are included as controls. The literature has mixed results on the impact of organisational size on innovation (Damanpour, 1991; Korac et al., 2017; Walker, 2006). Large public organisations have more resources and a higher innovation capacity leading to a favourable perspective on AI benefits. The size of the organisation is coded as very large (> 999 employees), large (500–999 employees), medium (100–499 employees), and small (< 100 employees). The level of AI adoption[4] is coded as non-adopters, piloting, and adopters. Sensemaking is expected to evolve as adoption and implementation progress and thus, this control accounts for the temporality. The level of government (federal, provincial, municipal) is used to control for fixed effects.

5 Stage 1: Quantitative Study Analysis

The partial least squares-structural equation modelling (PLS-SEM) is used for analysis using R Studio and SEMinR module. PLS-SEM is deemed suitable when the theory is in the initial stages of development (Hair et al., 2016). This paper is testing a model that explains sensemaking in a novel context of AI in public administration. In addition, the paper aims to maximise the predictive power of endogenous variables explaining the relationship between institutional pressures and sensemaking. Thus, the use of PLS-SEM is considered appropriate. PLS path modelling generates reliable results with smaller sample sizes and can handle complex cause-effect structural models (Henseler et al., 2009; Hulland, 1999).

The minimum sample size to test the model was determined as 156 considering guidelines suggested by Tabachnick and Fidell (2007), Bartlett et al. (2001), and Hair et al. (2016). Thus, the sample size of 272 is considered sufficient to test the model using PLS-SEM.

The model testing is done in two stages starting with the outer measurement model and then proceeding with the inner structural model (Hair et al., 2021).

5.1 Measurement Model

As our research model is reflective, the outer measurement model is first assessed for internal consistency reliability, convergent validity, and divergent validity. Table 4 shows the results summary.

The internal consistency reliability is assessed by examining Composite Reliability (CR) and Cronbach's Alpha (CA). Both CR and CA values are considered acceptable between the range of 0.6 – 0.7 for exploratory research and satisfactory between 0.70 – 0.95 (Hair et al., 2016). The values for CR and CA are in the satisfactory range for service coercive pressures (SCR), normative pressures (NOR), and perceived benefits of AI use (PBE); and consultant (CON) is a single-item construct. The CR and CA values for vertical coercive pressures (VCR) and mimetic coercive pressures (MIM) are within the acceptable range of 0.6–0.7. Since this is an exploratory model and supported by theory, the internal consistency reliability of the measurement model is considered acceptable.

The convergent validity is first assessed by examining construct-to-indicator loadings. Loadings greater than 0.7 are considered satisfactory; items with loadings between 0.4 – 0.7 should be only considered for elimination if it improves internal consistency reliability (Hair et al., 2016). All but two construct-to-indicators loadings are below 0.7: VCR → VC2 (0.675) and NOR → N1 (0.647). The indicators are retained with the following rationale. First, the deletion of the indicators does not improve internal consistency reliability. Second, the indicators are supported by theory and are in the higher range of acceptability. Furthermore, the average variance extracted (AVE) for all constructs is above the threshold of 0.50 (Hair et al., 2016), the lowest one being 0.56. Thus, the convergent validity of the measurement model is considered acceptable.

The discriminant validity was assessed by examining cross-loadings of the indicators with other constructs and conducting Fornell-Larcker and hetrotrait-monotrait (HTMT) analysis. The indicator loadings are greater

[4] Derived from the first two question that asked respondents "to what extent machine learning and natural language processing was being used in their organisation." Adopters are coded for those who stated "currently using ML or NLP"; piloting who stated "currently piloting or testing ML or NLP"; and the remaining as non-adopters who are not currently using ML or NLP.

Table 4 Results Summary for Reflective Measurement Model

Latent variables	Indicators	Convergent Validity		Internal Consistency Reliability		Discriminant Validity
		Loadings	AVE	Composite Reliability	Cronbach's Alpha	HTMT confidence intervals do not include 1
Service coercive pressures (SCR)	SC1	0.936	0.876	0.858	0.858	Yes
	SC2	0.936				
Vertical coercive pressures (VCR)	VC1	0.760	0.561	0.659	0.633	Yes
	VC2	0.675				
	VC3	0.805				
Mimetic pressures (MIM)	M1	0.737	0.562	0.613	0.610	Yes
	M2	0.700				
	M3	0.808				
Normative pressures (NOR)	N1	0.647	0.597	0.871	0.693	Yes
	N2	0.757				
	N3	0.894				
Perceived benefits of AI use (PBE)	PB1	0.886	0.777	0.945	0.942	Yes
	PB2	0.921				
	PB3	0.898				
	PB4	0.869				
	PB5	0.820				
	PB6	0.890				
Consultant pressures (CON)	C1	1.000	1.000	1.000	1.000	Yes

than cross-loadings with other constructs (Appendix B, Table 7). The Fornell-Larcker criterion analysis (Appendix B, Table 8) shows each of the constructs shares more variance with their indicators ($\sqrt{AVE}$) than with other constructs (Hair et al., 2016). Fornell-Larcker criteria may perform poorly when loadings only differ slightly and HTMT is considered a more robust analysis (Henseler et al., 2015). All values of the HTMT ratio were lower than the conservative 0.85 and bootstrapping with 5,000 sub-samples also does not reveal 1 between the confidence intervals. This supports HTMT statistics significantly different from 1 (Appendix B, Tables 9 and 10). Thus, discriminant validity is established.

The measurement model with the first-order reflective constructs is assessed as a good indicator of their constructs and suitable for the second-stage analysis of the structural model.

5.2 Structural Model

Table 5 shows the VIF and path coefficients. The results of the structural model analysis in SEMinR are shown in Fig. 3.

The collinearity assessment of the predictor constructs is conducted by examining the variance inflation factors (VIF) values. All predictors and controls for PBE were lower than the conservative threshold of 3, the highest one being 2.308 (Table 5). Thus, collinearity between the predictors is not an issue.

The hypothesised model is tested by examining the path coefficients, their significance, and the coefficient of determination (R^2). The significance estimates (t-statistics) were obtained by using SEMinR bootstrapping on 5,000 subsamples (Table 5).

Table 6 summarises the results of the hypothesis tests, five out of nine hypotheses were supported, and one was partially supported. Out of the four institutional pressures, only service coercive pressure is significant in effecting perceived benefits of AI use ($\beta = 0.208$, $t = 2.657$, $p < 0.01$); vertical coercive pressures ($\beta = 0.017$, $t = 0.222$, $p > 0.05$), mimetic pressures ($\beta = 0.066$, $t = 0.831$, $p > 0.05$), normative pressures ($\beta = 0.060$, $t = 0.947$, $p > 0.05$), and consultant pressures ($\beta = 0.042$, $t = 0.641$, $p > 0.05$) are non-significant.

Consultant pressures are significant in effecting all four institutional pressures: service coercive pressures ($\beta = 0.129$, $t = 2.053$, $p < 0.05$), vertical coercive pressures ($\beta = 0.320$, $t = 5.512$, $p < 0.001$), mimetic pressures ($\beta = 0.323$, $t = 5.404$, $p < 0.001$), and normative pressures ($\beta = 0.29$, $t = 4.645$, $p < 0.001$). Since the direct effect of consultant pressures on perceived benefits of AI use is non-significant and the effect of both consultant pressures on service coercive pressure and service coercive pressure on perceived benefits of AI use is significant, the effect of consultant pressures on perceived benefits of AI use is fully mediated by service coercive pressures (Hair et al., 2016). The total effect of

Table 5 VIF and Path coefficients

	Standardised coefficients	t statistics	VIF	Significance
Service coercive pressures—> Perceived benefits of AI use	0.208	2.657	1.282	$p<0.01$
Vertical coercive pressures—> Perceived benefits of AI use	0.017	0.222	1.387	n.s
Mimetic pressures—> Perceived benefits of AI use	0.066	0.831	1.653	n.s
Normative pressures—> Perceived benefits of AI use	0.060	0.947	1.227	n.s
Consultant pressures—> Service coercive pressures	0.129	2.053	-	$p<0.05$
Consultant pressures—> Vertical coercive pressures	0.320	5.512	-	$p<0.001$
Consultant pressures—> Mimetic pressures	0.323	5.404	-	$p<0.001$
Consultant pressures—> Normative pressures	0.290	4.645	-	$p<0.001$
Consultant pressures—> Perceived benefits of AI use	0.042	0.641	1.271	n.s
small—> Perceived benefits of AI use	-0.155	-2.184	1.239	$p<0.05$
medium—> Perceived benefits of AI use	-0.142	-2.449	1.14	$p<0.05$
large—> Perceived benefits of AI use	-0.120	-2.048	1.078	$p<0.05$
adopters—> Perceived benefits of AI use	0.129	2.460	1.154	$p<0.05$
pilot—> Perceived benefits of AI use	0.019	0.327	1.191	n.s
federal—> Perceived benefits of AI use	0.065	0.723	2.308	n.s
provincial—> Perceived benefits of AI use	-0.044	-0.522	2.096	n.s

consultant pressures on the perceived benefits of AI use is significant at 10% alpha ($\beta=0.113$, $t=1.807$, $p<0.10$).

In terms of the control variables, very large organisation size has a positive effect on the perceived benefits of AI use when compared to organisations of other sizes. The level of the government does not affect the perceived benefits of AI use. Organisations that identify as adopters have a positive effect on the perceived benefits of AI use when compared to non-adopters. However, there is no significant difference between non-adopters and those piloting AI applications.

The structural model explains 18.89% of the variance in perceived benefits of AI use ($R^2=0.1889$). To investigate the out-of-sample predictive power of the model, we use the $PLS_{predict}$ procedure with 10 folds, 10 repetitions, and a direct antecedent (predict_EA) approach (Hair et al., 2021). Root-mean-square-error (RMSE) was selected as the appropriate metric to quantify the prediction error after visual inspections of the plots showed them symmetric. All but one indicator for perceived benefits of AI use had lower RMSE values for out-of-sample PLS-SEM analysis when compared with a linear regression model benchmark, one indicator had the same RMSE values (Appendix C, Table 11). Thus, the model is assessed to have medium to high predictive power (Hair et al., 2021).

Finally, the model was compared with three other models: model 1 as the original model with organisational level controls (size, level of government, level of AI adoption), model 2 with individual level controls (gender, education, age, and position), model 3 with most relevant individual and organisational level controls (size, status of adoption, level of government, gender, and education) and model 4 with all controls. Examination of Bayesian information criteria (BIC) shows the original model has the lowest value (Appendix C, Table 12). R^2 and Adj R^2 for model 3 are marginally better than model 1. For model 4, R^2 increases while Adj R^2 decreases showing additional controls do not add any explanatory power. Thus, considering BIC and Adj R^2, the original model is considered the most parsimonious among the alternative models.

The low R^2 value suggests institutional pressures have an overall weak effect on the perceived benefits of AI use (Hair et al., 2016). The primary mechanism for this effect is through service coercive pressures. We do find a strong effect of consultants in generating all types of institutional pressures. However, the effect on perceived benefits of AI use is primarily indirect through service coercive pressures. In the qualitative study, we explore the mechanisms and deduce meta-inferences for these contrary results.

6 Stage 2: Qualitative Study Analysis

Template analysis was used for conducting a thematic analysis of the data collected from the semi-structured interviews (King, 2004). The interviews were audio recorded, transcribed, and analysed in NVivo. A research diary was maintained capturing pre- and post-interview reflections. An a priori template was developed based on the results of the quantitative study and theory. Each interview was coded iteratively line-by-line to retain interviewees' voices and viewpoints (Fereday & Muir-Cochrane, 2006).

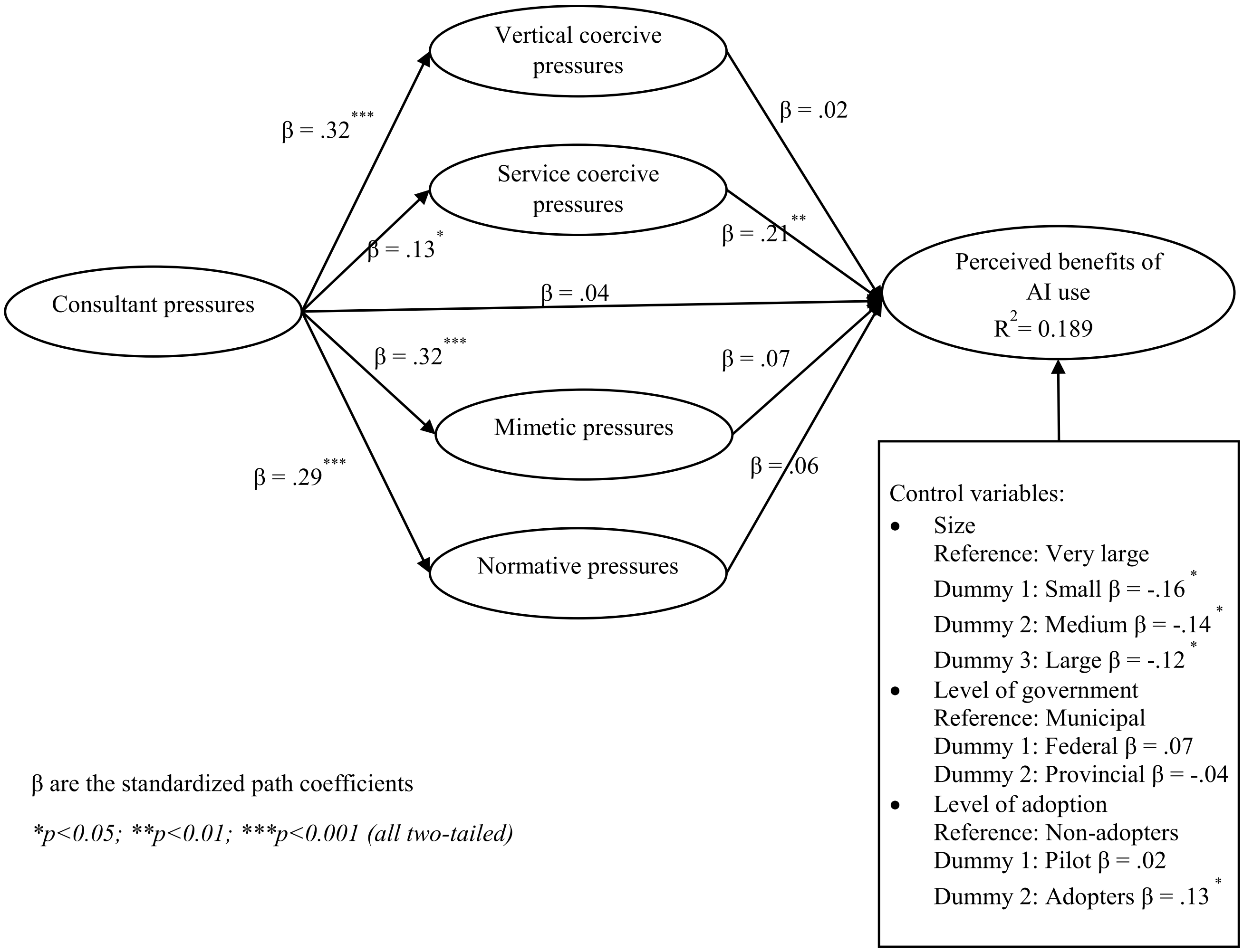

Fig. 3 Model Results

Table 6 Results of hypotheses tests

Research hypotheses	Supported?
H1a: Vertical coercive pressures positively affect the perceived benefits of AI use within the public administration	Non-significant
H1b: Service coercive pressures positively affect the perceived benefits of AI use within the public administration	Yes
H2: Mimetic pressures positively affect the perceived benefits of AI use within the public administration	Non-significant
H3: Normative pressures positively affect the perceived benefits of AI use within the public administration	Non-significant
H4: Consultant pressures positively affect the perceived benefits of AI use within the public administration	Non-significant direct effect Fully mediated
H5a: Consultant pressures positively affect vertical coercive pressures from using AI within the public administration	Yes
H5b: Consultant pressures positively affect service coercive pressures from using AI within the public administration	Yes
H6: Consultant pressures positively affect mimetic pressures from using AI within the public administration	Yes
H7: Consultant pressures positively affect normative pressures from using AI within the public administration	Yes

The coding was conducted in five steps. First, five diverse interviews were coded dissecting the text and attaching either an a priori code or a new code derived from the data. The codes were grouped into organising themes and conceptual themes and a revised template was developed. Quality and reflexivity checks were conducted using the research diary to ensure researcher bias was minimised (King & Brooks, 2016). In the second step, the template from the first step was used to code the next five interviews resulting in a revised template. This process was repeated for the next two sets of five interviews. In the fourth set of interviews, minimal new codes were identified. This was followed by coding another five interviews and no new codes were identified. Thus, theoretical saturation was achieved at 20 interviews and coding was completed at 25 interviews. The remaining interviews were read to identify relevant quotes. In the third step, the template was finalised through several iterations of classifying organising and conceptual themes and conducting further reflexivity checks. The final template is attached in Appendix E. In the final step, the template was used to reflect on the results of the quantitative study, explain the sensemaking mechanisms, and form meta-inferences synthesising the results of the two studies. These are discussed in the following sub-sections.

6.1 Relationship Between Institutional Pressures and Perceived Benefits of AI use

This section discusses the results of the qualitative study with a particular focus on explaining the results of the quantitative study.

6.1.1 Vertical Coercive Pressures

The quantitative study did not find support for vertical coercive pressures affecting the perceived benefits of AI use (H1a). The interviewees acknowledged there are no direct political pressures for using AI for service delivery or improving internal processes. This is expressed in the following quotes:

> *"…at no point did … the minister come along and say you need to do ML … and so I agree that doesn't really affect it [AI adoption]" (I1)*

The interviewees concede the indirect effect of political mandates that create operational imperatives for public administration. These mandates include evidence-based decision-making, experimentation and innovation, efficiencies, economic growth, red tape and bureaucracy reduction, and government modernisation. This is expressed in the following quote:

> *"a lot of these [mandates] aren't necessarily specifically geared towards you must use AI. It's about us looking at how can we use AI to help us achieve these overall objectives … to leverage our data to improve the way we make decisions and improve the way that we deliver services to Canadians" (I15)*

A few interviewees also discussed politicians adopting a cautious approach and avoiding advocating for AI due to political risks as expressed by the following interviewee:

> *"The government doesn't get excited about the use of AI … because that is fraught with political risk" (I20)*

Thus, with a lack of direct political interest or mandates, vertical coercive pressures do not play a role in forming perceptions of AI benefits or encouraging its adoption.

6.1.2 Service Coercive Pressures

The quantitative study finds support for service coercive pressures having a significant positive effect on the perceived benefits of AI use (H1b). This was confirmed by the interviewees as citizens have come to expect personalised and digital services as norms. AI-driven solutions are considered powerful tools to help achieve these service needs while facing fiscal pressures, resource limitations, and pressures to reduce the size of the government. This is illustrated in the following quote:

> *"… consumers are so used to this … we're actually a service industry … machine learning and giving a bit more of an individual service to our clients is, in my view, the future for government" (I10)*

6.1.3 Mimetic Pressures

The quantitative study did not find support for mimetic pressures significantly affecting the perceived benefits of AI use (H2).

Mimetic pressures emerge from competition between peer administrative agencies, different levels of government, and jurisdictions. Interviewees discussed the existence of competition between CIOs to adopt the latest technology trends to showcase their leadership within the government and the industry. Furthermore, imitation pressures are generated by comparing public service delivery to the private sector's use of AI as demonstrated by this quote:

> *"… a lot of them will look at like Apple or Google and say … this machine learning is … complex and good … what if we can harness that power" (I3)*

The hype generated by the media or consultants is also widely discussed as contributing to mimetic pressures as demonstrated by this quote:

> *"… senior decision-makers in the government … read Forbes magazine and things in the newspaper. They see all this stuff about … AI and machine learning and … say we've got to do that too … what is driving it? Hype." (I4)*

Even though most interviewees discussed the presence of mimetic pressures, they concurred the effect of such pressures is marginal and weak supporting the results of H2. The primary reason is attributed to a lack of peers with a demonstrable value from using AI while media narrative and citizen perceptions remain negative. The hype generated by consultants is not sufficient to form specific opinions on AI benefits. These are demonstrated in the following quotes:

"… comparing public sector to private sector, that kind of … pressure it could be there, but I think these are marginal marginal pressures" (I2)
"… in terms of … horizontal pressures you know … I think there's been mild, and it's been sporadic. And it's been ethereal like it's been when you say it doesn't last … So, I just don't think we've seen the take up the way that we ought to" (I20)

6.1.4 Normative Pressures

The quantitative study did not find support for normative pressures significantly affecting the perceived benefits of AI use (H3).

The interviewees discussed normative pressures emerging from participation in intra- and inter-governmental demonstrations, individuals changing jobs and bringing new expertise, benchmarking to industry standards, and guidelines on information systems development. The common message was that there are numerous pilots underway within the government and several demonstrations showcasing these initiatives. However, the benefits of using these technologies still need to be demonstrated at scale. Thus, normative pressures do not significantly affect the perceptions of AI benefits. This is demonstrated in the following quotes:

"… that was just an idea that we had demonstrated … this tool [ML-based solution] that we were trying to build … and they were quite interested in it. And I had a conversation with the director … and they were kind of, like, this is cool that you're using our open data … but beyond that, it didn't get anywhere … I didn't really hear much from them afterwards" (I2)
"… we're definitely not the sort of first adopter in terms of technology. So, we're going to sit back, and we'll see how it goes for the departments before we would adopt" (I5)

Thus, normative pressures are critical in building a positive narrative of AI successes and learning from other departments. However, the current state of adoption and use of AI is not at a stage where such pressures can significantly affect perceptions of AI benefits and demonstrate irrefutable value from its use. Notwithstanding bottom-up innovations and a plethora of technology leadership forums within the public administration, the benefits from the use of AI need to be demonstrated at scale supporting the results of H3.

6.1.5 Consultant Pressures

The quantitative results show a significant effect of consultant pressures on all four institutional pressures (H5a, H5b, H6, H7) and no direct effect on the perceived benefits of AI use (H4).

The influence and penetration of consultants were widely recognised by most interviewees as demonstrated by this quote:

"… we have every major firm [management consulting] on retainer … there is … the government tech consulting industrial complex. And, so these companies, they feed on … the hype because there is a great deal of money to be made by doing so and everyone wants government contracts" (I4)

There are several rationales provided for using consultants, such as augmenting internal resources for specific projects, providing industry expertise, kick-starting initiatives, and helping develop strategies.

Consultants generate vertical coercive pressures through lobbying politicians and senior administrators. Mimetic and normative pressures are generated by creating hype and inflated expectations via case studies, conferences, and professional events. The case studies and success narratives also contribute towards service pressures by highlighting citizens' perceived demands and expectations. These are demonstrated by the following quotes:

"… lot of technology companies came and made big promises about the use of AI for our risk modelling and for behavioural nudges …" (I20)
"I've personally dealt with is we'll have third party contractors pitch directly to our political leaders …. then that pressures us in government" (I3)
"… over the last 10 years, it has been very noticeable that the private sector consultancies, conferences, authors have had an opportunity to kind of shape the discourse …[on] artificial intelligence and … set our expectations … put some case studies in front of executives about how this municipality in Southern California is using AI … it saved them 50% over three years …" (I8)
"… what we [consultants] do in conversations … we're doing a lot of educating right now … when I speak with government customers … we're looking for those use cases [of AI] that are extremely high value to them. Look for the win right? Look for the value of what AI could bring …" (I27)

Notwithstanding the role of consultants in generating favourable narratives on AI benefits, the direct effect of consultants on the perceived benefits of AI use is limited. Interviewees discussed public administration has developed a sufficient level of technological maturity through past technology deployments and can withstand aggregated sales pitches. Others consider stringent procurement policies requiring a rigorous requirement and bidding process buffering consultants' offers. This is demonstrated by the following quote:

> *"… we don't believe the … government is particularly influenced by consultants, and we've got enough critical mass in terms that we tend to figure out what it is that we want, keep our tech partners on a fairly short leash. There's … big tech lobbying, lobbying government broadly for opportunities, but I think we tend to be pretty clear in terms of any go to market about what is wanted and how it's going to be approached rather than being led by tech offers" (I7)*

The consultant influence is only effective in forming opinions on AI benefits when they can provide solutions to specific service needs as highlighted in the quote below:

> *"Even if you have expertise, consultants are good … they've got that [exposure to] other jurisdictions, other organisations … they have a condensed exposure … something that might take you years. They can bring all that to the table … AI is huge … even machine learning … there are… 72 different techniques. You're unlikely to have a data science shop or whatever big enough … to have expertise in every single niche and every single new thing coming" (I16)*

Thus, the results of quantitative analysis are supported. Consultants have a significant role in generating institutional pressures but are not directly significant in terms of influencing the perception of AI benefits unless linked to specific service needs.

6.2 Perceived Benefits of AI use

The perceived benefits of AI use were discussed as cost savings through improved efficiency and effectiveness, better resource usage with human resources allocated to higher value tasks, enhanced decision-making capabilities and new insights for policy development, improving citizen engagement and inclusivity, meeting citizen demands, economic development through investments in local technology ecosystems, and enhancing employee and infrastructure safety with better monitoring. The interviews also revealed that perceived benefits of AI use are on a continuum and evolve through various stages of AI adoption as further discussed under sensemaking mechanisms in Section 4.2.3.

The quantitative study suggests a significant difference between how adopters and non-adopters perceive AI benefits and no significant difference between pilot and non-adopters. This was explained by interviewees by a lack of operational AI applications. The perception of AI benefits is not concrete unless there is wide acceptance by IT that the solution can be operationalised. These are demonstrated by the following quotes:

> *"… if you ask me, where is machine learning being used in government? I would have to scratch my head for a while … most of government has not used it really at all … these little boutique experiments which probably have a lifespan of 4 years, tops. They come … they're celebrated then they disappear" (I20)*
>
> *"… there is a need for… a bridge between IT and your data scientist… you're going to come up with a Python code that IT doesn't understand or find that there are a lot of security breaches there and it will not be deployed … it's happening … there is a big gap there …" (I13)*

The lack of a significant difference between pilot and non-adopters was attributed to the same fact that pilots do not demonstrate value unless the solution can be operationalised.

The quantitative study also shows a significant difference between very large organisations (> 999 employees) compared to other organisational sizes. This was attributed by interviewees as related to resources available to large high-profile organisations for innovation as demonstrated by this quote:

> *"… funding is hard to come by [for experimenting with AI], at least in our area … provincial government is quite a large enterprise … split into these 20 lines of business but … some of them generate more revenue than the others, and the ones that generate more revenue get to spend more money. So, it's the folks in energy and mines and forests transportation. A lot of them have the big budgets, whereas where I'm housed in the government, we tend to sort of step back and try not to spend too much money. That's the money problem" (I14)*

The quantitative study does not find any significant difference between levels of the government, either municipal, provincial, or federal. This was attributed to a homogenous Canadian context for the public sector and open sharing of best practices. Some participants did highlight municipal administrations are closer to their citizens and have a better understanding of citizen needs. However, such differences do not manifest significantly when it comes to new technologies and administrators seek other sectors for best practices as this quote demonstrates:

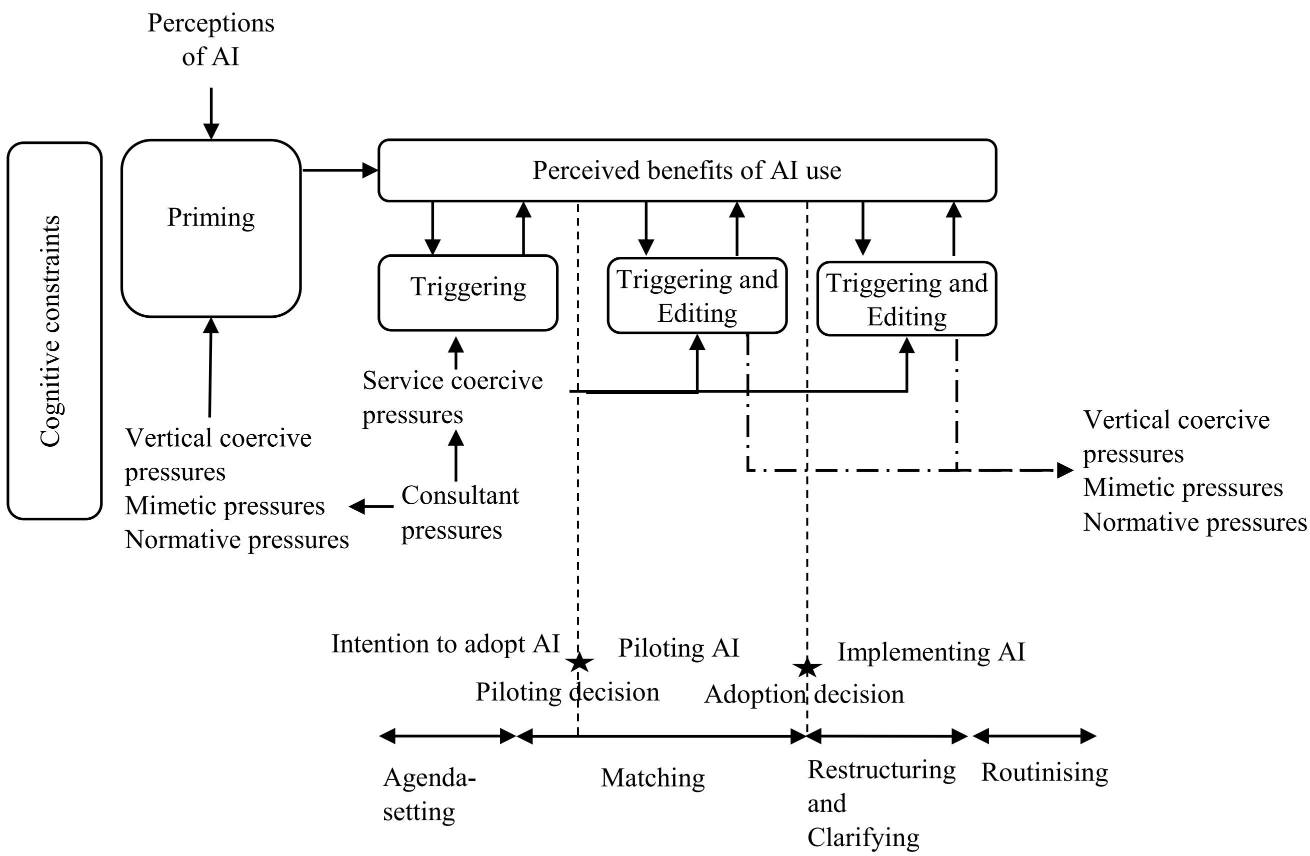

Fig. 4 Perceived benefits of AI use sensemaking mechanisms

> *"… part of a project that is the first to use AI … in call centres … not only for the 311 call centre that AI can be useful, we will demonstrate that for the other department in the cities … we can show the way for other cities … you have a lot of other cities in Canada that have call centres … what we are doing today is to show the way to other cities to do the same … [and] other governments … have call centres too" (I19)*

6.3 Sensemaking Mechanisms

The conceptual model developed from the qualitative analysis showcasing the underlying sensemaking mechanisms is shown in Fig. 4.

Three mechanisms that explain how institutional pressures affect sensemaking are identified as priming, triggering, and editing; cognitive constraints are identified as a global theme. These are discussed below.

6.3.1 Cognitive Constraints

Cognitive constraints were discussed as internalised institutional roles, structures, and values that constrain how AI can be implemented and used. It provides boundaries for the sensemaking of AI benefits. The four sub-themes identified are public value goals, risk aversion, structural constraints, and administrative law.

The public value goals of the government were discussed by several interviewees as the special context that distinguishes them from the private sector pursuing AI for commercial means. The goals for using AI in public administration need to incorporate maintaining public confidence and trust and being answerable to citizens. This is expressed in the following quote:

> *"… government is a tool to serve the people … means of distributing wealth for the benefit and equity of all society … government needs to stop whining about the private sector being able to do so much more with AI in order to save money. Usually, it needs to start … how can we be more trustworthy? How can we create systems that don't just meet the expectations and tests of administrative law, but also … meet the test of responsible government?" (I9)*

Risk aversion and structural constraints were primarily discussed as barriers. The low-risk appetite of public administration leads to an attitude of playing safe as captured in this quote:

"… a natural inclination on the part of public servants to just say no [to an AI solution], like, let's play it safe…" (I14)

Structural constraints were discussed as immutable attributes of public administration that limit choices on funding, design, procurement, and implementation of AI. The funding for projects through central ministries, often Treasury Board, requires demonstrating ROI in business cases. AI projects with unknown requirements and metrics are often challenging to meet these funding requirements. Traditional procurement is a major constraint limiting choices to qualified vendors and often involves long purchasing cycles not conducive for fast adopting AI technologies. Bureaucracy, hierarchical decision-making, and a functional organisational structure restrict agile approaches to AI development. Information systems guidelines and practices around centralised information systems restrict AI design and development choices such as central firewalls, centralised management of corporate websites, hosting of servers, etc. In addition, a unionised workforce limits which AI projects can be pursued and who can be involved. These are illustrated in the following quotes:

"…the government doesn't work well with agile because people who have the dollars, the purse strings, want to know what you're delivering well in advance before you even start" (I15)
"… there is still a very highly unionised workforce that doesn't necessarily give a lot of room to move … government tends to think of control over hiring and classification as a powerful lever for cost reduction rather than necessarily recognising the extent to which that might be limiting innovation" (I7)

Compliance with Canadian administrative law as the existential basis of public administration constraints options and applications of AI. Data collection, consent, and privacy are important elements of the law related to using AI that protects Canadians against illegitimate use of their personal information. However, this also restricts AI use cases involving aggregation of data from several agencies that require long approval processes and complex privacy assessments. The ethos of public service and the moral compass for making public decisions, even if within the law, further constrain cognitive choices available when evaluating the use of AI. These are expressed in the following quotes:

"… you need to have the outputs of an AI system compliant to the basic premise of rule of law, then you need to have a consistently applied set of rules. And ML by its very nature changes over time…" (I9)

"… procurement directives and governments tend to tell staff that they want them to take risks and failure is OK because you can't be innovative without failure. But that the accountability and the Toronto Star front page test really tends to squash that. Privacy is a huge issue…" (I10)

6.3.2 Priming

The priming mechanism was discussed as providing the frames of reference and the situational context that affects what cues are extracted and how are they interpreted. These extracted cues form the basis of sensemaking and subsequent actions. The main sub-themes are identified as perceptions of AI, vertical coercive pressures, mimetic pressures, normative pressures, and consultant pressures.

Perception of AI The perceptions of AI are formed by interviewees' exposure to popular media, contemporary debates, and science fiction. This was discussed as the main cause for negative views of AI being scary, antithetical to democracy and citizen rights, and leading to job losses. These ideas are expressed in the following quotes:

"… we have seen in Ontario … some concerns about things like the law enforcement use of Clearview facial recognition …and a lot of the Google work on the Toronto Waterfront [that got cancelled] … that kind of a smart city would end up using AI to de facto surveil people rather than just enhancing [quality of life] … I think there's a level of nervousness in terms of civic discourse that government is particularly wary of" (I7)
"… convince those people to participate in an AI project … [such as] use of virtual agents and the first question I had on-site is will I lose my jobs…" (I19)

The interviewees discussed raising awareness will help form realistic opinions that with enable extracting pragmatic cues. The awareness can be in the form of knowledge of AI, its current potential and limitations, and its implementation challenges.

Vertical Coercive, Mimetic, Normative, and Consultant Pressures Vertical coercive, mimetic, normative, and consultant pressures are discussed under Section 4.1. These pressures prime the organisation through awareness of peer successes and favourable narratives created by the consultants. They also provide cues in the form of political mandates which become critical once the sensemaking mechanism is triggered through specific events as discussed in the next section.

6.3.3 Triggering

Sensemaking can be triggered by service demands and events that create contradictions and compel public administration leaders to innovate and search for solutions. Two sub-themes for the triggering mechanism are service coercive pressures and triggering events.

The service coercive pressures, as discussed in Section 4.1, determine citizens' demands and expectations. These are the central goals that public administration needs to deliver to ensure its relevance.

The triggering events can be contradictions created by black swan events such as the financial crisis, pandemic, international conflict, civil unrest, etc. Public administration needs to respond to such crises and continue to function for citizen safety and well-being. Such crises need quick delivery of solutions often with insufficient information and resources. During regular operations, political mandates and citizen demands vastly exceed available resources requiring sensemaking and search for new solutions. This can be exacerbated when public administration might also need to adapt to the aftereffects of crises such as the pandemic. This was discussed by interviewees in the context of COVID-19 and severe resource limitations resulting from employees leaving public service and an ongoing lack of expertise. These are expressed in the following quotes:

> *"… we have a very short attention span in government. And if you can't deliver something for me within four months, six months max, forget it …" (I16)*
> *"… the general trend and sort of do more with less. If you have to deliver new programmes, more programmes and you're stuck with the same resources or potentially fewer resources and no like with the great resignation, people are retiring and work workforce shortages and all sectors and things that really put the pressure on so then that might drive people to more creative solutions in terms of okay, well, how can we do the same amount of work or more work with as many or fewer resources?" (I5)*

Other triggering events can be a result of bottom-up innovation when data scientists come up with novel AI-driven solutions to address citizen needs more effectively and ensue the sensemaking of AI benefits by superiors as discussed in the following quote:

> *"… one reflection that I have is … a tonne of people that are trying to see if AI works for X, Y Z … a lot of people … want to create an AI model that will do this and will predict this, will make sense of this massive chunk of data. And that I think we're seeing tonnes of experiments around the Government of Canada in that vein …" (I8)*

6.3.4 Editing

The editing mechanism ensues when organisations have piloted AI solutions and carried out demonstrations. This is the social feedback mechanism where potential users and management form or update their opinions on the perceived benefits of AI in their specific context. Furthermore, demonstrations to other governments and participation in seminars and conferences showcasing the pilot and its expected benefits generate vertical coercive, mimetic, and normative pressures for other organisations as previously discussed. These are demonstrated in the following quotes:

> *"… doing some initial proof of concepts … to demonstrate to the departments across government what AI … machine learning is able to achieve … So, those first proof of concepts have to be as quick to deliver [value] …." (I1)*
> *"… with AI you would like to create more adoption … more users to use it and to show the value there. So, there is a bit of extra step towards convincing people that there is a value of AI …" (I18)*

The social feedback and renewed perceived benefits of AI use determine the corresponding action of whether the AI solution needs more exploration and testing, is operationalisation, or is shelved. Once an AI application is operational, the editing mechanism is ongoing involving continuous feedback from internal users and demonstrations to external peers contributing towards the institutional pressures. The operational phase can also be affected by triggering events and adapting AI as new contradictions and demands emerge.

7 Discussion

The goal of this paper was to identify factors that affect the perceived benefits of AI use within public administration and explain how they operate. The results of the quantitative study show a significant effect of service coercive pressures on perceived benefits of AI use while no effect of vertical coercive, mimetic, and normative pressures. Consultant pressures have a significant effect on generating all four institutional pressures but only an indirect mediated effect on perceived benefits of AI use through service coercive pressures. The underlying sensemaking mechanisms further explain the results.

Cognitive constraints limit decision choices and engender conformance to the institutional environment. These constraints can also be viewed through the lens of public sector reforms. The results show a confluence of traditional public administration (themes of bureaucracy, risk aversion, and procurement), NPM ethos (themes of functional structures, information systems design practices, and performance-based funding), and PVM (theme of public value goals). The administrative laws and the Canadian context serve as the macro environment within which all public administration operates.

Vertical coercive, mimetic, and normative pressures affect on perceived benefits of AI use are limited to priming. Within the overarching cognitive constraints, these pressures serve to create mental models for the operational realities of public administration. Furthermore, priming is also influenced by the perceptions of AI formed through exposure to media and contemporary debates and the political climate regarding AI risks. This broad outlook, as an output of priming, can be described as the "organizing vision" of AI as it relates to public administration use (Swanson & Ramiller, 2004, p. 556). However, the organising vision is not sufficient to determine the perceived benefits of AI use which are conceptualised as the site-specific application of AI innovation. The results support Christensen et al. (2007) supposition of an institutional perspective of public organisations with cognitive constraints providing the institutional environment and the priming mechanism serving as the social context.

Service coercive pressures significantly affect the perceived benefits of AI use when AI is viewed as delivering value in meeting service demands. When service demands, resulting from citizen needs and political mandates, exceed available resources, sensemaking is triggered. The triggering mechanism is a crucial part of the innovation initiation process which can be mapped to Rogers's (2003) agenda-setting and matching stages of the innovation process. The triggering events are the initiators of agenda-setting. The timeframe for agenda-setting can be immediate for a crisis, short to medium-term for specific business problems, or long-term in response to gradual performance gaps within the system. During the matching stage, the search for potential solutions leads to the sensemaking of AI benefits. The organisation employs the organizing vision of AI to develop preliminary opinions on AI benefits related to the site-specific trigger. If AI is considered the most viable option, a deeper exploration of AI's potential is undertaken to lead to a decision to pilot AI or reject it in favour of a different solution, such as robotic process automation.

If AI is piloted, the matching process continues to evaluate the fit between AI and the site-specific problem. The perceived benefits of AI use are revised through the editing mechanisms gathering social feedback and testing assumptions and value propositions. If the revised AI benefits continue to be perceived in a positive light and demonstrate value, AI innovation is considered suitable for operationalisation. The matching stage also involves a critical internal analysis of the organisation's capabilities in terms of infrastructure, technical skills and expertise, and funding to be able to operationalise AI.

A favourable decision to adopt AI and commit to organisational resources initiates the implementation process that follows Rogers's (2003) processes of restructuring, clarifying, and routinising. Each of these stages will involve sensemaking and an update to the perceived benefits, especially the clarifying stage. The paper also reveals that perceived benefits of AI use do not significantly differ between the agenda-setting and matching stages. A significant update to perceived benefits emerges only when operational capability matching has been accomplished. During the routinising stage, perceived and actual benefits will start to merge with the widespread usage of AI. The triggering mechanisms can also be introduced during the implementation processes as new events emerge.

The evidence reveals the nascent state of AI adoption within the Canadian public administration. There are several pilots underway at the matching stage of innovation, however, very few applications have been implemented. These earlier stages of adoption and a lack of demonstrable site-specific value proposition were also identified as primary reasons for the lack of mimetic and normative pressures acting as triggers. This aligns with DiMaggio and Powell's (1983) and Tolbert and Zucker's (1983) supposition that during the early stages of the adoption of an innovation, organisational needs and performance concerns are the main drivers. Once an innovation diffuses and its value propositions are widely understood, adoption is driven by concerns of legitimacy and appropriateness. The perceived benefits of AI use being only influenced by service demands suggests AI is currently being only considered from a performance improvement perspective. When the use of AI is widespread and its value propositions clearly understood, mimetic and normative pressures are expected to become triggers and affect perceived benefits and adoption. In addition, there is strong evidence supporting organisational capabilities to operationalise AI as a key determinant of the implementation decision.

The influence and penetration of consultants are omnipresent in public administration. However, within the Canadian context, public administrators are generally wary of the value of consultants and sensitive to excessive pitching and hype. Even though positive narratives and hype contribute to institutional pressures, they fail to manifest any direct effect on the perceived benefits of AI use unless associated with a value proposition that is site-specific during the triggering or editing stages.

Below we summarise the theoretical and managerial implications of our results and limitations and future research opportunities.

7.1 Theoretical Implications

The theoretical implications of this paper are in two areas, institutions and sensemaking and the AI adoption phenomenon within the public administration context.

Weber and Glynn (2006) argue the traditional view of the institutional effect on sensemaking in terms of cognitive constraints is incomplete and propositioned three additional contextual mechanisms. This paper provides empirical support for these propositions. The paper illustrates that cognitive constraints are mere boundary conditions and priming, triggering, and editing are the key contextual mechanisms that link institution to sensemaking. Furthermore, the paper extends Weber and Glynn's (2006) conceptualisation by developing a processual model that encompasses spatial and temporal dimensions. We explain how cognitive constraints and the four institutional pressures interact with exogenous influences (media and consultant-driven perceptions and trigger events) generating each of the mechanisms. By introducing a time dimension, we illustrate which sensemaking mechanism is active at each stage of the innovation process and their effect on piloting and adoption decisions. The model progresses the understanding of how institutional forces affect the AI innovation process. The paper also illustrates how cognitive constraints can mitigate the effects of consultant pressures. Thus, it can be argued cognitive constraints also have a positive effect in shielding public administration from external pressures. Through the processual model, we also forward Mignerat and Rivard's (2009) call to examine the types of institutions and feedback processes, embedded in the type of institutional pressures, that are active at different stages of sensemaking and adoption.

The AI adoption phenomenon within the public administration, and more generally within the public sector, lacks empirical studies (Madan & Ashok, 2023). In the Canadian context, this paper provides empirical evidence that at the earlier stages of AI adoption associated with negative perceptions, political risks, and uncertain value propositions, only service coercive pressures affect forming concrete opinions on the benefits of AI. Thus, we can deduce that in the earlier stages of AI adoption, the demand pull is the major driver of adoption than the technology push.

7.2 Managerial Implications

The paper has four managerial implications. First, the results highlight the stark contrast between media narratives of the use of AI by governments for nefarious and authoritarian means and the formidable challenge of operationalising even rudimentary use cases of AI. The highly publicised AI failures in law enforcement and security are outliers than typical use cases in an administrative context. The political and administrative leadership seems hesitant to adopt any form of AI plagued by reputational and political risks. The public administration needs to raise awareness of current AI capabilities in the operational environment rather than through pilots. This positive narrative, grounded on ethical use and well-established guidelines, should help counter the negative perceptions and accelerate the adoption phenomenon. Positive momentum on showcasing the value of AI at scale should manifest as vertical coercive, mimetic, and normative pressures acting as triggers rather than just priming forces.

Second, the results show service demands considerably outweigh available resources. The resource constraints have worsened as public administration copes with the aftereffects of COVID-19. This resource contradiction has been and continues to be the primary trigger for the search for technological solutions. Notwithstanding AI's potential for a radical transformation of governments, the current problem context is likely to lead to limited AI implementations within the purview of current processes and practices. The current generation of administrators has been exhausted by the barrage of transformational projects and re-engineering initiatives. These were part of the platform projects replacing disparate legacy solutions, and many of these are still underway. The digital transformation theme has become a consulting buzzword that induces stress among non-technical roles. There are pockets of innovation and data science shops but the current direction for AI adoption seems to be driven by efficiency, service delivery, and cost-saving goals. The real potential of AI to reimagine government and governance is being missed within the reality of meeting operational demands. In addition to incorporating responsible AI practices, the administrative and political leadership needs to have a critical debate on the nature and function of government as AI becomes embedded in every facet of citizens' lives. Lacking a clear agenda, AI is bound to be limited to an extension of the current technological implementations and only provide marginal gains.

Third, the penetration of consultants in public administration and their role in generating hype conducive to their commercial interests is no surprise. However, the cognitive constraints and a suitable maturity in systems design help shield public servants from exaggerated sales pitches. The consultants will have more success and in turn, benefit their clients if they focus on outlining the role of AI for site-specific operational solutions rather than pitching templated solutions which might have been successful somewhere else.

Fourth, the sensemaking mechanisms showcase an ever-evolving perception of AI benefits as organisations move through various stages of adoption. The transition from pilot to operationalisation is the most challenging and significant. The AI team not only needs to demonstrate the value proposition of AI but also work with IT, policy, legal, procurement, and other stakeholders to showcase the feasibility of an operational solution. Thus, the value propositions not only need to demonstrate the tangible benefits of the use of AI but also how the operationalisation will be achieved. This second implementation aspect is often ignored during pilot phases leading to a low-rate transition to operations.

7.3 Limitations and Future Research

The paper suffers from several limitations. First, the context of the research is Canadian public administration. The results have generalisability in other G7 and advanced economies, especially those with Westminster-style governments. However, similar studies in other public administration contexts will help establish the external validity of the findings. Second, the research was limited to public administration and excluded public organisations in healthcare, education, law enforcement, defence, and utilities. The results may not apply to these organisations operating within unique institutional environments. There is an opportunity for future research in these specific contexts to better understand the similarities and differences. Third, the research only focussed on machine learning and natural language processing, thus data-centric approaches to AI. Future research exploring the adoption phenomenon of other AI technologies such as blockchain, robotic vision, etc. can shed light on technology-specific variations in the adoption process. Fourth, our proposition of a change in the effect of institutional forces when AI is more widely diffused needs to be tested. A future study can help validate these suppositions and establish a temporal contingent dimension to the AI innovation process. Fifth, given institutional pressures have a weak effect on the perceived benefits of AI use, future researchers can consider testing the effect of organisational level variables (such as absorptive capacity, innovative culture, and technological maturity) as mediators between institutional pressures and the perceived benefits of AI use.

In terms of methodological limitations, the quantitative study is based on a cross-sectional survey and the same respondents were used for capturing both dependent and independent variables. We established the temporal dimension by surveying organisations at different stages of adoption. A future study can mitigate single source bias by using different respondents for dependent and independent variables and establish external validity of temporal dimensions by using panel data at various stages of AI adoption. For the qualitative study, an explanation of the quantitative results was the main goal. There is a chance of researcher bias during interviews and coding focusing on the quantitative model rather than a grounded approach. Future research can undertake grounded approaches and in-depth case studies of AI adoption to build the external validity of the results.

8 Conclusions

This paper's objective was to explain the AI adoption phenomenon within the Canadian public administration. Institutional theory and sensemaking were used to develop a conceptual model hypothesising four institutional pressures and consultant pressures affecting sensemaking, measured as perceived benefits of AI use. Using an explanatory mixed-method design, the study was conducted in two phases, quantitative followed by a qualitative study. The quantitative study tested the model using a cross-section survey. Only service coercive pressures were identified as significantly affecting the perceived benefits of AI use. The follow-up qualitative study based on 34 interviews helps explain the results. At the earlier stages of AI adoption, service demands are the only triggers for sensemaking and search for site-specific benefits of AI use. All other pressures are marginal with a lack of demonstrable value from the use of AI in an operational instance and at scale. Furthermore, a meta-inference of the two studies identifies three primary sensemaking mechanisms priming, triggering, and editing. These are mapped to the innovation decision process providing a spatial and temporal view of the AI adoption process. The paper extends the theory by providing a processual model of sensemaking mechanisms linking the macro-institutional environment to micro-level sensemaking. As well as the paper provides empirical evidence to suggest earlier stages of AI adoption are driven by demand pull rather than technology push.

Appendix A: Survey instrument

Construct	Item	References
Service coercive pressures	SC1. Citizen demands drive the adoption of new technologies SC2. Citizen expectations drive the adoption of new technologies	(Korac et al., 2017; Walker, 2006; Walker et al., 2011)

Construct	Item	References
Vertical coercive pressures	VC1. Political changes drive the adoption of new technologies	(Korac et al., 2017; Walker, 2006; Walker et al., 2011)
	VC2. Political leadership and central ministry mandates/ requirements drive the adoption of new technologies	
	VC3. Audits, reports, or pressures from oversight bodies drive the adoption of new technologies	
Normative pressures	N1. Employees of our organisation regularly visit other governmental organisations/ departments	(Jansen et al., 2005)
	N2. Our organisation periodically organises special meetings with citizens, industry associations or third parties to acquire new knowledge	
	N3. Employees regularly approach third parties such as consultants, technology vendors, industry associations	
Mimetic pressures	M1. Competition with other peer governmental organisations drive the adoption of new technologies in our organisation	(Korac et al., 2017; Walker, 2006; Walker et al., 2011)
	M2. Economical changes drive adoption of new technologies	
	M3. Citizen demographical changes drive adoption of new technologies	
Consultant pressures	C1. External consultants/ advisors drive the adoption of new technologies in our organisation	

Construct	Item	References
Perceived benefits of AI use	PB1. The use of AI will help my organisation to make better decisions	Kuan and Chau (2001) Mikalef et al. (2021)
	PB2. The use of AI will help my organisation to improve operational efficiency	
	PB3. The use of AI will help my organisation to speed up processing applications	
	PB4. The use of AI will help my organisation to reduce clerical errors (e.g. duplicate data sets)	
	PB5. The use of AI will help my organisation to improve citizen engagement	
	PB6. The use of AI will help my organisation to improve service delivery and customer satisfaction	

Appendix B: Measurement model analysis

Table 7 Cross loadings

	SCR	VCR	MIM	NOR	PBE	CON
SC1	**0.936**	0.242	0.413	0.173	0.265	0.103
SC2	**0.936**	0.230	0.413	0.188	0.247	0.139
VC1	0.246	**0.760**	0.403	0.138	0.027	0.247
VC2	0.109	**0.675**	0.339	0.076	0.152	0.109
VC3	0.192	**0.805**	0.309	0.218	0.090	0.306
M1	0.228	0.234	**0.737**	0.327	0.098	0.310
M2	0.281	0.426	**0.700**	0.203	0.169	0.192
M3	0.489	0.385	**0.808**	0.229	0.197	0.212
N1	0.148	0.157	0.277	**0.647**	0.114	0.103
N2	0.236	0.201	0.263	**0.757**	0.106	0.150
N3	0.117	0.159	0.283	**0.894**	0.140	0.330
PB1	0.227	0.082	0.089	0.147	**0.886**	0.140
PB2	0.249	0.071	0.158	0.205	**0.921**	0.115
PB3	0.238	0.064	0.170	0.107	**0.898**	0.076
PB4	0.240	0.130	0.231	0.084	**0.869**	0.134
PB5	0.292	0.155	0.283	0.157	**0.820**	0.164
PB6	0.208	0.080	0.158	0.122	**0.890**	0.115
C1	0.129	0.320	0.323	0.290	0.139	**1.000**

The numbers in bold are the highest outer loading for the indicators. All indicators show higher correlation with their construct, as compared to other constructs

Table 8 Fornell Locker Criteria Analysis

	SCR	VCR	MIM	NOR	PBE	CON
SCR	**0.936**					
VCR	0.252	**0.749**				
MIM	0.441	0.455	**0.750**			
NOR	0.193	0.211	0.343	**0.773**		
PBE	0.274	0.108	0.203	0.155	**0.881**	
CON	0.129	0.320	0.323	0.290	0.139	Single-item

The bold numbers along the diagnol are square root of AVE

Table 9 HTMT ratios

	SCR	VCR	MIM	NOR	PBE	CON
SCR						
VCR	0.325					
MIM	0.613	0.759				
NOR	0.275	0.301	0.523			
PBE	0.306	0.156	0.277	0.187		
CON	0.140	0.365	0.406	0.296	0.145	

Table 10 Confidence intervals for HTMT ratios

	Original Est	Bootstrap Mean	Bootstrap SD	T Stat	5% CI	95% CI
SCR—> VCR	0.325	0.328	0.074	4.405	0.209	0.452
SCR—> MIM	0.613	0.616	0.080	7.664	0.483	0.745
SCR—> NOR	0.275	0.275	0.072	3.794	0.162	0.398
SCR—> CON	0.140	0.139	0.063	2.201	0.039	0.248
SCR—> PBE	0.306	0.306	0.075	4.083	0.181	0.429
VCR—> MIM	0.759	0.764	0.094	8.121	0.606	0.911
VCR—> NOR	0.301	0.316	0.090	3.346	0.171	0.468
VCR—> CON	0.365	0.366	0.074	4.965	0.245	0.486
VCR—> PBE	0.156	0.186	0.057	2.761	0.105	0.292
MIM—> NOR	0.523	0.527	0.083	6.269	0.389	0.662
MIM—> CON	0.406	0.405	0.074	5.462	0.277	0.521
MIM—> PBE	0.277	0.286	0.078	3.547	0.163	0.420
NOR—> CON	0.296	0.297	0.076	3.896	0.172	0.423
NOR—> PBE	0.187	0.202	0.063	2.984	0.108	0.312
CON—> PBE	0.145	0.147	0.059	2.474	0.054	0.249

Appendix C: Structural model analysis

Table 11 PLS predict

	RMSE PLS out-of-sample	RMSE—LM out-of-sample
PB1	1.395	1.429
PB2	1.386	1.411
PB3	1.365	1.385
PB4	1.269	1.269
PB5	1.406	1.415
PB6	1.363	1.393

Table 12 Model comparisons

	Model 1	Model 2	Model 3	Model 4
BIC	14.873	49.753	37.073	62.855
R^2	0.189	0.133	0.206	0.213
Adj R^2	0.151	0.083	0.153	0.143

All models are based on the same measurement and structural model with varying levels of controls:

Model 1: Original measurement and structural model with organisational level controls (size, level of government, level of AI adoption)

Model 2: Original measurement and structural model with individual level controls (gender, education, age, and position)

Model 3: Original measurement and structural model with most relevant individual and organisational level controls (size, status of adoption, level of government, gender, and education)

Model 4: Original measurement and structural model with all controls (size, level of government, level of AI adoption, gender, education, age, and position)

Appendix D: Interview Guide

1 Can you briefly discuss your role?
2 What is your opinion on the use of machine learning and/or natural language processing within the government and public administration context?
3 What do you think are the key drivers of AI adoption?
4 Who are the main actors, influencers, and decision-makers?
5 In our quantitative study, we looked at horizontal pressures, competitive pressures, vertical political pressures, citizen pressures, and perceived benefits of AI use. What is your opinion on the extent of these pressures affecting perception of AI benefits and driving AI adoption and use?

Appendix E: Final template

1. Consultant pressures
   1.1. Generate hype
      1.1.1. Create favourable narratives and generate hype
      1.1.2. Generate political or administrative pressures and interest
   1.2. No direct influence
   1.3. Provide specific expertise
   1.4. Resource replacements
2. Institutional pressures
   2.1. Mimetic pressures
      2.1.1. Competition and collaborations
         2.1.1.1. Competition and collaborations between departments
         2.1.1.2. Competition between senior level staff
         2.1.1.3. Competition between different government levels or jurisdictions
      2.1.2. Imitation pressures
         2.1.2.1. Comparisons to private sector
         2.1.2.2. Hype
      2.1.3. Reputation building
      2.1.4. Weak pressures specific to AI
   2.2. Normative pressures
      2.2.1. Demonstrations and awareness
      2.2.2. Benchmarking to internal associations
      2.2.3. People changing jobs
   2.3. Coercive pressures
      2.3.1. Service coercive pressures
         2.3.1.1. Citizen demands
         2.3.1.2. Citizen expectations
      2.3.2. Vertical coercive pressures
         2.3.2.1. Political changes
         2.3.2.2. Political leadership
         2.3.2.3. Political mandates
            2.3.2.3.1. Evidence-based decision making
            2.3.2.3.2. Experimentation and innovation
            2.3.2.3.3. Mandates for efficiency
            2.3.2.3.4. Mandates about economy
            2.3.2.3.5. Mandates for red tape and bureaucracy reductions
            2.3.2.3.6. Modernisation
         2.3.2.4. Cautious approach towards AI
         2.3.2.5. No direct political pressures
3. Perceived benefits of AI use
   3.1. Cost savings
   3.2. Decision support

3.2.1. Better use of existing or new data
3.2.2. Improve decision making
3.2.3. New insights for policy development and interventions
3.3. Improving citizen engagement
3.3.1. Enhance citizen engagement
3.3.2. Improve inclusivity
3.4. Improve resource usage
3.5. Improving effectiveness
3.6. Improving efficiency
3.7. Improving safety and security
3.7.1. Improve employee safety
3.7.2. Protect IT infrastructures
3.8. Jurisdictional development
3.8.1. Attract citizens
3.8.2. Develop technology sector local ecosystem
3.9. Meet citizen demands
4. Sensemaking mechanisms
4.1. Cognitive constraints
4.1.1. Public value goals distinct from the business sector
4.1.2. Risk aversion
4.1.3. Structural constraints
4.1.3.1. Bureaucracy
4.1.3.2. Functional structure
4.1.3.3. Funding
4.1.3.4. Information systems design and implementation guidelines
4.1.3.5. Procurement
4.1.3.6. Unionised workforce
4.1.4. Subject to administrative law
4.1.4.1. Canadian administrative laws
4.1.4.2. Canadian context
4.1.4.2.1. Defence of democratic authority
4.1.4.2.2. Public administration ethos
4.1.4.2.3. Reconciliation
4.1.4.3. Data protections
4.2. Priming
4.2.1. Vertical coercive pressures
4.2.2. Mimetic pressures
4.2.3. Normative pressures
4.2.4. Consultant pressures
4.2.5. Perceptions of AI
4.2.5.1. AI perceptions created by print and social media and popular culture
4.2.5.2. Awareness of AI and its potential
4.2.5.2.1. Awareness of implementation challenges

4.2.5.2.2. Awareness of AI benefits
4.2.5.2.3. Basic knowledge of AI
4.2.5.2.4. Limitations and current potential
4.2.5.3. Negative perceptions
4.2.5.3.1. Job losses
4.2.5.3.2. Scared of use of AI
4.3. Triggering
4.3.1. Service coercive pressures
4.3.2. Triggering events
4.3.2.1. Black swan events
4.3.2.2. Experimental and bottom-up innovation
4.3.2.3. Fiscal pressures
4.3.2.4. Quick delivery of solutions
4.3.2.5. Resource limitations
4.3.2.6. Solutions to business problems
4.3.3. Ethical use of AI
4.4. Editing
4.4.1. Demonstrations
4.4.2. Value propositions and justify ROI

Acknowledgements Not applicable

Authors' Contributions Rohit Madan: Conceptualisation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.
Mona Ashok: Supervision, Writing – review & editing.

Funding The authors did not receive funding/support from any organisation for the submitted work.

Data Availability The dataset generated during the current study is not publicly available as it contains primary data collected from governmental agencies and is being used for an ongoing PhD project. Information on how to obtain it and reproduce the analysis is available from the corresponding author on request.

Declarations

Competing Interests The authors have no relevant financial or nonfinancial interests to disclose.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Ahn, M. J., & Chen, Y.-C. (2022). Digital transformation toward AI-augmented public administration: The perception of government employees and the willingness to use AI in government. *Government Information Quarterly, 39*(2), 101664. https://doi.org/10.1016/j.giq.2021.101664

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *Artificial Intelligence, 6*, 26–2018.

Altayar, M. S. (2018). Motivations for open data adoption: An institutional theory perspective. *Government Information Quarterly, 35*(4), 633–643. https://doi.org/10.1016/j.giq.2018.09.006

Andrews, L. (2019). Public administration, public leadership and the construction of public value in the age of the algorithm and 'big data' [https://doi.org/10.1111/padm.12534]. *Public Administration, 97*(2), 296–310. https://doi.org/10.1111/padm.12534

Ann Glynn, M., & Watkiss, L. (2020). Of Organizing and Sensemaking: From Action to Meaning and Back Again in a Half-Century of Weick's Theorizing. *Journal of Management Studies, 57*(7), 1331–1354. https://doi.org/10.1111/joms.12613

Ashok, M., Madan, R., Joha, A., & Sivarajah, U. (2022). Ethical framework for Artificial Intelligence and Digital technologies. *International Journal of Information Management, 62*, 102433. https://doi.org/10.1016/j.ijinfomgt.2021.102433

Bartlett, J., Kotrlik, J., & Higgins, C. (2001). Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. *Information Technology, Learning, and Performance Journal, 19*(1), 43.

Bernier, L., Hafsi, T., & Deschamps, C. (2015). Environmental Determinants of Public Sector Innovation: A study of innovation awards in Canada. *Public Management Review, 17*(6), 834–856. https://doi.org/10.1080/14719037.2013.867066

Berry, F. S., & Berry, W. D. (1999). Innovation and diffusion models in policy research. In P. A. Sabatier (Ed.), *Theories of the policy process* (pp. 223–260). Westview Press.

Bijker, W. E. (2009). Social Construction of Technology. In J. K. B. O. Friis, S. A. Pedersen, & V. F. Hendricks (Eds.), *A Companion to the Philosophy of Technology* (pp. 88–94). Wiley-Blackwell.

Campbell, D. T. (1955). The informant in quantitative research. *American Journal of Sociology, 60*(4), 339–342.

Campion, A., Gasco-Hernandez, M., Jankin Mikhaylov, S., & Esteve, M. (2022). Overcoming the Challenges of Collaboratively Adopting Artificial Intelligence in the Public Sector. *Social Science Computer Review, 40*(2), 462–477. https://doi.org/10.1177/0894439320979953

Chen, T., Ran, L., & Gao, X. (2019). AI innovation for advancing public service: The case of China's first Administrative Approval Bureau. *In Proceedings of the 20th Annual International Conference on Digital Government Research* (pp. 100–108)

Christensen, T., Lægreid, P., Roness, P. G., & Røvik, K. A. (2007). *Organization Theory and the Public Sector: Instrument*. Taylor & Francis.

Christensen, P. T., & Lægreid, P. P. (2013). *Transcending New Public Management: The Transformation of Public Sector Reforms*. Ashgate Publishing Limited.

CIFAR. (2020). *Pan-Canadian AI Strategy Impact Assessment Report*. Retrieved March 6, 2022 from: https://cifar.ca/wp-content/uploads/2020/11/Pan-Canadian-AI-Strategy-Impact-Assessment-Report.pdf

Clarke, A. (2020). Digital government units: What are they, and what do they mean for digital era public management renewal? *International Public Management Journal, 23*(3), 358–379. https://doi.org/10.1080/10967494.2019.1686447

Collington, R. (2022). Disrupting the Welfare State? Digitalisation and the Retrenchment of Public Sector Capacity. *New Political Economy, 27*(2), 312–328. https://doi.org/10.1080/13563467.2021.1952559

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Criado, J. I., & Zarate-Alcarazo, L. O. (2022). Technological frames, CIOs, and Artificial Intelligence in public administration: A socio-cognitive exploratory study in Spanish local governments. *Government Information Quarterly, 39*(3), 101688. https://doi.org/10.1016/j.giq.2022.101688

Damanpour, F. (1991). Organizational innovation: A meta-analysis of effects of determinants and moderators. *Academy of Management Journal, 34*(3), 555–590. https://doi.org/10.2307/256406

Damanpour, F., & Schneider, M. (2006). Phases of the Adoption of Innovation in Organizations: Effects of Environment, Organization and Top Managers. *British Journal of Management, 17*(3), 215–236. https://doi.org/10.1111/j.1467-8551.2006.00498.x

de Sousa, W. G., de Melo, E. R. P., Bermejo, P. H. D. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. *Government Information Quarterly, 36*(4), 101392. https://doi.org/10.1016/j.giq.2019.07.004

De Vries, M., & Nemec, J. (2013). Public sector reform: An overview of recent literature and research on NPM and alternative paths. *International Journal of Public Sector Management, 26*(1), 4–16. https://doi.org/10.1108/09513551311293408

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

Desouza, K. (2014). *Realizing the promise of big data* (Washington, DC: IBM Center for the Business of Government, Issue.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 147–160.

Dunleavy, P., Margetts, H., Bastow, S., & Tinkler, J. (2005). New Public Management Is Dead—Long Live Digital-Era Governance. *Journal of Public Administration Research and Theory, 16*(3), 467–494. https://doi.org/10.1093/jopart/mui057

Eaves, D., & Goldberg, D. (2017). UK Government Digital Service: Moving Beyond a Website. *Harvard Business Review*.

Elbanna, A., & Linderoth, H. C. J. (2015). The formation of technology mental models: The case of voluntary use of technology in organizational setting. *Information Systems Frontiers, 17*(1), 95–108. https://doi.org/10.1007/s10796-014-9513-6

Eom, S.-J., & Lee, J. (2022). Digital government transformation in turbulent times: Responses, challenges, and future direction. *Government Information Quarterly, 39*(2), 101690. https://doi.org/10.1016/j.giq.2022.101690

Esmark, A. (2016). Maybe It Is Time to Rediscover Technocracy? An Old Framework for a New Analysis of Administrative Reforms in the Governance Era. *Journal of Public Administration Research and Theory, 27*(3), 501–516. https://doi.org/10.1093/jopart/muw059

European Commission. (2021). *Selected AI cases in the public sector. European Commission, Joint Research Centre (JRC)*. Retrieved April 5, 2022 from http://data.europa.eu/89h/7342ea15-fd4f-4184-9603-98bd87d8239a

Fatima, S., Desouza, K. C., Buck, C., & Fielt, E. (2022). Public AI canvas for AI-enabled public value: A design science approach. *Government Information Quarterly, 39*(4), 101722. https://doi.org/10.1016/j.giq.2022.101722

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *International Journal of Qualitative Methods, 5*(1), 80–92.

Fleming, P. (2019). Robots and Organization Studies: Why Robots Might Not Want to Steal Your Job. *Organization Studies, 40*(1), 23–38. https://doi.org/10.1177/0170840618765568

Fountain, J. E., Fountain, P. J. E., & Institution, B. (2001). *Building the Virtual State: Information Technology and Institutional Change*. Brookings Institution Press.

Frumkin, P., & Galaskiewicz, J. (2004). Institutional Isomorphism and Public Sector Organizations. *Journal of Public Administration Research and Theory, 14*(3), 283–307. https://doi.org/10.1093/jopart/muh028

Galwa, J., & Vogel, R. (2021). In search of legitimacy: conflicting logics and identities of management consultants in public administration. *Public Management Review*, 1–25. https://doi.org/10.1080/14719037.2021.1974713

Geels, F. W. (2020). Micro-foundations of the multi-level perspective on socio-technical transitions: Developing a multi-dimensional model of agency through crossovers between social constructivism, evolutionary economics and neo-institutional theory. *Technological Forecasting and Social Change, 152*, 119894. https://doi.org/10.1016/j.techfore.2019.119894

Goto, M. (2022). Accepting the future as ever-changing: Professionals' sensemaking about artificial intelligence. *Journal of Professions and Organization, 9*(1), 77–99. https://doi.org/10.1093/jpo/joab022

Government of Canada. (1962). *The Royal Commission on Government Organization*.

Government of Canada. (2023). *Responsible use of artificial intelligence (AI)*. Retrieved May 3, 2023 from: https://www.canada.ca/en/government/system/digital-government/digital-government-innovations/responsible-use-ai.html

Greve, C. (2015). Ideas in Public Management Reform for the 2010s. Digitalization, Value Creation and Involvement. *Public Organization Review, 15*(1), 49–65. https://doi.org/10.1007/s11115-013-0253-8

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. SAGE Publications.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.

Hartley, J., Sørensen, E., & Torfing, J. (2013). Collaborative Innovation: A Viable Alternative to Market Competition and Organizational Entrepreneurship. *Public Administration Review, 73*(6), 821–830.

Harvey, D. (2007). *A Brief History of Neoliberalism*. Oxford University Press.

Heimstädt, M., & Reischauer, G. (2019). Framing innovation practices in interstitial issue fields: Open innovation in the NYC administration. *Innovation, 21*(1), 128–150. https://doi.org/10.1080/14479338.2018.1514259

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). *The use of partial least squares path modeling in international marketing*. Emerald Group Publishing Limited.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115–135.

Hong, S., Kim, S. H., & Kwon, M. (2022). Determinants of digital innovation in the public sector. *Government Information Quarterly, 39*(4), 101723. https://doi.org/10.1016/j.giq.2022.101723

Hood, C. (1991). A public management for all seasons? [Article]. *Public Administration, 69*(1), 3–19. https://doi.org/10.1111/j.1467-9299.1991.tb00779.x

Hood, C. (1995). Contemporary public management: A new global paradigm? *Public Policy and Administration, 10*(2), 104–117. https://doi.org/10.1177/095207679501000208

Hood, C. (2000). Paradoxes of public-sector managerialism, old public management and public service bargains. *International Public Management Journal, 3*(1), 1–22. https://doi.org/10.1016/S1096-7494(00)00032-5

Howlett, M., & Migone, A. (2014). Making the invisible public service visible? Exploring data on the supply of policy and management consultancies in Canada. *Canadian Public Administration, 57*(2), 183–216. https://doi.org/10.1111/capa.12065

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal, 20*(2), 195–204.

Janowski, T. (2015). Digital government evolution: From transformation to contextualization. *Government Information Quarterly, 32*(3), 221–236. https://doi.org/10.1016/j.giq.2015.07.001

Jansen, J. J. P., Van Den Bosch, F. A. J., & Volberda, H. W. (2005). Managing Potential and Realized Absorptive Capacity: How Do Organizational Antecedents Matter? *The Academy of Management Journal, 48*(6), 999–1015. https://doi.org/10.2307/20159726

Jensen, T. B., Kjærgaard, A., & Svejvig, P. (2009a). Two Perspectives on Information System Adaptation: Using Institutional Theory with Sensemaking. *Journal of Information Technology, 24*(4), 343–353.

Jensen, T. B., Kjærgaard, A., & Svejvig, P. (2009b). Using Institutional Theory with Sensemaking Theory: A Case Study of Information System Implementation in Healthcare. *Journal of Information Technology, 24*(4), 343–353. https://doi.org/10.1057/jit.2009.11

Jun, K.-N., & Weare, C. (2010). Institutional Motivations in the Adoption of Innovations: The Case of E-Government. *Journal of Public Administration Research and Theory, 21*(3), 495–519. https://doi.org/10.1093/jopart/muq020

Keast, R., Mandell, M., & Brown, K. (2006). Mixing state, market and network governance modes: The role of government in "Crowded" policy domains. *International Journal of Organization Theory & Behavior, 9*(1), 27–50. https://doi.org/10.1108/IJOTB-09-01-2006-B002

Kernaghan, K., Borins, S. F., & Marson, D. B. (2000). *The New Public Organization*. Institute of Public Administration of Canada.

King, N., & Brooks, J. M. (2016). *Template Analysis for Business and Management Students*. SAGE Publications.

King, N. (2004). Using template analysis in the thematic analysis of text. In 'Essential guide to qualitative methods in organizational research'.(Eds G Symon, C Cassell) pp. 256–270. In. Sage: London.

Kipping, M. (2021). From Private Advice to Public Policy? The Evolution of Consultancy Think Tanks. *Critical Perspectives on Think Tanks Power, Politics and Knowledge*, 36–55.

Klein, H. K., & Kleinman, D. L. (2002). The Social Construction of Technology: Structural Considerations. *Science, Technology, & Human Values, 27*(1), 28–52. https://doi.org/10.1177/016224390202700102

Kohtamäki, M., Whittington, R., Vaara, E., & Rabetino, R. (2022). Making connections: Harnessing the diversity of strategy-as-practice research. *International Journal of Management Reviews, 24*(2), 210–232. https://doi.org/10.1111/ijmr.12274

Korac, S., Saliterer, I., & Walker, R. M. (2017). Analysing the environmental antecedents of innovation adoption among politicians and public managers. *Public Management Review, 19*(4), 566–587. https://doi.org/10.1080/14719037.2016.1200119

Krishnamurthy, R., & Desouza, K. C. (2014). Big data analytics: The case of the social security administration. *Information Polity: The International Journal of Government & Democracy in the Information Age, 19*(3/4), 165–178. https://doi.org/10.3233/IP-140337

Kuan, K. K. Y., & Chau, P. Y. K. (2001). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management, 38*(8), 507–521. https://doi.org/10.1016/S0378-7206(01)00073-8

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

Lapsley, I., & Oldfield, R. (2001). Transforming the public sector: Management consultants as agents of change. *European Accounting Review, 10*(3), 523–543. https://doi.org/10.1080/713764628

Lee, C.-P., Chang, K., & Berry, F. S. (2011). Testing the Development and Diffusion of E-Government and E-Democracy: A Global

Perspective. *Public Administration Review, 71*(3), 444–454. https://doi.org/10.1111/j.1540-6210.2011.02228.x

Lindquist, E. A. (2022). The digital era and public sector reforms: Transformation or new tools for competing values? *Canadian Public Administration, 65*(3), 547–568. https://doi.org/10.1111/capa.12493

Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*(404), 1198–1202. https://doi.org/10.1080/01621459.1988.10478722

Luna-Reyes, L. F., Andersen, D. F., Black, L. J., & Pardo, T. A. (2021). Sensemaking and social processes in digital government projects. *Government Information Quarterly, 38*(2), 101570. https://doi.org/10.1016/j.giq.2021.101570

Madan, R., & Ashok, M. (2022). A public values perspective on the application of Artificial Intelligence in government practices: A Synthesis of case studies. In F. D. Jose Ramon Saura (Ed.), *Application of Artificial Intelligence in Government Practices and Processes*. IGI Global, 2022.

Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly, 40*(1), 101774. https://doi.org/10.1016/j.giq.2022.101774

Maitlis, S., & Christianson, M. (2014). Sensemaking in organizations: Taking stock and moving forward. *The Academy of Management Annals, 8*(1), 57–125. https://doi.org/10.1080/19416520.2014.873177

Marciano, R. (2022). Beyond consultocracy and servants of power: Explaining the role of consultants in policy formulation. *Governance*, *n/a*(n/a). https://doi.org/10.1111/gove.12743

Margetts, H., & Dunleavy, P. (2013). The second wave of digital-era governance: A quasi-paradigm for government on the Web. *Philosophical Transactions of the Royal Society a: Mathematical, Physical and Engineering Sciences, 371*(1987), 20120382. https://doi.org/10.1098/rsta.2012.0382

McNeal, R. S., Tolbert, C. J., Mossberger, K., & Dotterweich, L. J. (2003). Innovating in Digital Government in the American States*. *Social Science Quarterly, 84*(1), 52–70. https://doi.org/10.1111/1540-6237.00140

Mergel, I. (2018). Open innovation in the public sector: drivers and barriers for the adoption of Challenge.gov [Article]. *Public Management Review, 20*(5), 726–745. https://doi.org/10.1080/14719037.2017.1320044

Mergel, I., Dickinson, H., Stenvall, J., & Gasco, M. (2023). Implementing AI in the public sector. *Public Management Review*, 1–13. https://doi.org/10.1080/14719037.2023.2231950

Mignerat, M., & Rivard, S. (2009). Positioning the institutional perspective in information systems research. *Journal of Information Technology, 24*(4), 369–391. https://doi.org/10.1057/jit.2009.13

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., Gupta, M., & Niehaves, B. (2021). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Government Information Quarterly*, 101596. https://doi.org/10.1016/j.giq.2021.101596

Momani, B. (2013). Management consultants and the United States' public sector. *Business and Politics, 15*(3), 381–399. https://doi.org/10.1515/bap-2013-0001

Moore, M. H. (1995). *Creating public value: Strategic management in government*. Harvard University Press.

Morin, D. (2008). Auditors general's universe revisited: An exploratory study of the influence they exert on public administration through their value for money audits. *Managerial Auditing Journal.*

Morin, D. (2014). Auditors General's impact on administrations: a pan-Canadian study (2001–2011). *Managerial Auditing Journal*.

Mundkur, A., & Venkatesh, M. (2009). The role of institutional logics in the design of E-governance systems. *Journal of Information Technology & Politics, 6*(1), 12–30. https://doi.org/10.1080/19331680802698943

Neumann, O., Guirguis, K., & Steiner, R. (2022). Exploring artificial intelligence adoption in public organizations: a comparative case study. *Public Management Review*, 1–28. https://doi.org/10.1080/14719037.2022.2048685

Oliver, C. (1997). Sustainable competitive advantage: Combining institutional and resource-based views. *Strategic Management Journal, 18*(9), 697–713. https://doi.org/10.1002/(SICI)1097-0266(199710)18:9%3c697::AID-SMJ909%3e3.0.CO;2-C

Osborne, D., & Gaebler, T. (1992). *Reinventing Government: How the Entrepreneurial Spirit is Transforming the Public Sector*. Addison-Wesley Publishing Company.

Osborne, S. P. (2010). Introduction The (New) Public Governance: a suitable case for treatment? In *The new public governance?* (pp. 17–32). Routledge.

Pencheva, I., Esteve, M., & Mikhaylov, S. J. (2020). Big Data and AI–A transformational shift for government: So, what next for research? *Public Policy and Administration, 35*(1), 24–44. https://doi.org/10.1177/0952076718780537

Pina, V., Torres, L., & Royo, S. (2010). Is E-Government Promoting Convergence Towards More Accountable Local Governments? *International Public Management Journal, 13*(4), 350–380. https://doi.org/10.1080/10967494.2010.524834

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

Provan, K. G., & Lemaire, R. H. (2012). Core Concepts and Key Ideas for Understanding Public Sector Organizational Networks: Using Research to Inform Scholarship and Practice [Article]. *Public Administration Review, 72*(5), 638–648. https://doi.org/10.1111/j.1540-6210.2012.02595.x

Ranerup, A., & Henriksen, H. Z. (2019). Value positions viewed through the lens of automated decision-making: The case of social services [Article]. *Government Information Quarterly*, *36*(4). https://doi.org/10.1016/j.giq.2019.05.004

Richter, D. (2014). Demographic change and innovation: The ongoing challenge from the diversity of the labor force. *Management Revue*, *25*(3), 166–184. http://www.jstor.org/stable/24331317

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press.

Roy, J. (2017). Digital government and service delivery: An examination of performance and prospects. *Canadian Public Administration, 60*(4), 538–561. https://doi.org/10.1111/capa.12231

Sager, F., & Rosser, C. (2009). Weber, Wilson, and Hegel: Theories of Modern Bureaucracy. *Public Administration Review, 69*(6), 1136–1147. https://doi.org/10.1111/j.1540-6210.2009.02071.x

Saint-Martin, D. (1998). The new managerialism and the policy influence of consultants in government: An historical–institutionalist analysis of Britain, Canada and France. *Governance, 11*(3), 319–356.

Savoldelli, A., Codagnone, C., & Misuraca, G. (2014). Understanding the e-government paradox: Learning from literature and practice on barriers to adoption. *Government Information Quarterly, 31*, S63–S71. https://doi.org/10.1016/j.giq.2014.01.008

Schaefer, C., Lemmer, K., Samy Kret, K., Ylinen, M., Mikalef, P., & Niehaves, B. (2021). Truth or dare?–how can we influence the adoption of artificial intelligence in municipalities? *In Proceedings of the 54th Hawaii International Conference on System Sciences* (pp. 2347-2356).

Scott, W. R. (2014). *Institutions and organizations: ideas, interests, and identities* (4th ed.). SAGE Publications.

Seligman, L. (2006). Sensemaking throughout adoption and the innovation-decision process. *European Journal of Innovation Management, 9*(1), 108–120. https://doi.org/10.1108/14601060610640050

Sherer, S. A., Meyerhoefer, C. D., & Peng, L. (2016). Applying institutional theory to the adoption of electronic health records in the U.S. *Information & Management, 53*(5), 570–580. https://doi.org/10.1016/j.im.2016.01.002
Sørensen, E., & Torfing, J. (2011). Enhancing Collaborative Innovation in the Public Sector [Article]. *Administration & Society, 43*(8), 842–868. https://doi.org/10.1177/0095399711418768
Speers, K. (2007). The invisible private service: Consultants and public policy in Canada. *Policy analysis in Canada: The state of the art*, 573–600.
Stapper, E., Van der Veen, M., & Janssen-Jansen, L. (2020). Consultants as intermediaries: Their perceptions on citizen involvement in urban development. *Environment and Planning C: Politics and Space, 38*(1), 60–78. https://doi.org/10.1177/2399654419853583
Stoker, G. (2006). Public Value Management: A New Narrative for Networked Governance? *The American Review of Public Administration, 36*(1), 41–57. https://doi.org/10.1177/0275074005282583
Sturdy, A. J., Kirkpatrick, I., Reguera, N., Blanco-Oliver, A., & Veronesi, G. (2022). The management consultancy effect: Demand inflation and its consequences in the sourcing of external knowledge. *Public Administration, 100*(3), 488–506. https://doi.org/10.1111/padm.12712
Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare [Article]. *Government Information Quarterly, 36*(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008
Suzuki, K., Ha, H., & Avellaneda, C. N. (2020). Direct and non-linear innovation effects of demographic shifts. *Australian Journal of Public Administration, 79*(3), 351–369. https://doi.org/10.1111/1467-8500.12424
Swanson, E. B., & Ramiller, N. C. (2004). Innovating Mindfully with Information Technology. *MIS Quarterly, 28*(4), 553–583. https://doi.org/10.2307/25148655
Tabachnick, B. G., & Fidell, L. S. (2007). *Using Multivariate Statistics (5th ed.)*. Allyn & Bacon/Pearson Education.
Tan, E., & Crompvoets, J. (2022). Chapter 1: A new era of digital governance. In *The new digital era governance: How new digital technologies are shaping public governance* (pp. 300–317). Wageningen Academic Publishers.
Tan, B., Pan, S. L., Chen, W., & Huang, L. (2020). Organizational Sensemaking in ERP Implementation: The Influence of Sensemaking Structure. *MIS Quarterly*, *44*(4).
Teddlie, C., & Tashakkori, A. (2009). *Foundations of Mixed Methods Research: Integrating Quantitative and Qualitative Approaches in the Social and Behavioral Sciences*. SAGE Publications.
Tolbert, P. S., & Zucker, L. G. (1983). Institutional Sources of Change in the Formal Structure of Organizations: The Diffusion of Civil Service Reform, 1880–1935. *Administrative Science Quarterly, 28*(1), 22–39. https://doi.org/10.2307/2392383
Tourangeau, R., Rips, L. J., & Rasinski, K. (2012). The psychology of survey response. *Cambridge University Press*. https://doi.org/10.1017/cbo9780511819322
Turner, M., Kim, J., & Kwon, S.-H. (2022). The Political Economy of E-Government Innovation and Success in Korea. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(3), 145.
van de Poel, I. (2020). Three philosophical perspectives on the relation between technology and society, and how they affect the current debate about artificial intelligence. *Human Affairs, 30*(4), 499–511. https://doi.org/10.1515/humaff-2020-0042
van Noordt, C., & Misuraca, G. (2022). Exploratory insights on artificial intelligence for government in Europe. *Social Science Computer Review, 40*(2), 426–444. https://doi.org/10.1177/0894439320980449
Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the Qualitative-Quantitative Divide: Guidelines for Conducting Mixed Methods Research in Information Systems. *MIS Quarterly*, *37*(1), 21–54. http://www.jstor.org/stable/43825936
Verhoest, K., Verschuere, B., & Bouckaert, G. (2007). Pressure, legitimacy, and innovative behavior by public organizations. *Governance, 20*(3), 469–497. https://doi.org/10.1111/j.1468-0491.2007.00367.x
Walker, R. M. (2006). Innovation type and diffusion: An empirical analysis of local government [Article]. *Public Administration, 84*(2), 311–335. https://doi.org/10.1111/j.1467-9299.2006.00004.x
Walker, R. M., Avellaneda, C. N., & Berry, F. S. (2011). Exploring the diffusion of innovation among high and low innovative localities. *Public Management Review, 13*(1), 95–125. https://doi.org/10.1080/14719037.2010.501616
Wang, Y., Singgih, M., Wang, J., & Rit, M. (2019). Making sense of blockchain technology: How will it transform supply chains? *International Journal of Production Economics, 211*, 221–236. https://doi.org/10.1016/j.ijpe.2019.02.002
Wang, Y., Zhang, N., & Zhao, X. (2020). Understanding the determinants in the different government AI adoption stages: Evidence of local government chatbots in China [Article]. *Social Science Computer Review*. https://doi.org/10.1177/0894439320980132
Wang, C., Teo, T. S., & Janssen, M. (2021). Public and private value creation using artificial intelligence: An empirical study of AI voice robot users in Chinese public sector. *International Journal of Information Management, 61*, 102401.
Weber, K., & Glynn, M. A. (2006). Making sense with institutions: Context, thought and action in Karl Weick's theory. *Organization Studies, 27*(11), 1639–1660. https://doi.org/10.1177/0170840606068343
Weerakkody, V., Dwivedi, Y. K., & Irani, Z. (2009). The diffusion and use of institutional theory: A cross-disciplinary longitudinal literature survey. *Journal of Information Technology, 24*(4), 354–368. https://doi.org/10.1057/jit.2009.16
Weerakkody, V., Omar, A., El-Haddadeh, R., & Al-Busaidy, M. (2016). Digitally-enabled service transformation in the public sector: The lure of institutional pressure and strategic response towards change. *Government Information Quarterly, 33*(4), 658–668. https://doi.org/10.1016/j.giq.2016.06.006
Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking [Article]. *Organization Science, 16*(4), 409–421. https://doi.org/10.1287/orsc.1050.0133
Weick, K. E. (1995). *Sensemaking in organizations* (Vol. 3). Sage.
Wirtz, B. W., Langer, P. F., & Fenner, C. (2021). Artificial intelligence in the public sector - a research agenda. *International Journal of Public Administration, 44*(13), 1103–1128. https://doi.org/10.1080/01900692.2021.1947319
Ylönen, M., & Kuusela, H. (2019). Consultocracy and its discontents: A critical typology and a call for a research agenda. *Governance, 32*(2), 241–258. https://doi.org/10.1111/gove.12369
Zheng, D., Chen, J., Huang, L., & Zhang, C. (2013). E-government adoption in public administration organizations: Integrating institutional theory perspective and resource-based view. *European Journal of Information Systems, 22*(2), 221–234. https://doi.org/10.1057/ejis.2012.28
Zuiderwijk, A., Chen, Y.-C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly, 38*(3), 101577. https://doi.org/10.1016/j.giq.2021.101577

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Rohit Madan is a Lecturer of Information Systems at Queen's Business School, Queen's University Belfast. Rohit is a mixed-methods researcher and conducts research in artificial intelligence adoption and diffusion, algorithmic management, AI ethics, and innovation. Prior to academia, Rohit has extensive experience in management consulting, project management, and technology deployments in both public and private sector organisations.

Mona Ashok is an Associate Professor of Digital Transformation at Henley Business School, University of Reading. She is a Fellow of the UK Higher Education Academy, a member of the Institute of Chartered Accountants of India, a Certified Software Quality Analyst, and a Six Sigma Master Black Belt. She has 20 years of corporate leadership experience in global IT and accounting firms; she has worked in Asia, Australia, Europe, and Northern America. Nine years in Higher Education, she has led post-experienced postgraduate and undergraduate programmes. Mona's research and practical work have received tremendous commendations. She has been invited to deliver seminars-keynotes by international think tanks (Asian Development Bank Institute), Government bodies, professional bodies, organisations and universities in the UK and internationally. Mona has successfully secured research funding, including for Knowledge Transfer Partnerships projects, funded by UK Research and Innovation. She has extensive board experience.