Artificial Intelligence adoption in Canadian public administration: A mixed-methods study

Thesis submitted in partial fulfilment for the degree of

Doctor of Philosophy

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Rohit Madan

12 November 2023

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Dedication

I dedicate this thesis to the two most important women in my life. My wife, Ms Karla Amirault, whose love and support have no bounds. My mother, Dr Amita Madan, my biggest fan and critic and wants the best in me.

Publications and presentations

The papers included in this thesis have been presented and published at the following venues. These have been mapped to the receptive chapters and research questions of the thesis.

	Research questions	Chapters			
		2	3	4	5
Presentations					
Making sense of AI benefits: A mixed-methods study in Canadian public administration presented at the Henley IRC and Holloway DOS joint PhD event at Royal Holloway, University of London, June 2023.	RQ4.1: What factors affect the perceived benefits of AI use in public administration? RQ4.2: How do these factors affect the perceived benefits of AI use in public administration?			✓	
Artificial Intelligence Adoption in Canadian Public Administration: A Mixed-Methods Study presented at the UK Academy of Information Systems (UKAIS) 2023 Doctoral Consortium at University of Kent, April 2023.	RQ4.1: What factors affect the perceived benefits of AI use in public administration? RQ4.2: How do these factors affect the perceived benefits of AI use in public administration?			✓	
Artificial Intelligence Diffusion in Public Administration presented at 5th AAAI/ACM Conference on AI, Ethics, and Society, University of Oxford, Aug 2022.	RQ3.2: What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?		✓		
AI Adoption and Diffusion in Public Administration: A Systematic Literature Review and Future Research Agenda presented at the Informatics Research Centre Seminars, Henley Business School, March 2022.	RQ3.1: What are the key factors discussed in the literature that influence AI adoption in public administration? RQ3.2: What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?		✓		

	Research questions	Chapters			
		2	3	4	5
Publications					
Madan, R and Ashok, M, 2023. AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly*, 40 (1): 101774.	RQ3.1: What are the key factors discussed in the literature that influence AI adoption in public administration? RQ3.2: What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?		✓		
Madan, R. and Ashok, M., 2022. A Public Values Perspective on the *Application of Artificial Intelligence in Government Practices: A Synthesis of Case Studies*. In Handbook of Research on Artificial Intelligence in Government Practices and Processes (pp. 162-189). IGI Global.	RQ2.1: How is AI being used in governments? RQ2.2: What are the factors that impact citizen adoption of AI-driven governmental services?	✓			
Madan, R, 2022. Artificial Intelligence Diffusion in Public Administration. *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*.	RQ3.2: What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?		✓		
Madan, R and Ashok, M (2023) Making sense of AI benefits: A mixed-methods study in Canadian public administration. [Manuscript submitted for publication].	RQ4.1: What factors affect the perceived benefits of AI use in public administration? RQ4.2: How do these factors affect the perceived benefits of AI use in public administration?			✓	
Madan, R and Ashok, M (2023) Developing organisational and technological readiness to enable AI adoption: A mixed-methods study in Canadian public administration. [Manuscript submitted for publication].	RQ5.1: What resources and capabilities enable AI adoption within the public administration? RQ5.2: How are the capabilities that enable AI adoption within the public administration developed?				✓

Abstract

The economic and political climate expects public administration to do more with less. Artificial Intelligence (AI) technologies can add immense value towards achieving these goals. However, AI use is accompanied by negative externalities on the environment and already at-risk populations. Against this backdrop of increasing rhetoric of AI benefits and its associated harms, this study explains the AI adoption phenomenon in public administration both from outside-in and inside-out perspectives. The context of the study is Canadian public administration, and the scope is limited to machine learning and natural language processing.

This thesis consists of four papers. The first paper is an exploratory literature review. Through a cross-case analysis of thirty AI implementations, a typology of AI use cases is developed. The second paper is a systematic literature review and identifies technological, organisational, and environmental factors that influence AI adoption in public administration. The third and fourth papers are mixed-methods studies that draw on a cross-sectional survey (n=277) and semi-structured interviews (n=39). The third paper is grounded in institutional and sensemaking theories and explains factors that affect the perceived benefits of AI use in public administration and how they operate. The fourth paper is grounded in the resource-based view (RBV) of the firms and explains what resources and capabilities enable AI adoption in public administration and how these capabilities are developed.

The study contributes to both theory and practice. Theoretical contributions include an updated AI innovation process expanding the diffusion of innovation theory within the context of AI. The study demonstrates black-box assumptions of the institutional theory and RBV can be explained by enumerating underlying mechanisms. Practitioner contributions include guidelines on four AI capability development paths with associated risks and benefits and recommendations on assessing organisational and technological AI readiness, crossing the operationalisation chasm, and managing negative perceptions of AI.

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List of acronyms

AGI	Artificial General Intelligence
AI	Artificial Intelligence
ANOVA	Analysis of Variance
AVE	Average Variance Extracted
BIC	Bayesian Information Criteria
BOLD	Big, Open, and Linked Data
CA	Cronbach's Alpha
CB-SEM	Covariance-based Structured Equation Modelling
CEO	Chief Executive Officer
CIFAR	Canadian Institute For Advanced Research
CIO	Chief Information Officer
CR	Composite Reliability
CRA	Canada Revenue Agency
CRM	Customer Relationship Management
DEG	Digital-era Governance
DOI	Diffusion of Innovation
ERP	Enterprise Resource Planning
GDPR	General Data Protection Regulation
GPT	General Purpose Technology
HTMT	Hetrotrait-Monotrait
ICT	Information, Communications, and Technology
InCiSE	International Civil Service Effectiveness
IS	Information Systems
IT	Information Technology
ML	Machine Learning
NCAP	Neural Computation and Adaptive Perception Program
NLP	Natural Language Processing
NPG	New Public Governance
NPM	New Public Management
OECD	Organisation For Economic Co-Operation And Development
OPSI	Observatory of Public Sector Innovation

PLS-SEM	Partial Least Squares-Structural Equation Modelling
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PVM	Public Value Management
R^2	Coefficient of Determination
RBV	Resource Based View
RMSE	Root Mean Square Error
SCOT	Social Construction of Technology
SCT	Social Cognitive Theory
SEM	Structured Equation Modelling
SNB	Service New Brunswick
TAM	Technology Acceptance Model
TEF	Technology Enactment Framework
TOE	Technology, Organisation, and Environment
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UK	United Kingdom
US	United States
UTAUT	Unified Theory of Acceptance and Use of Technology
VAM	Value-based Technology Adoption Model
VIF	Variance Inflation Factors
VRIN	Valuable, Rare, Inimitable, Nonsubstitutable

1 Introduction

"I believe that at the end of the century [20th century] the use of words and generated opinions will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted."

(Turing, 1950: 442)

"The Government of Canada is increasingly looking to use artificial intelligence to make or support administrative decisions to improve service delivery. The government is committed to using artificial intelligence in a manner that is compatible with core principles of administrative law such as transparency, accountability, legality, and procedural fairness."

(Government of Canada, 2023a)

1.1 Introducing the study

The human desire to create intelligent machines that can perform cognitive tasks and communicate in natural language has come a long way from Turing's vision of thinking machines to the current global phenomenon driven by the power of deep learning and generative Artificial Intelligence (AI) models. As the quote at the beginning of this chapter showcases, Turing foresaw the use of intelligent machines in everyday life by the end of the 20th century. Turing's predictions were quite close as demonstrated by the ubiquity of digital technologies in the first decade of the 21st century and the use of AI taken for granted in today's digital applications. Governments are also enthusiastic about adopting AI for service delivery as illustrated by the Canadian government's declaration in the quote above. This datafication of society has accustomed citizens to rely on digital applications for everyday transactions and expect the same when interacting with the public administration. Citizens willingly provide their data on health, finance, relationships, and biometrics for convenience and as a means of interacting within the new digital society. The projected data created and consumed is expected to reach 180 zettabytes by 2025 (Statista, 2022). Private sector organisations have been able to extract and use this data using AI technologies to harness monumental profits comparable to natural resource extractions (Dwivedi et al., 2021). Public administration also possesses vast amounts of sensitive and rich citizen data but has been slow in adopting AI despite keen interest from political and administrative leadership (Daly, 2023). Public administration can use its data warehouses for modelling a lean and efficient administration with a myriad of applications such as predicting fires and weather events, managing traffic, monitoring disease outbreaks, personalising government-citizen relationships, managing resources, and automating case management in licensing, immigration, and social security (Kuziemski and Misuraca, 2020; Wirtz et al., 2021). However, scholars have warned about the adverse effects of AI use on the environment and already at-risk population clusters, and call for investing resources in developing responsible AI practices and curating data quality (Bender et al., 2021; Ashok et al., 2022). Against this backdrop of increasing rhetoric of AI benefits and its associated harms, this study explains the AI adoption phenomenon in public administration both from outside-in and inside-out perspectives through a series of four papers.

Canada's digital government strategy expounds on the role of technology in meeting public service challenges stating, "digital government is about modernizing … the way we work to make the Government … responsive … resilient … and better at serving people" (Government of Canada, 2022b). And specifically, "Artificial intelligence (AI) technologies offer promise for improving how the Government of Canada serves Canadians" (Government of Canada, 2023b). However, the operational reality of adopting and implementing AI within public administration is still a distant dream with stark reminders of previous technological implementation challenges and failures. For example, the failure of the Canadian government's Phoenix Pay System. This new software system was implemented to replace a 40-year-old legacy pay system (Auditor General of Canada, 2018). The lack of project controls and sufficient testing led to a failed implementation resulting in federal employees not getting paid and retired employees unable to get pensions with no resolution for several years (Ibid.). Canadian Government currently has 495 existing or planned information technology (IT) projects over CAD 1 million, a vast majority of them being legacy systems replacements (Ottawa Civic Tech, n.d.). This technical debt and a legacy of previous failures matter in how public administration pursues AI adoption. Thus, public administration leaders need a higher risk tolerance to contend with the ever-increasing concerns of ethical impacts of AI use and develop distinct capabilities to champion an AI vision for their organisations (Ashok et al., 2022; Madan and Ashok, 2023b).

This chapter is organised as follows. In the next section, AI is defined for this study. This is followed by introducing five bodies of literature as the theoretical frameworks for the study, diffusion of innovation (DOI), public administration, institutional theory, sensemaking theory, and the resource-based view (RBV) of the firms. The Canadian public administration is discussed next as the specific context for this study. This is followed by a discussion of the research paradigm, research methodology, research design, value of the research, outline of this thesis, and finally the conclusion.

1.2 Defining AI

The definition of AI is characterised by ambiguity and has been used as an umbrella term to signify a concept, a field of study, AI techniques, or an amalgamation of software and hardware as a system or a service (Bawack et al., 2021; Samoili et al., 2020; Zuiderwijk et al., 2021; Valle-Cruz et al., 2019; Dwivedi et al., 2021). Definitional vagueness can be countered by contextualising the use of the term AI as per the discipline and the research goals (Dwivedi et al., 2021). Following this line of thought, this research looks at sensitising the concept of AI as it is used in both information systems and policy research. Technical researchers generally refer to specific technologies when discussing AI while legal and policy scholars emphasise the potential abilities of emerging technologies to carry out tasks that require learning, dialogue, and reasoning, traits associated with human cognitive faculties (Krafft et al., 2020; Raisch and Krakowski, 2020). European Commission defines AI as “systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions” (AI HLEG, 2019: 6). The Government of Canada defines AI as “information technology that performs tasks that would ordinarily require biological brainpower to accomplish, such as making sense of spoken language, learning behaviours or solving problems” (Government of Canada, 2023a). This study attempts to synthesise information systems and policy definitional streams for the current context. This theme is further explored in Chapter 2 using AI use cases and the resulting definition of AI as “a cluster of digital technologies that enable machines to learn and solve cognitive problems autonomously without human intervention.”

The literature discusses AI capabilities or taxonomies in terms of perception, comprehension, learning, and acting (Bawack et al., 2021; Samoili et al., 2020). Perception capabilities refer to the ability of the system to detect and gather input from its environment (Bawack et al., 2021). The sub-domains or technologies supporting perception are computer vision, audio processing, identity recognition, and IoT devices (van Noordt and Misuraca, 2022; Samoili et al., 2020). Comprehension refers to the ability of the system to reason and plan by modelling input data and providing optimal output parameters as per the user’s intent (Samoili et al., 2020). Communication and dialogue with the user is also considered part of comprehension (Bawack et al., 2021). Several sub-domains related to comprehension and communication are discussed in the literature such as knowledge representation, optimisation, natural language processing, automated reasoning, and predictive analytics (van Noordt and Misuraca, 2022; Samoili et al., 2020). AI is most widely associated with its ability to learn from large data sets through supervised, semi-supervised, or unsupervised techniques or reinforcement learning using trial and error (Sarker, 2021). The acting capabilities relate to AI's abilities for machine-to-human interaction enabled by other three capabilities such as robotics and automation, conversational virtual agents, and automated vehicles (Bawack et al., 2021; Samoili et al., 2020). In both public administration and information systems literature, AI is often discussed in terms of benefits enabled by these capabilities such as automating case processing, predicting risk, and resource allocations (Valle-Cruz et al., 2019; van Noordt and Misuraca, 2022; Zuiderwijk et al., 2021; Kuziemski and Misuraca, 2020; Wirtz et al., 2021; Dwivedi et al., 2021). In Chapter 2, a typology of AI use cases is developed using a cross-case analysis of AI implementations in the government: compliance, organisational management, public service delivery, and regulatory functions.

The interest of this research is in the machine's ability to solve cognitive problems and learn autonomously. The key AI capabilities supporting cognitive outcomes are comprehension, including communication, and learning. These capabilities are primarily supported by machine learning (ML) and natural language processing (NLP) (Bawack et al., 2021; Samoili et al., 2020). As discussed in Chapter 2, the literature shows majority of AI use cases in public administration are geared towards achieving the goals of cognition and are enabled by ML and NLP as well (Madan and Ashok, 2022; European Commission, 2021). Hence, the scope of this study is limited to two specific clusters of digital technologies, ML and NLP.

1.3 Theoretical frameworks

Since this study aims to explain the AI adoption phenomenon in public administration (further discussed in Section 1.6), several literature streams were reviewed to identify theoretical frameworks for the research: technology adoption, public administration, innovation, and strategic management.

Technology adoption literature has a rich theoretical and empirical landscape exploring antecedents of adoption at the individual and organisational levels. The stream of research at the individual level measures adoption or intention to adopt a technology as a function of technological, social, and individual characteristics. These models include the theory of reasoned action (TRA) (Fishbein and Ajzen, 1977), the technology acceptance model (TAM)

(Davis, 1989), the theory of planned behaviour (TPB) (Ajzen, 1980), the extended technology acceptance models (TAM2 and TAM3) (Viswanath and Fred, 2000; Venkatesh and Bala, 2008), the social cognitive theory (SCT) (Bandura and Walters, 1977), and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). A second stream of research is focused on explaining the adoption of technology at the organisational level and primarily includes two models, the technology-organisation-environment (TOE) framework (Tornatzky and Fleischer, 1990) and the diffusion of innovation (DOI) theory (Rogers, 2003). Since the unit of analysis for this research is at the organisational level, public administration organisations, TOE and DOI were chosen as the supporting frameworks for conceptualising AI adoption.

TOE argues that technology adoption within the organisation is not only a function of technological characteristics but is also affected by organisational and environmental factors (Tornatzky and Fleischer, 1990). The TOE does not prescribe specific variables within each of the three contexts and thus, has been widely adopted as a high-level framework in both public and private sector contexts. Such as open government data initiatives and e-government, cloud computing, big data, and social media adoption (Wang and Lo, 2016; Hossain et al., 2021; Krishnan et al., 2017; Sharif et al., 2015; Sun et al., 2018). The technological context is associated with the availability of the technology, either internally or externally, characteristics of specific technologies, and expected benefits (Baker, 2012). In other studies, the technology context has been extended to test the compatibility of new technology with existing technologies, existing infrastructure and capabilities, and employee’s technical expertise (Awa et al., 2017). The organisational context relates to the organisational culture, innovation capabilities, size, routines, leadership, and amount of slack (Baker, 2012). The environmental context, in particular for the public administration context, relates to political structure, media scrutiny, and inter-governmental networks (Verhoest et al., 2007; Korac et al., 2017; Walker et al., 2011).

Public administration literature provides the core theoretical background since the research is situated in the public administration domain. Strategic management literature suggests organisational innovation is a balancing act between the exploitation of existing resources and the exploration of new opportunities guided by the external environment (Teece et al., 1997; Lavie et al., 2010; Gupta et al., 2006; Chesbrough et al., 2014; Chesbrough and Bogers, 2014). Public sector innovation studies also identify internal (related to exploitation), environmental (related to exploration), and innovation constructs as antecedents of innovation (Choi and Chandler, 2015; Hong et al., 2022; Cinar et al., 2019; Demircioglu and Audretsch, 2017; Damanpour and Schneider, 2006; Borins, 2000; De Vries et al., 2016). Similar dimensions are identified within the TOE contexts (Tornatzky and Fleischer, 1990). Hence, it can be deduced, in addition to the AI specific characteristics, the explanation of the AI adoption phenomenon requires both inside-out and outside-in perspectives to account for organisational and environmental effects (Zheng et al., 2013; Dubey et al., 2019; Oliver, 1997).

Two popular theories used in innovation literature to explain the effect of organisational variables on innovation are the upper echelon theory and the resource-based view (RBV) of the firms (Hong et al., 2022; Camelo et al., 2010; Waldman et al., 2004; Crossan and Apaydin, 2010; Lockett et al., 2009; Newbert, 2007; Liang et al., 2010). The upper echelon perspective states leader’s characteristics moderated by external and internal situational factors impact strategic choices and organisational performance (Hambrick and Mason, 1984). The RBV explains firm outcomes as a function of its resources (Lockett et al., 2009). The use of the upper echelon is suited for studying innovation determinants at the individual or group level (Crossan and Apaydin, 2010). RBV provides explanations related to managerial levers at the organisational level (Ibid.). As this research is at the organisational level, RBV was selected to provide the theoretical lens for an inside-out perspective.

To identify theoretical frameworks for the outside-in perspective, philosophical perspectives related to technology and society were considered. The philosophy of technology discusses two contrasting views on the interactions between technology and society, technological determinism and social shaping of technology (SCOT). Technological determinism stipulates technology evolution is not significantly affected by human choice (Bijker, 2009). New technologies and breakthroughs are considered inevitable and a yardstick for societal progress (Poel, 2020). The impact of technology on society is thus deterministic following a “teleological, linear and one-dimensional” direction (Bijker, 2009: 89). This deterministic view is evident in the contemporary AI debates related to both techno-optimism and techo-pessimism (Poel, 2020). In both cases, the underlying assumption is that AI development will progress irrespective of human actions and choices.

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). Thus, technologies are a product of human values and interests and can be shaped accordingly (Poel, 2020). This perspective is evident in the current efforts of governments, technology companies, and supranational bodies in directing the ethical development of AI through globally agreed human values captured in the AI ethical guidelines (Ashok et al., 2022).

Both perspectives have been critiqued for providing partial explanations of the technological phenomenon. The deterministic perspective lacks consideration of institutional structures and focuses on technological artefacts as objective manifestations of laws of nature following their own developmental trajectories (Weerakkody et al., 2009; Geels, 2020; Poel, 2020). SCOT perspective has also been critiqued for lacking consideration of the effect of social structures on the development of technological frames (Klein and Kleinman, 2002). SCOT ascribes undue emphasis on a social group's agency while ignoring power structures and historical contexts (Ibid.). Since the social groups operate and are part of established structures and existing power dynamics, scholars have advocated incorporating structural and institutional logic in SCOT (Klein and Kleinman, 2002; Mundkur and Venkatesh, 2009).

Yet another perspective advocates the co-evolution of technology and society recognising the "non-malleability" and "novelty" of technology (Poel, 2020: 504). The novelty of technological innovation carries risks of unintended consequences on society and democracy (Ashok et al., 2022). New technologies are hard to govern, both as a result of technological complexity and inertial forces from institutional structures, leading to non-malleability (Poel, 2020). Notwithstanding industry and governmental efforts to direct responsible AI development, unintended risks and non-malleability of AI are evident in recent instances of AI failures both in government and industry (McGregor, 2021; Rinta-Kahila et al., 2023; Yampolskiy, 2019). This study aligns with this co-evolution perspective. Specific to public administration, institutional logic, political negotiations, and historical context are essential components of enacted technology (Fountain et al., 2001; Cordella and Iannacci, 2010). SCOT perspective, lacking institutional effects, is better suited for explaining AI development and implementation as a function of political negotiations between social groups and the evolution of their technological frames (Poel, 2020). However, during the pre-adoption stages, institutional logic is required to explain the formation of technological frames (Klein and Kleinman, 2002). These frames later serve as the contextual condition for SCOT once an adoption decision is made. Hence, this study adopts institutional theory as the theoretical framework for the outside-in perspective to explain how the external environment is manifested in terms of AI adoption decisions in public administration. Furthermore, sensemaking theory provides the theoretical lens to explain how technological frames of various social groups are formed in the first place influenced by institutional pressures and exogenous signals (Jensen et al., 2009b).

Figure 1.1 shows the four bodies of literature used for this study to ground the inside-out and outside-in perspectives of AI adoption in public administration. Furthermore, each perspective is supported by DOI theory to conceptualise the innovation process model. These are discussed below.

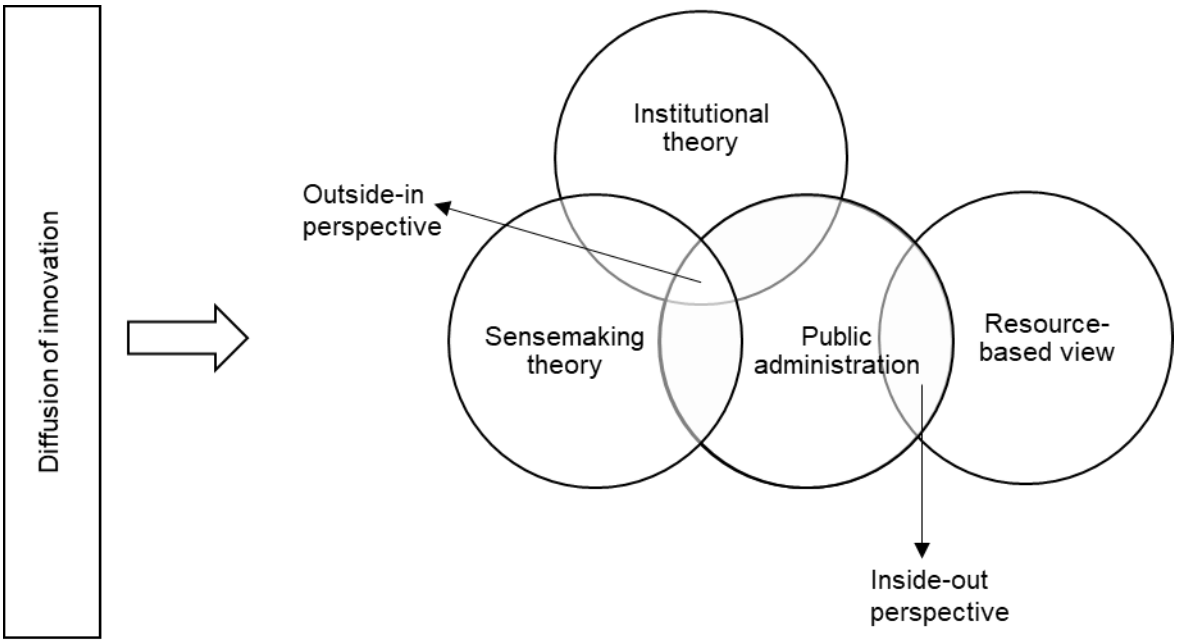

Figure 1.1. Theoretical frameworks

1.3.1 Diffusion of innovation (DOI)

Innovation is defined as “an idea, practice, or object that is perceived as new by an individual” or an organisation (Rogers, 2003: 12). Innovation encompasses two key characteristics that distinguishes it from invention, perceived novelty and implementation (De Vries et al., 2016). The research on innovation has been conducted at multiple levels, industry, organisation or teams, and individuals (Damanpour et al., 2018). Furthermore, the literature identifies two dimensions of innovation research, process and outcome (Crossan and Apaydin, 2010). This study falls in the innovation as a process stream of research examining the AI adoption process. Scholars have argued that understanding the innovation process is critical in being able to manage the outcomes and the change resulting from the innovation (Tidd and Bessant, 2020; Rogers, 2003).

The literature discusses five generations of innovation process models: linear models of demand pull and technology push, coupling model involving interacting between various elements and feedback loops, parallel lines model involving upstream and downstream cross-functional integrations, and systems integration and networking models emphasising partnerships, alliances, and learning (Hobday, 2005). All process-oriented models of innovation imply stages or phases that broadly encompass three steps, a need and a search for solutions, selection of an innovation, and implementation (Tidd and Bessant, 2020). The linear and non-linear models differ in terms of whether these stages are sequential or overlapping with feedback loops (Eveleens, 2010). As well as, all innovation processes converge towards an adoption decision as a temporal point when the organisation decides to implement an innovation and allocates resources in hopes of a future payoff (Ibid.).

Diffusion of innovation (DOI) theory encompasses a linear technology innovation process model and has been widely used to explain the adoption of technologies at the organisational level (Rogers, 2003; Dwivedi et al., 2017; Rad et al., 2018; Zhang et al., 2015). The key tenets of DOI are derived from sociology exploring how innovations are communicated over time within particular social systems (Rogers, 2003). DOI introduces the adoption and implementation of innovation within an organisation as a five-stage process consisting of agenda-setting, matching, redefining/restructuring, clarifying, and routinising (Ibid.). Agenda-setting is the triggering stage where business needs are identified and a possible search for innovations within or outside the organisation is initiated to solve the business problem (Ibid.). The matching stage relates to the organisation conducting a feasibility analysis of the innovation specific to the business problem and the compatibility of the innovation within the organisation (Ibid.). This stage also incorporates an assessment of resources and capabilities required to implement the innovation (Ibid.). The output of the matching stage results in a positive or a negative decision on innovation adoption by the organisational decision-makers (Ibid.). If the organisation decides to adopt an innovation, the redefining and restructuring stage involves adapting the innovation to the organisational context or changing the organisational processes and structures to achieve a better fit with the innovation (Ibid.). In essence, the organisation either customises a technological solution to its environment or changes its processes to use an off-the-shelf application with minimal customisation. The clarifying stage is a post-implementation stage when the innovation is started to be used in a production environment and the impacts of the new technology on day-to-day work become more evident for the organisational members (Rogers, 2003). And finally, routinizing is achieved when the innovation becomes incorporated into the day-to-day processes and culture of the organisation (Ibid.).

Since this research aims to explain the processual nature of AI adoption in terms of its antecedents and temporal steps leading to the AI adoption decision, a linear model of innovation was deemed suitable to conceptualise the major stages pre- and post-adoption. Hence, DOI theory is employed to conceptualise AI adoption in terms of the organisational innovation decision process (Rogers, 2003). Furthermore, since this study is situated in the technology co-evolutionary perspective drawing on SCOT and recognising the institutional and social context are important drivers, the underlying mechanisms under each stage are explored non-linearly grounded in the other four theories – public administration, institutional theory, sensemaking theory, and RBV – as discussed in the next sub-sections. The theoretical grounding of DOI also addresses its primary critique that innovation is not an isolated event and is embedded in the wider social and institutional context (Hobday, 2005).

1.3.2 Public administration

Public organisations differ from private enterprises on three dimensions: ownership, access and control, and agency (Perry and Rainey, 1988). As opposed to the market control mechanisms, public organisations are politically controlled and funded by taxpayers (Wamsley and Zald, 1973). The context for this study is public administration which represents public organisations acting as the executive branch of the elected government (Holzer and Schwester, 2015). Public administration manages substantial public resources, implements government policies, and provides public services. The survival of such organisations is driven by showcasing legitimacy and trust through alignment with political mandates and citizen will rather than market dominance (Piening, 2013).

Weber's ideal type bureaucracy has been the dominant organisational structure for public administration appropriate for providing stable and reliable public services through centralised decision-making and rules and procedures (Hartley et al., 2013). Reforms under the umbrella of new public management (NPM) in the 1980s and 90s were critical of red tape and inefficiency associated with large bureaucracies and aimed to introduce market-based mechanisms in public administration (Kamarck, 2004). Such reforms touted introducing quasi-markets, managerial discipline, performance-based incentives, and reducing the size of the administration through privatisation (Hood, 1991). However, NPM had mixed results generally leading to incremental rather than transformative innovations and unable to achieve its touted goals of lean and efficient administration (Hartley et al., 2013; Torfing, 2019). Several post-NPM reforms, such as new public governance (NPG) and public value management (PVM), aimed to restore the public service ethos and focus on collaborations, networked governments, and broader public value goals (De Vries and Nemec, 2013; Hood, 1991; Ranerup and Henriksen, 2019; Dunleavy et al., 2005; Andrews, 2019).

In tandem with these reform movements, the first wave of technological innovation in public administration in the 1980s and 90s was limited to the automation of back-office administrative processes driven by goals of productivity and efficiency in line with the NPM reforms (Djellal et al., 2013). Scholars argue although large investments were undertaken for electronic service delivery and automating administrative processes, penetration remained low and transformational impact on the administration scant (Coursey and Norris, 2008; Savoldelli et al., 2012; Hung et al., 2006; Dunleavy et al., 2005). Furthermore, technology was never the centrepiece of policy development but an afterthought to develop IT applications to support specific policy objectives (Dunleavy et al., 2005).

The emerging Digital-era governance (DEG) paradigm advocates for the central role of technology in delivering public services through re-integration and centralisation (Dunleavy et al., 2005: 480). As opposed to centralisation, new technological innovations and the austerity measures of the 2008 financial crisis are having both centralisation and decentralisation effects in a second wave of DEG (Margetts and Dunleavy, 2013). The adoption of advanced technologies such as AI and blockchains is discussed as the contemporary form of DEG (Tan and Crompvoets, 2022). This current wave of DEG has a decentralisation effect resulting from the contemporary focus on data, migration to the cloud, focus on predictive modelling, and re-organisations driven by data exchange optimisation and building data capabilities (Ibid.). This concurs with Bloom et al. (2014)'s conclusions given these only represent information technology innovations. However, the centralisation effect resulting from advances in communication technologies (see OFCOM (2022)) is missing in the DEG discussed solely in reference to AI. Thus, it can be deduced, that arguments for both centralisation and decentralisation effects are still relevant with AI. The technology enactment framework (TEF) 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). Scholars contend the political discourse now expects public administration to be more data-driven using advanced analytics and data captured during prior e-government implementations (van Ooijen et al., 2019; Reis et al., 2019a). Thus, the current wave of DEG represents a second wave of technological development enabled by emerging technologies such as AI and is guided by the institutional environment to enable specific sets of organisational values, such as centralisation or decentralisation.

The challenges associated with the first wave of e-government are well-documented across technological and organisational domains. In terms of technology, Information Communications and Technology (ICT) infrastructure has been a primary challenge with compatibility issues, either with legacy systems or other existing systems, a lack of interoperable architecture, a lack of standards and networking capabilities, and a lack of in-house expertise leading to reliance on consultants (Alshehri and Drew, 2010; Zhang et al., 2014). In addition, data ownership and policies on security and privacy have been concerning (Lam, 2005). In terms of the organisational domain, the key challenges include resistance to change and user acceptance, a lack of top management support, a lack of financial resources, and poor vision and leadership (Zhang et al., 2014; Kumar et al., 2002). Furthermore, public administration has followed traditional waterfall project management approaches for managing large IT projects that involve time-consuming documentation of requirements, issuance of an RFP and lengthy procurement processes, set-up of project governance structures, and phase-oriented software development and deployment cycles (Public Services and Procurement Canada, 2019). In recent years, agile practices have gained popularity to mitigate failures in large technology implementations and to better manage changes in long-term contracts as user requirements evolve during the design and testing phases (Mergel, 2016).

The adoption and implementation of AI solutions also experience similar organisational and managerial challenges such as cultural and change inertia, lack of top management support, lack of strategic vision, and managing perceptions of job losses and economic impacts (Zuiderwijk et al., 2021). However, AI projects add four unique dimensions not witnessed in previous implementations. First, AI projects require organisational maturity in data that encompasses accessibility to good quality and quantity of data, data science and AI capabilities, and data governance processes (Janssen et al., 2020a; Bérubé et al., 2021). Second, a shift from developing on-premise IT infrastructure to cloud capabilities that enable scalability and distributed infrastructure necessary to manage computing-intensive techniques such as deep learning (Zhang et al., 2017). Third, AI as a general-purpose technology (GPT) needs experimentation and involves a lag before its potential for specific application areas can be realised (Crafts, 2021). The adoption of traditional enterprise applications, such as Customer Relationship Management (CRM) or Enterprise Resource Planning (ERP), with deterministic logic and established use cases starts with requirements elicitation. In contrast, AI development necessitates pilot and experimentation as the starting point given it's a GPT with probabilistic logic and represents a wide array of use cases. Pilots help establish AI fitness to a problem context before requirements elicitation can be conducted (Desouza et al., 2020; van Veenstra and Kotterink, 2017). As well as agile procurement practices are needed that support iterative development and experimental approaches. Fourth, AI introduces several tensions as a result of conflict between competing goals and these need to be managed during implementation and diffusion. Five distinct AI tensions are discussed in Chapter 3: “automation versus augmentation; nudging versus autonomy; data accessibility versus security and privacy; predictive accuracy versus discrimination, biases, citizen rights; and predictive accuracy versus transparency and accountability.”

1.3.3 Institutional theory

Institutional theory helps explain why organisations "engage in activities that are legitimate in the symbolic realm rather than the material one" (Suddaby, 2010: 15). In essence, it argues strategic choices and organisational member's behaviours are driven by conformance to the institutional logic for gaining legitimacy rather than by rational choices geared towards utility maximisation (DiMaggio and Powell, 1983). The organisational field in public administration can be defined as consisting of governmental ministries and administrative agencies at all levels of the government (local, regional, and national), broader public sector organisations supporting administration, private sector suppliers and consultants, citizens, and special interest groups. The emergence of institutions through the structuration of this organisational field involves the homogenisation of the organisations through mechanisms of coercive, mimetic, and normative isomorphism (DiMaggio and Powell, 1983). Thus, the pursuit of innovation is driven by the adoption of best practices and structures of other leading organisations within the institutional environment rather than for productivity goals.

Scott (2013: 56) defines an institution as comprising three pillars representing "regulative, normative, and cultural-cognitive elements that, together with associated activities and resources, provide stability and meaning to social life". The regulative pillar consists of formal and informal laws that guide and constrain an organisation's actions. The regulative pillar is sustained through coercive isomorphic pressures in the form of political mandates, resources, and trust with citizens (Madan and Ashok, 2023c). The normative pillar consists of values and norms of the institution ascribed within the organisation and sustained through normative isomorphic pressures of professionalisation and organisational learning (DiMaggio and Powell, 1983). And finally, the cultural-cognitive pillar represents "shared conceptions that constitute the nature of social reality" (Scott, 2013: 67). These are communicated and maintained by mimetic isomorphic pressures of imitation during periods of uncertainty (Scott, 2013). Institutional theory has been widely employed in the literature for exploring technology adoption and implementation (Teo et al., 2003; Weerakkody et al., 2009; Mignerat and Rivard, 2009). The theory provides a strong conceptual foundation for exploring digital transformations in the public administration context given the lack of competition and public value goals of trust and legitimacy (Weerakkody et al., 2009).

The literature discusses four major approaches to studying institutionalism: normative, rational choice, historical, and empirical (Peters, 2000; Hall and Taylor, 1996; Suddaby, 2010). The normative approach subscribes to the logic of appropriateness argument that individual or organisational behaviour is best explained through conformance to the institutional environment in pursuit of legitimacy (March and Olsen, 1984). Rational choice institutionalism argues organisational members are not affected by institutional pressures and try to maximise their utilities by playing within the rules and incentive structures established by the institutional environment (Hall and Taylor, 1996). Historical institutionalism derives from path dependence arguing that strategic options in the present are a function of policy and structural decisions made in the past (Ibid.). And empirical institutionalism approach tests the effect of institutions on strategic choices (Peters, 2000).

The binding theme across all institutionalism approaches is the influence of institutions, either formal or informal structures, on decision-making (Barley and Tolbert, 1997). These approaches divert in their definitions of what comprises institutions and the way organisational members interact with the institutions (Peters, 2000). These several strands of institutionalism, and especially the empirical approach, have been critiqued for providing macro-level black-box explanations of the effect of institutions on organisational outcomes while assuming organisational actors as passive recipients of institutional rules (Jensen et al., 2009a). The two seminal publications on institutionalism by Zucker (1977) and Meyer and Rowan (1977) discuss how organisational members extract cues from their environment and attribute rationality to actions. These seminal works highlight both meaning systems and structural aspects of institutions (Suddaby, 2010). Thus, the use of institutionalism purely from a structuration viewpoint, the current usage, fails to account for the importance of the central question on organisational members' motivations in pursuing specific choices (Ibid.).

In terms of establishing the institutional definition for the study, the study builds on the public administration paradigms discussed in the previous section. Bureaucracy continues to be dominant in the public administration structure despite the NPM and post-NPM reforms (Christensen and Lægreid, 2013; Esmark, 2016). 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. Thus, the current institutional environment is characterised by a strong path dependency leading to varying levels of values associated with each of the reform movements (Lindquist, 2022).

To address the critique related to the black-box explanation of the effect of institutions, the study uses sensemaking theory to explore how organisational members at the micro-level engage with the institutional logic at the macro-level forming preferences and in turn affecting technology adoption decisions.

1.3.4 Sensemaking theory

Weick et al. (2005: 409) discuss sensemaking as a transient process where meaning is formed that informs future action and as “an interplay of action and interpretation.” Two integral components of sensemaking are cues and frames (Weick, 1995). The traditional sensemaking process is retrospective and used by individuals to help understand crises and novel events in the past (Maitlis and Christianson, 2014). However, contemporary literature has also applied it in a prospective lens for understanding future probable events and as a precursor for strategic actions (Kaplan and Orlikowski, 2013; Luna-Reyes et al., 2021; Gattringer et al., 2021; Goto, 2022; Wang et al., 2019; Tan et al., 2020).

Sensemaking is triggered by cues from the external environment (Maitlis, 2005). In the retrospective version, cues relate to the chaos that something is not working and there are violated expectations (Weick, 1995). Sensemaking involves noticing and bracketing these cues using mental models (Weick et al., 2005). The mental models are informed by frames of reference that are primed by the individual’s experiences and the social context (Ibid.). The bracketing of cues helps communicate with other organisational or social group members (Ibid.). The bracketing stage is followed by labelling and assigning categories to the experience (Maitlis and Christianson, 2014). Labelling involves “functional deployment … imposing labels on interdependent events in ways that suggest plausible acts of managing, coordinating, and distributing” (Weick et al., 2005: 411). The labels themselves are socially constructed and help guide future action within the institutional and social context (Ibid.). Hence, sensemaking is a social process that involves the transformation of abstract cues into discrete categories that help understand and develop a shared meaning of the event within the social group and thus, invoke suitable future actions (Maitlis and Christianson, 2014).

The literature on sensemaking discusses several forms applied to specific contexts or derived from specific cues; two of these in particular are widely discussed as sensegiving and sensebreaking (Maitlis and Christianson, 2014). Sensegiving is defined as “the process of attempting to influence the sensemaking and meaning construction of others toward a preferred redefinition of organizational reality” (Gioia and Chittipeddi, 1991: 442). Sensegiving explains how organisational leaders and managers influence the sensemaking of organisational members through cultural artefacts and symbols (Maitlis, 2005). Sensebreaking is defined as “the destruction or breaking down of meaning” (Pratt, 2000: 464). Sensebreaking involves individuals questioning cultural and taken-for-granted assumptions and rethinking the future course of action (Maitlis and Christianson, 2014).

Viewed from a prospective lens, relevant to technology adoption and diffusion decisions, cues may relate to a lack of knowledge and uncertainty about probable future states resulting from the new technology (Luna-Reyes et al., 2021). In this case, sensemaking incorporates negotiations between organisational members with competing probable future states and narratives (Gattringer et al., 2021). Managers pursuing innovations undertake sensebreaking to challenge the status quo and set the stage for change, engage in sensegiving to influence organisational members' perceptions towards the innovation, and form a collective coalition and shared understanding regarding the innovation (Röth et al., 2019).

There are ontological differences in whether sensemaking is a cognitive or a social process (Maitlis and Christianson, 2014). This research aligns with the social process view of sensemaking and that the individual cognitive process exaggerates the agency of organisational members as rational actors (Weick, 1995; Weick et al., 2005). From an institutional theory perspective, the study argues institutional structures play a critical role in establishing mental models and the frames of reference used to bracket and label cues or probable future states. Weber and Glynn (2006) propose three contextual mechanisms that link institutional effect to sensemaking, priming, triggering, and editing. The priming mechanism provides the frames of reference for extracting cues from the external environment, the triggering mechanism evaluates the extracted cues and initiates sensemaking, and editing is the social feedback mechanism that forms shared meaning and understanding (Weber and Glynn, 2006). In addition, cognitive constraints established by the institutional structure guide and restrict what strategic options and frames of reference are available for interpretation (Ibid.).

1.3.5 Resource-based view (RBV)

The basic tenant of RBV is that valuable, rare, inimitable, and nonsubstitutable (VRIN) resources create sustainable competitive advantage under similar exogenous factors (Barney et al., 2001). RBV has been used in many contexts and has strong empirical support (Newbert, 2007; Liang et al., 2010). However, RBV has been critiqued for lacking the characteristics of a theory and forwarding a tautological argument making it more suited as a framework for how firms operate (Kraaijenbrink et al., 2010). The application of RBV is not constrained by specific assumptions with the key premise being that firm performance is determined, at least in part, by the acquisition and use of VRIN resources (Ibid.). One school of thought considers resources as a bundle of tangible assets and intangibles such as business processes, human skills, and relationships (Bryson et al., 2007; Seddon, 2014). Another school of thought advocates resources as assets should be defined separately from intangible capabilities. It is argued that mere possession of VRIN resources is not a sufficient condition for superior performance, the capabilities to determine the appropriate resource configurations and the ability to deploy them is what drives competitive advantage (Andrews et al., 2016). RBV can provide a higher explanatory power and more insights when resources and capabilities are treated separately (Kraaijenbrink et al., 2010). This study adopts this latter perspective by analysing resources and capabilities as distinct constructs.

A resource is defined as “an asset or input to production (tangible or intangible) that an organization owns, controls, or has access to on a semi-permanent basis” (Helfat and Peteraf, 2003: 999). Organisational capabilities refer to “the ability of an organisation to perform a coordinated set of tasks, utilizing organisational resources, for the purpose of achieving a particular end result’’ (Helfat and Peteraf, 2003: 999). Thus, capabilities are the outcomes of purpose-driven organisational activities and can be operational or dynamic. Operational capability consists of a bundle of organisational routines and individual skills to perform day-to-day operations using resources (Steininger et al., 2022). Organisational routines are simple decision rules that are assimilated into the organisational norms and provide a reliable and efficient means of using organisational resources (Dosi et al., 2008). The individual skills consist of technological competence, developed through formal qualifications and job-specific training, and organisational competence, developed through knowledge of organisational norms and contributes towards organisational routines (Dosi et al., 2008). On the other hand, dynamic capabilities are the abilities to reconfigure and build operational capabilities as the external environment changes (Teece et al., 1997).

Viewing capabilities from this perspective highlights two key points. First, the role of managers in building and sustaining both operational and dynamic capabilities. Managerial decision-making plays a critical role in sensing a need for a change, determining resource functionality, and matching available resources, and within bounds acquiring new resources, to build capabilities to implement strategy (Lockett et al., 2009). Thus, RBV, and in particular dynamic capabilities, suggests a link between the external environment triggering opportunities and threats and the endogenous firm conduct as an outcome of the managerial decisions in response to the external environment (Lockett et al., 2009). RBV assumes managers are rational actors making resource configuration decisions in pursuit of efficiency and productivity. This view also concurs with the sociological foundation of organisations that postulates transformational leadership can influence and change organisational culture through actions and symbolic roles (Trice and Beyer, 1993; Schein, 2006). This perspective has been dominant in both organisational cultural studies and practice (Sarros et al., 2008).

Second, it highlights the path dependence of RBV where both resources and capabilities are heavily influenced by the historical context and are cumulative, thus, alluding to historical institutionalism (Hall and Taylor, 1996). This results in a paradox in the sense operational capabilities required to deliver on operational goals become entrenched within the culture and fabric of the organisation leading to routine rigidity and inertia to change (Clark, 2005). Public organisations are characterised by inertia that resists creative destruction required for innovation and to build new capabilities (Ashok et al., 2021). This further highlights the role of managers and transformational leaders in managing change and exhibiting dynamic capabilities.

Public organisations can be viewed from instrumental or institutional perspectives (Christensen et al., 2007). The instrumental perspective based on the functionalist view posits managerial decisions are aimed at maximising efficiency and effectiveness (Mignerat and Rivard, 2009). The institutional perspective argues rational choices cannot explain everything and institutional context needs to be considered for explaining irrational choices. Institutional perspective draws on the institutional theory that argues for the "logic of appropriateness" whereby organisations operate within a social context of values and norms and behaviour is driven by concerns for legitimacy and social fitness with the environment (Christensen et al., 2007: 3). There continues to be an ongoing debate whether innovation in public administration is pursued for institutional conformance or efficiencies (Piening, 2013).

Scholars argue institutionalism and rational choice perspectives are complimentary (Zheng et al., 2013; Dubey et al., 2019; Oliver, 1997). The institutional environment established public value goals based on legitimacy and conformity at the political level. However, the resource configuration decisions to deliver on these goals at the organisational level are driven by managerial choices and transformational leaders who negotiate for resources and lead innovation and change in pursuit of these goals. Hence, this study argues institutional theory provides the appropriate theoretical lens for explaining the outside-in perspective related to AI adoption. And RBV provides the theoretical lens for explaining the inside-out perspective.

1.4 The Canadian context

Canada is recognised as a leader in civic service effectiveness ranking among the top five countries in the International Civil Service Effectiveness (InCiSE) 2019 index (InCiSE Index, 2019). Once recognised as a front-runner in digital government, Canada's initial lead has been in decline slipping from the 3rd place in 2010 to being ranked 28th in 2020 in the UN E-Government Survey (UN, n.d.). Even though Canadian governments continue to make impressive strides in digitilisation, the rankings have been affected by increased investments in digital technologies by other countries (Government of Canada, 2022b). The peaks and troughs of e-government in Canada closely mirror the NPM reforms and the conservative versus liberal governments' agendas (Roy, 2017).

The NPM reforms were introduced in Canada under Brian Mulroney's conservative government in 1984 in tandem with similar reforms in the United Kingdom (UK) and the United States (US) (Glor, 2001). These reforms introduced several structural changes in the federal and provincial governments such as the greater delegation to provincial governments, the creation of special operation agencies separating policy from service delivery, the creation of internal markets between departments to buy and sell services, and increased financial and personnel management autonomy to undertake technology projects (Glor, 2001). For example, Service New Brunswick (SNB) was created in the 1990s as a provincial crown corporation which later became the first Canadian multi-service agency (Dutil et al., 2010). And the creation of the Canada Revenue Agency (CRA) in 1999 from a traditional government department to an autonomous agency (Roy, 2017). This decentralisation has led to a fragmented approach to IT infrastructures resulting in the inoperability of systems and the accumulation of technical debt in disparate and ageing legacy systems (Government of Canada, 2022b). Service Canada was modelled on SNB as a service integrator across the federal government but centralisation tendencies for cross-government coordination led to a stunted service digitisation agenda (Roy, 2017). Similar challenges were witnessed by Service Ontario as the province-wide integrator in Ontario resulting in a low uptake of electronic services (Office of the Auditor General of Ontario, 2013).

The conservative government[1] record, especially under Stephen Harper, is mired with extreme neoliberal and conservative ideology towards a tight control of government communications and giving little credence to evidence-based policy (Healy and Trew, 2015). For example, the government suppressed the mandatory long-form census, a hallmark of Canadian representative democracy, that maintains a demographical record of the Canadian population since the establishment of the Canadian Confederation in 1867. Other examples include blanket restrictions in funding feminist organisations, restricting funding for national Aboriginal health organisations, and the closure of the Canadian Health Council that monitored the performance of provincial health care systems (ibid.). However, in stark contrast, several

[1] Brian Mulroney (1984-1993), Stephen Harper (2006-2015) (Parliament of Canada, n.d.)

technological initiatives were supported by the Harper government such as GCpedia and GCConnex[2], Web 2.0 Practitioners Group[3], and Blueprint 2020[4].

The hallmarks of the Liberal government's[5] agenda are openness, digital government, and support for data-driven policies (Clarke et al., 2017). In 1999, the Government On-Line initiative was introduced to accelerate the development of online services making Canada among the most connected countries at the turn of the twentieth century (OECD, 2018). In 2015 after the election of Justin Trudeau, the Treasury Board's mandate letter outlined the government's expectations on innovation and mandated each department to use a percentage of their spending to engage in experimentation (ibid.). Several initiatives encouraging innovation were launched such as the Free Agent programme (an initiative to facilitate the availability of flexible talent across the public service), the Talent Cloud pilot (a technology platform to better match employees' skills with needs across the public service) and the Policy Community Project (ibid.).

Lepage-Richer and McKelvey (2022) provide a fascinating narrative on the role of two Trudeaus in the proliferation of technology and intelligent government in Canada. Influenced by Marshall McLuhan's work, Pierre Trudeau became a big proponent of communication technologies and modelling government on a centralised information-centric model supported by the latest technologies (Lepage-Richer and McKelvey, 2022). Decades later his son, Justin Trudeau, has been a driving force towards the adoption of innovations and AI after the disastrous years of Harper's closed government agenda (Ibid.). In 2018, Trudeau appointed Canada's first minister for digital government. In 2021, Canada released its first digital operations strategic plan geared towards advanced technologies adoption, modernisation of the government's IT systems, and digital service delivery (Government of Canada, 2021b; Government of Canada, 2021a). In response to COVID-19 and several digital challenges laid out in Canada's Digital Government Strategy, Canada's Digital Ambition statement released in 2022 states: "To enable delivery of government in the digital age for all Canadians. This will be done by providing modernized and accessible tools to support service delivery that

[2] GCpedia was established in 2008 to help public servants engage with technology and laid the groundwork for later collaborative platforms such as GCConnex in 2009 and GCCollab in 2017 (OECD, 2018)

[3] Web 2.0 Practitioners Group established in 2009 has been influential in launching several technology initiatives (OECD, 2018)

[4] In 2011, Deputy Minister Committee on Public Service Renewal embarked on a foresight study that led to Blueprint 2020 and development of several innovation labs (OECD, 2018)

[5] Pierre Elliot Trudeau (1968-1979, 1980-1984), Jean Chrétien (1994-2004), and Justin Trudeau (2015-present) (Parliament of Canada, n.d.)

expresses the best of Canada in the digital space" (Government of Canada, 2022a). These strategies are complemented by the Beyond 2020 programme which focuses on making public service more agile, inclusive, and digitally equipped (Government of Canada, 2022c). Central to Canada's digital transformation efforts is the Canadian Digital Service launched in 2017 with the mandate "to help government improve how it delivers services, using modern approaches and tools … partner with departments across the federal government to design and build public-facing services together, creating demonstrations of, and resources that help enable, digital-first delivery in government to meet Canadians' modern expectations that services be easy to use, fast, inclusive, reliable, safe, and transparent" (Government of Canada, 2019). Similar initiatives have been underway at the provincial level where seven out of ten governments have dedicated digital offices. This level of political support for the digital government agenda is further supported by the Canadian government's intent to maintain Canada's lead in AI research through the Pan-Canadian AI strategy (CIFAR, 2020).

The present breakthroughs in AI are widely recognised to be the result of advances in deep learning and neural networks (Zhang and Lu, 2021). Several of these innovations are rooted in Canada as a result of national strategies and its unique research-led AI development model becoming a host nation to global minds in deep learning and neural networks (The Economist, 2017). The Canadian Institute for Advanced Research (CIFAR) was established in 1982 and was envisioned as a global multi-disciplinary research institution encouraging open knowledge sharing to "foster basic, conceptual research of high quality at an advanced level across the full spectrum of knowledge in the humanities, social sciences, natural sciences and life sciences" (CIFAR, n.d.). Geoffrey Hinton, convinced of the power of neural networks and their potential for deep learning, set up CIFAR's Neural Computation & Adaptive Perception program (NCAP), now called Learning in Machines and Brains, in the early 2000s (CIFAR, n.d.). Its members included Yoshua Bengio and Yann LeCun among other researchers in neuroscience, computer science, biology, electrical engineering, physics, and psychology (CIFAR, n.d.). Today, the trio are widely recognised as pioneers of deep learning and were awarded the 2018 A.M. Turing Award "for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing" (ACM, 2019).

CIFAR has also played a critical role in developing the AI industry and related ecosystems (Kuziemski and Misuraca, 2020). The Government of Canada appointed CIFAR to support the Pan-Canadian AI strategy and received CAD 125 million in federal funding (CIFAR, 2020). The goal of the strategy is to bolster national and regional AI ecosystems by recruiting and retaining global researchers in AI and prioritising the progression of AI for societal and environmental good (CIFAR, 2020). Canada introduced the first-ever national AI strategy in 2017 (Kuziemski and Misuraca, 2020). The Pan-Canadian strategy enabled the creation of AI research superclusters such as Alberta Machine Intelligence Institute (Amii); Mila – Quebec AI Institute, a partnership between Université de Montréal and McGill University; and the Vector Institute for Artificial Intelligence in Toronto. The Canada 150 Research Chairs Program provided one-time funding to universities attracting international scholars to Canada to support fundamental research in AI (CIFAR, 2020). The second phase of the Pan-Canadian AI strategy provides an additional investment of CAD443 million to further accelerate the research and commercialisation of AI (Innovation Science and Economic Development Canada, 2022). These initiatives have created a vibrant ecosystem of leading researchers and attracted private-sector technology firms making Canada fifth on the Stanford Global AI Vibrancy index and third among the G7 nations (Maslej et al., 2023).

In summary, the Canadian government's vision to once again become a front-runner in digital government, a vibrant ecosystem of AI research and breakthroughs, and equally innovative private-sector firms commercialising these breakthroughs makes Canadian public administration an appropriate context for this study. At these earlier stages of AI adoption, different levels of government are at different stages of adoption and provide good variation in the data to explain AI adoption mechanisms.

1.5 Research aim and paradigm

1.5.1 Research aim

The overall aim of this study is to examine the AI adoption phenomenon in public administration in terms of its antecedents and mechanisms. The unit of analysis is at the organisational level.

The initiation phase of innovation is comprised of agenda-setting and matching stages (Rogers, 2003). In this phase, business need is identified, and potential innovations are explored and proposed to the leadership for adoption (Damanpour and Schneider, 2006). For this study, AI adoption refers to the adoption decision at the end of this initiation phase where organisational leaders decide to adopt AI to meet the business needs and allocate resources. AI implementation and diffusion are post-adoption phases where AI is operationalised and comprises “events and actions that pertain to … preparing the organization for its use, trial use, acceptance of the innovation by the users [and finally] use of the innovation until it becomes a routine feature of the organization” (Damanpour and Schneider, 2006: 217).

The focus of the research is to enumerate the AI adoption process leading to the adoption decision and its primary antecedents. And explain how the adoption process unfolds through the interactions of these antecedents. Thus, the research questions are stated as:

RQ1: What are the antecedents of AI adoption in public administration?

RQ2: How is the adoption process shaped by the interaction of these antecedents?

The two research questions are broken down into eight sub-questions as shown in Table 1.1. These are answered in a series of four scholarly papers, as outlined in Section 1.8.

Table 1.1. Research questions and sub-questions

Primary research questions	**Sub-research questions and chapters**
RQ1: What are the antecedents of AI adoption in public administration?	Paper 1 (Chapter 2) – RQ2.2: What are the factors that impact citizen adoption of AI-driven governmental services? Paper 2 (Chapter 3) – RQ3.1: What are the key factors discussed in the literature that influence AI adoption in public administration? Paper 3 (Chapter 4) – RQ4.1: What factors affect the perceived benefits of AI use in public administration? Paper 4 (Chapter 5) – RQ5.1: What resources and capabilities enable AI adoption within the public administration?
RQ2: How is the adoption process shaped by the interaction of these antecedents?	Paper 1 (Chapter 2) – RQ2.1: How is AI being used in governments? Paper 2 (Chapter 3) – RQ3.2: What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration? Paper 3 (Chapter 4) – RQ4.2: How do these factors affect the perceived benefits of AI use in public administration? Paper 4 (Chapter 5) – RQ5.2: How are the capabilities that enable AI adoption within the public administration developed?

1.5.2 Research paradigm

Research paradigm encompasses "theoretical and methodological traditions … [that provide] researchers an intellectual context … to conduct their research" (Crotty, 1998: 97). Kuhn conceptualised the term "paradigm" in a scientific context to mean the dominant and shared beliefs of the time as "universally recognized models and concepts within a community of practitioners" (Smith, 1998: 193-197). However, in social sciences, the concept of paradigm has been used to mean different levels of generality of the shared belief systems of particular research disciplines (Morgan, 2007). Morgan (2007) outlines four versions of paradigm in use in today's research: worldviews as an "all-encompassing ways of experiencing and thinking about the world" (pg.50); epistemological stances as the "way of inquiring into the nature of the world" (Easterby-Smith, 2018: 63) or "how we know what we know" (Crotty, 1998: 8); shared beliefs within the community of researchers; and, finally, model examples of how research should be conducted in a specific field.

The first two usages have been adopted by leading social science methodologists who identify ontology, epistemology, axiology, and methodology as dimensions of a research paradigm (Creswell and Clark, 2007; Teddlie and Tashakkori, 2009). Using these dimensions, the literature identifies four paradigms[6] for research: positivism/post-positivism, constructivism/interpretivism, transformative, and pragmatism. The traditional paradigm wars relate to the tensions between the positivistic/post-positivist view of a singular objective reality and constructivism/interpretivism which contends multiple subjective realities (Feilzer, 2009). The positivism/post-positivism paradigm is generally associated with quantitative methods of inquiry using statistical approaches with the goal of knowledge generation driven by replicability and generalisability (Creswell and Clark, 2007). Constructivists/interpretivists favour qualitative methods of inquiry to develop a subjective meaning of the phenomenon based on participants' lived experiences and perspectives (Scotland, 2012). Transformative paradigm is an emancipatory approach that places "central importance on the lives and experiences of marginalized groups" (Mertens, 2003: 139-140).

Pragmatism as a philosophical tradition has the starting point in the classic maxim of Charles Sanders Peirce: "consider what effects, which might conceivably have practical bearings, we conceive the object of our conception to have. Then, our conception of these

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[6] Creswell and Clark (2007) identify four paradigms while Teddlie and Tashakkori (2009) identify five distinguishing between positivism and post-positivism. The basic assumptions of positivism and post-positivism are the same of an objective reality and a deductive approach to epistemology and makes post-positivism a successor to positivism than a distinct paradigm (Hall, 2013).

effects is the whole of our conception of the object" (Olshewsky, 1983: 199). Morgan (2014) builds on John Dewey's work on interpreting the maxim to outline three key tenets of the pragmatic philosophy. First, the knowledge of the world is inseparable from human experience (Ibid.). This knowledge is contextual and socially constructed through actions (Ibid.). There exists a feedback loop between actions and beliefs, actions are driven by beliefs and beliefs themselves are ever-evolving based on the reflection on the actions (Ibid.). Second, research as a process of inquiry is about asking questions and making choices on the likely outcomes of future actions based on current beliefs (Ibid.). Thus, the contextual dependency of these beliefs results in fallibility in predicting the outcomes of the actions (Kaushik and Walsh, 2019). Third, the claim of knowledge and the meaning of the hypotheses is more suited towards its utility for social progress rather than a mere representation of reality (Feilzer, 2009). Thus, pragmatists advocate the starting point of philosophy should be an inquiry into real-world problems rather than metaphysical concepts of truth and the nature of reality (Morgan, 2014).

Pragmatism as a research paradigm rejects the traditional notions of a dichotomy between objective and subjective realities and recognises both are equally important (Feilzer, 2009). The objective reality exists independent of human experience (Morgan, 2007). However, experiences are the only means to access this reality and human experiences are mired with ever-evolving beliefs creating multiple layers of subjective reality (Feilzer, 2009). Thus, rather than adopting a specific view of reality, pragmatism advocates an emphasis on experiences and knowledge creation through assertions resulting from actions and outcomes (Ibid.). Pragmatism accepts that the measurable world consists of layers of both objective and subjective realities (Morgan, 2007). Hence, the epistemological concerns of accessing and measuring these layers can be achieved through quantitative and qualitative methods to measure aspects of the same phenomenon and furnish a richer view (Morgan, 2007).

The research questions guided the choice of the research paradigm for the study. The two research questions pertain to examining the AI adoption phenomenon in terms of the key variables and explaining the underlying mechanisms generated by the interaction of these variables. As discussed in Section 1.3, a rich theoretical landscape exists on technology adoption in public administration. Thus, to answer the first research question, a reductionist approach is deemed suitable to conceptualise the phenomenon (Haig, 2014). Discrete variables deduced from theory will be hypothesised and statistically tested (Blaikie, 2010). With regard to the second question, an interpretive approach is necessary to explore the actors' experience with the phenomenon and the subjective realities constructed to explain the results of hypothesis testing (Crotty, 1998). Thus, the study requires adopting both objective and subjective realities and aligns with the pragmatist paradigmatic position. Furthermore, the research also focuses on the inquiry of real-world problems that have clear utility strengthening the alignment with the pragmatist position.

This study adopts a pragmatic research paradigm recognising the primacy of the research aim and considering the utility of the research findings in guiding theory and practice. The research acknowledges the explanation of the objective phenomena, measured through quantitative methods, is best accomplished by interpreting multiple subjective realities constructed by the actors through interactions with the phenomenon (Morgan, 2007).

1.6 Research methodology

Inspired by Dewey's model of inquiry (Morgan, 2014), the study follows a five-step process as shown in Figure 1.2 and discussed below.

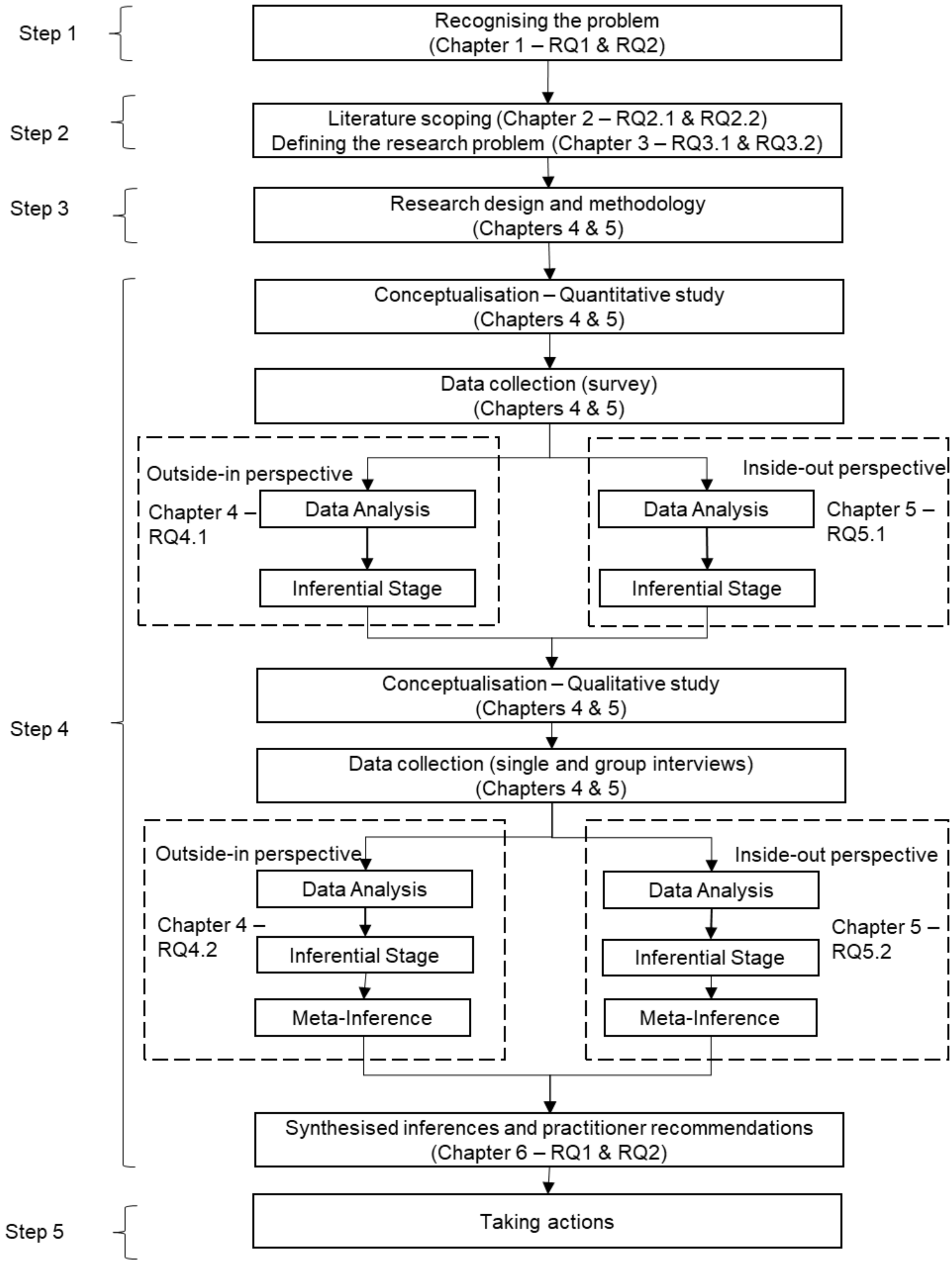

Figure 1.2. Research methodology

(adapted from Morgan (2014: 1048) and Teddlie and Tashakkori (2009: 138))

The first step is the recognition of the problem. The research problem and the goals were informed by the author’s own experience in managing technology projects in public administration, prior research in public sector innovation, and informal discussions with public administrators and technology consultants.

The second step involves defining the research problem and the questions. An exploratory literature review was conducted to identify literature gaps, critique how AI is currently positioned within the public administration paradigms, and develop a typology of how AI is being used in governments. This literature review is discussed in Chapter 2. This exploratory review informed the research protocol for a follow-up systematic literature review on the antecedents and tensions associated with AI adoption and diffusion in public administration. The results of the systematic literature review identified the literature and practitioner gaps and helped outline the research agenda for further empirical studies. This review is discussed in Chapter 3.

The third step involves research design and methodology decisions for solving the research questions identified in the previous stage. Mixed-methods research was identified as the optimal methodology to help answer the research questions. Two studies were conceptualised to study the outside-in and inside-out perspectives individually to ensure parsimonious models. 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; Jankin et al., 2018; Madan, 2022). Thus, a quantitative study followed by a qualitative study was considered appropriate (Venkatesh et al., 2013).

The fourth step involves conducting research and evaluating results in terms of their likely consequences. This was achieved through a mixed-method research design which is discussed in detail in the next sub-section. A deductive approach was used for a confirmatory study testing the significance of antecedents identified from the literature in the specific context of AI adoption within the public administration. An inductive approach was used to explain and elaborate the relationships between the antecedents and the underlying mechanisms that produced the results. 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 resulting in the quantitative results (Venkatesh et al., 2013: 39). In the first study, Chapter 4, the meta-inference resulted in a processual sensemaking model. In the second study, Chapter 5, the meta-inference resulted in an AI capability development model. Furthermore, the synthesis of the results of the two empirical studies involved further deduction to develop the final set of conclusions and recommendations which are discussed in Chapter 6.

The final step of taking action is outside the scope of the current thesis and will be achieved through the development of policy papers for the practitioner and governmental community post-PhD.

1.6.1 Research design

The two empirical papers (Chapters 4 and 5) adopt an explanatory sequential mixed-methods research design to answer their respective research questions (Teddlie and Tashakkori, 2009) as shown in Figure 1.1 in step 4. The purpose of the mixed-methods study was "completeness" and "expansion" (Venkatesh et al., 2013: 26). The study's goal is geared towards developing a complete picture of the AI adoption phenomena and the qualitative study helps provide explanations and expansion on the quantitative results.

The *conceptualisation stage of the quantitative study* was informed by the theoretical frameworks, exploratory and systematic literature reviews, and other empirical studies in e-government. Two conceptual models were developed for testing the outside-in and inside-out perspectives.

The *data for the quantitative study* was collected through a cross-sectional survey. To ensure rigour and confidence in the results, the scales for the conceptual models were adapted from the literature. To assess the quality, reliability, and construct validity, the survey was pilot-tested (n=34). Following the results of the pilot, two questions were reworded[7], and one question was split into three for better clarity[8]. The data were collected using an online questionnaire designed in Qualtrics and included scales for both conceptual models. 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 data

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[7] In one question, "customers (citizens, private business)" was replaced with just citizens to better reflect public administration usage. In the second question, "management consultants" was replaced with "external consultants/advisors" for the same reason as above.

[8] The earlier question "Social and economic changes drive the adoption of new technologies" was changed to three new questions for further clarity based on expert feedback following poor loadings on one of the constructs: 1) "Political changes drive the adoption of new technologies" 2) "Economical changes drive adoption of new technologies" 3) "Citizen demographical changes drive adoption of new technologies."

collection was conducted in April – June 2022 in two waves[9]. All respondents were required to consent to participate in the study on a volunteer basis before proceeding with the survey. The consent form and the survey are attached in Appendix A. To improve the accuracy of the responses, invitations explained the context and any subsequent questions were addressed. 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). The missing data was below the threshold of 5% for both variables and cases (Hair et al., 2016). Little's MCAR test was conducted to ensure missing data was at random (Little, 1988). Harmon one-factor test was conducted to check for common method bias (Podsakoff et al., 2003). To check for non-response bias, analysis of variance (ANOVA) was conducted to identify any significant differences between complete and incomplete variables, the two waves of responses, and the duration of the responses.

The *data analysis* was conducted using partial least squares-structural equation modelling (PLS-SEM) for testing both models. As the conceptual models are based on latent constructs measured by their respective items, include more than one dependent variable, and capture theoretically derived casual relationships, structural equation modelling (SEM) methods were needed for quantitative testing (Hair et al., 2011). The criteria suggested by Hair et al. (2011) and Hair et al. (2016) were considered before choosing PLS-SEM instead of covariance-based structural equation modelling (CB-SEM). CB-SEM is suited when the conceptual model is based on a strong theory and research goals are driven by theory confirmation (Hair et al., 2011). Thus, CB-SEM uses goodness-of-fit criteria based on minimising the variance between empirical and theoretical covariance matrix (Hair et al., 2016). In the earlier stages of theory development involving new constructs and relationships, the research objective is geared towards predicting key driver constructs and PLS-SEM is more suited (Ashok et al., 2016; Hair et al., 2016). As well as PLS-SEM being non-parametric does not require distributional assumptions other than ensuring measurement model specifications meet the thresholds to minimise PLS bias (Sarstedt et al., 2016).

PLS path modelling is suited for complex models with several latent variables, indicator items, and model paths (Henseler et al., 2009; Hair et al., 2011). The model complexity was high for this study. The conceptual model tested in Chapter 4 consists of six lateral constructs, five predictors and one dependent, and seven single-item constructs as controls; 16 paths;

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

and 25 reflective indicators. The conceptual model tested in Chapter 5 consists of 14 latent variables, including two second-order predictors and two dependent constructs, and five single-item constructs as controls; 15 paths; and 44 reflective indicators.

The goal of this study was to explain the key driver constructs of AI adoption in the new context of public administration. The study also develops two new constructs, and the conceptual models are complex. Hence, the research objectives are geared towards the initial stages of theory development and maximising the predictive power of endogenous variables to explain the dependent variable(s) rather than theory confirmation. Thus, the use of PLS-SEM was considered appropriate for this study.

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). The model testing was done in two stages starting with the outer measurement model and then proceeding with the inner structural model (Hair Jr et al., 2021). In the first stage, the outer measurement model was assessed for internal consistency reliability, convergent validity, and divergent validity using the thresholds suggested by Hair et al. (2016). In the second stage, the structural model was assessed for collinearity, and bootstrapping was used to generate the significance of path coefficients. The examination of path coefficients and their significance and the coefficient of determination (R^2) were used to *infer* the results for both models.

The results of the quantitative study informed the *conceptualisation of the qualitative study component*. The *data collection for the qualitative study* was based on semi-structured interviews involving single and group interviews. All interviewees consented to participate in the study and were required to sign a consent form. A copy of the information sheet and consent form is attached in Appendix B. The interviews explored AI adoption and diffusion within the Canadian public administration. The interviewees were asked about their opinions on the use of AI, its benefits, drivers, the role of the institutional context, the organisational capabilities required for adopting AI, and the results of the quantitative study. The interviews were audio recorded, transcribed, and analysed in NVivo. A research diary was maintained capturing pre- and post-interview reflections.

Data analysis for the qualitative study was conducted using template analysis (King, 2004). An a priori template was developed based on the results of the quantitative study and theory. The coding was conducted line-by-line to retain interviewees' voices dissecting the text and attaching either an a priori code or a new code derived from the data (Fereday and Muir-Cochrane, 2006). The process involved five iterations. First, five distinct interviews were coded, and a revised template was developed. Reflexivity checks were conducted using the research diary (King and Brooks, 2016). In the second iteration, the revised template was used to code the next five interviews and revise the template. This process was repeated until theoretical saturation was achieved. In the third step, the template was finalised through several iterations of classifying organising and conceptual themes and conducting further reflexivity checks. In the final step, the template was used to reflect on the results of the quantitative study and form meta-inferences synthesising the results of the two studies.

Instead of discussing the validity of qualitative studies, scholars suggest establishing trustworthiness and rigour in qualitative research (Galdas, 2017). This is achieved by showcasing credibility, transferability, and confirmability (Lincoln and Guba, 1985). The credibility of the qualitative study was demonstrated by showcasing prolonged engagement, triangulation, saturation, and member-checking. The author of the study has spent sufficient time in the Canadian public administration and had rapport with the interviewees. The author has worked in technology deployments and is well-versed in the culture, norms, and social settings. Triangulation was demonstrated by synthesising quantitative and qualitative results to develop meta-inferences. Saturation was demonstrated by conducting the interviews until theoretical saturation was achieved and no new codes emerged with several new interviews. Member-checking was accomplished by validating the results of the quantitative study with not only participants who completed the survey but also new interviewees. As well as coding of the qualitative data was done in blocks of five interviews and any emerging themes were validated with the next set of interviews.

The transferability of the study was established through thick descriptions. The themes are discussed using quotes demonstrating the voices of the interviewees. As well as the meta-inferences of the quantitative and qualitative studies provide a complete and rich description of the phenomena.

Confirmability was established through an external audit, audit trail, and reflexivity. The external audit was accomplished by discussing and validating the results and conclusions with the primary academic supervisor who was involved in the interviews or the coding process. The audit trail was maintained by following the template analysis method and outlining the process steps, developing an a priori template, and the final template. The raw data and categories are maintained in NVivo and showcase data reconstruction and themes. As well as a reflexive diary was maintained that captures pre- and post-observations for each of the interviews, non-verbal and environmental cues, values and beliefs of the author that could have been a source of bias, and a reflection on the evolution of the author's values and interests.

Finally, *meta-inferences* were developed by reflecting on the results of the quantitative study in light of the qualitative study results

1.7 Value of the research

The literature reviews presented in Chapters 2 and 3 highlight three key gaps in the literature regarding AI adoption in public administration. First, the literature on AI adoption is focused on the private sector and the role of governments as a regulator and as an antecedent. Research on the adoption and use of AI in public administration is scarce even though public administration is increasingly becoming a significant user of AI (Kuziemski and Misuraca, 2020; Medaglia et al., 2021). Valle-Cruz et al. (2019) study of AI in government reveals AI scholarship is lacking in the study of AI implementations in the public sector. The mechanisms behind public value creation through the use of AI are not well understood (Wang et al., 2021). This represents an urgent policy and theoretical gap in understanding how the adoption of AI will enable public administration transformation and foster public value creation (Hung et al., 2006; Criado and Gil-Garcia, 2019).

Second, the literature highlights a lack of research on environmental antecedents, organisational capabilities, and challenges with AI adoption in public administration contexts (Alsheibani et al., 2018; Jankin et al., 2018). Wirtz et al. (2019)'s literature review showcases research gaps in public sector challenges related to AI applications. Research on understanding the underlying mechanisms and interactions between the antecedents will help explain how AI adoption is shaping public management practices (Ojo et al., 2019).

Third, a deeper understanding of the micro-processes is required regarding the role of consulting companies in shaping the adoption process and thus the public value outcomes. Current AI regulation is moving towards voluntary standards and self-governance and disregards its effects on AI design and implementation (Kuziemski and Misuraca, 2020). National AI strategies are focused on attracting investments and market development and much less attention has been paid to how the design of AI embedded in private agents' goals will affect public services and government operations (Misuraca et al., 2020).

In response to the above literature gaps, the theoretical and practical value of the study are briefly discussed below.

1.7.1 Theoretical value

The theoretical value of the study is in four aspects. First, the study systematically synthesises the current scholarship on the phenomenon of AI adoption and diffusion in public administration. The review identifies technological, organisational, and environmental antecedents of AI adoption and enumerates five distinct AI tensions during the AI implementation and diffusion process. Second, the study provides empirical evidence on the environmental drivers of AI adoption in public administration and the role of consultants. Furthermore, the study develops an expanded AI innovation process in public administration and introduces the concept of operationalisation chasm. Third, the study develops two new constructs of organisational AI readiness and technological AI readiness as measures of maturity and related organisational capabilities to adopt and implement AI within the public administration. Furthermore, the study explains how these capabilities on technological and non-technological dimensions are formed in the first place and their effect on AI adoption. Fourth, the study showcases how the use of a mixed-methods approach can alleviate key limitations of established theoretical frameworks. In Chapter 4, the study showcases the underlying mechanisms of how institutional pressures at the macro level affect sensemaking at the micro level which then drives AI adoption decisions. In Chapter 5, the study mitigates the critique of black-box explanations associated with RBV's suppositions by demonstrating the underlying capability development paths and the contextual impacts of managerial decisions.

1.7.2 Managerial value

The practitioner value of the study is in four aspects. First, the study provides recommendations on countering the negative perceptions and political risks associated with AI use in the public administration context. Second, the study identifies a need for critical debates on the nature and function of AI use within the public administration in order to realise its full potential beyond the marginal gains in efficiency and cost savings. Third, a need for demonstrating value at scale and operationalisation potential is realised to cross the operationalisation chasm and ensure a higher rate of transition from pilots to production solutions. Fourth, four distinct AI capability development paths are developed with associated risks and benefits providing a roadmap for AI adoption. In addition, the study provides dimensions for conducting organisational and technological AI readiness assessments to identify an appropriate AI capability development path.

1.8 Outline of the study

This thesis consists of this introductory chapter, four scholarly papers, and a conclusion and discussion chapter. One paper has been published as a book chapter and another one as a journal article in Government Information Quarterly, these are reprinted here as Chapters 2 and 3 respectively. Two other papers (Chapters 4 and 5) have been submitted for publication in premier information systems journals. For all the chapters, the author of this thesis (and first author for all papers) carried out the conceptualisation, research design, data collection, analysis, and writing of the articles. The second author, and the primary academic supervisor, provided academic supervision and feedback on methods, analysis, and draft versions of the papers. Notwithstanding all research questions and the respective chapters are geared towards explaining the AI adoption phenomenon in public administration, the paper-based structure of this thesis leads to some arbitrariness in addressing specific questions and inferences in each chapter. This is acknowledged as a shortcoming of this thesis.

The outline of the thesis is shown in Table 1.2 and the chapters are introduced below. Each of the eight sub-questions in their respective chapters has been mapped to the two primary questions.

Table 1.2. PhD thesis outline

Chapter	**Title**	**Research questions**		**Empirical component**	**Publication**
1	Introduction	RQ1: What are the antecedents of AI adoption in public administration?	RQ2: How is the adoption process shaped by the interaction of these antecedents?		
2	Paper 1: A Public Values Perspective on the Application of Artificial Intelligence in Government Practices: A Synthesis of Case Studies	RQ2.2: What are the factors that impact citizen adoption of AI-driven governmental services?	RQ2.1: How is AI being used in governments?	A cross-case analysis of 30 government AI implementations	Book chapter (Published)

Chapter	Title	Research questions		Empirical component	Publication
3	Paper 2: AI adoption and diffusion in public administration: A systematic literature review and future research agenda	RQ3.1: What are the key factors discussed in the literature that influence AI adoption in public administration?	RQ3.2: What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?	Systematic literature review of 73 publications	Government Information Quarterly (Published)
4	Paper 3: Making sense of AI benefits: A mixed-methods study in Canadian public administration	RQ4.1: What factors affect the perceived benefits of AI use in public administration?	RQ4.2: How do these factors affect the perceived benefits of AI use in public administration?	Cross-sectional survey (n=272) Semi-structured interviews (n=34)	Submitted for publication
5	Paper 4: Developing organisational and technological readiness to enable AI adoption: A mixed-methods study in Canadian public administration	RQ5.1: What resources and capabilities enable AI adoption within the public administration?	RQ5.2: How are the capabilities that enable AI adoption within the public administration developed?	Cross-sectional survey (n=277) Semi-structured interviews (n=35)	Submitted for publication
6	Conclusion and discussion	RQ1: What are the antecedents of AI adoption in public administration?	RQ2: How is the adoption process shaped by the interaction of these antecedents?		

1.8.1 Chapter 2: A public values perspective on the application of Artificial Intelligence in government practices: A synthesis of case studies

Chapter 2 is an exploratory literature review and a cross-case analysis of AI implementations. It explores the use of AI in governments and argues for adopting a PVM perspective for the use of AI in governments. The two research questions for this chapter are: *How is AI being used in governments? What are the factors that impact citizen adoption of AI-driven governmental services?* The chapter critiques the public administration paradigms of Weber's bureaucracy, NPM, and DEG as they relate to the proliferation of AI and increasing concerns regarding the ethical dimensions of algorithmic governance. The critique advocates for adopting a PVM perspective as a complementary paradigm to DEG in light of ethical dilemmas and recognising the primacy of public service in delivering public value goals of duty, social, and service. Owing to scant empirical evidence on how AI is being implemented in governments (Mikalef et al., 2019), the chapter uses a sample of 30 representative case studies of AI implementations to develop a typology of current AI use cases and explore which public value goals are dominant. Finally, drawing on the Value-based Technology Adoption Model (VAM), the perceived value associated with AI-driven governmental service is identified as the determinant of citizen adoption intention. Furthermore, citizens' perception of public values (a proxy for benefits) and consideration of AI ethical principles (a proxy for sacrifices) are propositioned as affecting citizens' perceived value of AI-driven services.

1.8.2 Chapter 3: AI Adoption and Diffusion in Public Administration: A Systematic Literature Review and Future Research Agenda

Building on Chapter 2's typology of AI use cases and a need for a public values perspective, Chapter 3 is a systematic literature review grounded in PVM and RBV. The review attempts to explore the AI innovation phenomenon in public administration to understand the factors influencing AI adoption and key tensions during AI implementation and diffusion toward achieving the goals of public value creation. The two research questions for this chapter are: *What are the key factors discussed in the literature that influence AI adoption in public administration? What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?* Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology for systematic literature reviews, 73 publications are identified. Qualitative synthesis is conducted on these publications using the template analysis method. The data extracted includes the type of study (quantitative, qualitative, mixed-methods, conceptual); AI technology or application; public administration paradigms; key constructs, measures, and relationships; benefits and outcomes; risks and challenges; and tensions. Deriving from the technology-organisation-environment (TOE) framework, contextual factors under technology, organisation, and environment are identified as influencing AI adoption. The review also identifies five sets of AI tensions that impact the outcomes of AI implementation and diffusion in terms of public value creation and public sector transformation. Using the results of the review and the theoretical frameworks, a future research agenda is developed for the adoption, implementation, and diffusion of AI innovation.

1.8.3 Chapter 4: Making sense of AI benefits: A mixed-methods study in Canadian public administration

Chapter 4 builds on the two literature reviews and explores the environmental factors that affect the sensemaking of AI benefits. This is a mixed-methods study based on a cross-sectional survey (n=272) and semi-structured interviews (n=34) in the Canadian public administration. The two research questions for this study are: *What factors affect the perceived benefits of AI use in public administration? How do these factors affect the perceived benefits of AI use in public administration?* The study is grounded in public administration literature, institutional theory, and sensemaking theory. Deducing from the external contextual factors identified in Chapter 3 and further informed by the above theories, a conceptual model is developed for quantitative testing using PLS-SEM. The model hypothesises that four environmental pressures – vertical coercive, service coercive, mimetic, and normative – affect the sensemaking of AI benefits from its use within the public administration. The output of this sensemaking process, perceived AI benefits, is modelled as the dependent variable. Furthermore, consultant pressures are hypothesised as affecting all four institutional pressures as well as directly affecting perceived AI benefits. The results of quantitative testing are validated through a qualitative study using the template analysis method. The results of both the quantitative and the qualitative study are synthesised to develop meta-inferences and a processual model of AI sensemaking is developed encompassing both the spatial and temporal dimensions.

1.8.4 Chapter 5: Developing organisational and technological readiness to enable AI adoption: A mixed-methods study in Canadian public administration

Chapter 5 also builds on the two literature reviews and explores technological and organisational contextual factors that affect AI adoption. This is a mixed-methods study based on a cross-sectional survey (n=277) and semi-structured interviews (n=35) in the Canadian public administration. The two research questions for this study are: *What resources and capabilities enable AI adoption within the public administration? How are the capabilities that enable AI adoption, within the public administration, developed?* The study is grounded in public organisational theory and RBV. Deducing from the organisational and technological contextual factors identified in Chapter 3 and further informed by the above theories, two new constructs of organisational AI readiness, reflecting the degree of maturity in organisational innovative resources and capabilities that enables AI adoption, and technological AI readiness, reflecting the degree of maturity in technological resources and capabilities that enables AI adoption, are developed. A conceptual model is developed that hypothesises technological AI readiness and organisational AI readiness have a positive effect on AI adoption. AI adoption is measured using two dependent variables for ML adoption and NLP adoption. Furthermore, it is hypothesised that organisational AI readiness has a positive effect on technological AI readiness. The model is tested using PLS-SEM. The results of quantitative testing are validated through a qualitative study using the template analysis method. The results of both the quantitative and the qualitative study are synthesised to develop a novel AI capability development model. The model identifies four distinct paths for AI capability development as a function of maturity on the two dimensions of organisational and technological AI readiness.

1.8.5 Chapter 6: Conclusion and discussion

The final chapter discusses the overall conclusions of the study. Synthesising the results of the four scholarly papers, an expanded AI innovation process model is developed comprising a two-stage matching process. The concept of operationalisation chasm is introduced referring to the inertia in transitioning pilot AI projects to production AI solutions. Overall contributions to theory and methodology are discussed and several managerial recommendations are developed. Finally, the conclusion chapter is closed with a personal reflection on the PhD journey.

1.9 Conclusion

This introductory chapter introduces the study and its main goal to explain the AI adoption phenomenon in public administration both from outside-in and inside-out perspectives through a series of four papers. The chapter provides some background on the four bodies of literature used in this thesis comprising public administration, institutional theory, sensemaking theory, and RBV. Following this, the chapter discusses the Canadian context of this thesis and the unique position of Canada as a leader in AI research complemented by an enthusiastic government currently in power whose key agenda is the digitalisation of governmental services. The chapter then dives into the adoption of the pragmatic paradigm for this study and a description of the research methodology. The chapter then discusses the mixed-methods approach and the steps taken to ensure the validity of the empirical studies. Finally, a brief outline of the thesis is provided and each of the remaining chapters is introduced.

2 Paper 1: A public values perspective on the application of Artificial Intelligence in government practices: A synthesis of case studies

This chapter is based on: MADAN, R and ASHOK, M (2022) 'A public values perspective on the application of Artificial Intelligence in government practices: A Synthesis of case studies'. In: Jose Ramon Saura, F D (Ed.) *Application of Artificial Intelligence in Government Practices and Processes*. IGI Global, 2022.

2.1 Introduction

The first wave of technological innovation in governments focussed on digitising back-office operations with the goals of efficiency and cost savings inspired by the New Public Management (NPM) reforms of the 1980s. NPM was driven by the neo-liberal agenda and critique of large bureaucratic structures associated with red tape and cumbersome processes (Kamarck, 2004; Bernier et al., 2015). However, technology took a backseat and was considered simply a tool for achieving managerialism. Succeeding this initial technology implementation which has had mixed results in meeting its innovation goals (Dunleavy et al., 2005; Hung et al., 2006), the second wave driven by Artificial Intelligence (AI), however, is transforming the roles and functions of government. Often referred to as the next frontier of digital-era governance (DEG) (Dunleavy et al., 2005), this technologically-centred model of governance enabled by AI has the potential for a lean government providing personalised services that are efficient and cost-effective. The use of AI also introduces new risks and ethical challenges such as biased data, fairness, transparency, the surveillance state, and citizen behavioural control (Helbing et al., 2019; Ashok et al., 2022). Maintaining citizen trust and legitimacy of AI-driven governmental services and processes is vital more than ever for sustaining democratic processes (Janssen and van den Hoven, 2015).

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

Dwivedi et al. (2021) discuss the terminological challenges associated with defining AI. The meaning of artificial vs natural is derived from the epistemological assumptions of objectivist or constructivist ideas and scientists and philosophers still do not have a good grasp of what intelligence entails (Ibid.). Following Dwivedi et al. (2021: 24) “institutional hybrid” approach, AI for this chapter is defined as “a cluster of digital technologies that enable machines to learn and solve cognitive problems autonomously without human intervention”. Scholars (von Krogh, 2018; Sousa et al., 2019; Raisch and Krakowski, 2020) generally agree on the three components of AI: input, often big data; task processing algorithms; and output, either digital or physical. Other key terms and definitions are summarised in Table 2.1.

Table 2.1. Key terms and definitions

AI for Compliance	AI is used for governmental activities to ensure citizens, private actors, and other governmental agencies adhere to the legislated rules and regulations.
AI for Organisational Management	AI is used for activities related to the management of internal governmental processes and resources.
AI for Public Service Delivery	AI is used for the delivery of public services to citizens, businesses, and other governmental/NGO bodies.
AI for Regulatory Functions	AI is used for activities related to policy development and research.
Digital-era Governance	An emerging public administration paradigm that situates technology at the centre of governmental processes and advocates for a lean and data-driven governance model.
Public Value Management	The government's organisational values and processes are geared towards achieving duty, service, and social-oriented goals that citizens regard as pertinent.
New Public Management	Public administration reforms of the 1980s that propagated adoption of private sector organisational management practices in public sector organisations. These included quasi-markets, managerialism, employee empowerment, public entrepreneurialism, and performance management practices.

The primary applications of AI in government are process automation, virtual agents, predictive analytics, resource management, and threat intelligence and security (Wirtz et al., 2019; Ojo et al., 2019). The associated benefits include efficiencies, accelerated processing of cases, workforce redistribution to productive tasks, and enhanced satisfaction and trust in public authorities (Wirtz and Müller, 2019; Susar and Aquaro, 2019). AI represents radical innovation transforming internal organisational structures and introducing new governance models (Ashok et al., 2016). However, the use of AI for making policy decisions is accompanied by ethical dilemmas of fairness, transparency of black-box algorithms, privacy concerns, and respect for human rights (Wirtz et al., 2019; Ashok et al., 2022; Ribeiro-

Navarrete et al., 2021). Kuziemski and Misuraca (2020) and Helbing et al. (2019) discuss externalities from the use of AI leading to the detriment of human dignity and well-being such as mass surveillance, profiling, and nudging for incentivising compliance with government direction akin to programming citizens. Mehr et al. (2017) caution AI should not be used solely for its innovation potential but adapted towards a broader social development goal. Citizens expect responsive governments able to meet their personalised needs with the adoption of AI-driven governmental services. The level of trust and legitimacy of government determines expectations of privacy and a fair, equitable, and secure outcome. The erosion of this trust with mismanagement of ethical issues undermines democratic institutions and impacts adoption.

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

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

Literature identifies two primary stakeholders and their associated benefits from technology adoption in the government, citizens and administrators (Rowley, 2011). Citizens play a dual role in technology adoption acting not only as consumers of technology seeking effectiveness but also as taxpayers seeking efficiency and open, transparent, and accountable governance through their elected political representatives (Aberbach and Christensen, 2005). Administrators on the other hand seek to fulfil the political mandates and deliver public services in the most efficient manner (Rowley, 2011). Hence, the chapter argues, that citizens represent the demand side of AI adoption while administrators fulfil the role of the supply side. To answer the first research question of this thesis related to identifying the antecedents of AI adoption, it is imperative to explore both the citizens' and administrators' antecedents. This chapter adopts citizen's adoption perspective specifically as users of AI, Chapters 3 and 4 focus on both administrator's perspective and citizen's role as taxpayers, and Chapter 5 is focused solely on the administrator's perspective.

In light of these literature gaps and adopting the demand perspective, the objective of this chapter is two-fold. First, develop a typology of the use of AI in governments. Second, enumerate the factors that impact citizen/user adoption of AI-driven governmental services. The two research questions are stated as:

RQ2.1: How is AI being used in governments?

RQ2.2: What are the factors that impact citizen adoption of AI-driven governmental services?

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

2.2 Literature review

2.2.1 Public Administration Paradigms

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

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

A confluence of neo-liberalism and economic climate led to the set of reforms categorised under NPM beginning in the 1980s with successful political campaigns in the UK, US, and Canada highly critical of governmental bureaucracy (Kamarck, 2004; Bernier et al., 2015). However, following the limited success of NPM and concurrently technology assuming the dominant role of a social actor, two new paradigms are emerging, Public Value Management (PVM) and Digital-era Governance (DEG) (De Vries and Nemec, 2013; Dunleavy et al., 2005; Hood, 1991).

2.2.1.1 New Public Management (NPM)

NPM became the dominant public administration paradigm in the 1980s seen as a pragmatic synthesis of operating principles borrowed from private sector successes. The three main themes of NPM are "disaggregation" through the splitting up of large governmental hierarchies, "competition" adopting marketisation of public services, and "incentivization" through empowering employees and rewarding performance-based management (Dunleavy et al., 2005: 470). The American reform movement by Osborne and Gaebler (1992) argued for downsizing public services by focusing on policy development and marketizing service delivery functions while Hood (1991; 1995) in the European context argued for improving the quality of public service delivery by adopting management practices but maintaining the central role of the government. These reforms introduced quasi-markets, managerialism, and performance management metrics (Hartley et al., 2013; Torfing, 2019).

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

Second, public administration scholars (Dunleavy et al., 2005; Torfing, 2019; Bryhinets et al., 2020; Rainey and Bozeman, 2000) concur that NPM was politically motivated than based on empirical evidence and has failed to deliver on its promises of reinvention. Dunleavy et al. (2005) argue that NPM’s performance and disaggregation principles damaged public service ethos and reduced citizens’ engagement with government. Skålén (2004: 251) empirical research in Sweden contradicts NPM claims of performance-based pay summarising ‘‘NPM creates heterogeneous, conflicting and fluid organizational identities, rather than the uniform and stable business identity it is supposed to.” NPM led to unintentional consequences of “overbidding” and “free-riding” problems (Hartley et al., 2013: 823).

Third, NPM marketisation principles have been critiqued for the implicit assumption of the superiority of market control. Scholars argue pursuit of efficiency initially seen as a means towards social goals became an end in themselves (Harvey, 2007; Dunleavy et al., 2005; Bannister and Connolly, 2014). Performance management goals compelled public managers to focus on specific short-term institutional goals while ignoring the broader vision of public service (Bryhinets et al., 2020).

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

The first two critiques on the incongruity and adverse effects of applying market control principles to governments have led to a reversal of NPM changes since early 2000 (Dunleavy et al., 2005). The disaggregated agencies have been consolidated into coherent government-wide processes, however, performance management, marketisation, and incentivisation persist (Ibid.). The first wave of information technology (IT) implementations within the governments was driven by NPM principles of efficiency and cost savings (Cordella and Bonina, 2012). These projects failed to consider the critical importance of technology and its role in transformational change of governments and society at large, the narrative was centred on technology as a tool enabling managerial values (Dunleavy et al., 2005). Ojo et al. (2019) contend that NPM even worked against the digital transformation of government through outsourcing and the failure of large IT implementations. With the current wave of digital transformation through AI, technology needs to be central and hence, a new paradigm of DEG is emerging.

Following the critiques on the NPM discourse of serving society exclusively through economic goals (Dunleavy et al., 2005) and the proliferation of AI inducing ethical dilemmas, the paradigm of PVM is emerging.

2.2.1.2 Digital-era Governance (DEG)

DEG encompasses “complex…changes, which have IT…at their centre, …[and] spread…in many more dimensions simultaneously than was the case with previous IT influences” (Dunleavy et al., 2005: 478). The vision of DEG is a lean and smarter state administration driven by big data and advanced analytics (Andrews, 2019). DEG represents a transformation change often described as the second wave of technological development and takes a step further from e-government in locating human-machine interactions at the core of government service delivery; citizens and private agents are governed through co-producing big data and machine interactions (Williamson, 2014).

Dunleavy et al. (2005: 480) discuss three primary themes of DEG: “reintegration”, “needs-based holism”, and “digitalization changes”. First, reintegration encompasses consolidating distinct agencies created as a result of the disaggregation agenda of NPM and the establishment of central shared services for efficient and effective government (Ojo et al., 2019). Second, needs-based holism characterises transformational change between government and citizens through end-to-end reengineering, digital citizen engagement, crowdsourcing of policy ideas, and concepts like agile government (Ibid.). Third, integrating the other two themes is digitalisation change referring to the global trend towards open government and transparency (Ibid.). Paradoxically, the quantification of citizen transactions and surveillance without checks leads to a manifestation of Orwell's fictional big brother state (Kuziemski and Misuraca, 2020; Chris and Susan, 2018).

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

2.2.1.3 Public Value Management (PVM)

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

Bannister and Connolly (2014: 120) define values as "a mode of behaviour, either a way of doing things or an attribute of a way of doing things, that is held to be right." In the context of technological change in public administration, values ascribe public servants' behavioural intention towards goals that "citizens … consider … to be right" (Ibid.). This definition concurs with Schein's (2006) conceptualisation of values as basic underlying assumptions that drive acceptable norms and are the primary source of motivation and coordination of organizational activity (Daher, 2016; Gregory et al., 2009). Pant and Lachman (1998: 197) refer to these as core values that exert “high consensus and high control.”

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

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

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

Dunn and Miller (2007: 353) argue instrumental rationality is embedded in both NPM and Weber’s bureaucracy with the main goal of “control of human and material nature on the basis of knowledge.” This deduction can be expanded to DEG in the form of digital

Weberianism where the role of scientific, professional, and technocrat expertise is being assumed by algorithms (Chris and Susan, 2018). From a critical theory perspective, there is a large gap in the theory and practice of public administration on the “emancipatory” rationality concerned with “critical self-reflection and creation of institutions through moral discourse and ethical reflection” (Dunn and Miller, 2007: 354). In addition, ethical dilemmas introduced with the implementation of AI in government further strengthen the need for assuming “emancipatory” rationality in both research and practice. PVM provides an opportunity for such ethical discussions and offers a complementary perspective to DEG in light of AI implementations.

2.2.2 Technology Adoption

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

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

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

2.3 Methodology

To answer the research questions, the research undertakes a case study synthesis approach exploring the phenomenon of AI implementations within governments. Given the scarcity of empirical studies on AI implementations, secondary case studies are used to achieve theoretical saturation on AI use and determinants of adoption. Khan and VanWynsberghe (2008) argue that cross-case analysis assists with identifying commonalities and differences in the phenomenon and contributes towards conditional generalisations. Stake (2006: 6) discusses themes identified through cross-case analysis that can be used to make assertions about the “quintain”, the phenomenon or object being studied. In the current analysis, this is an AI-enabled governmental service or process. As well as cross-case comparisons can also support the identification of clusters sharing certain configurations and help build typologies of the phenomenon (Khan and VanWynsberghe, 2008). Denzin (2001) suggests identifying essential elements and components of a phenomenon across multiple cases. These essential elements when clustered within a social context can assist with developing typologies.

2.3.1 Case selection

The chapter follows the widely used ‘Preferred Reporting Items for Systematic Reviews and Meta-Analyses’ (PRISMA) (Moher et al., 2009) methodology to conduct a systematic review and qualitative synthesis of the case studies. The public sector innovation case study archive maintained by OPSI (2020) was used that includes details on 396 cases of public sector innovation (as of March 2021). Using the search terms “artificial intelligence”, “big data”, and “machine learning”, 70 cases were identified for a full-text review. Twenty cases were finally selected for coding after excluding ones that did not involve AI or government context. In addition, through a Google Scholar search and following the same exclusion criteria, ten more relevant cases were identified from UNESCAP and Google (2019), World Economic Forum (2020a), and Berryhill et al. (2019). The final 30 representative cases are summarised in Table 2.2.

Table 2.2. Case studies summary

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
1	Annie™ MOORE (Matching and Outcome Optimization for Refugee Empowerment): ML and optimization methods to recommend optimal placements of refugees (OPSI, 2020)	US	Public services delivery	Service Social	Autonomy Beneficence Non-maleficence
2	AuroraAI: personalised AI-driven services for citizens and businesses (Berryhill et al., 2019)	Finland	Public services delivery	Service Social	Beneficence
3	City of Things: development of a smart city (OPSI, 2020)	Belgium	Public services delivery	Social	Beneficence
4	Queensland Land Use Mapping Program (QLUMP): ML and computer vision to automatically map and classify land use features in satellite imagery (OPSI, 2020)	Australia	Public services delivery	Service Social	Explicability
5	MyService: a digital solution enabled by AI/ML to improve veterans'	Australia	Public services delivery	Service	N/A*

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
	experience when accessing health care (OPSI, 2020)				
6	R2D3: active-waiting robot to at the reception desk of the Department's Home for Disabled Persons (OPSI, 2020)	France	Public services delivery	Service	Beneficence
7	Services Guide: a digital catalogue that centralizes all information regarding public services and Jaque, a virtual clerk based on AI (OPSI, 2020)	Brazil	Public services delivery	Duty Service	Explicability
8	TradeMarker: AI-enabled system for detecting similar trademarks (UNESCAP and Google, 2019)	Israel	Public services delivery	Service	Autonomy
9	UNA: a virtual assistant (OPSI, 2020)	Latvia	Public services delivery	Service	Explicability
10	Aylesbury Vale District Council (AVDC): AI-powered voice control (OPSI, 2020)	UK	Public services delivery	Service	Explicability
11	The Work: a service that recommends jobs without the need to conduct individual searches (OPSI, 2020)	Korea	Public services delivery	Service Social	Explicability
12	Insights.US: a tool that helps governments and cities obtain insights directly from their stakeholders (OPSI, 2020)	Israel	Public services delivery Regulatory functions	Duty Service	N/A*
13	Converlens: digitally-enabled community engagement in policy and programme design (OPSI, 2020)	Australia	Public services delivery Regulatory functions	Duty Service	Autonomy Explicability
14	Farming the Future: AI in the agricultural sector for sowing	India	Public services delivery	Service Social	Explicability

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
	advisory and commodity price forecasting (UNESCAP and Google, 2019)		Regulatory functions		
15	Better Reykjavik: a crowdsourcing platform for solutions to urban challenges, agenda-setting, participatory budgeting, and policymaking (OPSI, 2020)	Iceland	Regulatory functions	Duty	Beneficence
16	Bomb in a box: use of AI for risk-based reviews of air cargo records (Berryhill et al., 2019)	Canada	Regulatory functions	Service	Explicability
17	CitizenLab: a platform to automatically classify and analyse thousands of contributions collected on citizen participation platforms. (Berryhill et al., 2019)	Belgium	Regulatory functions	Duty	Autonomy Explicability
18	Department for Business, Energy & Industrial Strategy: technological solution to help analyse the cumulative effect of different regulations on business (World Economic Forum, 2020a)	UK	Regulatory functions	Service	Explicability
19	UK Food Standards Agency: the predictive capability to mitigate against food safety risks (World Economic Forum, 2020a)	UK	Regulatory functions	Service	Explicability
20	Policing: ML within a policing context for human trafficking mapping; crime ‘solvability’ estimates; misclassified crime detection; missing person anticipation; geospatial predictive mapping (UNESCAP and Google, 2019)	Unknown	Compliance Regulatory functions	Service	Autonomy Explicability Justice

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
21	AELOUS: a mid-altitude airborne maritime sensor platform (OPSI, 2020)	Ireland	Compliance	Service	Explicability
22	Fraud detection in social security payments (UNESCAP and Google, 2019)	Australia	Compliance	Justice	Explicability
23	Counterfeit drug detection using Blockchain and AI (OPSI, 2020)	Mongolia	Compliance	Social	Beneficence
24	Serenata de Amor: AI for financial transparency finding misuse of public money by congress members (UNESCAP and Google, 2019)	Brazil	Compliance	Duty Service	Explicability
25	Statement of Interests and Assets system (DIP): monitoring assets and potential conflicts of interest of officials through business intelligence (OPSI, 2020)	Chile	Compliance	Duty Service	N/A*
26	Slavery from Space: satellite remote sensing data with ML algorithms to detect slavery and monitor antislavery intervention (OPSI, 2020)	UK	Compliance	Social	Beneficence
27	Text analysis: help several government institutions in streamlining and automating their processes, conducting document management audit, removing personal information from nearly 80,000 expired court sentences (OPSI, 2020)	Estonia	Organisational management	Service	N/A*
28	Big Data Analysis for HR efficiency improvement: improve efficiency, develop organisational capacity,	Slovenia	Organisational management	Service	Non-maleficence

Case No.	Cases and summary	Country	AI Use Case	Public Values	AI Principles
	improve effectiveness and efficiency, and staff satisfaction. (OPSI, 2020)				
29	Emergency services forecasting: inform sophisticated machine learning forecasts of hazard probabilities (e.g. flood, cyclone, fire, road crash, rescue, etc.) and evolving exposures (e.g. people, assets) over the coming 10 years (OPSI, 2020)	Australia	Organisational management	Service	Explicability
30	R&D Platform for Investment and Evaluation ("R&D PIE"): provides an evidence-based policy platform to monitor, analyse and manage technologies, talents, and regulatory issues via the PIE model (OPSI, 2020)	Korea	Organisational management	Service	Explicability

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

A range of data was collected for these cases using desk research to enable triangulation and build the external validity of the findings. These sources included case descriptions published on the case archive databases, government reports, presentations, blogs, news releases, media documents, and website archives.

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

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

2.4 Results

Four themes of AI use are identified. First, compliance involves the use of AI for ensuring citizens, private actors, and governmental agencies abide by the rules and regulations of the land. Second, organisational management involves the use of AI for government administration and internal processes. Third, public service delivery involves the use of AI for delivering public services to a range of stakeholders. Fourth, regulatory functions involve the use of AI for research and policy development. Table 2.3 shows the definitions and related codes.

Table 2.3. AI use case definitions and related codes from thematic analysis

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

Figure 2.1 shows cases by AI use case. The highest percentage of AI use cases relate to public services delivery at 47% followed by 30% for regulatory functions, 23% for

compliance, and 13% for organisational management. Some cases relate to more than one use case and percentages are not exclusive.

Figure 2.2 shows the cases by country. The sample is global with the largest number of cases from Australia (17%) and the UK (13%).

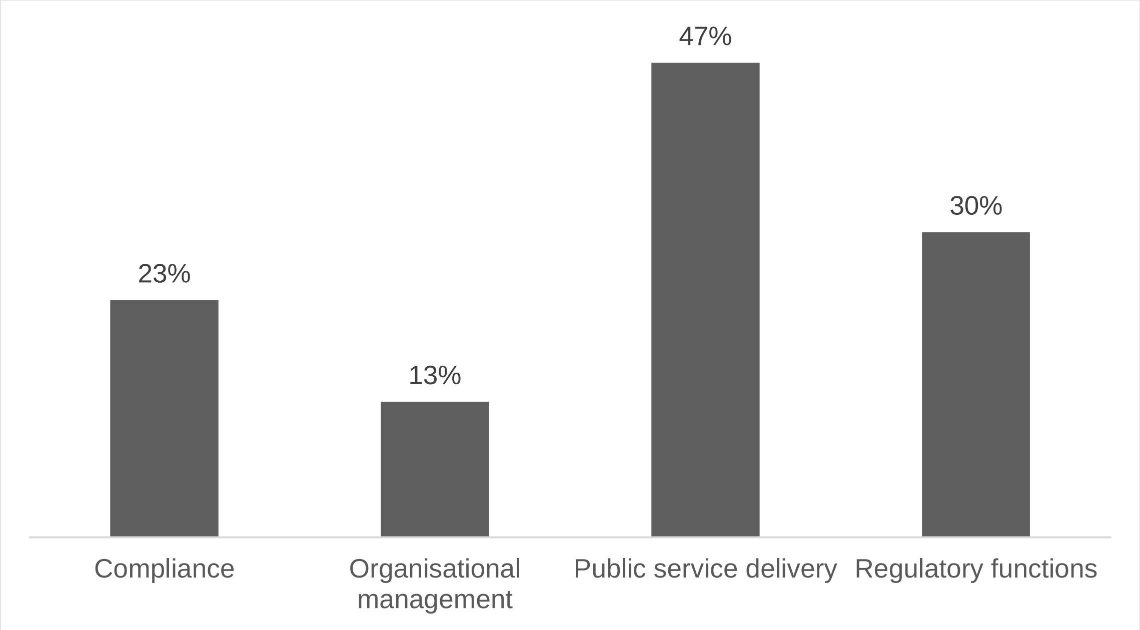

Figure 2.1. Cases by AI use case

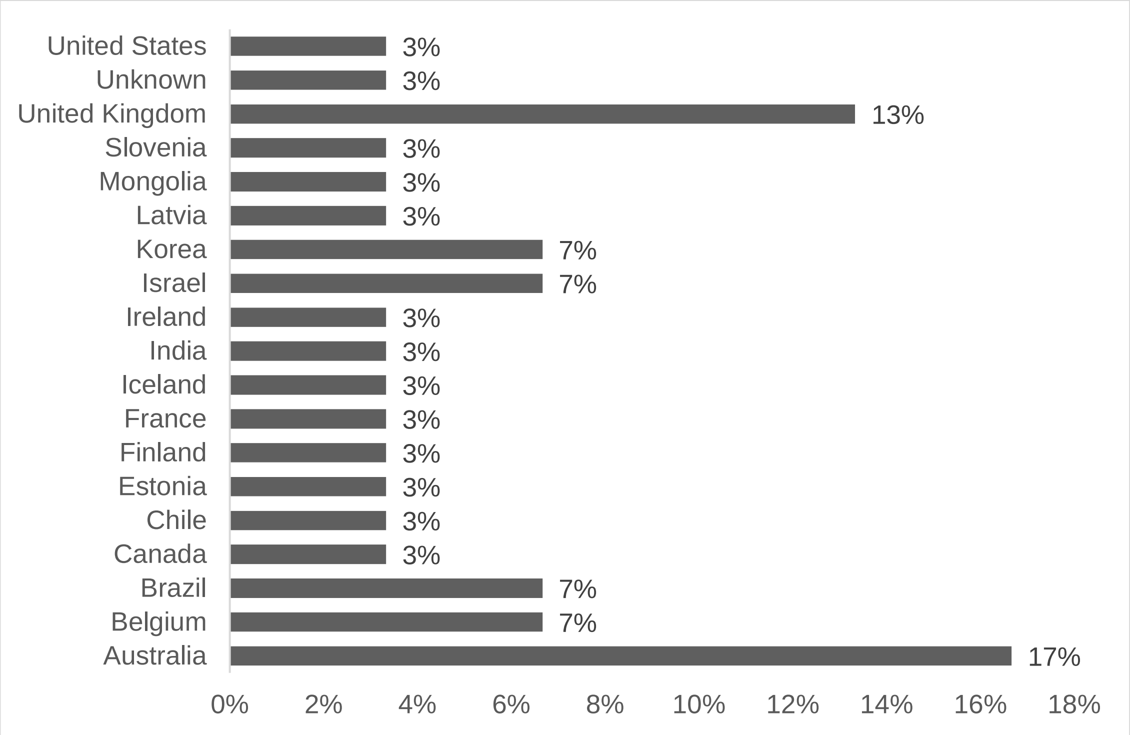

Figure 2.2. Cases by country

Table 2.4 shows the definitions and codes of public values and AI principles identified from the literature and supported by the cases. A map of public values and AI principles by AI use case is shown in Figure 2.3. The percentages represent the number of cases that mention a particular public value or AI principle by use case; a case may mention more than one public value or AI principal and hence, the percentages are not exclusive.

AI use type	**AI Principles**					**Public Values**		
	Autonomy	Bene-ficence	Explicability	Justice	Non-maleficence	Duty	Service	Social
Compliance	14%	29%	43%	29%	0%	29%	71%	29%
Organisational management	0%	0%	50%	0%	25%	0%	100%	0%
Public service delivery	21%	29%	50%	0%	7%	21%	93%	43%
Regulatory functions	44%	11%	78%	11%	0%	44%	78%	11%

Key:
cited in over 2/3rd cases
cited in between 1/3rd and 2/3rd cases
cited in less than 1/3rd of cases

Figure 2.3. Public values and AI principles by AI use type

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

Table 2.4. Public values and AI principles definitions and codes

Constructs	**Measures and definitions**	**Codes**
Public Values (Bannister and Connolly, 2014: Table 2, 123)	Duty orientation: "responsibility to the citizen, politicians, efficient use of public funds, integrity and honesty, democratic will"	Citizen participation, citizen needs, dialogue on the public sphere, inclusive and responsive engagement, government transparency
	Service orientation: "responsiveness, effectiveness, efficiency, transparency"	Streamline processes, resources, and budgets, effectiveness, quality, better planning, efficiency, reducing time, service experience

Constructs	Measures and definitions	Codes
	Social orientation: “inclusiveness, justice, fairness, equality, respect for citizens, accountability”	Community development, quality of life, access to employment, elimination of counterfeit drugs, environmental concerns, humanitarian efforts, social value
AI Principles (Floridi and Cowls, 2019: 6-8)	Non-maleficence: “do no harm and avoid misuse of privacy and security”	Data privacy, data security, the confidentiality of personal data
	Autonomy: “the power to decide”	Augmenting decision making, free up time for humans to make crucial value judgements
	Explicability: “the knowledge of how AI works and who to hold responsible for its outcomes”	Quality of data, accuracy, explainable AI, trust and awareness, transparency
	Beneficence: “promoting well-being, preserving dignity, and sustaining the planet”	Community development, wellbeing, happiness, quality of life, save lives, inform liberation
	Justice: “the quality of being fair and eliminating discrimination ensuring equal access to the benefits of AI”	Protect vulnerable populations, social biases in machine learning

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

The success criteria and lessons learned were coded into two global themes of external and internal. As the objective of this analysis is citizen adoption, the chapter focuses on the external theme. Three constituent themes were identified under external as shown in Table 2.5. First, the dominant external theme relates to co-design practices and public-private partnerships. 73% of the cases report a collaborative design process involving citizens and businesses and encouraging public-private collaborations as key to successful adoption. Second, 17% of the cases report communication of benefits vital in successful take-up. Third, 13% report product design as a relevant determinant of higher adoption and discuss simple intuitive design and adaptability of the applications.

Table 2.5. Externally focussed success criteria and related codes

Global theme	**Constituent themes**	**Codes**	**Percentage of cases**
External	Market the benefits	Communication and promotion of benefits, manage expectations, market the project to citizens, clients understand the benefits	17%
	User interface	Attractive design, lightweight, intuitive to use, make apps interesting to use, human-centred design, design thinking	13%
	Co-design with citizens and stakeholders	Co-design and feedback cycle between all users and stakeholders, consulting process with citizens and businesses, understanding of target users, results of citizen work are used, engagement from different stakeholders, co-creation, bottom- approaches, public-private collaborations, civic volunteers, connecting local knowledge and experience to machine learning, citizen-science platform, social acceptability	73%

2.5 Discussion

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

Figure 2.3 shows service is the dominant public value irrespective of the AI use case. This concurs with the literature that NPM values of efficiency and cost savings are still driving the majority of AI implementations in government. The use case of public service delivery shows social is the second-ranked public value explicating support for external orientation geared towards customer satisfaction and societal reforms. In these cases, AI has been delegated the role of a public agent interacting with citizens and businesses. For fully automated solutions, such as Aylesbury Vale District Council's AI-powered voice control, citizen-government interactions become citizen-AI interactions. The self-learning capabilities of AI risk divergence from its original design towards unexpected influence on citizens' choices.

When AI is used for decision augmentation, such as US' Annie™ MOORE on refugee settlement, employees increasingly rely on options suggested by AI which might have a detrimental effect on human learning and knowledge (Berente et al., 2021). AI becomes a salient techno-rational actor in learning and influencing public decisions.

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

The results also support DEG themes outlined in the literature. The reintegration, needs-based holism, and digitising change themes of DEG (Dunleavy et al., 2005: 480) are reflected in Finland's National AI Strategy. This strategy document summarised "developing new operating models to shift from organisation-based activities to systems-wide approaches"; "improve the interoperability of government data, and open up this data to fuel innovation in all sectors"; " public discussion on AI ethics"; and "break down silos within … public services" (Berryhill et al., 2019: 144-148). The specific case of AuroraAI within this national strategy holistically integrates public services from different agencies around three life events: "moving away from study, remaining in the labour market, and family wellbeing after a divorce" (Ibid.). The Services Guide case from Brazil provides another example of DEG themes of reintegration and digitising change by integrating scattered information on public services as an open data digital catalogue and the use of AI as a virtual clerk.

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

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

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

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

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

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

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

Deducing from the success criterion themes three constructs are identified. First, perceived citizen collaboration is identified as a key determinant of adoption intention. When citizens perceive a strong collaborative process was followed and their needs were considered as evidence of democratic involvement, adoption of such public services will be higher (Lopes et al. 2019; Rose et al. 2015). Second, the “effort expectancy” construct from the UTAUT model (Venkatesh et al., 2003: 450) is identified as representing the theme of an attractive, intuitive, and adaptive user interface. Third, the “perceived usefulness” construct from the TAM model (Davis, 1989: 320) is identified as a measure of the theme around communication of benefits. Hence, three final propositions are stated as:

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

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

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

To test these propositions, a Public Values-based Adoption Model is developed as shown in Figure 2.4.

The definitions of public value and AI principles constructs are derived from literature and case analysis as shown in Table 2.3. Furthermore, perceived value is defined as the “overall evaluation of the user regarding the benefit and cost of using” an AI-based public service (Kim et al., 2017: 1153). Adoption intention is defined as “a desire to use” the new AI-based public service compared to e-government or paper-based alternative (Kim et al., 2017: 1153). Effort expectancy is defined as “the degree of ease associated with the use of [AI-based public service]” (Venkatesh et al., 2003: 450). Perceived usefulness is defined as “the degree to which [citizens] believe an [AI-driven public service] would enhance" personal and societal goals (Davis, 1989: 320). Perceived collaboration is defined as an overall evaluation of the level of collaboration between the public sector, citizens, and the private sector when developing the AI-based public service.

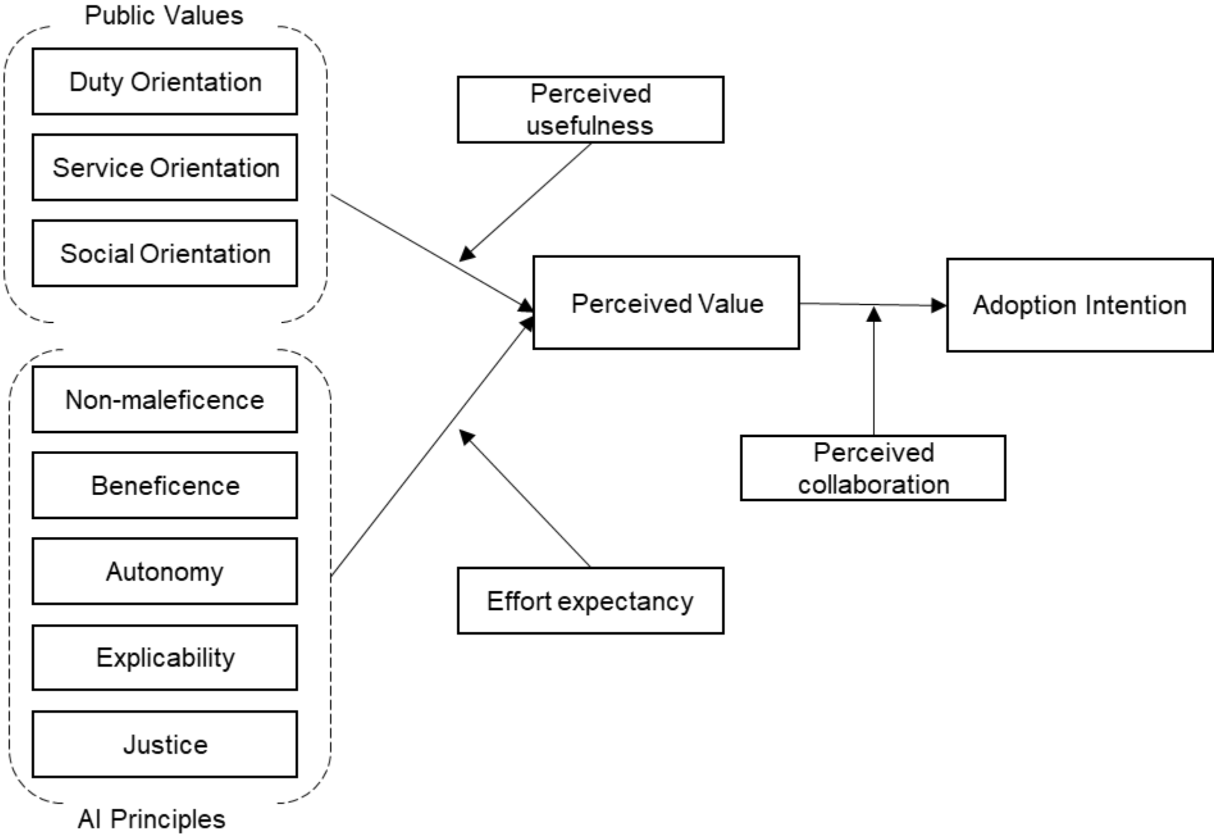

Figure 2.4. Public value-based adoption model
(authors' conceptualisation)

2.6 Conclusion

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

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

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

2.6.1 Theoretical implications

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

2.6.2 Practical implications

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

2.6.3 Limitations and future research

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

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

3 Paper 2: AI Adoption and Diffusion in Public Administration: A Systematic Literature Review and Future Research Agenda

This chapter is based on: MADAN, R and ASHOK, M (2023) 'AI adoption and diffusion in public administration: A systematic literature review and future research agenda'. *Government Information Quarterly*, 40 (1): 101774.

3.1 Introduction

Technological innovation driven by Artificial Intelligence (AI) is making headways in public administration on the heels of the last decade's e-government innovations focused on the goals of efficiency and cost savings. The smart technology-centric model of public governance engages citizens through digital platforms and advocates for a lean service delivery without compromising quality (Dunleavy et al., 2005; Wirtz and Müller, 2019). AI-driven innovation is expected to have a profound impact on not only public sector employees but also on citizens and society. When AI becomes an agent for making public decisions, a profound transformation of public administration ensues questioning the roles and functions of government in society. The age-old dilemmas of power, trust, and legitimacy become embedded in AI influencing citizens' lives and societies. A comprehensive understanding of contextual variables influencing the adoption and diffusion is essential for determining public value creation from the use of AI in public administration.

As discussed in Chapters 1 and 2, machine learning (ML) and natural language processing (NLP) characterise most public administration AI applications and are the focus of this review. The context for this chapter is public administration which is defined as public organisations that implement government policies and may contribute to its development.

The implementation of AI represents radical innovations involving not only technology but also culture, processes, and workforce (Agarwal, 2018; Kattel et al., 2019; Ashok et al., 2016). The use of AI in public administration is riddled with ethical tensions such as questions of fairness, transparency, privacy, and human rights (Kuziemski and Misuraca, 2020; Wirtz and Müller, 2019; Ashok et al., 2022). Notwithstanding the use of AI provides immense benefits, the risks of harm to society require the assessment of the overall impact of AI from a public values perspective (Medaglia et al., 2021).

Several governments and technology companies have published ethical guidelines on the use of AI such as EU's ethical guidelines (European Commission, 2019), Canada's Algorithmic Impact Assessment (Government of Canada, 2020), UK's guidance (UK, 2019b), etc. In the context of public administration, these ethical principles at the macro level provide overall boundaries for the use of AI. However, at the meso and micro levels of public administration, the resolution of AI tensions resulting from public value conflicts remains elusive. Morley et al. (2020) state that AI scholars need to translate the largely agreed AI principles to the 'what' and 'how' of implementation.

The majority of AI literature views the government as a regulator. The discussion of the role of public administration from a vantage of a user of AI is scarce even though public administration is increasingly becoming a significant user of AI (Kuziemski and Misuraca, 2020; Medaglia et al., 2021). Wirtz et al. (2019)'s literature review showcases research gaps in public sector challenges related to AI applications. Chapter 2's cross-case analysis highlights the scarcity of research on the implementation and use of AI within governments. The mechanisms behind public value creation through the use of AI are not well understood (Wang et al., 2021). Scholars (Alsheibani et al., 2018; Misuraca et al., 2020; Valle-Cruz et al., 2019; Pencheva et al., 2020; Medaglia et al., 2021; Wang et al., 2021) have called for research to develop a theoretical framework of environmental factors, organisational capabilities, and challenges with AI adoption and diffusion in public administration.

In light of these literature gaps, this review intends to answer two research questions:

RQ3.1: What are the key factors discussed in the literature that influence AI adoption in public administration?

RQ3.2: What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?

AI adoption is the process of "integration of new and diverse knowledge through the creation…of new capabilities, technologies and training programmes" (Ashok et al., 2016: 1008). AI implementation and diffusion refers to "events and actions that pertain to … preparing the organization for its use, trial use, acceptance of the innovation by the users [and finally] use of the innovation until it becomes a routine feature of the organization" (Damanpour and Schneider, 2006: 217).

The review adopts a multi-disciplinary approach using theories from technology adoption, strategic management, and public administration literature. In the next section, public value theory, the resource-based view (RBV), and the technology-organisation-environment (TOE) framework are introduced as key theoretical underpinnings for this review. The following section details the systematic literature review methodology followed by a summary of key themes and results. In the corresponding discussion section, the resulting themes are synthesised to develop a future research agenda.

3.2 Theoretical Framework

3.2.1 Public Value Management

Public values management (PVM) argues public managers' key role is determination and pursuit of public values through engagement and deliberation with elected politicians, stakeholders, and citizens (Stoker, 2006; Moore, 1995). Stoker (2006) contends public values debate grew as a response to the narrow economic focus of New Public Management (NPM) reforms. NPM tried to limit the role of politics in determining public goals and reducing them to efficiency and performance-based measures (Ibid.). Technology not only serves as a catalyst for value creation as enabled by digitalisation but also as a platform for higher engagement with citizens (Ranerup and Henriksen (2019). Thus, PVM's focus on citizen and political engagement provides an appropriate democratic means for the resolution of tensions emerging from the implementation of AI in public administration (Panagiotopoulos et al., 2019; Andrews, 2019).

The generative perspective of PVM suggests public value is context-driven and part of the deliberations themselves (Davis and West, 2008). The institutional perspective focuses on developing a typology of public values such as Hood (1991) and Bannister and Connolly (2014: 123). This research adopts an integrated framework adapted from Davis and West (2008) consolidating generative and institutional perspectives. The chapter builds on the already established typology of public values developed by Bannister and Connolly (2014) in the context of technology. The chapter argues dominant public value orientations are embedded in the fabric of organisational routines as cultural values and beliefs. Stakeholder engagement might challenge existing values and give rise to new public values in specific contexts, especially in terms of tensions put forth by AI implementation. Drawing on Moore's (1995) strategic triangle, the chapter further contends a key role of a public manager is to build capabilities in pursuit of these public values, existing or emergent. Hence, as opposed to external strategy-based planning, public managers need to focus on internal capabilities building. In this respect, a resource-based view of the firm is suitable for exploring the implementation of AI and the corresponding transformation it entails. The resource-based view (RBV) is discussed in the next section as a key theoretical underpinning for this chapter.

3.2.2 Resource-based View and Dynamic Capabilities

The resource-based view (RBV) has been extensively used in literature to explain organisational performance in terms of the heterogeneity of internal resources (Barney, 1991).

Public organisations generally control large societal resources both in terms of workforce and tangible assets such as land, buildings, infrastructure, etc. (Harvey et al., 2010; Clausen et al., 2020). Organisational capabilities, distinct from resources, refer to business capabilities, enterprise systems and processes, and culture. Organisations function as a collection of resources and capabilities that are aimed at value creation by putting resources to their best use (Piening, 2013). The flip side of organisational capabilities is incumbent inertia in the form of routine rigidity inhibiting change and the development of new capabilities (Leonard-Barton, 1992).

Public administration faces a constantly changing external environment characterised by ongoing policy changes and election cycles. The external environment turbulence and a need for public value deliberations require public managers to develop internal knowledge processes to navigate opposing demands and counter inertia to change (Ashok et al., 2021). Thus, public managers need to build dynamic capabilities defined as “a firm’s ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments” (Teece et al., 1997: 516). Derived from the RBV, dynamic capabilities are essential for public administration, just as the private sector, to successfully renew core capabilities and overcome routine rigidity; this is because dynamic capabilities enable public sector organisations to fulfil policies and provide services (Piening, 2013).

Moore's (1995) strategic triangle consists of public values, legitimacy and support, and internal capabilities. In the context of AI implementation, internal capabilities can be viewed as dynamic capabilities and internal knowledge processes needed to implement such radical innovations with a multitude of public value configurations. Legitimacy and support for AI come from the political leadership and central governments pursuing digital transformation agendas. Citizens’ co-creation and adoption of AI-driven services act as another aspect of legitimacy and support. And the specific AI characteristics and design determine public value creation. Thus, three key contexts emerge influencing AI innovations: technology, organisation, and environment. In the next section, the use of the technology-organisation environment (TOE) framework is discussed for exploring our research questions.

3.2.3 Technology-Organisation-Environment Framework

The Technology-Organisation-Environment (TOE) framework (Tornatzky and Fleischer, 1990) has been extensively used in literature to explore technology adoption in different settings. The key premise of the TOE framework is that organisational and environmental contexts are equally important as technological contexts when studying technology adoption and diffusion at the organisational level.

AI introduces a higher level of complexity to change associated with its implementation. AI-driven public administration builds on e-government initiatives introducing AI as an agent of the government and governance shifts to citizen-AI-government interactions (Williamson, 2014). This resulting "institutional matrix" consists of human contextual knowledge, AI technologies, and data (Chris and Susan, 2018: 207; Gao and Janssen, 2020). Crawford (2021: 8) argues AI in the current version is far from being artificial or intelligent but depends on a "set of political and social structures … designed to serve … dominant interests [and] in this sense a registry of power". Similarly, Coombs et al. (2021: 5) ask the pertinent question as to "whose interests do AI serve [and] who owns the machines". The political and democratic institutions influenced by technology companies driving the AI agenda in public administration will determine if AI can reduce or enhance the problems of inequality and power.

Thus, the adoption and diffusion of AI within public administration are not only driven by the purported benefits of the technology but also by citizens, organisational culture, and institutional arrangements. The TOE framework provides a theoretical lens to explore these variables.

3.3 Research Methodology

The 'Preferred Reporting Items for Systematic Reviews and Meta-Analyses' (PRISMA) methodology was used to conduct a systematic literature review and qualitative synthesis (Moher et al., 2009). The objective of this review was "theory landscaping" (Okoli, 2015b: 888) to synthesise key constructs and relationships discussed in the literature related to the phenomenon of AI adoption in public administration and the key tensions that are likely to be associated with AI implementation and diffusion. A critical realist approach was adopted toward theory landscaping goals and both empirical and conceptual studies were included in the review (Okoli, 2015a). The empirical studies, quantitative or qualitative, help identify what concepts and relationships have been tested and explanations provided for the underlying mechanisms. The conceptual studies propose constructs and relationships that may produce the phenomena based on existing theory, discursive analysis, philosophical deduction, or legal argumentation. The qualitative synthesis of empirical and conceptual studies thus provides a rich snapshot of the current thought in the multi-disciplinary disciplines and the empirical evidence related to the phenomenon for future theory development and testing.

The review was conducted in three phases as shown in the PRISMA flow in Figure 3.1.

The goal during the identification stage was literature sensitisation and identification of a range of keywords. A combination of seven keyword strings (as shown in Table 3.1) was used to conduct a literature search[10] in three databases: EBSCO Host, SCOPUS and Web of Science. The search strings include the terms AI, machine learning, algorithms, and natural language processing denoting AI technologies within the scope of this review; and big data and blockchains as technologies supporting these applications. This string was combined with a range of public administration terms and paradigms. The search criteria were limited to English language publications or conference proceedings published after 2010. The research protocol was developed outlining the inclusion and exclusion criteria. The inclusion criterion was quantitative, qualitative, mixed-methods, literature reviews or conceptual papers on AI in public administration settings, papers related to big data in the context of AI, and technical papers that at a minimum discuss AI development or implementation. The exclusion criteria included: eGovernment papers that do not discuss AI or big data; AI technologies other than ML or NLP; studies not focusing on public administration applications such as smart city, medicine, universities, policing, healthcare; open data, data governance, cyber security that do not discuss AI applications; use of AI in the public sector for promoting private sector innovation; macro-level studies on AI policies and guidelines developed by national and supranational bodies; and big data and blockchain studies that do not discuss these technologies in the context of AI.

[10] The search was conducted in March-April 2021 and an update using the same keywords was undertaken in August 2021. Additional papers suggested by reviewers were added through the peer-review process when relevant.

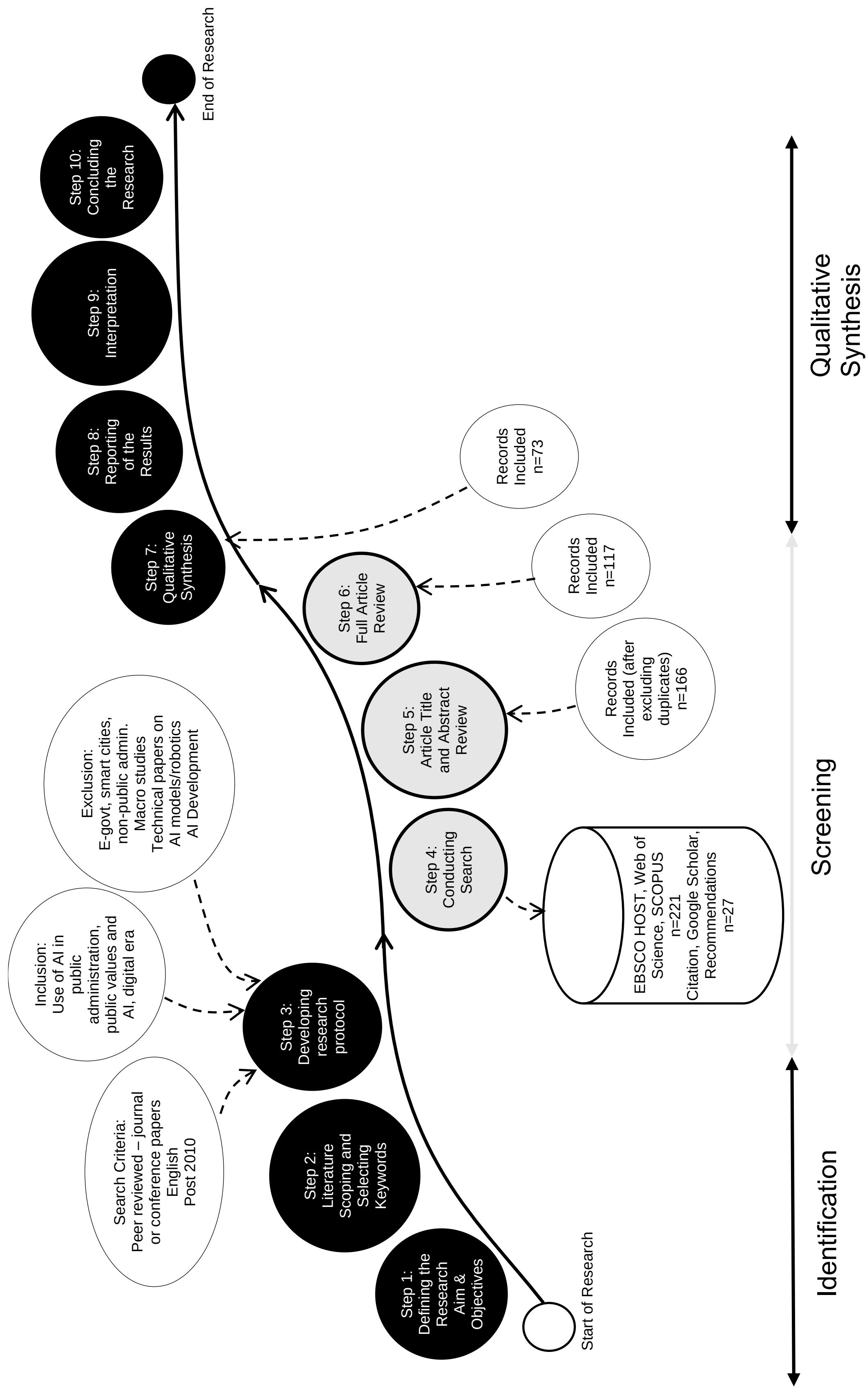

Figure 3.1. PRISMA flow

Table 3.1. Keyword strings used for systematic literature review

Search 1	(digital AND era AND governance) AND (ai OR "artificial intelligence" OR "machine learning" OR blockchain* OR "big data" OR algorithm* OR "natural language processing" OR nlp)
Search 2	("public value*") AND (ai OR "artificial intelligence" OR "machine learning" OR blockchain* OR "big data" OR algorithm* OR "natural language processing" OR nlp)
Search 3	e-government AND adoption AND (ai OR "artificial intelligence" OR "machine learning" OR blockchain* OR "big data" OR algorithm* OR "natural language processing" OR nlp)
Search 4	e-government AND diffusion AND (ai OR "artificial intelligence" OR "machine learning" OR blockchain* OR "big data" OR algorithm* OR "natural language processing" OR nlp)
Search 5	(government OR "public sector" OR "public administration") AND (ai OR "artificial intelligence" OR "machine learning" OR blockchain* OR "big data" OR algorithm* OR "natural language processing" OR nlp) AND adoption
Search 6	(government OR "public sector" OR "public administration") AND (ai OR "artificial intelligence" OR "machine learning" OR blockchain* OR "big data" OR algorithm* OR "natural language processing" OR nlp) AND diffusion
Search 7	(npm OR "new public management") AND (ai OR "artificial intelligence" OR "machine learning" OR blockchain* OR "big data" OR algorithm* OR "natural language processing" OR nlp)

In the screening stage, a total of 221 records were identified following the above search protocol. Furthermore, through citation review, recommendations from other scholars and reviewers, and a Google Scholar search (first five result pages) 27 additional records were identified. After removing duplicates, 166 total publications were identified for the title and abstract review. This screening of the records resulted in 117 papers for the full-text article review. Following the full article review, 73 papers (shown in supplementary materials in Appendix C) were finally included in the qualitative synthesis.

During the qualitative synthesis stage, template analysis was conducted using a three-step analysis (King, 2004). In step one, an a priori template (as shown in Table 3.2) was developed using the theoretical frameworks discussed above. In step two, each publication was coded to explore the phenomenon of AI adoption and diffusion in public administration identifying factors influencing adoption, outcomes, and AI tensions as discussed in the literature. The data extraction included the type of study (quantitative, qualitative, mixed-methods, conceptual); AI technology or application; public administration paradigms; key constructs, measures, and relationships; benefits and outcomes; risks and challenges; and tensions. After coding a set of five papers, organising and conceptual themes were identified (Attride-Stirling, 2001). This was repeated as a new set of papers was coded and reflectivity checks were conducted. After a further reorganisation of themes and discussions between the authors, the final template was developed. In step three, the results of the analysis were synthesised.

Table 3.2. A priori template

1. Factors influencing adoption
1.1. Technological Context
1.2. Organisational Context
1.3. Environmental Context
2. Outcomes
2.1. Public Values
2.1.1. Duty
2.1.2. Service
2.1.3. Social
3. AI tensions/principles
3.1. Explicability versus beneficence
3.2. Explicability versus non-maleficence
3.3. Explicability versus justice
3.4. Autonomy versus justice
3.5. Justice versus non-maleficence
3.6. Beneficence versus non-maleficence

3.4 Results

This section discusses the results of the analysis. The first part provides a descriptive analysis of the publications included in the review followed by content analysis which discusses the findings of qualitative synthesis.

3.4.1 Descriptive analysis

The review included 73 publications of which 66% were journal articles and 34% were conference proceedings as shown in Table 3.3. The highest number of articles (ten) were published in Government Information Quarterly and the highest number of conference proceedings (eight) were from the Annual International Conference on Digital Government Research. Figure 3.2 shows the distribution of the journals by year; 85% of the publications are since 2019 showing the recency of the discussions on AI in public administration.

Table 3.3. Publications included in the review

Journal articles	
Publication	**Count**
Government Information Quarterly	10
Social Science Computer Review	6
Information Polity	3
International Journal of Information Management	2
International Journal of Public Sector Management	2
Public Policy and Administration	2
Berkeley Technology Law Journal	1
Business Horizons	1
Canadian Public Administration-Administration Publique Du Canada	1
Critical Social Policy	1
Futures	1
Georgetown Law Journal	1
Indiana Journal of Global Legal Studies	1
Information Processing & Management	1
International Journal of Public Administration	1
Journal of Asian Public Policy	1
Journal of Organizational Computing and Electronic Commerce	1
Journal of Theoretical and Applied Electronic Commerce Research	1
Perspectives on Public Management and Governance	1
Policy and Internet	1
Policy Sciences	1
Psychology, Public Policy, and Law	1
Public Administration	1
Public Management Review	1
Public Performance and Management Review	1
SSRN	1

Sustainability (Switzerland)	1
Telecommunications Policy	1
Transforming Government: People, Process and Policy	1
Conference proceedings	
Conference proceedings	**Count**
Annual International Conference on Digital Government Research	8
International Conference on Theory and Practice of Electronic Governance	2
International Conference on Electronic Participation, ePart	2
Hawaii International Conference on System Sciences	2
IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society	1
IFIP WG 5.5 Working Conference on Virtual Enterprises	1
Iberian conference on information systems and technologies (CISTI)	1
Conference on Fairness, Accountability, and Transparency	1
Conference on Human Factors in Computing Systems	1
European Conference on Cyber Warfare and Security	1
NA International Conference on Industrial Engineering and Operations Management	1
Annual conference of the Italian Chapter of AIS	1
International Forum on Digital and Democracy. Towards A Sustainable Evolution, IFDaD	1
International Conference on Digitization: Landscaping Artificial Intelligence, ICD	1
International Conference on Electronic Government	1

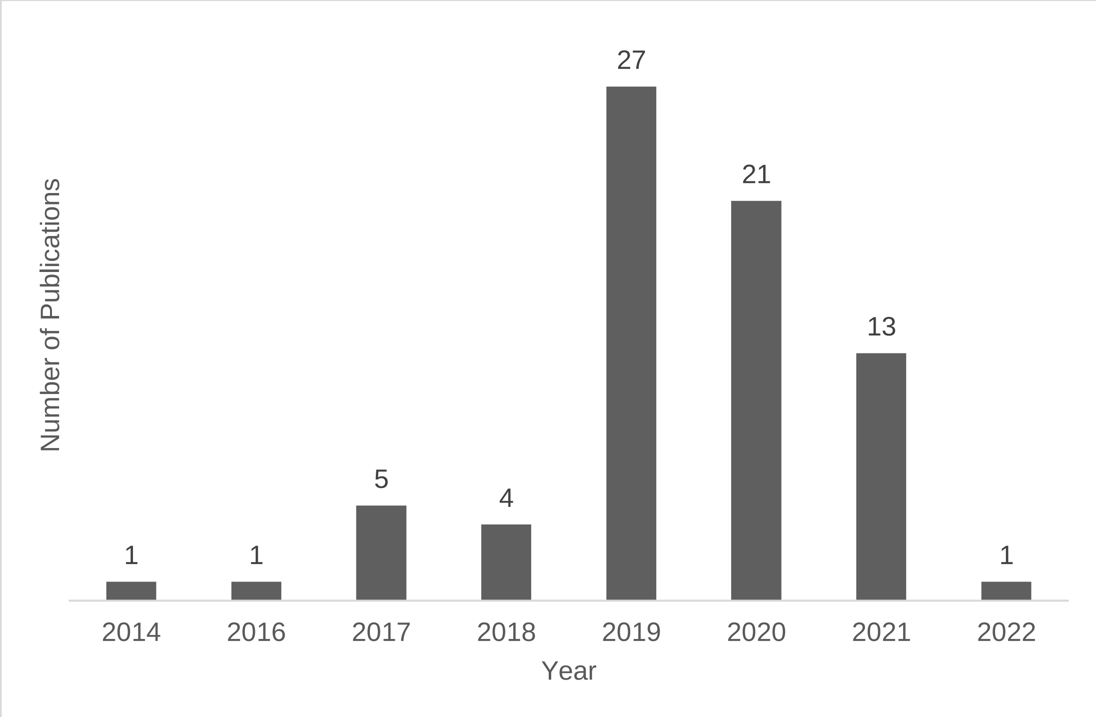

Figure 3.2. Year of publications

As shown in Figure 3.3, there is a lack of quantitative research and testing of conceptual models with only 7 publications (10%) in this category. 58% of publications are either conceptual or literature reviews. 29% are qualitative studies and represent the second-highest type of publications; 4% are mixed-methods studies.

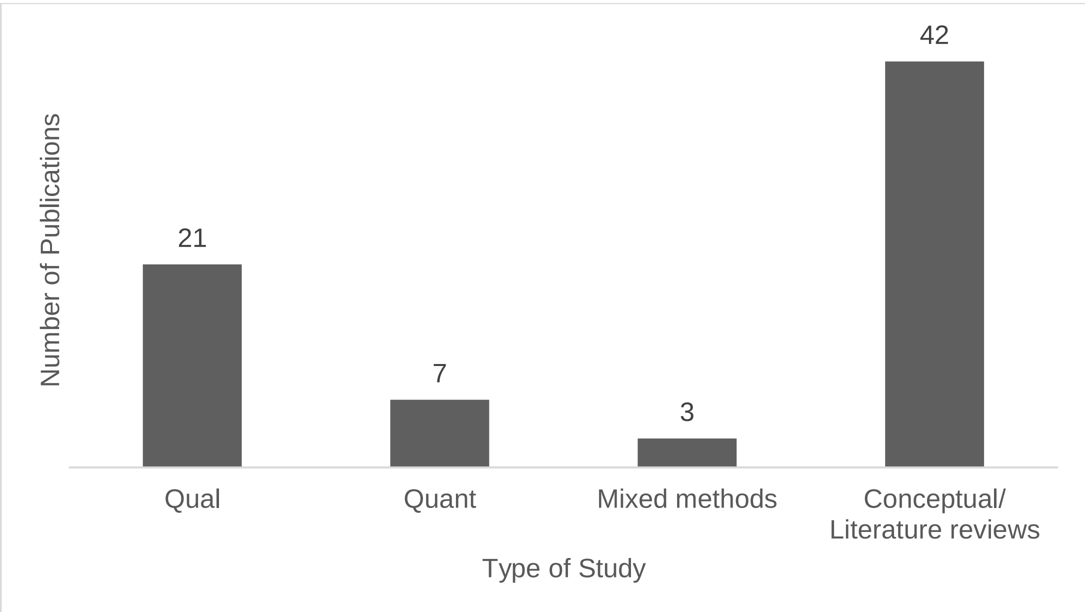

Figure 3.3. Study type

As shown in Figure 3.4, in terms of technology discussed in the papers, 37% of the publications mention AI broadly and focus on the application outcomes such as crowdsourcing, delivery of e-services, citizen engagement, achieving efficiency, process automation, etc. Another 12% of the studies refer to several related technologies and applications that can be categorised as cognitive computing including ML, big data analytics, image processing, machine vision, NLP, etc. 45% of the studies discuss AI in terms of machine learning, big data analytics, algorithmic decision making, automated decision making. And 5% of the studies refer specifically to natural language processing in terms of the implementation of text or voice chatbots or processing of large documents and texts as a percussor to machine learning and automation.

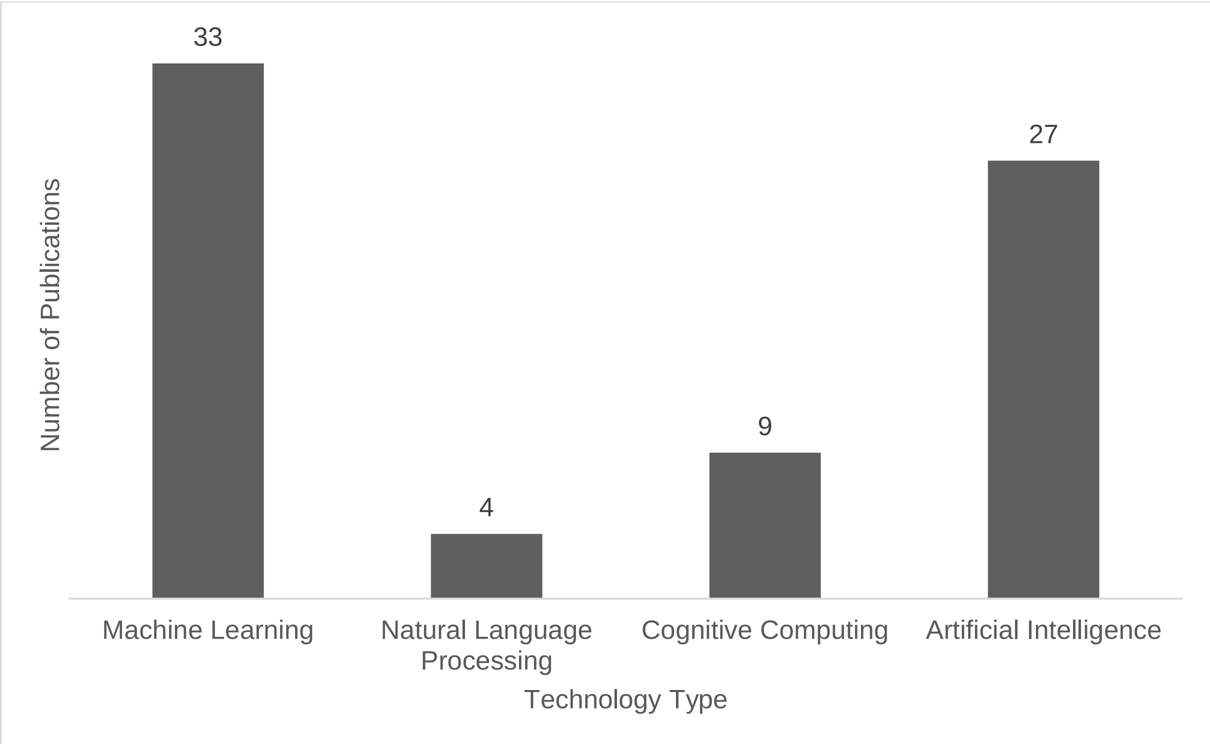

Figure 3.4. Technology type

3.4.2 Content

This sub-section discusses the findings of the qualitative synthesis. The factors influencing AI adoption, implementation strategies related to AI implementation, and outcomes related to AI diffusion, as discussed in the literature, are outlined. Finally, the themes of AI tensions and data governance embedded in both the implementation and diffusion stages are discussed. The final template developed from template analysis is attached in the supplementary materials as Appendix D.

3.4.2.1 Factors influencing AI adoption

Deriving from the TOE framework, contextual factors under technology, organisation, and environment are identified as influencing AI adoption. A global theme of absorptive capacity also emerged influencing AI adoption from the literature review. Table 3.4 summarises the main themes and codes, which are discussed below.

Table 3.4. Factors influencing AI Adoption

Conceptual themes	**Organising themes**	**Codes**	**References**
Technology context	IT assets	• Cloud computing capabilities • Current digital infrastructure: high connectivity and bandwidth, processing power and server hardware, networks, system integration • Compatibility of existing assets • Data quality, availability, accessibility • Database management infrastructure • Data ownership and sharing • Storage – cloud or on-premises • Data governance maturity • Enterprise architecture	(Coglianese and Lehr, 2017; Van Noordt and Misuraca, 2020a; Desouza et al., 2020; Wirtz and Müller, 2019; Schedler et al., 2019; Chatfield and Reddick, 2018; van Noordt and Misuraca, 2020b; Erkut, 2020; Mikalef et al., 2019; Rogge et al., 2017; Wirtz et al., 2019; Fatima et al., 2021; Ballester, 2021; Gao and Janssen, 2020; Ojo et al., 2019; Gong and Janssen, 2021; Campion et al., 2020; Pencheva et al., 2020; Vogl et al., 2019; Makasi et al., 2021; Janssen et al., 2020a)
	IT capabilities	• Current capabilities in managing IT assets • Staff's knowledge of AI and big data • Data-oriented culture • Big data and analytics specialists and experts	(Desouza et al., 2020; Van Noordt and Misuraca, 2020a; Chen et al., 2019; Campion et al., 2020; Pencheva et al., 2020; Ojo et al., 2019; Casalino et al., 2020; Giest, 2017;

Conceptual themes	**Organising themes**	**Codes**	**References**
		• Ecosystem of commercial partners and experts	Clarke and Margetts, 2014; van Noordt and Misuraca, 2020b; Chatfield and Reddick, 2018; Ballester, 2021; Janssen et al., 2020a; Medaglia et al., 2021; Alexopoulos et al., 2019; Makasi et al., 2021; Wirtz and Müller, 2019)
	Perceived benefits	• Expected benefits • Simple intuitive design • Users' needs • Direct benefits of costs and novel solutions • Indirect benefits of increased collaboration with peers and industry	(Mikalef et al., 2021; Cordella and Dodd, 2019)
Organisational context	Organisational culture	• Innovativeness, risk-taking, experimentation • Institutional arrangements such as NPM orientation, e-government • Technology and strategy alignment, cross-agency collaborations	(Van Noordt and Misuraca, 2020a; van Noordt and Misuraca, 2020b; Zuiderwijk et al., 2021; Giest, 2017; Ojo et al., 2019; Schedler et al., 2019; Pencheva et al., 2020; Campion et al., 2020; Kuziemski and Misuraca, 2020)
	Leadership	• Transformational leadership, institutionalising learning, and experimentation • CIO's leadership and technical expertise	(Campion et al., 2020; Schedler et al., 2019; De Vries et al., 2016; Borins, 2002; Alblooshi et al., 2020; Jia et al., 2018; Chatfield and Reddick, 2018)

Conceptual themes	**Organising themes**	**Codes**	**References**
	Inertia	• Bureaucracy and centralised decision-making • Status-quo bias • Lack of employee empowerment • Resistance to data sharing • Resource scarcity • Cost versus benefits for experimental projects • Resistance from unions	(Chen et al., 2019; Pencheva et al., 2020; Campion et al., 2020; van Noordt and Misuraca, 2020b; Fatima et al., 2021; Zuiderwijk et al., 2021; Schedler et al., 2019; Mikalef et al., 2019; Wirtz et al., 2019; Young et al., 2019)
Environmental context	Vertical pressures	• Political environment, election cycles • Policy signals, directives, mandates • Regulations, laws, procurement practices • National AI guidelines	(Schedler et al., 2019; Clarke and Craft, 2017; Pencheva et al., 2020; Wang et al., 2020; Janssen et al., 2020a; Wang et al., 2021)
	Horizontal pressures	• Inter-governmental competitive pressures • Media scrutiny and oversight • Citizen demands • Industry pressure	(Wang et al., 2021; Misuraca, 2020; Giest, 2017; Lopes et al., 2019; Chohan et al., 2021; Criado and Gil-Garcia, 2019)
Absorptive capacity	Absorptive capacity	• Path-dependency • Knowledge management practices • Dynamic capabilities	(Casalino et al., 2020; Campion et al., 2020; Ballester, 2021; Janssen et al., 2020a; Aboelmaged and Mouakket, 2020; Erkut, 2020; Ojo, 2019; Medaglia et al., 2021; Janssen et al., 2020b; Kuziemski and Misuraca, 2020)

3.4.2.1.1 Technology Context

The technology context identifies two themes of IT assets and capabilities. These encompass the current level of e-government adoption and digitalisation capabilities. The third theme is identified as characteristics of adopting technology in terms of its perceived benefits.

The theme of IT assets identifies an organisation's digital maturity as the determinant of AI adoption. IT assets include cloud computing capabilities (Coglianese and Lehr, 2017); digital infrastructure in terms of connectivity, bandwidth, processing power, and networks (Van Noordt and Misuraca, 2020a; Desouza et al., 2020; Wirtz and Müller, 2019; Schedler et al., 2019; Chatfield and Reddick, 2018; van Noordt and Misuraca, 2020b); "compatibility" of existing assets with new AI technologies (Schaefer et al., 2021: 6); and ability to integrate systems and data (Erkut, 2020; Mikalef et al., 2019; Rogge et al., 2017). The data related assets are identified as data accessibility, internally within the organisation or externally, and quality (Wirtz et al., 2019; Fatima et al., 2021; Ballester, 2021; Gao and Janssen, 2020); database management infrastructure and enterprise architecture (Ojo et al., 2019; Gong and Janssen, 2021); ownership and sharing of data between governmental agencies (Campion et al., 2020; Rogge et al., 2017; Pencheva et al., 2020; Vogl et al., 2019; Makasi et al., 2021; Janssen et al., 2020a); and cloud storage (Coglianese and Lehr, 2017).

The related theme of IT capabilities identifies current capabilities in managing IT assets, basic employee knowledge in AI and big data, and a data-oriented culture essential to building AI capabilities (Desouza et al., 2020; Van Noordt and Misuraca, 2020a; Chen et al., 2019; Campion et al., 2020; Pencheva et al., 2020; Ojo et al., 2019; Casalino et al., 2020; Giest, 2017; Clarke and Margetts, 2014; van Noordt and Misuraca, 2020b; Chatfield and Reddick, 2018; Ballester, 2021; Janssen et al., 2020a; Medaglia et al., 2021). Specialised capabilities are required to develop, deploy, and manage AI assets. A lack of AI experts within public administration requires access to an ecosystem of commercial partners and external AI specialists (Alexopoulos et al., 2019; Desouza et al., 2020; Makasi et al., 2021; Campion et al., 2020; Wirtz and Müller, 2019; Medaglia et al., 2021).

The third theme of perceived benefits encompasses adopting AI's direct benefits such as cost savings, novel solutions and the ability to meet users' needs or indirect benefits of increased collaboration with peers and industry partners (Mikalef et al., 2021; Cordella and Dodd, 2019).

3.4.2.1.2 Organisational Context

The organisational context identifies three themes of organisational culture, leadership, and inertia.

The theme of an organisational culture incorporates innovative culture as more receptive to AI adoption and successful diffusion given these new technologies represent high risks and an experimentation attitude (Van Noordt and Misuraca, 2020a; van Noordt and Misuraca, 2020b; Zuiderwijk et al., 2021; Kuziemski and Misuraca, 2020). Ojo et al. (2019) and Schedler et al. (2019) discuss institutional arrangements such as NPM orientation, bureaucratic structure, or digital-era governance mandates embedded in the culture of the organisations that influence AI-related innovations. These arrangements further manifest in terms of alignment between the organisational structure and big data (Giest, 2017), cross-agency collaborations, and the need for a redesign of processes and routines (Pencheva et al., 2020; Campion et al., 2020).

The theme of leadership stresses transformational leadership traits in leading change associated with AI adoption and diffusion (Campion et al., 2020; Schedler et al., 2019; De Vries et al., 2016; Borins, 2002). Transformational leaders can influence culture by establishing personal and social identification related to innovation and institutionalising learning (Alblooshi et al., 2020; Jia et al., 2018). Such leaders motivate employees to experiment and consider novel ways of working with AI. Specific to AI adoption and diffusion, the leadership qualities of the CIO are also highlighted as critical. CIOs should not only have technical knowledge of AI but also political acumen to effectively influence enterprise systems design within and across governmental agencies (Chatfield and Reddick, 2018).

The theme of organisational inertia specific to public administration was identified as a major inhibiting factor for AI adoption and diffusion. Inertia can be in terms of routine rigidity associated with bureaucracy, centralised decision-making, lack of employee empowerment, status-quo bias, and resistance to sharing data within or across agencies (Chen et al., 2019; Pencheva et al., 2020; Campion et al., 2020; van Noordt and Misuraca, 2020b; Fatima et al., 2021; Zuiderwijk et al., 2021). Or inertia can manifest in terms of resource rigidity with resource scarcity for innovative projects, high demand for AI experts, economic investment requiring political approvals, and insufficient budget for piloting and experimentation (Campion et al., 2020; Schedler et al., 2019; Mikalef et al., 2019; Wirtz et al., 2019). In addition, there is expected to be resistance from unions to the perceived threat to the workforce and displacement of jobs (Young et al., 2019).

3.4.2.1.3 Environmental Context

The mandates of public administration are determined by the political leadership and often influenced by election cycles. In addition, such organisations are influenced by peer governmental bodies, citizen demands, private industry, and media scrutiny. Thus, two themes under the environmental context are identified as vertical pressures and horizontal pressures.

The theme of vertical pressure relates to policy signals, directives, and mandates encouraging digital service delivery and automation (Schedler et al., 2019; Clarke and Craft, 2017; Pencheva et al., 2020; Wang et al., 2020; Janssen et al., 2020a). Examples include the digital-first directives in Canada (Government of Canada, 2021a), UK's GovTech fund under the AI Sector Deal (UK, 2019a), US's National AI Initiative (National Artificial Intelligence Initiative Office, 2021), and UAE's National AI Strategy 2031 (UAE, 2021). The vertical pressure is further influenced by macro-level guidelines, regulations, and procurement practices related to the use of AI. Such as algorithmic impact assessment by the Government of Canada (Government of Canada, 2020), the EU's General Data Protection Regulation (European Union, 2016), and the UK's AI procurement in a box (World Economic Forum, 2020b).

The theme of horizontal pressures incorporates intergovernmental competition, citizen demands, industry pressure, and media scrutiny. Public administration is under pressure to implement innovations when its shown to improve performance, save costs, and satisfy citizen demands for personalised and 24/7 services (Wang et al., 2021). The availability of AI technologies to meet these citizen demands exerts industry pressures (Schaefer et al., 2021). This pressure is further influenced by the public sector's fishbowl effect with constant media scrutiny and opposition parties' critiques (Desouza et al., 2020) forcing public administrative bodies to emulate peer agencies' successes. Citizens' perceptions of sharing data and its use by algorithms to make public decisions play a crucial role in public value deliberations related to innovations (Misuraca, 2020; Giest, 2017; Lopes et al., 2019; Chohan et al., 2021; Criado and Gil-Garcia, 2019). Wang et al. (2021) highlight the dual role of public value creation with AI and consider citizens' perception as the demand component. The supply side is driven by political and administrative contexts as discussed under organisational and environmental contexts.

3.4.2.1.4 Absorptive Capacity

A global theme of absorptive capacity emerged across all the TOE contexts. In the context of AI adoption, absorptive capacity is manifested through a strong path dependency on existing infrastructure developed through previous e-government innovations, collaborations between organisations, and a network of external technical specialists (Casalino et al., 2020; Campion et al., 2020; Ballester, 2021; Janssen et al., 2020a; Aboelmaged and Mouakket, 2020; Kuziemski and Misuraca, 2020). The knowledge management practices developing technical skills and data-oriented culture facilitate the exploration of AI technologies in response to citizens' needs, external environmental pressures, and fiscal austerity. Dynamic capabilities ensure optimal resource configurations can be mobilised during the assimilation of AI technologies (Erkut, 2020; Ojo, 2019; Medaglia et al., 2021). The experience acquired through the use of deterministic systems facilitates clarity on the public value outcomes desired from AI than just following the herd and succumbing to external pressures (Janssen et al., 2020b).

3.4.2.2 Implementation strategies

The AI implementation strategies discussed are similar to those used in technology implementation projects in public administration such as requirements identification, collaboration with citizens, a need for clear communications, change management, and skills training. Two specific themes emerge as distinct for AI-related technologies: innovative procurement and experimentation. Table 3.5 summarises the themes and codes which are discussed below.

Table 3.5. AI implementations strategies

Conceptual themes	Organising themes	Codes	References
Implementation strategies	Experimentation	• Pilot testing • Experimentation • Proliferation of innovation labs • Build on smaller successes	(Fatima et al., 2021; Alexopoulos et al., 2019; Desouza et al., 2020; van Veenstra and Kotterink, 2017)
	Innovative procurement	• Agile procurement enabling iterative development lifecycles	(Desouza et al., 2020)
	Collaboration and co-creation	• Co-creation • Citizen collaboration • Collaboration with employees	(Fatima et al., 2021; Lopes et al., 2019; Criado and Gil-Garcia, 2019; van Veenstra and Kotterink, 2017;

Conceptual themes	Organising themes	Codes	References
		• Inter and intra-agency collaborations • Collaboration with technology companies	Ojo et al., 2019; Alexopoulos et al., 2019; Janssen et al., 2020a; Gao and Janssen, 2020)
	Project management	• Agile practices • Strong project management culture • Complexity and coordination • Stakeholder engagement • Change management • Risk management	(Campion et al., 2020; Giest, 2017; van Noordt and Misuraca, 2020b; Young et al., 2019; Pencheva et al., 2020)

3.4.2.2.1 Experimentation

Pilot testing and experimentation are considered critical for AI applications in public administration to identify and mitigate risks of failure which may prove disastrous in eroding citizen trust (Fatima et al., 2021). The majority of ML projects in governments are currently pilot applications (Alexopoulos et al., 2019). The proliferation of innovation labs is a testament to a realised need for experimentation with new technology applications. Smaller successes enable organisations to mature and build capabilities before undertaking a large-scale AI-driven challenge (Desouza et al., 2020; van Veenstra and Kotterink, 2017).

3.4.2.2.2 Innovative procurement

To support experimentation, the standard government procurements used for established technologies involving comprehensive bidding and evaluation processes are not suitable. Instead, the agile procurement process allows iterative development lifecycles through the acquisition of hardware and software in stages (Desouza et al., 2020). This ensures early access to industry expertise and focuses on defining the problem than developing detailed solution specifications.

3.4.2.2.3 Collaboration and co-creation

Co-creation of AI solutions with stakeholders provides varied viewpoints and helps develop a clear definition of the problem (Fatima et al., 2021). Citizen collaboration enhances positive perceptions of AI decisions and higher adoption (Lopes et al., 2019; Criado and Gil-Garcia, 2019; van Veenstra and Kotterink, 2017). Collaborating with employees on service design alleviates concerns about AI replacing jobs and enhances internal use and adoption (Ojo et al., 2019). Collaboration and sharing of data between government departments (Alexopoulos et al., 2019; Janssen et al., 2020a) help develop better models. Collaboration with private technology companies is key for the development of AI solutions in public administration which generally lack technical expertise (Gao and Janssen, 2020).

3.4.2.2.4 Project management

In addition to agile being the preferred implementation approach, a strong project management culture remains a critical component for AI implementations. Project management best practices are required to support citizen and stakeholder engagement (Campion et al., 2020). Furthermore, collaboration and sharing between government departments increase complexity and require additional coordination (Giest, 2017). Project management practices are also required to manage inertia towards sharing of data between government departments, status quo bias, and resistance from unions (van Noordt and Misuraca, 2020b; Young et al., 2019; Pencheva et al., 2020).

3.4.2.3 Outcomes

The outcomes of AI diffusion are discussed as two themes: public values and public sector transformation. Table 3.6 summarises these outcomes and is discussed below.

Table 3.6. AI diffusion outcomes

Conceptual themes	Organising themes	Codes	References
Public Values	Duty	• Facilitating democratic will • Citizen engagement and participation • Enabling the wisdom of the crowd toward policy development	(Schedler et al., 2019; Rogge et al., 2017; Fatima et al., 2021; Marri et al., 2019; Höchtl et al., 2016; Ojo, 2019; Young et al., 2019; Kuziemski and Misuraca, 2020)

Conceptual themes	**Organising themes**	**Codes**	**References**
		• Strengthening integrity, honesty, and accountability of public funds	
	Service	• Personalised services and enhanced responsiveness • Instant case approvals and feedback • 24/7 services and access to reliable information • Efficiency goals • Allocation of human resources to higher-order tasks • Augmented decision making	(Ojo, 2019; Androutsopoulou et al., 2019; Marri et al., 2019; Rogge et al., 2017; Chatfield and Reddick, 2018; Giest, 2017; Fatima et al., 2021; van Noordt and Misuraca, 2019; Wang et al., 2020; Chen et al., 2019; Young et al., 2019; Mikalef et al., 2019; Ojo et al., 2019; Lopes et al., 2019; Gao and Janssen, 2020)
	Social	• Primarily discussed as ethical AI principles and AI tensions (discussed in table 3.7)	
Public administration transformation	Public administration transformation	• Reconfiguration of organisational structures • Digital-era governance • Positive aspects in achieving duty and service values • Negative aspects of job losses, re-	(Desouza et al., 2020; Henman, 2019: 74; Young et al., 2019; Mikalef et al., 2021; James and Whelan, 2021; Bullock et al., 2020; Fatima et al., 2021; Al Mutawa and Rashid, 2020)

Conceptual themes	Organising themes	Codes	References
		skilling, workforce displacement	

3.4.2.3.1 Public values

The three public values themes are duty, service, and social.

The public value of duty is characterised by using AI in facilitating the democratic will by enabling citizen engagement and participation at scale (Schedler et al., 2019; Rogge et al., 2017; Fatima et al., 2021; Marri et al., 2019). Technologies such as NLP enable public managers to collect unstructured data taking into account the wisdom of the crowd as input to policy development and decision-making (Höchtl et al., 2016). Citizens and businesses can co-produce public services using AI-enabled platforms (Ojo, 2019). AI-based decision-making is discussed as techno-rational eliminating human biases and being objective and neutral (Young et al., 2019; Kuziemski and Misuraca, 2020). This objectivity strengthens values of integrity, honesty, and accountability in the efficient use of public funds.

The use of AI in public administration is mostly discussed in terms of enhancing service-oriented public values. AI technologies enhance external public service delivery capabilities through personalisation, responsiveness, and citizen orientation. Personalised services providing relevant information at the point of interest are achieved by developing detailed profiles of individuals and businesses (Ojo, 2019; Androutsopoulou et al., 2019; Marri et al., 2019; Rogge et al., 2017; Chatfield and Reddick, 2018). This enables responsiveness to the needs of micro-clusters of citizens (Giest, 2017). Automation of application processes enables instant approval and feedback (Fatima et al., 2021; Androutsopoulou et al., 2019) improving quality and service time. Intelligent virtual agents and chatbots enable 24/7 access to information quickly and reliably (van Noordt and Misuraca, 2019; Wang et al., 2020). The internal aspect of service-oriented values relates to the use of AI in achieving efficiency goals. The automation of simple processes and repetitive tasks enables the allocation of human resources towards higher-order tasks alleviating workloads, improving efficiency, and enhancing productivity (Chen et al., 2019; Young et al., 2019; Mikalef et al., 2019; van Noordt and Misuraca, 2019; Androutsopoulou et al., 2019; Wang et al., 2020; Fatima et al., 2021). For complex interdependent problems, AI-augmented decision-making uncovers new options, anomaly detection, rigorous risk identification, and better service planning and interventions (Ojo et al., 2019; Lopes et al., 2019; Gao and Janssen, 2020).

Socially oriented public values are sparsely discussed as specific planned outcomes from the use of AI. Societal outcomes are instead considered in terms of ethical AI principles and implicit values. These are discussed either as secondary benefits or tensions when pursuing service and duty-oriented values. For example, citizen collaboration (duty values) helps with equality and inclusiveness (Ojo et al., 2019; Van Noordt and Misuraca, 2020a). Or, the ability to redirect public managers toward complex societal issues by automation of mundane tasks (service values) (Ojo, 2019).

3.4.2.3.2 Public administration transformation

The adoption of AI in public administration represents disruptive innovation leading to a reconfiguration of organisational structures (Desouza et al., 2020). This is a step towards realising the DEG vision envisaged with the first wave of technological innovation. Referred to as algorithmic bureaucracy, the use of AI transforms street-level bureaucrats into system-level (Henman, 2019: 74). The positive aspects of the transformation are manifested in terms of achieving duty and service-oriented values as discussed in Section 4.2.3.1. Scholars have argued building AI capabilities leads to a more innovative culture and thus a virtuous cycle ensues further re-enforcing DEG vision (Young et al., 2019; Mikalef et al., 2021; James and Whelan, 2021). The accompanying negative aspect is distancing public servants from citizens and inhibiting a rich knowledge generation avenue (Young et al., 2019; Bullock et al., 2020). Other negative implications include the social costs of job losses, re-skilling, and workforce displacement (Fatima et al., 2021; Al Mutawa and Rashid, 2020). Similar to the public values discussion, the resolution of AI tensions drives the positive and negative aspects of public sector transformation with the use of AI.

3.4.2.4 AI tensions

The theme of AI tensions emerged as a global construct impacting the outcomes of AI implementation and diffusion in terms of public value creation and public sector transformation. Five sets of tensions are identified that arise as a result of a conflict between competing values. Such tensions can be “true dilemmas” where two or more values are inherently contradictory or “dilemmas in practice where tensions are not inherent” but as a result of limitations of technology or resources (Whittlestone et al., 2019: 24). Table 3.7 summarises the themes and codes related to AI tensions which are discussed below.

Table 3.7. AI tensions and data governance

Conceptual themes	**Organising themes**	**Codes**	**References**
AI tensions	Automation versus augmentation	• Automation of repetitive and low discretionary tasks • Augmentation for higher discretionary tasks • Tensions between cost and efficiency motives versus novel inputs to decision making and protecting citizens from algorithmic harm • Impact on the labour markets	(Mikalef et al., 2019; Ahmad et al., 2017; Bullock et al., 2020; Young et al., 2019; Ballester, 2021; Liu et al., 2020; Veale et al., 2018; James and Whelan, 2021; Wirtz et al., 2019; Misuraca, 2020; Ahn and Chen, 2020; Androutsopoulou et al., 2019; Van Noordt and Misuraca, 2020a; Reis et al., 2019b; Zuiderwijk et al., 2021; Casares, 2018)
	Nudging versus autonomy	• Collective rights versus individual freedoms • State surveillance and behaviour control for achieving policy goals using AI • Citizen's right to object to being governed by AI • Personalised services and creation of filter bubbles	(Reis et al., 2019b; Erkut, 2020; Misuraca, 2020; Pencheva et al., 2020; Liaropoulos, 2019; van Noordt and Misuraca, 2020b; Pariser, 2011; Wirtz and Müller, 2019; Kuziemski and Misuraca, 2020)
	Data accessibility versus security and privacy	• Accessibility and use of existing citizen data collected for other purposes • Consent and providing data as a	(Pencheva et al., 2020; Veale et al., 2018; Marri et al., 2019; Ojo, 2019; Chen et al., 2019; Schedler et al., 2019; Fatima et al., 2021;

Conceptual themes	**Organising themes**	**Codes**	**References**
		precondition for receiving public services • Constant threats to the security of sensitive data	Rogge et al., 2017; Wirtz et al., 2019; Reis et al., 2019b; Erkut, 2020; Ojo et al., 2019; Clarke and Margetts, 2014; Van Noordt and Misuraca, 2020a; Al Mutawa and Rashid, 2020; Coglianese and Lehr, 2017; Kuziemski and Misuraca, 2020)
	Predictive accuracy versus discrimination, biases, citizen rights	• Use of sensitive variables for higher predictive power versus embedding biases and discrimination • Acceptable error rates against the risk of marginalisation of vulnerable communities • Digital divide • Negative learnings from the environment • Correlational knowledge versus contextual human knowledge	(Scurich and Krauss, 2020; Young et al., 2019; van Noordt and Misuraca, 2020b; Janssen et al., 2020a; Criado et al., 2020; Marri et al., 2019; Henman, 2019; Coglianese and Lehr, 2017; Andrews, 2019; Wirtz et al., 2019; Ojo et al., 2019; Zuiderwijk et al., 2021; Fatima et al., 2021; Selbst et al., 2019; Höchtl et al., 2016; Liaropoulos, 2019; Harrison and Luna-Reyes, 2020; Ahn and Chen, 2020; Casares, 2018; Valle-Cruz et al., 2019)
	Predictive accuracy versus transparency and accountability	• Higher predictive accuracy versus transparency and	(Young et al., 2019; Harrison and Luna-Reyes, 2020; Mulligan and Bamberger, 2019;

Conceptual themes	**Organising themes**	**Codes**	**References**
	versus gaming the system	interpretation of results • Lacks casual intuition • Accountability and responsibility of AI decisions • Justification of AI based public decisions • Ability to game the system with higher transparency	Janssen et al., 2020b; Makasi et al., 2021; Zuiderwijk et al., 2021; Janssen et al., 2020a; Veale and Brass, 2019; Wirtz et al., 2019; Henman, 2019; Chen et al., 2019; Ojo et al., 2019; Veale et al., 2018; Sousa et al., 2019)
Data governance	Data governance	• Big, Open, and Linked Data (BOLD is dependent on multiple organisations or systems with different data management practices • AI lacking contextual domain knowledge can exacerbate the data quality and validity issues • Analogous management practices towards higher data quality and trustworthiness • Increasing the data literacy of public administrators	(Janssen et al., 2020a; Alexopoulos et al., 2019; Harrison and Luna-Reyes, 2020; Gong and Janssen, 2021)

3.4.2.4.1 Automation versus augmentation

The essence of automation versus augmentation tension can be distilled into three related issues. First, the level of control and public decision-making power humans should retain over AI. Second, is the pursuit of efficiency and cost-saving goals. Third, is the debate on the impact of technological advancement on jobs.

The common agreement among scholars is that automation using AI is only appropriate for repetitive and low-discretionary tasks (Mikalef et al., 2019; Ahmad et al., 2017; Bullock et al., 2020). Gesk and Leyer's (2022: 8) analysis shows citizen disposition toward humans for delivery of specific public services while the acceptance of AI for general services is inhibited by “fear of failure” reflecting citizens’ perception of AI’s inability to handle exceptions. Higher discretionary tasks that may directly impact an individual or community are typically characterised by fuzzy success criteria and multiple interdependent systems that are difficult to model (Young et al., 2019; Ballester, 2021). The use of AI as an augmented decision-support system for such tasks has immense benefits for generating hybrid knowledge combining complex analytical correlational options and human contextual intelligence (Mikalef et al., 2019; Ahmad et al., 2017; Liu et al., 2020). Tensions arise between those seeking to implement AI for generating novel inputs to public decision-making versus those seeking efficiency (Veale et al., 2018; James and Whelan, 2021). In a fiscally constrained environment, the pressures to adopt AI for achieving efficiency and cost savings might seem obligatory. The unknown risk of losing control to self-learning algorithms managing machine-to-machine interactions and critical public resources needs to be balanced against the apparent advantage in terms of task scalability and costs (Young et al., 2019; Wirtz et al., 2019). The socially-oriented ethos of protecting citizens from algorithmic harm might conflict with the temptations of efficiency and cost savings (Misuraca, 2020). Ahn and Chen (2020: 249) ask the pertinent question, “how far are we going to allow AI to make [public] decisions?” and “… the process of reconciliation when there is a conflict … with human-based decisions.”

The impact of AI on labour markets continues the age-old debate on workforce substitution and job losses with technological advancement. However, with AI able to automate or augment cognitive tasks, both front-line and managerial jobs are at risk (Androutsopoulou et al., 2019; Van Noordt and Misuraca, 2020a; Wirtz et al., 2019; Reis et al., 2019b; Zuiderwijk et al., 2021; Casares, 2018). Public administration is one of the largest employers in society and the replacement of employees with AI will have significant societal implications.

3.4.2.4.2 Nudging versus autonomy

The tension between nudging and autonomy can be viewed from the vantage of collective rights versus individual freedoms. State surveillance and behavioural control are often justified in terms of maintaining security and advancing collective well-being. This contrasts with individual values of liberalism and self-determination. When a public administration adopts AI, citizens do not have the right to object to receiving public services (Reis et al., 2019b). Large-scale surveillance enables governments to observe citizens and use algorithmic predictions to plan interventions influencing people's lives, decisions, and economies (Erkut, 2020; Misuraca, 2020; Pencheva et al., 2020). The question of legitimacy and trust in officials in power becomes even more critical. Behavioural science and social engineering techniques using AI to influence citizens toward a policy goal might be socially beneficial but can be equally exploited for political or private motives (Liaropoulos, 2019; van Noordt and Misuraca, 2020b; Kuziemski and Misuraca, 2020). Others argue such nudging even for altruistic policy goals threatens the core of modern democratic and liberal societies characterised by autonomy, free decision, and self-determination (Wirtz and Müller, 2019).

The pursuit of personalised services using AI enhances service-oriented values and customer satisfaction. However, this level of personalisation can create filter bubbles (Pariser, 2011) against the ethos of public service delivery in providing consistent services and messages to all citizens alike. The filter bubbles can further enable classification and behavioural control of citizens ensuing in a negative feedback loop towards algorithmic authoritarianism benefiting individuals or groups in power in the name of collective well-being.

3.4.2.4.3 Data accessibility versus security and privacy

Data privacy and security are among the most contentious topics debated in media and politics. Such debates have motivated national data protection legislation in several countries such as the EU's General Data Protection Regulation (GDPR) (European Union, 2016). Governments generally have access to sensitive data related to taxes, health records, properties, and social benefits. The use of this data can provide a near accurate profile of citizens classified into micro-population clusters (Pencheva et al., 2020). Citizens and front-line bureaucrats are unaware of how data generated through their interactions might be used downstream for data mining and machine learning (Veale et al., 2018) raising concerns about consent. In some cases, the government can go to the extreme in encouraging citizens to part with data in return for getting services (Marri et al., 2019). Thus, accessibility to data and its use by governments for purposes other than what was collected raises severe privacy-related concerns. On one hand use of data can lead to superior public policy and service delivery towards duty and service-oriented public values. However, at the same time undermines the social public value of privacy.

A related tension is due to limitations in technology and a constant threat to the security of collected data. This requires specialised skills and technology to properly secure sensitive data and constantly monitor for threats that can become cost-prohibitive (Ojo, 2019; Chen et al., 2019; Schedler et al., 2019; Fatima et al., 2021; Rogge et al., 2017; Wirtz et al., 2019; Reis et al., 2019b; Erkut, 2020; Ojo et al., 2019; Clarke and Margetts, 2014; Van Noordt and Misuraca, 2020a; Al Mutawa and Rashid, 2020; Coglianese and Lehr, 2017; Kuziemski and Misuraca, 2020).

3.4.2.4.4 Predictive accuracy versus discrimination, biases, citizen rights

The tension between service and social-oriented values is the most severe in terms of achieving predictive accuracy at the cost of undermining citizen rights and amplifying biases and discrimination. A related debate is on the appropriateness of the type of knowledge used for decision-making by AI, i.e. correlational versus causation.

The use of sensitive variables such as gender, religion, and race can increase the predictive power of algorithms. Even when such variables are prohibited from use in AI models, other related variables such as employment stability, two-parent households, neighbourhoods, etc can become proxies for race and socio-economic clusters leading to higher predictability (Scurich and Krauss, 2020). However, this accuracy comes at the cost of propagating human biases and discrimination inherent in the data used for machine training (Young et al., 2019; van Noordt and Misuraca, 2020b; Janssen et al., 2020a). Public managers must decide on the acceptable error rates against the risk of marginalisation of vulnerable communities (Criado et al., 2020; Marri et al., 2019; Henman, 2019; Coglianese and Lehr, 2017; Andrews, 2019; Valle-Cruz et al., 2019). The issue of the digital divide can become a double-edged sword. Disadvantaged groups are unable to provide sufficient data in the first place due to socio-economic barriers. Any policy interventions based on AI models will lack statistically significant perspectives on such clusters and thereby further exasperating the digital divide (Valle-Cruz et al., 2019).

AI systems are prone to failures and malfunctions from time to time learning negative behaviour from the environment (Wirtz et al., 2019; Ojo et al., 2019; Zuiderwijk et al., 2021). This will be detrimental to the well-being and justice of citizens and public administration employees (Fatima et al., 2021; Selbst et al., 2019). Maintenance of AI to ensure the detection and rectification of models can become cost-prohibitive requiring specialised skills and ongoing audits (Höchtl et al., 2016).

Another aspect of the predictive power of AI relates to the epistemology of knowledge. Predictions generated through AI are based on historical data and correlational analysis of signs and associations found in the data (Liaropoulos, 2019; Höchtl et al., 2016). This epistemological stance of rationality lacking theory and context is contrasted with human traits of emotions, values, and ethics. These traits combined with domain knowledge establish causal links for making decisions on high-discretion tasks (Wirtz et al., 2019; Harrison and Luna-Reyes, 2020). When moral judgements are transformed into probabilistic ratios, the questions of power and legitimacy become critical. One needs to consider who is coding whose interests and the nature of the objective truth when communicated by algorithms (Ahn and Chen, 2020; Casares, 2018). AI making public sector decisions is akin to reducing citizens to data points, efficient and accurate but impersonal and non-democratic (Coglianese and Lehr, 2017).

3.4.2.4.5 Predictive accuracy versus transparency and accountability versus gaming the system

Ensuring transparency with higher predictive accuracy presents tension in the design process. AI architectures such as neural networks are challenging to reverse engineer to determine factors and weights that produce model outputs (Young et al., 2019). Private sector firms that develop such models regard this as intellectual property and are reluctant to provide design specifications (Harrison and Luna-Reyes, 2020; Mulligan and Bamberger, 2019). This lack of transparency puts accountability and responsibility for AI-based decisions into question. Janssen et al.'s (2020b) experiment shows transparency leads to more correct decisions when algorithmic options are used to support human decisions. However, a related tension ensues in the ability to game the system if such models were to become fully transparent.

AI systems are commonly referred to as black-box designs transforming input variables into predictions or classifications. The correlational analysis of large amounts of data is characterised by opaqueness in how information is handled (Makasi et al., 2021; Zuiderwijk et al., 2021). It lacks casual intuition on the statistical significance of explanatory variables (Coglianese and Lehr, 2017). Public decisions supported by AI that cannot be explained, and more importantly justified, constitute challenges to legal accountability (Janssen et al., 2020a; Veale and Brass, 2019; Sousa et al., 2019). There is a lack of a legal framework as to the liability of algorithmic public decisions (Wirtz et al., 2019; Henman, 2019). Should the responsibility lie with the public administration, the technology company, or the technology itself (Chen et al., 2019)? What is the role of public servants as mediators of algorithmic decisions (Janssen et al., 2020a)? Is there a need to develop a legal stature for technology similar to businesses so that they can be held liable?

Transparency and explainability in AI-based decisions can garner higher trust both from public administration employees and citizens. However, the drawback of increased transparency is the ability to game the system for private motives (Ojo et al., 2019; Janssen et al., 2020a). A new industry might emerge in being able to manipulate public sector algorithmic decisions if the logic is transparent. Another concern is internal gaming by public administration employees towards opportunistic behaviours similar to performance measures being manipulated to meet specific targets for funding (Veale et al., 2018).

Thus, public administration leaders and technology vendors need to ensure a balance between opaqueness to prevent gaming of the systems against ensuring decisions can be explained and justified in a legal setting.

3.4.2.5 Data Governance

The theme of data governance emerged across AI tensions as a critical component of managing such tensions. Table 3.7 summarises the themes and codes and is discussed below.

The data driving AI technologies in public administration, in particular machine learning, is Big, Open, and Linked Data (BOLD) consisting of structured and unstructured formats, generated in real-time, and dependent on multiple organisations or systems with different data management practices (Janssen et al., 2020a; Alexopoulos et al., 2019; Harrison and Luna-Reyes, 2020; Gong and Janssen, 2021). In addition, AI lacking contextual domain knowledge can exacerbate data quality and validity issues (Harrison and Luna-Reyes, 2020). Data governance principles within public administration can ensure analogous management practices toward higher data quality and trustworthiness (Janssen et al., 2020a). Another component of governance is increasing the data literacy of public administrators to be able to promote and maintain such practices and question data validity and reliability within their domain knowledge (Harrison and Luna-Reyes, 2020)

3.5 Discussion

Adopting a processual view of innovation, the AI adoption stage consists of “activities that pertain to recognizing a need, searching for solutions, becoming aware of existing innovations, identifying suitable [AI] innovations and proposing some for adoption" (Damanpour and Schneider, 2006: 217). Implementation of advanced computing technologies like AI needs to be first piloted and tested with low-risk applications (Desouza et al., 2020). The AI implementation stage is the post-adoption phase reflecting project initiation, resource allocations and funding, iterative implementation of AI solutions, and preparing the organisation for its use (Damanpour and Schneider, 2006: 217). Finally, AI diffusion represents the rollout of a full-scale product for wider operational use following several pilot applications when its use "becomes a routine feature of the organization" (Damanpour and Schneider, 2006: 217). The AI innovation stage model is shown in Figure 3.5 and each stage is discussed in the following sub-sections.

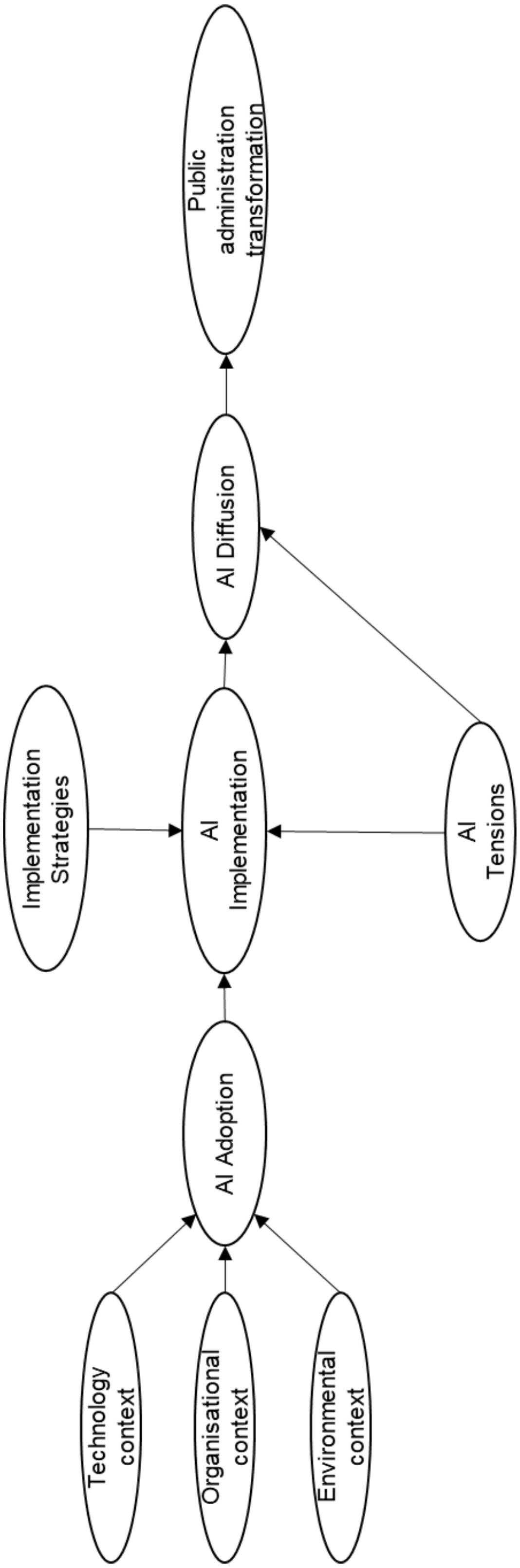

Figure 3.5. AI innovation stage model

3.5.1 AI Adoption

The TOE framework provided a theoretical lens for categorising factors influencing AI adoption, as discussed in the literature, under technology, organisational, and environmental context as discussed in section 3.4.2.1. The findings concur with Mikalef and Gupta's (2021) construct of AI capabilities consisting of tangible and human (reflected in the technology context) and intangible (reflected in the organisational context) resources. The emergence of the absorptive capacity construct as a global theme suggests a strong path dependency on past technology implementations and existing infrastructure, knowledge management processes, and innovative culture. Lane et al. (2006) describe two antecedents of absorptive capacity – internal and external. External factors relate to environmental conditions, knowledge characteristics, and learning relationships. Internal refers to mental models, structures, and organisational strategies. This concurs with technology and environmental contexts as external factors and organisational contexts as internal factors in the results of the review.

The environmental pressures act as external triggers for public administration to respond to specific stimuli. The extent to which public managers can align their resource configurations to this external trigger is determined by their dynamic capabilities, organisational routines, and existing knowledge. Absorptive capacity enables the exploration and evaluation of AI technologies as solutions to these triggers. Thus, future qualitative and quantitative studies need to explore and test the effect of technology, organisation, environment contextual variables, and absorptive capacity on AI adoption.

3.5.2 AI Implementation

The results showcase the importance of a strong project management culture for the design and implementation of AI technologies within public administration. Similar to prior technology implementations in public administration, AI implementation involves the coordination of several stakeholders, management of change related to both automation and augmentation, vendor management, and management of project costs. In addition, the unique aspects of AI implementation call for using agile methods and new innovative procurement methodologies. Thus, future research should explore AI implementations in public administration through in-depth case studies or ethnographic studies outlining the underlying mechanisms and dynamics of AI projects. Quantitative studies can test the applicability of established conceptual models of technology implementations within the AI context.

3.5.3 AI Diffusion

As highlighted in the results, the three public value outcomes from AI diffusion are duty, service, and social. Public administration by its very nature has several competing interests and demands, the pursuit of this pluralism often leads to conflicts between these public values. In the context of AI diffusion, conflicts between public values are embodied in AI tensions. The decisions made on a wide spectrum of such apparent opposing poles during the design and implementation are deemed to emphasise certain values over others. Several pertinent research questions need to be explored related to each of the five AI tensions as outlined in Table 3.8. Future researchers can consider qualitative studies to explore each tension in-depth. In addition, scales can be developed and tested to measure each tension on a continuum between two opposing dimensions.

AI tensions can also be viewed from a perceptual perspective in the way governments communicate management of these tensions impacting employees' and citizens' acceptance. Thus, future research will need to test the effect of decisions on AI tensions on citizen adoption.

Strong governance policies relating to acquiring, preparing, and ongoing auditing of the data can help identify and eliminate biases (Medaglia et al., 2021). This can partially alleviate tensions between predictive accuracy and discrimination. Similarly, data governance principles on accessibility (see Table 1 in Janssen et al., 2020a) can help alleviate tensions related to privacy and security. Data stewardship and separation of control can become key aspects of the legal framework to define accountability of public decisions and enumerate delegation between humans and machines (Pencheva et al., 2020; Janssen et al., 2020a). Public administrators with advanced statistical knowledge and data management capabilities can provide domain expertise to software developers and evaluate the quality of AI outcomes improving the accuracy of these models towards the desired public value goals (Harrison and Luna-Reyes, 2020). Hence, future research needs to explore the role of data governance in the management of AI tensions toward public value creation.

3.5.4 Future research agenda

Using the results of the qualitative synthesis and the theoretical framework, a future research agenda is developed for the adoption, implementation, and diffusion of AI innovation. Furthermore, the decisions on AI tensions are made during the implementation stages while their effects materialise in the diffusion stage. These are discussed under diffusion given their embeddedness with public value creation. The research agenda is shown in Table 3.8 and discussed below.

Table 3.8. Future research agenda for AI adoption, implementation, and diffusion in the public administration

AI Innovation Stage	**Research Questions**
AI Adoption	• What is the effect of technology contextual constructs, such as IT assets, IT capabilities, and perceived benefits on AI adoption by public administration? • What is the effect of organisational contextual constructs, such as leadership, culture, and inertia on AI adoption by public administration? • What is the effect of environmental contextual constructs, such as horizontal and vertical pressures, on AI adoption by public administration? • What is the effect of absorptive capacity on AI adoption by public administration?
AI Implementation	• How are AI projects in public administration managed? What are the unique attributes compared to previous technology implementation projects? • How are AI solutions/ development procured within the public administration?

AI Tensions and Data Governance	• Automation versus augmentation
	  o What level of control and public decision-making power humans should retain over AI?
	  o What is the acceptable risk to labour markets in the short to medium term with AI automation and/or augmentation in public administration?
	• Nudging versus autonomy
	  o How are algorithmic predictions used for planning policy interventions?
	  o What is the effect of using such interventions on citizens and societies?
	  o What is the effect of personalising public services?
	• Data accessibility versus security and privacy
	  o How is the use of existing citizen data justified for training machine learning models?
	  o What is the future of public service delivery when providing data becomes a precondition for receiving services?

AI Innovation Stage	**Research Questions**
	○ What is the cost versus benefits of securing citizens' sensitive data from cyber threats and malicious actors? • Predictive accuracy versus discrimination, biases, citizen rights ○ To what extent are sensitive variables being used to train machine learning models in public administration? ○ How to ensure machine learning models do not learn negative behaviour from the environment? ○ How will AI-driven public policy affect already at-risk population clusters? ○ What is the effect of public policy based on correlational analysis from machine learning models? • Predictive accuracy versus transparency and accountability versus gaming the system ○ How do public managers interpret the results of AI? ○ Who will be accountable for public decisions based on AI? ○ What is the effect of increased transparency and openness of AI decisions? Data Governance • How is data governance being used to manage AI tensions?
AI Diffusion	• What is the effect of the resolution of AI tensions as an aggregate on public value creation? • What is the effect of the resolution of AI tensions on citizen adoption of AI?

3.6 Contribution and Limitations

3.6.1 Theoretical contributions

This review aimed to synthesise current scholarship on the phenomenon of AI adoption and diffusion in public administration. Four theoretical contributions are outlined. First, adopting a multi-disciplinary approach and a processual view of innovations, the full life cycle from AI adoption to diffusion was explored. The use of a critical realist perspective in a systematic literature review enabled highlighting underlying constructs at each stage of the process. The absorptive capacity and a comprehensive list of variables under technology, organisational, and environmental context were identified as factors influencing AI adoption as discussed in the literature. Thus, a TOE model is proposed within the specific context of AI and public administration for future testing contributing to the technology adoption and public administration literature. Second, this review addresses the calls for using a public value-based perspective when exploring the implementation and use of AI in public administration. AI outcomes are viewed from a vantage of public value creation leading to the identification of AI tensions. Third, this is the among the first reviews that outlines five primary AI tensions that may be experienced as dilemmas or paradoxical tensions when implementing and using AI in public administration. Fourth, the suggested research questions highlight the current lack of understanding of the AI phenomenon within public administration. This also lays out a future research agenda for developing and testing theory in this area.

3.6.2 Limitations

This review does come with limitations. First, this review synthesises both conceptual and empirical literature to provide a theoretical landscape of the current thought and empirical evidence. The findings are geared towards future theory development and testing and should be used within this context. Second, the review was limited to two specific AI technologies, ML and NLP, and the public administration context. Future literature reviews can expand the scope of technologies as well as include a broader public sector context including law enforcement, healthcare, city planning, etc. Third, following a systematic literature review, the review intended to encompass extant literature within the defined research protocol. However, AI in public administration is an active area of research and this review might have missed important publications published following our search.

3.7 Conclusion

The use of AI technologies in public administration is expeditiously accelerating with the prospect of efficient low-cost public service delivery and higher levels of citizen engagement. A long-awaited techno-centric governance model is around the corner. However, similar to private sector applications, public leaders are grappling with the tensions AI introduces in service design and delivery. Notwithstanding several guidelines and frameworks that have been introduced by central governments and supra-national bodies, their application at the meso and micro level of public administration remains elusive. This review attempted to explore the phenomenon of AI in public administration with specific goals of understanding the factors influencing AI adoption and key tensions during AI diffusion as discussed in the literature, both toward achieving the goals of public value creation. A multi-disciplinary approach was adopted using theories from IS, management and public administration literature.

Through a systematic literature review, TOE variables are identified as factors influencing AI adoption. The construct of absorptive capacity emerged as a new theme during our analysis. Using a public value framework, the results align with the perspective that public administration leaders and managers are not just passive executors of political direction but play an important role in building the potential absorptive capacity of their organisation sensing changes in the political environment and responding to customer needs and horizontal pressures from other agencies. Public managers strive to maximise public value through the optimal use of resources. However, several tensions arise during the design and implementation of AI technologies. Trade-offs made by public managers impact aggregate public value that can be realised from AI and ultimately the citizen adoption of such technologies. Data governance maturity is further identified as an important component of managing some aspects of AI tensions.

The suggested future research agenda lays the groundwork for addressing important research questions pertaining to understanding the AI phenomenon in public administration from a processual view. The novel theoretical contribution of this review is the identification of five AI tensions. Practitioners can also use the identified AI tensions to undertake a cost-benefit analysis before the design or acquisition of an AI solution for public administration needs.

4 Paper 3: Making sense of AI benefits: A mixed-methods study in Canadian public administration

This chapter is based on: MADAN, R and ASHOK, M (2023) Making sense of AI benefits: A mixed-methods study in Canadian public administration. [Manuscript submitted for publication].

4.1 Introduction

Public administration is under immense pressure to deliver on service demands and political mandates while enduring austerity measures and systemic resource deficits (Madan and Ashok, 2023a). Artificial Intelligence (AI) technologies are increasingly being considered ideal instruments to be able to meet these challenges. However, there are also intense debates on the ethics of AI (Buergi et al., 2023). Public administrators are bombarded with conflicting signals that swing between the transformational aspects of AI-driven service delivery to counternarratives on job losses, political power grabs, surveillance, and citizen control. Against this backdrop, this chapter explores the factors and mechanisms that affect the sensemaking of AI benefits in public administration.

AI can accelerate digital government benefits in a myriad of ways. The vision of a lean and platform-based public service delivery seems feasible (Dunleavy et al., 2005). The benefits of using AI in public administration include improving efficiency and effectiveness, saving costs, increasing service delivery, better citizen engagement, citizen centricity, transparency, etc. (Wirtz and Müller, 2019; Madan and Ashok, 2022). At the same time, there is a universal acceptance of negative externalities in terms of societal and ethical impacts (Ashok et al., 2022; Madan and Ashok, 2023a).

Perceived benefits have been identified as a key determinant of technology adoption in the literature (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012; Rana et al., 2015). A question remains as to how these perceptions are formed in the first place. Fountain et al.'s (2001) technology enactment framework (TEF) highlights the role of organisational forms and institutional arrangements in determining enacted technology. Cordella and Iannacci (2010) discuss e-government policies, embedding logics of political negotiations, which also play a role in technology enactment. 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). These socially constructed attitudes on the benefits of technology are then manifested in the adoption decision and the enacted technology. The role of the institutional environment on sensemaking is extensively discussed in the literature (Weick et al., 2005; Mignerat and Rivard, 2009; Seligman, 2006). Viewed from these perspectives, the chapter argues that perceived AI benefits, as a precursor to AI adoption and determinant of implementation decisions, are a result of sensemaking by public administrators influenced by the institutional and social context. However, there is limited empirical work on exploring the mechanisms that link the institutional environment at the macro level to sensemaking at the micro level (Ann Glynn and Watkiss, 2020; Mignerat and Rivard, 2009).

This chapter aims to explain the AI adoption phenomenon at the organisational level and uncover underlying mechanisms that link institutions to sensemaking. Thus, the research question is stated as:

RQ4.1: What factors affect the perceived benefits of AI use in public administration?

RQ4.2: How do these factors affect the perceived benefits of AI use in public administration?

The context for this research is Canadian public administration. To explain adoption at the organisational level, perceived benefits of AI use refer to perceptions of public administrators within the organisation. The chapter focuses on two specific data-driven AI technologies: machine learning (ML) and natural language processing (NLP)[11].

The chapter sheds light on the institutional pressures that are most significant in effecting the sensemaking of AI benefits within the Canadian public administration. The chapter also contributes to institution and sensemaking theory by expounding on the mechanisms and interactions of institutional pressures at different stages of the adoption process.

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

4.2 Literature Review

This study draws on three disciplines as discussed below.

4.2.1 Public administration

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

[11] For brevity, the term AI is used to denote both technologies and discussed separately when variations are relevant.

fundamental building block of public organisations (Esmark, 2016). Bureaucratic structures are characterised by hierarchal decision-making, rules and procedures, and specialised professionals distinct from political interests (Sager and Rosser, 2009).

The neo-liberalism wave of the late 1970s and 80s 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 was incongruent with the ethos of public service geared towards democratic and societal goals (Christensen et al., 2007; Hood, 1991). The rapid trajectory of technological innovations and limited successes from NPM (De Vries and Nemec, 2013; Hood, 1991; Dunleavy et al., 2005) led to its downward spiral 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 involving public and private organisations and citizens. 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 public organisations should pursue public values through their activities (Moore, 1994: 1995). These values are determined through democratic engagement with stakeholders building legitimacy and understanding of the public sphere (Andrews, 2019; Ranerup and Henriksen, 2019). The operational capabilities required to deliver on these public values shift the focus from economic goals, as in NPM, to broader societal goals (Madan and Ashok, 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) advocates for the central role of technology in delivering public services. Tan and Crompvoets (2022) discuss a more contemporary form of DEG with the adoption of advanced technologies such as AI, blockchain, etc.

Scholars have argued bureaucracy is still persistent notwithstanding NPM and post-NPM reforms (Christensen and 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 a specific set of values and organisational configurations influenced by the societal, political, and institutional environment. This study builds on this perspective to view AI innovation as a carrier of institutionalism and as an enacted technology (Fountain et al., 2001) rather than a distinct reform movement. In the next section, we discuss the institutional and sensemaking theory as the basis of our hypotheses.

4.2.2 Institutional theory

Christensen et al. (2007) discuss structural-instrumental and institutional approaches as two theoretical perspectives 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 and 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: 3). Oliver (1997) argues that even though 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 and 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 of technology adoption within the public administration context (Altayar, 2018; Savoldelli et al., 2014; Sherer et al., 2016; Pina et al., 2010).

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

4.2.3 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: 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 (Goto, 2022; Luna-Reyes et al., 2021; Wang et al., 2019; Tan et al., 2020; Elbanna and Linderoth, 2015).

This chapter 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: 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: 1640) identify three contextual mechanisms of priming, triggering, and editing operating between the institutional environment and sensemaking.

This chapter builds on Weber and Glynn's (2006) sensemaking mechanisms and uses an explanatory mixed-methods research design (Teddlie and Tashakkori, 2009). The research was conducted in two sequential phases, the quantitative study followed by the qualitative study. The purpose of a mixed-methods approach was two-fold: completeness and expansion (Venkatesh et al., 2013). For the quantitative study, the chapter draws on e-government and public sector innovation studies to develop and test our hypotheses related to the effect of the institutional environment on the sensemaking of AI benefits. The qualitative study is used to explain the results of quantitative analysis and develop meta-inferences to form a complete picture of the AI adoption phenomenon. Each phase is discussed in the following sections.

4.3 Quantitative Study

4.3.1 Hypotheses

The coercive, mimetic, and normative institutional isomorphic mechanisms (DiMaggio and Powell, 1983) are hypothesised as the primary environmental pressures that affect the sensemaking of AI benefits from its use within the public administration. The output of this sensemaking process, perceived AI benefits, is modelled as the dependent variable. Figure 4.1 shows the conceptual model.

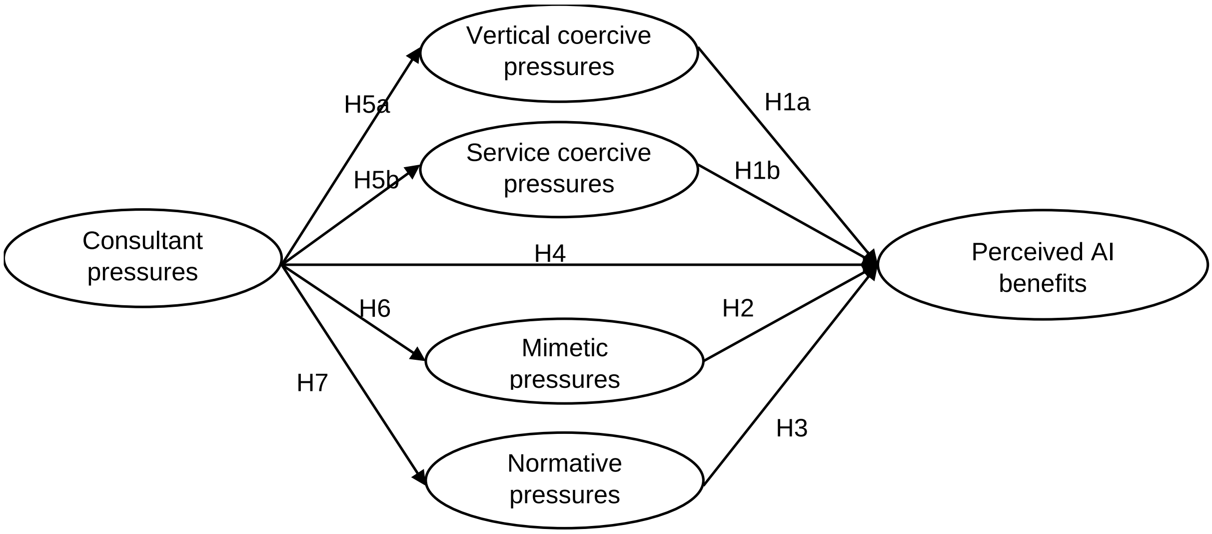

Figure 4.1. Conceptual model of drivers of perceived AI benefits

4.3.1.1 Coercive pressures

Coercive pressures can be either formal or informal (DiMaggio and 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 for supporting 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 and 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 and 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 for rewarding or sanctioning specific innovations might exert coercive pressures for compliance with government mandates (Madan and Ashok, 2023a; 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, 2014; Morin, 2008). 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 (Wang et al., 2021; Chen et al., 2019). Research has shown a positive impact of citizen demands and public pressures on all types of innovation including technological (Walker et al., 2011; Berry and Berry, 1999; Walker, 2006; Korac et al., 2017; Hong et al., 2022).

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

H1a: Vertical coercive pressures affect perceived benefits of AI use within the public administration.

H1b: Service coercive pressures affect perceived benefits of AI use within the public administration.

4.3.1.2 Mimetic pressures

The need to imitate similar organisations when faced with uncertainty results in mimetic pressures (DiMaggio and 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 and 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 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 for showcasing 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, the third hypothesis is stated as:

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

4.3.1.3 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 and Berry, 1999). These can also manifest as indirect pressures through organisational leaders engaging in their professional networks (Damanpour and 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; Sørensen and Torfing, 2011; Provan and Lemaire, 2012). 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, the fourth hypothesis is stated as:

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

4.3.1.4 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: 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: 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, the fifth hypothesis is stated as:

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

Consultants can influence political leadership through explicit sales pitches for adopting AI (Mignerat and 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 and Kuusela, 2019). Hence, the next two hypotheses are stated as:

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

H5b: Consultant pressures 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 and Oldfield, 2001). Consulting firms are associated with the diffusion of similar business practices and models through developing solutions using standardised templates (DiMaggio and 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 and Kuusela, 2019). Thus, consultants act as institutional carriers of solutions highlighting their role in providing instrumental rationality (Scott, 2013). Hence, the eighth hypothesis is stated as:

H6: Consultant pressures 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 and 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). Hence, the last hypothesis is stated as:

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

4.3.2 Operationalisation of variables

To test the hypothesised model (Figure 4.1), scales are adapted from the literature for five constructs: vertical coercive pressures, service coercive pressures, normative pressures, mimetic pressures, consultant pressures, and perceived AI benefits. 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 E provides a summary of the items used for each construct.

For the measurement of the dependent construct, perceived AI benefits, 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 ask 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 meetings 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; Walker, 2006; Korac et al., 2017). 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[12] is coded as non-adopters, piloting, and adopters. Sensemaking is expected to evolve as adoption and implementation progresses and thus, this control accounts for the temporality. The level of government (federal, provincial, municipal) is used to control for fixed effects.

4.3.3 Data

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 are at different stages of adoption and provide 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

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[12] 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.

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[13], LinkedIn, and emails gathered from open government directories. The data collection was conducted in April – June 2022 in two waves[14]. 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 4.1 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[15]. 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).

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

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

[15] 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 of greater than 10,000. At least one informant at each of these organisations was targeted.

Table 4.1. Respondent sample demographic

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%

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, variance on several variables and between complete and incomplete variables were analysed and no significant response bias was found. The two waves of responses were also analysed and no significant difference was found. Finally, the duration of the response was analysed and no significant difference was found.

4.3.4 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 (Ashok et al., 2016; Hair et al., 2016). This chapter is testing a model that explains sensemaking in a novel context of AI in public administration. In addition, the chapter 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 estimates are reliable 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 Jr et al., 2021).

4.3.4.1 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 4.2 shows the results summary.

Table 4.2. 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 (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

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 AI benefits (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 than cross-loadings with other constructs (Appendix F – Table 7.1). The Fornell-Larcker criterion analysis (Appendix F – Table 7.2) 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 F – Tables 7.3 and 7.4). 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.

4.3.4.2 Structural Model

Table 4.3 shows the VIF and path coefficients. The results of the structural model analysis in SEMinR are shown in Figure 4.2.

Table 4.3. VIF and path coefficients

	Standardised coefficients	**T Stat.**	**VIF**	**Significance**
Service coercive pressures -> Perceived AI benefits	0.208	2.657	1.282	p<.01
Vertical coercive pressures -> Perceived AI benefits	0.017	0.222	1.387	n.s.
Mimetic pressures -> Perceived AI benefits	0.066	0.831	1.653	n.s.
Normative pressures -> Perceived AI benefits	0.060	0.947	1.227	n.s.
Consultant pressures -> Service coercive pressures	0.129	2.053	-	p<.05
Consultant pressures -> Vertical coercive pressures	0.320	5.512	-	p<.001
Consultant pressures -> Mimetic pressures	0.323	5.404	-	p<.001
Consultant pressures -> Normative pressures	0.290	4.645	-	p<.001
Consultant pressures -> Perceived AI benefits	0.042	0.641	1.271	n.s.
small -> Perceived AI benefits	-0.155	-2.184	1.239	p<.05
medium -> Perceived AI benefits	-0.142	-2.449	1.14	p<.05
large -> Perceived AI benefits	-0.120	-2.048	1.078	p<.05
adopters -> Perceived AI benefits	0.129	2.460	1.154	p<.05
pilot -> Perceived AI benefits	0.019	0.327	1.191	n.s.
federal -> Perceived AI benefits	0.065	0.723	2.308	n.s.
provincial -> Perceived AI benefits	-0.044	-0.522	2.096	n.s.

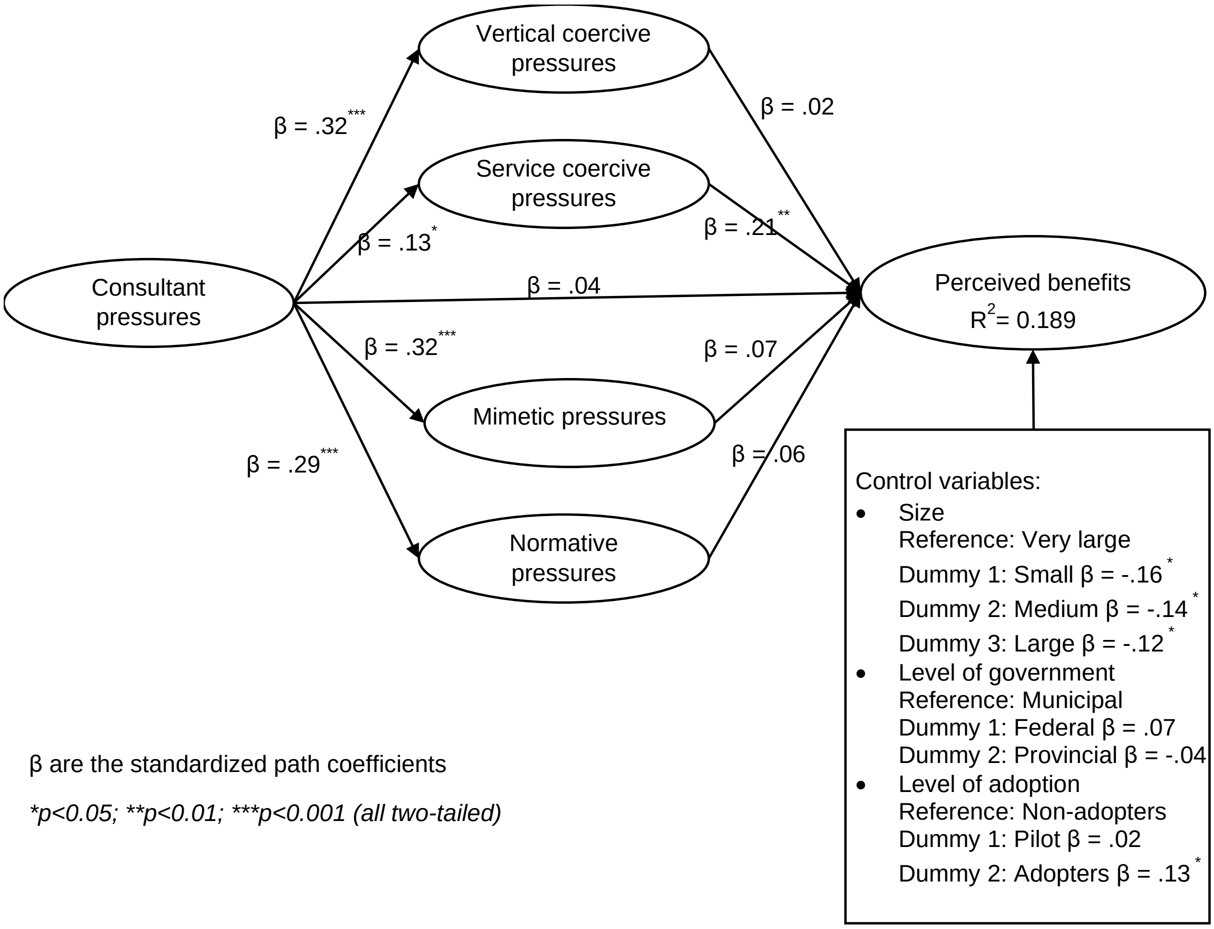

Figure 4.2. Model results

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 4.3). 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 4.3).

Table 4.4 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 AI benefits ($\beta = 0.208$, $t = 2.657$, $p < 0.01$); 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 is non-significant and the effect of both consultant pressures on service coercive pressure and service coercive pressure on perceived AI benefits is significant, the effect of consultant pressures on perceived AI benefits is fully mediated by service coercive pressures (Hair et al., 2016). The total effect of consultant pressures on perceived AI benefits 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 perceived AI benefits when compared to organisations of other sizes. The level of the government does not affect perceived AI benefits. And organisations that identify as adopters have a positive effect on perceived AI benefits when compared to non-adopters. However, there is no significant difference between non-adopters and those piloting AI applications.

Table 4.4. Results of hypotheses tests

Research hypotheses	**Supported?**
H1a: Vertical coercive pressures affect perceived benefits of AI use within the public administration.	Insignificant
H1b: Service coercive pressures affect perceived benefits of AI use within the public administration.	Yes
H2: Mimetic pressures affect perceived benefits of AI use within the public administration.	Insignificant
H3: Normative pressures affect perceived benefits of AI use within the public administration.	Insignificant
H4: Consultant pressures affect perceived benefits of AI use within the public administration.	Insignificant direct effect Fully mediated
H5a: Consultant pressures affect vertical coercive pressures for using AI within the public administration.	Yes
H5b: Consultant pressures affect service coercive pressures for using AI within the public administration.	Yes

Research hypotheses	Supported?
H6: Consultant pressures affect mimetic pressures for using AI within the public administration.	Yes
H7: Consultant pressures affect normative pressures for using AI within the public administration.	Yes

The structural model explains 18.89% of the variance in perceived AI benefits (R^2=0.1889). To investigate the out-of-sample predictive power of the model, $PLS_{predict}$ procedure was used with 10 folds, 10 repetitions, and a direct antecedent (predict_EA) approach (Hair Jr 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 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 F – Table 7.5). Thus, the model is assessed to have medium predictive power (Hair Jr 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 F – Table 7.6). 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 perceived AI benefits. The primary mechanism for this effect is through service coercive pressures. Vertical coercive pressures are found to be insignificant contrary to the literature that suggests a strong effect of such pressures on e-government adoption (Mergel, 2018; Walker et al., 2011; Desouza et al., 2020; Walker, 2006; Korac et al., 2017). Furthermore, literature suggests mimetic and normative pressures are context dependent (Desouza, 2014; Korac et al., 2017; Damanpour and Schneider, 2006; Walker, 2006; Hong et al., 2022; Walker et al., 2011; Berry and Berry, 1999). These are found to be insignificant in the current context of AI and public administration. The results do show a strong effect of consultants in generating all types of institutional pressures. However, the effect on perceived AI benefits is primarily indirect through service coercive pressures. In the qualitative study, the underlying mechanisms are explored and meta-inferences are deduced that explain the weak effect of institutional pressures and a lack of support for four hypotheses.

4.4 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 G. In the second part of the interview, organisational capabilities required to enable AI adoption were explored. These are further discussed in Chapter 5.

The group interviews provide the opportunity for two or three participants to interact in response to the questions posed by the interviewer (Gibbs, 2012). Thus, the data from group interviews is socially constructed through comparing and sharing individual narratives and viewpoints (Morgan et al., 2016). This allows differences and similarities in the experience of the phenomenon to become evident and provide insights into alternative explanations (Morgan et al., 2013). The triangulation of the data from individual and group interviews provides a more thorough explanation of a complex phenomenon and enhances the trustworthiness of the findings (Lambert and Loiselle, 2008). Since this study is situated in the social constructivist perspective (as discussed in Chapter 1, Section 1.3), group interviews enabled showcasing credibility of the findings through member-checking the themes generated from the individual interviews in a group interview format (Lincoln and Guba, 1985).

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 mins, the first part relevant to this chapter ranged from 30-50% of the interview. Table 4.5 shows the participant profiles and the length of the interviews.

Table 4.5. 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 and Chief Privacy Officer	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

Interview	Position	Gender	Level of the government / industry	Length of the interview (in min)
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

The interviews were audio recorded with consent, transcribed, and analysed in NVivo. A research diary was maintained capturing pre- and post-interview reflections. Template analysis was used for conducting a thematic analysis of the data (King, 2004). An a priori template was developed based on the results of the quantitative study and theory (Appendix H – Table 7.7). Each interview was coded iteratively line-by-line to retain interviewees' voices and viewpoints (Fereday and Muir-Cochrane, 2006). For the group interviews, special attention was paid to similarities and differences, the flow of discussions and dyadic interactions on specific themes, and the status between the participants (Lambert and Loiselle, 2008).

The coding was conducted in five steps. First, five diverse individual 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 and 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. Member-checking was conducted by using this template in the next set of interviews as well as conducting group interviews. The same coding process was repeated for the next two sets of five interviews, including transcripts from both single and group 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 H – Table 7.8. 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.

4.4.1 Relationship between institutional pressures and perceived AI benefits

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

4.4.1.1 Vertical coercive pressures

The quantitative study did not find support for vertical coercive pressures affecting perceived AI benefits (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.

4.4.1.2 Service coercive pressures

The quantitative study finds support for service coercive pressures having a significant positive effect on perceived AI benefits (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)*

4.4.1.3 Mimetic pressures

The quantitative study did not find support for mimetic pressures significantly affecting perceived AI benefits (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)*

4.4.1.4 Normative pressures

The quantitative study did not find support for normative pressures significantly affecting perceived AI benefits (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.

4.4.1.5 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 perceived AI benefits (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 perceived benefits 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 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.

4.4.2 Perceived AI benefits

The perceived AI benefits 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 AI benefits are on a continuum and evolve through various stages of AI adoption as further discussed under sensemaking mechanisms in section 4.4.3.

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 pilots 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:

"… 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)

4.4.3 Sensemaking mechanisms

The conceptual model developed from the qualitative analysis showcasing the underlying sensemaking mechanisms is shown in Figure 4.3.

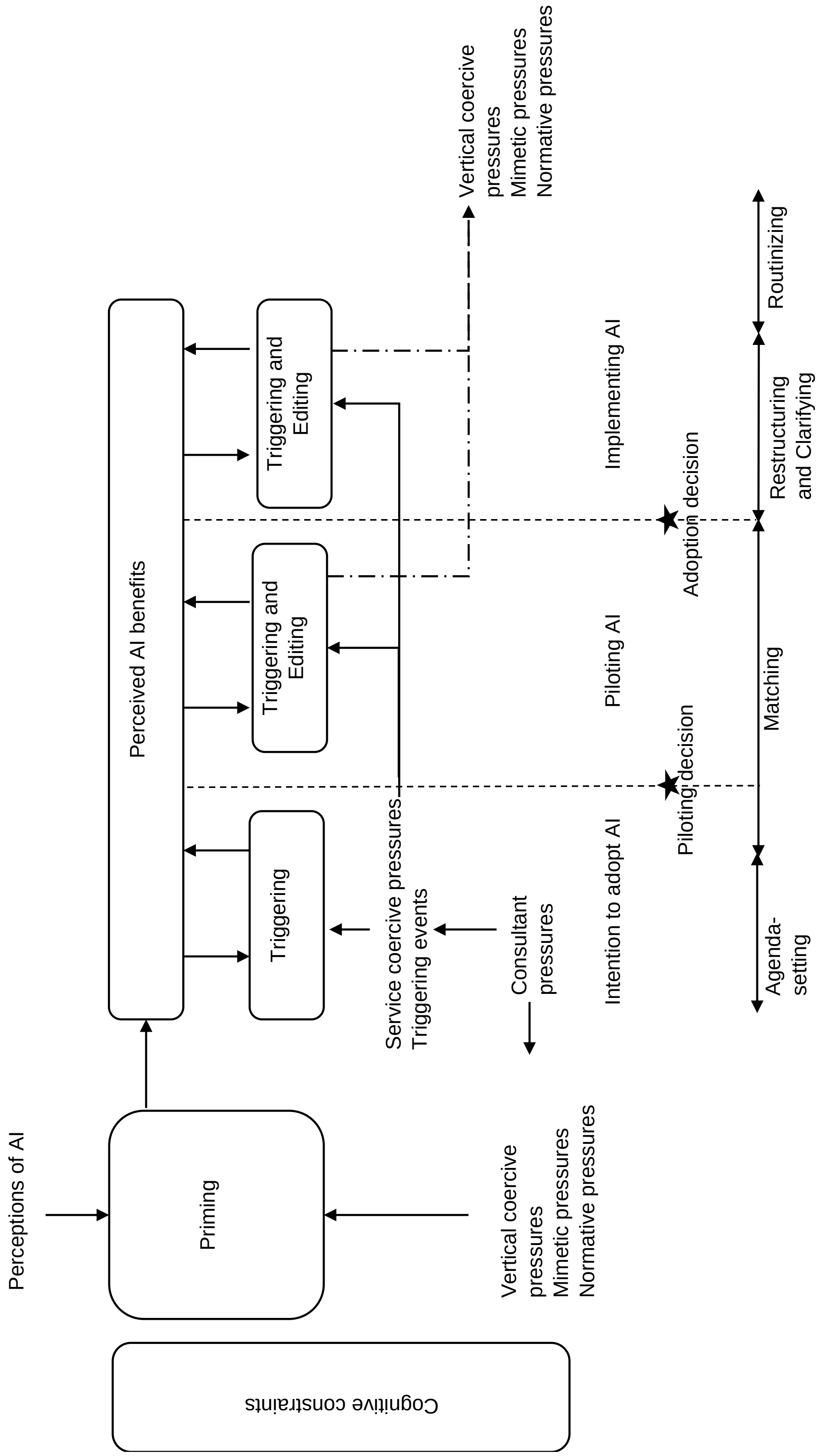

Figure 4.3. Perceived AI benefits sensemaking mechanisms
(authors' conceptualisation)

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.

4.4.3.1 Cognitive constraints

The effect of institutions on sensemaking is widely discussed in the literature in terms of "internalized cognitive constraint" (Weber and Glynn, 2006: 1640). These constraints are characterised by taken-for-granted assumptions and impede decision options that are not aligned with institutional or cultural norms (Barley and Tolbert, 1997). Such cognitive constraints were discussed as a global theme characterised by overall boundaries that constrain how AI can be implemented and used. Cognitive constraints encompass internalised institutional roles, structures, and values. 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, 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 adapting 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 constraints 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)*

4.4.3.2 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.

4.4.3.2.1 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.

4.4.3.2.2 Vertical coercive, mimetic, normative, and consultant pressures

Vertical coercive, mimetic, normative, and consultant pressures are discussed under section 4.4.1. These pressures serve as situational context providing cues towards future action formation. These cues include awareness of peer successes and industry trends and favourable narratives created by the consultants. They also provide cues in the form of political mandates. The cumulative effect of these extracted cues leads to situational framing and priming the organisation that guides decision making once sensemaking is triggered through specific events as discussed in the next subsection.

4.4.3.3 Triggering

Sensemaking can be triggered by service demands and events that create contradictions and compels 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 puts 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)

4.4.3.4 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 seminar and conferences showcasing the pilot and its expected benefits generates 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 AI benefits determine the corresponding action of whether the AI solution needs more exploration and testing, is operationalised, 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.

4.5 Discussion

The goal of this chapter was to identify factors that affect perceived AI benefits within the public administration and explain how they operate. The results of the quantitative study show a significant effect of service coercive pressures on perceived AI benefits 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 AI benefits 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 effects on perceived AI benefits 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 “organising vision” of AI as it relates to public administration use (Swanson and Ramiller, 2004: 556). However, the organising vision is not sufficient to determine the perceived benefits of AI 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 perceived AI benefits 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 the diffusion of innovation (DOI)’s agenda-setting and matching stages of the innovation process (Rogers, 2003). 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 organising 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 leading 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 AI benefits 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 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 results also reveal that perceived AI benefits 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 AI benefits 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 into any direct effect on the perceived benefits of AI unless associated with a value proposition that is site-specific during the triggering or editing stages.

Below the theoretical and managerial implications of the results are summarised and limitations and future research opportunities are identified.

4.5.1 Theoretical implications

The theoretical implications of this chapter 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 results provide empirical support for these propositions. The results illustrate that cognitive constraints are mere boundary conditions and priming, triggering, and editing are the key contextual mechanisms that link institutions to sensemaking. Furthermore, the chapter extends Weber and Glynn's (2006) conceptualisation by developing a processual model that encompasses spatial and temporal dimensions. The results 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, the results illustrate which sensemaking mechanism is active at what 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 results also illustrate 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, the chapter also forwards 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 and Ashok, 2023a). In the Canadian context, this chapter 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, it can be deduced that in the earlier stages of AI adoption, the demand pull is the major driver of adoption than the technology push.

4.5.2 Managerial implications

The chapter 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.

4.5.3 Limitations and future research

The chapter 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 ML and NLP, thus data-centric approaches to AI. Future research exploring the adoption phenomenon of other AI technologies, such as robotics and computer vision, 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.

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. The chapter 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 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.

4.6 Conclusions

This chapter'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 AI benefits. Using an explanatory mixed-methods 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 perceived AI benefits. 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, meta-inferences of the two studies identify three primary sensemaking mechanisms of priming, triggering, and editing. These are mapped to the innovation decision process providing a spatial and temporal view of the AI adoption process. The chapter extends the theory by providing a processual model of sensemaking mechanisms linking the macro-institutional environment to micro-level sensemaking. As well as the chapter provides empirical evidence to suggest earlier stages of AI adoption are driven by demand pull rather than technology push.

5 Paper 4: Developing organisational and technological readiness to enable AI adoption: A mixed-methods study in Canadian public administration

This chapter is based on: MADAN, R and ASHOK, M (2023) Developing organisational and technological readiness to enable AI adoption: A mixed-methods study in Canadian public administration [Manuscript submitted for publication].

5.1 Introduction

The economic and political climate expects public administration to do more with less. Public administration needs to meet varied stakeholder demands, manage societal problems, and deliver public services at par with the private sector (Moore and Hartley, 2008; Hartley et al., 2013). Technology is ubiquitous in every aspect of our lives and public administration is no exception. The datafication of today's society and great strides in information and communication technologies provide a fertile environment for the adoption of Artificial Intelligence (AI) to help alleviate such challenges (Madan and Ashok, 2023c). AI provides immense benefits by automating administrative functions, personalising public services, predicting risk, managing resource allocations, and strengthening trust in public bodies (Madan and Ashok, 2023a). However, AI is also associated with many ethical challenges distinct from previous technology implementations (Ashok et al., 2022). Thus, the proliferation of AI necessitates new leadership styles, work practices, and technological maturity (Gil-Garcia et al., 2018). The resources and capabilities necessary to adopt emerging technologies such as AI are a prime area of concern for public administration leaders (Government of Canada, 2022b).

AI adoption is characterised by several unique challenges such as data quality and accessibility, technical debt, governance, legal requirements, scalability, etc. (Baier et al., 2019). Public administration needs to increase its maturity in both technological and organisational domains. Technology and organisational factors are well established in the literature as enabling e-government (Dwivedi et al., 2012). There is a growing body of literature on capabilities for deploying AI and generating value from its use (Weber et al., 2022; Mikalef et al., 2023; Sjödin et al., 2021). However, the literature lacks an understanding of how organisational and technological dimensions interact to form these capabilities in the first place. Should managers pursue a strategy for building in-house expertise and encouraging innovation? Or should they fast-track technological maturity through external expertise? Against this backdrop, the research questions for this chapter are:

RQ5.1: What resources and capabilities enable AI adoption within the public administration?

RQ5.2: How are the capabilities that enable AI adoption within the public administration developed?

The scope of the research is limited to two specific technology clusters: machine learning (ML) and natural language processing (NLP)[16]. The context for this research is public administration.

The chapter draws on the resource-based view (RBV) of the firms to develop two new AI readiness constructs, organisational AI readiness and technological AI readiness. Furthermore, the chapter demonstrates how the interactions between these two dimensions lead to four capability development paths. The chapter contributes to the RBV by developing a novel model of AI capability development. As well as develop several practitioner recommendations for AI adoption.

The chapter is organised as follows. First, a literature review of public organisations and RBV is discussed as the theoretical framework for this research. This is followed by the development of the hypotheses and discussion of the mixed-methods research design, the quantitative study testing the hypotheses, and the qualitative study developing an AI capability development model. Finally, the discussion section provides meta-inferences of the two studies, contributions, and limitations.

5.2 Literature Review

This chapter draws on two disciplines, public organisational theory and RBV.

5.2.1 Public organisations

Public organisations can be viewed from two perspectives, instrumental and institutional (Christensen et al., 2007). The institutional perspective studies the role of the institutional environment in determining strategic choices (DiMaggio and Powell, 1983). Weber's ideal type bureaucracy has been the dominant public organisational structure aimed at providing stable and reliable public services (Parker, 2000). The contemporary sentiment of a flawed bureaucracy model leading to red tape and inefficiency is a result of decades of political rhetoric promoting market-based mechanisms in public organisations under the umbrella of new public management (NPM) reforms (Kamarck, 2004). With mixed results from NPM, post-NPM reforms, such as digital-era governance (DEG) and public value management (PVM), aimed to restore the public sector ethos and highlight the central role of technology (Dunleavy et al., 2005). The implementation of these reforms and the persistence of the historical context

[16] For brevity, the term AI is used to denote both technologies and discussed separately when variations are relevant.

have led to a mix of state, market, and network governance approaches that serve as the institutional environment for public administration (Lindquist, 2022).

On the other hand, the instrumental perspective advocates rational managerial decisions for achieving efficiency and effectiveness (Christensen et al., 2007). Oliver (1997) argues institutionalism and rational choice perspectives are complimentary. The institutional environment affects resource selection based on legitimacy and conformity goals at the political level. However, resource configuration decisions are driven by managerial choices. Research has shown the institutional environment significantly impacts goal setting and limits strategic choices, but managerial decisions are significant in resource allocation as it relates to technology adoption (Zheng et al., 2013; Dubey et al., 2019).

Chapter 4 finds in the early stages of AI adoption within the public administration, service demands rather than institutional pressures are significant in forming intentions to adopt AI. The chapter follows this thread to argue even though the institutional environment guides funding and goal setting, the AI adoption phenomenon in public administration is driven by an instrumental perspective. Thus, the hypotheses are based on the RBV discussed in the next section.

5.2.2 Resource-based view (RBV)

The RBV is widely used in organisational research to explain firm outcomes as a function of its resources (Lockett et al., 2009). RBV has also been used in public organisations to explain higher-performing organisations, open government data capacity, and e-government adoption (Zhao and Fan, 2018; Andrews et al., 2016; Zheng et al., 2013; Chan et al., 2011; Pablo et al., 2007).

Notwithstanding its universal appeal and empirical support (Newbert, 2007; Liang et al., 2010), RBV has been critiqued for ambiguity in resource definition (Kraaijenbrink et al., 2010). In the seminal paper, Barney (1991) provides an all-encompassing definition that includes both tangible and intangible resources. Another school of thought argues for a distinction between resources and capabilities. Resources, as assets or inputs to production, are not sufficient for superior performance, the deployment capabilities drive firm outcomes (Andrews et al., 2016). In a technology context, organisational capabilities are needed to deploy and generate value from IT assets (Mikalef et al., 2023). Liang et al. (2010) show an indirect-effect model with capabilities as mediators have a higher explanatory power than a direct-effect model of resources. RBV can provide a higher explanatory power when resources and capabilities are viewed separately (Kraaijenbrink et al., 2010). This latter perspective is adopted in this chapter considering resources and capabilities as distinct constructs.

Drawing on Moore's (1995) strategic triangle and adopting an RBV perspective, the public manager’s role is twofold. First, sense changes in the political realm and citizens’ needs to determine public value goals. Second, determine and implement optimal resource configurations to deliver on these public value goals. Organisation and technological readiness enable how technology, and specifically AI, is explored, deployed, and used to meet these goals.

The quantitative study is grounded in the instrumental perspective and RBV to test how organisational and technological readiness enables AI adoption. The qualitative study then reveals the underlying mechanisms of capability development.

5.3 Quantitative Study

Drawing on the literature review, organisational and technological AI readiness are hypothesised as the determinants of AI adoption. Two dependent variables are used to test the adoption of ML and NLP. Figure 5.1 shows the conceptual model and the hypotheses.

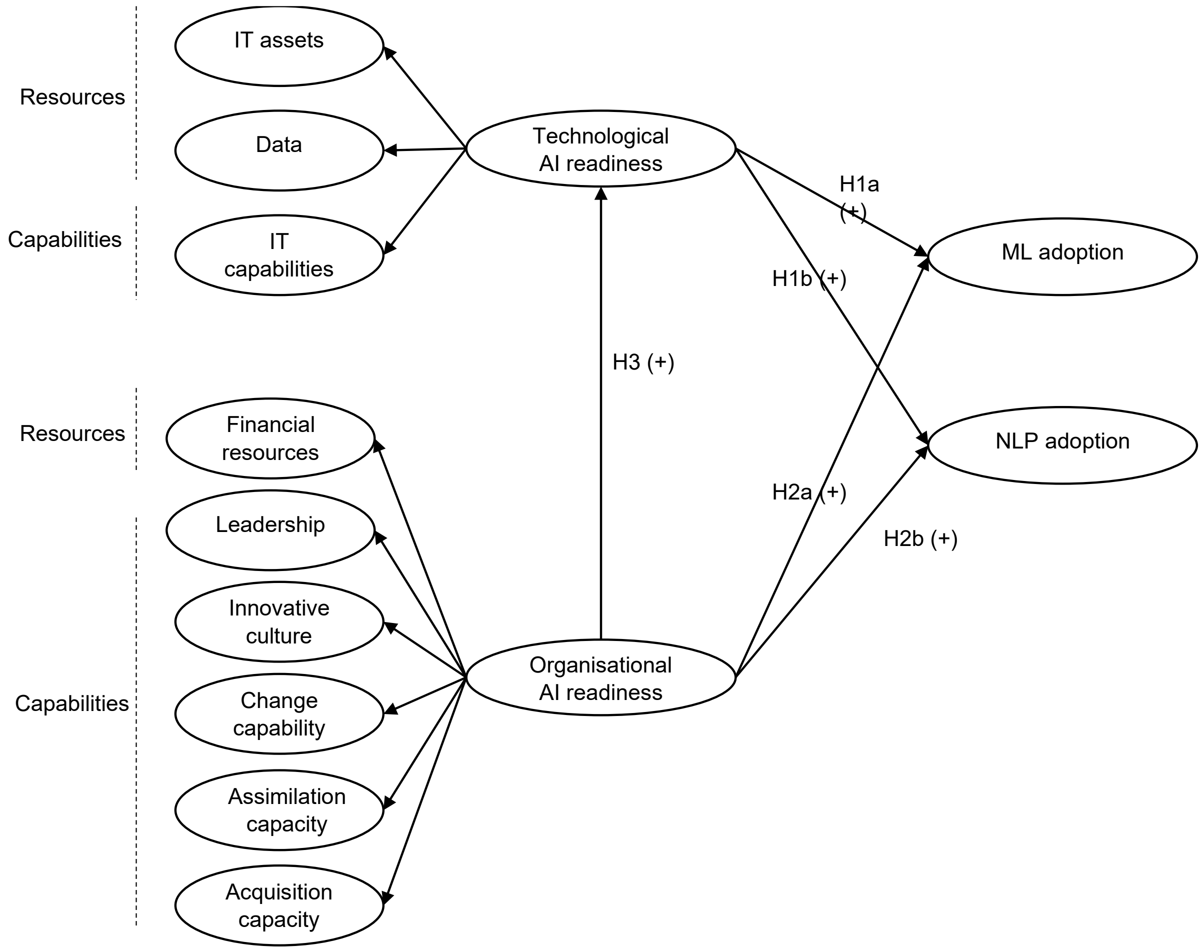

Figure 5.1. Conceptual model of determinants of AI adoption

5.3.1 Hypotheses

Chapter 3 identifies organisational and technological determinants of AI adoption within the public administration. Building on the chapter and informed by public sector innovation and e-government studies, this chapter identifies innovative culture, leadership, inertial mitigators – funding and change capabilities, and absorptive capacity, as reflective of organisational AI readiness. Furthermore, the chapter identifies data, IT assets, and IT capabilities as reflective of technological AI readiness. These are discussed below.

5.3.1.1 Technological AI readiness

Building on Nguyen et al.'s (2019) definition of digital readiness, technological AI readiness is defined as the degree of maturity in technological resources and capabilities to enable the adoption of AI.

5.3.1.1.1 IT Assets

The maturity and robustness of existing technological infrastructure serve as the facilitating conditions for technology adoption (Aboelmaged, 2014). The technological infrastructure required to pilot and operationalise AI is a critical component of technological readiness and a determinant for AI adoption decisions (Madan and Ashok, 2023c).

The success of data-driven techniques, such as deep learning, requires the use of large training data sets and complex models (Mayer and Jacobsen, 2020). The infrastructure needed for this scale of training needs to be distributed with multiple graphics processing units and efficient networking architecture that enables high throughput of data batches (Zhang et al., 2017). Cloud computing is a ubiquitous choice that provides modularity, security, and scalability (Madan and Ashok, 2023a). Cloud infrastructure can also accommodate fluctuations in capacity as applications mature from pilot to operational (Mikalef and Gupta, 2021).

5.3.1.1.2 Data

Data is the essential component of AI technologies used to train the models and generate predictions within the acceptable error rate. The quality of data used for training AI models is paramount for developing responsible and non-biased AI applications (Madan and Ashok, 2023a). In addition to accuracy, data quality dimensions also include completeness and consistency (Taleb et al., 2016).

Data challenges often enumerated by governmental agencies include data quality, managing unstructured data, integration from multiple systems, accessibility, security, and data sharing (Zuiderwijk et al., 2021; Rogge et al., 2017). Data needs to be in sufficient quantity and quality (Weber et al., 2022). The data can be structured, semi-structured, or unstructured and each poses its unique challenges (Sidi et al., 2012). Public administration generally has vast swathes of administrative data (Madan and Ashok, 2023c). In addition, external data from other agencies can enable the development of novel models and deeper insights into policy and service delivery. Accessibility of this data is of utmost importance to be able to extract value and is facilitated by data governance policies granting data scientists authorised access within and across agencies (Jöhnk et al., 2021).

5.3.1.1.3 IT capability

To develop and maintain AI solutions, data management capabilities are required with skills in data science, programming, databases, and keeping up to date on the latest developments in AI research (Harrison et al., 2019). As well as, human resources with IT skills in deploying AI solutions and managing related IT assets (Madan and Ashok, 2023a). These capabilities can be supported by either in-house expertise or through an ecosystem of technology consultants and academic institutes (Alexopoulos et al., 2019; Desouza et al., 2020; Wirtz and Müller, 2019).

IT capabilities have been shown as a significant antecedent to technology adoption (Garrison et al., 2015; Bag et al., 2021; Aboelmaged, 2014). The lack of technical skills in terms of limited staff knowledge, in-house talent, and access to AI specialists has been recognised as a major challenge for AI adoption (Medaglia et al., 2021; Zuiderwijk et al., 2021). Technical capabilities are equally important as technological assets and may make a difference between the success and failure of AI implementations (Yu et al., 2023; Weber et al., 2022).

Hence, the chapter argues, technological AI readiness, reflected in IT assets, data, and IT capabilities, is an important determinant of AI adoption and states our first set of hypotheses as:

H1a: Technological AI readiness has a positive effect on ML adoption.

H1b: Technological AI readiness has a positive effect on NLP adoption.

5.3.1.2 Organisational AI readiness

Organisational AI readiness is defined as the degree of maturity in organisational innovative resources and capabilities that enable the adoption of AI (Weiner, 2009).

5.3.1.2.1 Financial resources

Public administration is dependent on central ministries for resources. The innovation portfolio of public administration is determined by political mandates. The availability of financial resources and incentives for adopting new technologies is a critical antecedent of AI adoption (Madan and Ashok, 2023a). AI needs experimentation and piloting to determine its fitness for the specific problem domain (Desouza et al., 2020). With service demands exceeding available resources, dedicated resources to support experimentation in emerging technologies are critical for public administration to adopt AI (Jöhnk et al., 2021). In addition, digital leadership requires significant investments in technological and human resources to be able to adopt AI. Thus, financial resources to support innovation and long-term investments in technological readiness are required as a precursor for AI adoption.

5.3.1.2.2 Change capability

Public organisations are characterised by a strong inertial force through status quo bias and resistance to changing deeply entrenched processes that resist innovation (Ashok et al., 2021; Taylor and Wright, 2004; Pencheva et al., 2020). Novelty and implementation are the two key characteristics of innovation and inherently involve change (Gault, 2018). For an innovation to be successful, change management capabilities are essential to overcome the inertial force. The resistance to technological innovation, and in particular AI, rests in the fear of job displacements and loss of personal fiefdoms (Fountaine et al., 2019). Wade and Hulland (2004) identify change management as a critical component needed to integrate external environment responsiveness with internal capabilities. Change management capabilities are essential to successfully adopt and operationalise AI at scale (Jöhnk et al., 2021).

5.3.1.2.3 Leadership

Transformational leadership is considered critical for spearheading innovation through creating and championing an inspiring vision (Wright and Pandey, 2010). Transformational leaders encourage employees to experiment and explore novel ways of working (Sarros et al., 2011). Research shows a strong relationship between transformational leadership and innovation in the public sector (Kim and Yoon, 2015; Kim and Chang, 2009; Agolla Joseph, 2016; Zhang et al., 2014).

AI adoption is akin to radical innovation resulting in new business processes and job displacements (Wirtz et al., 2019). There are several ethical tensions that need to be planned and managed (Madan and Ashok, 2023a). Public administration associated with risk aversion needs to adopt a higher risk threshold (Chen and Bozeman, 2012). Top management support is essential to signal a willingness to support AI projects, provide resources, and encourage bottom-up innovations (Jöhnk et al., 2021). Transformational leadership that champions new technologies and showcases a digital vision will signal organisational imperatives to experiment and adopt AI (Yu et al., 2023). Klievink et al. (2017) demonstrate internal commitment and vision as components of organisational capabilities for big data adoption in the public sector. Neumann et al. (2022) comparative case study of Swiss public organisations identifies top management support as important at all AI maturity levels.

5.3.1.2.4 Innovative culture

Innovative culture has been identified as an important determinant of public sector innovation and adoption of new technologies (Arundel et al., 2015; Bugge and Bloch, 2016; De Vries et al., 2016; Yu et al., 2023). It is associated with values of risk-taking, responsiveness to opportunities as they arise, and taking individual responsibility (Sarros et al., 2005).

The norms associated with experimentation, creativity, and risk-taking are strongly associated with innovation in the public sector (Damanpour and Schneider, 2006; Borins, 2000). Government structures receptive to innovation and risk-taking are associated with e-government adoption (Reddick, 2009; Holden et al., 2003; Wang and Feeney, 2016).

Pilot testing and experimentation are hallmarks of AI development and require innovative culture (Fatima et al., 2021; Keller et al., 2019). Schedler et al. (2019) identify risk aversion and low incentives for innovation as a barrier to smart government adoption. van Noordt and Misuraca (2020b) identify innovative culture as an antecedent of AI-enabled innovation in the public sector.

5.3.1.2.5 Acquisition and assimilation capacity

The construct of absorptive capacity helps explain a firm's competitive advantage as a function of its ability to sense and exploit emerging technological trends (Cohen and Levinthal, 1989). Zahra and George (2002) explicate four dimensions of absorptive capacity: acquisition, assimilation, transformation, and exploitation. The first two dimensions of acquisition and assimilation play an important role during AI adoption. The acquisition capacity is a function of prior knowledge and investments in e-government that determines the speed, intensity, and direction of external knowledge acquisition (Campion et al., 2020; Kuziemski and Misuraca, 2020). The assimilation capacity enables organisations to evaluate AI benefits within their context and may trigger the development of new capabilities to facilitate adoption (Chatfield and Reddick, 2018; Erkut, 2020).

Hence, in summary, organisational AI readiness, reflected in funding for innovation and new technologies, and innovation capabilities with the elements of transformational leadership, innovative culture, acquisition, and assimilation capacity, is a determinant of AI adoption. Thus, the second set of hypotheses is stated as:

H2a: Organisational AI readiness has a positive effect on ML adoption.

H2b: Organisational AI readiness has a positive effect on NLP adoption.

Wade and Hulland (2004)'s typology consists of outside-in, spanning, and inside-out resources. The inside-out resources are used as a response to outside triggers, and dynamic capabilities facilitated by spanning resources help to build inside-out resources if these are found inappropriate to be able to respond to exogenous factors. From a public administration perspective, acquisition capabilities are argued as outside-in resources; funding and technological resources and capabilities as inside-out resources; and leadership, innovation, and change capabilities as spanning resources. Thus, organisational AI readiness will affect technological AI readiness as a response to external triggers enabled by the absorptive capacity. Hence, the third hypothesis is stated as:

H3: Organisational AI readiness has a positive effect on technological AI readiness.

5.3.2 Operationalisation of variables

To test the hypothesised model, scales were adapted from the literature. The items were measured on a 7-point Likert-like scale with 1 for strongly disagree and 7 for strongly agree. A new scale was developed to measure ML adoption and NLP adoption. The survey instrument was pilot tested (n=34) in Jan-Mar 2022 to assess the quality, reliability, and construct validity; no changes to the scale were required. The unit of analysis is at the organisational level. Appendix I shows the survey instrument.

For the measurement of the two dependent variables, ML adoption and NLP adoption, the respondents were asked to rate their organisational level of adoption. Technological AI readiness is a second-order reflective construct measured using three first-order reflective constructs of IT assets, data, and IT capability. Organisational AI readiness is also a second-order reflective construct measured using six first-order reflective constructs of leadership, innovative culture, financial resources, change capability, assimilation capability, and acquisition capability.

Two organisational factors are included as controls. The literature identifies organisation size is associated with technology adoption and innovation (Damanpour, 1991; Walker, 2006). Large organisations are deemed to have slack resources and higher technical maturity to pursue AI innovations (Yu et al., 2023). 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 government (federal, provincial, municipal) is used to control for fixed effects.

5.3.3 Data

The data for this analysis is based on the same cross-sectional survey discussed in Chapter 4, Section 4.3.3.

Table 5.1 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 277 final usable responses representing a 31% response rate[17]. The sample represents a wide heterogeneous pool of 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.

Table 5.1. Respondent sample demographic

Demographic characteristics		**No. of respondents N=277**	**% of total**
Gender	Male	168	61%
	Female	106	38%
	Other	3	1%
Age	29 and under	18	6%
	30-39	64	23%
	40-49	88	32%
	50-59	83	30%
	60 and above	24	9%
Education	Diploma/ certificate or below	29	11%
	Bachelor's degree	84	30%
	Professional degree	23	8%
	Master's degree	117	42%
	Doctoral degree	24	9%
Position	Executive	20	7%
	Senior Director/Head of Department	22	8%
	Director	34	12%
	Senior Manager	43	16%
	Functional Manager/Project Manager	44	16%
	Team Lead	31	11%
	Consultant/ Advisor	34	12%
	Other (please specify)	49	18%
Level of government	National	151	55%

[17] The population size was determined as all federal government agencies excluding defence; all provincial government ministries and agencies excluding law enforcement and health services; and all towns and cities with a population greater than 10,000.

Demographic characteristics		No. of respondents N=277	% of total
	Provincial	78	28%
	Municipal	48	17%
Organisation size	>50	14	5%
	50-99	16	6%
	100-249	20	7%
	250-499	22	8%
	500-749	15	5%
	750-999	8	3%
	<1000	182	66%

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 37.38% and below the 50% threshold. To check for non-response bias, variance on dependent variables and between complete and incomplete variables was analysed and no significant response bias was found. The two waves of responses were also analysed and no significant difference was found. Finally, the duration of the response was analysed and no significant difference was found.

5.3.4 Analysis

The partial least squares-structural equation modelling (PLS-SEM) is used for analysis using R Studio and SEMinR module. This chapter is testing novel readiness constructs that enable AI adoption in public administration. The current literature is nascent and lacks empirical support on adoption antecedents (Madan and Ashok, 2023a). Thus, being in the initial stages of theory development, PLS-SEM is a suitable method (Hair et al., 2016; Ashok et al., 2016). The aim of maximising the predictor power of endogenous variables also supports the use of PLS-SEM. 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 277 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 Jr et al., 2021).

5.3.4.1 Measurement Model

As our model involves second-order constructs, the measurement model assessment is conducted in two steps. The standard model evaluation criteria are applied to the lower-order constructs followed by assessing loadings and convergent validity, internal consistency reliability, and discriminant validity metrics for the reflective-reflective higher-order constructs (Sarstedt et al., 2019). Two-stage method and mode_A for weights are used for specifying both reflective-reflective second-order constructs in SEMinR (Ray and Danks, 2020).

Table 5.2 shows the results summary for the lower-order constructs. The internal consistency reliability is assessed by examining Composite Reliability (CR) and Cronbach's Alpha (CA). Both CR and CA values are considered satisfactory between 0.70 – 0.95 (Hair et al., 2016). All values lie within this range and the internal consistency reliability of lower-order constructs 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 three construct-to-indicators loadings are below 0.7: AQC→AQC2(0.691), ITA→ITA5 (0.661), and ITD→ITD1 (0.691). These 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 are above the threshold of 0.50 (Hair et al., 2016), the lowest one being 0.57. Thus, the convergent validity of the lower-order constructs is considered acceptable.

Table 5.2. Results summary for lower order reflective constructs in the measurement model

Latent variable	**Indicators**	**Convergent Validity**		**Internal Consistency Reliability**		**Discriminant Validity**
		Loadings	**AVE**	**Composite reliability**	**Cronbach's Alpha**	**HTMT confidence intervals do not include 1**
Leadership (LED)	LED1	0.877	0.720	0.932	0.921	Yes
	LED2	0.878				
	LED3	0.884				

Latent variable	Indicators	Convergent Validity		Internal Consistency Reliability		Discriminant Validity
		Loadings	**AVE**	**Composite reliability**	**Cronbach's Alpha**	**HTMT confidence intervals do not include 1**
	LED4	0.881				
	LED5	0.702				
	LED6	0.853				
Innovative culture (CUL)	CUL1	0.922	0.834	0.906	0.900	Yes
	CUL2	0.926				
	CUL3	0.892				
Financial resources (FIN)	FIN1	0.868	0.792	0.757	0.740	Yes
	FIN2	0.911				
Change capability (CNG)	CNG1	0.874	0.715	0.867	0.867	Yes
	CNG2	0.842				
	CNG3	0.860				
	CNG4	0.805				
Acquisition capability (ACQ)	AQC1	0.754	0.570	0.768	0.753	Yes
	AQC2	0.691				
	AQC3	0.825				
	AQC4	0.744				
Assimilation capability (ASC)	ASC1	0.718	0.734	0.866	0.817	Yes
	ASC2	0.923				
	ASC3	0.914				
IT Assets (ITA)	ITA1	0.777	0.623	0.857	0.847	Yes
	ITA2	0.838				
	ITA3	0.852				
	ITA4	0.804				
	ITA5	0.661				
Data (ITD)	ITD1	0.691	0.648	0.893	0.890	Yes
	ITD2	0.849				
	ITD3	0.842				
	ITD4	0.751				
	ITD5	0.869				
	ITD6	0.815				

Latent variable	Indicators	Convergent Validity		Internal Consistency Reliability		Discriminant Validity
		Loadings	**AVE**	**Composite reliability**	**Cronbach's Alpha**	**HTMT confidence intervals do not include 1**
IT capability (ITC)	ITC1	0.790	0.684	0.876	0.845	Yes
	ITC2	0.706				
	ITC3	0.892				
	ITC4	0.903				

The discriminant validity is 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 than cross-loadings with other constructs (Appendix J – Table 7.9). The Fornell-Larcker criterion analysis (Appendix J – Table 7.10) 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 ratios were lower than the threshold of 0.90 (Hair et al., 2016) and the confidence interval from bootstrapping with 5,000 sub-samples does not include 1 (Appendix J – Tables 7.11 and 7.12). This supports HTMT statistics significantly different from 1. Thus, discriminant validity is established.

The items for lower-order constructs are assessed as a good indicator of their respective constructs and suitable for the second-order construct and outer model analysis.

Table 5.3 shows the results summary for the outer measurement model. For the second-order constructs, the lower-order constructs are interpreted as indicators for their respective second-order construct. The internal consistency reliability is assessed as acceptable with both CR and CA for all constructs being above 0.70. For assessing convergent validity, construct-to-indicator loadings show all but one below 0.70: ORG→ACQ (0.571). The indicator is retained as it is above the lower threshold of 0.40, is supported by theory, and its deletion does not improve internal consistency reliability. In addition, the AVEs for all constructs are above the threshold of 0.50. Thus, convergent validity is established. For assessing discriminant validity, indicator loadings are greater than cross-loadings with other constructs (Appendix J – Table 7.13); Fornell-Larcker criterion analysis shows each of the constructs shares more variance with their indicators than with other constructs (Appendix J – Table 7.14); and, all values of the HTMT ratios were lower than the threshold of 0.90 and bootstrapping with 5,000 sub-samples also does not reveal 1 between the confidence intervals (Appendix J – Tables 7.15 and 7.16). Thus, discriminant validity is established.

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

Table 5.3. Results summary for measurement model analysis

Latent variable	**Indicators**	**Convergent Validity**		**Internal Consistency Reliability**		**Discriminant Validity**
		Loadings	**AVE**	**Composite reliability**	**Cronbach's Alpha**	**HTMT confidence intervals do not include 1**
Organisational AI readiness (ORG)	Leadership (LED)	0.872	0.619	0.883	0.872	Yes
	Innovative culture (CUL)	0.846				
	Financial resources (FIN)	0.722				
	Change capability (CNG)	0.868				
	Acquisition capability (ACQ)	0.571				
	Assimilation capability (ASC)	0.799				
Technological AI readiness (TECH)	IT Assets (ITA)	0.759	0.709	0.810	0.793	Yes
	Data (ITD)	0.880				
	IT capability (ITC)	0.881				

Latent variable	Indicators	Convergent Validity		Internal Consistency Reliability		Discriminant Validity
		Loadings	**AVE**	**Composite reliability**	**Cronbach's Alpha**	**HTMT confidence intervals do not include 1**
ML adoption (MLA)	MLA1	1.000	1.000	1.000	1.000	Yes
NLP adoption (NLPA)	NLPA1	1.000	1.000	1.000	1.000	Yes

5.3.4.2 Structural Model

Table 5.4 shows the VIF and path coefficients. The results of the structural model analysis are shown in Figure 5.2.

Table 5.4. VIF and path coefficients

	Original Est.	T Stat.	VIF	Significance
Organisational AI readiness -> Technological AI readiness	0.675	19.506	-	p<.001
Organisational AI readiness -> ML adoption	-0.095	-1.255	1.991	n.s.
Organisational AI readiness -> NLP adoption	-0.002	-0.021	1.991	n.s.
Technological AI readiness -> ML adoption	0.374	5.193	1.995	p<.001
Technological AI readiness -> NLP adoption	0.286	3.651	1.995	p<.001
small -> ML adoption	-0.211	-3.814	1.208	p<.001
small -> NLP adoption	-0.180	-3.866	1.208	p<.001
medium -> ML adoption	-0.218	-3.778	1.088	p<.001
medium -> NLP adoption	-0.243	-5.023	1.088	p<.001
large -> ML adoption	-0.065	-1.052	1.067	n.s.
large -> NLP adoption	-0.103	-1.704	1.067	p<.100
federal -> ML adoption	0.104	1.386	2.137	n.s.
federal -> NLP adoption	0.277	4.715	2.137	p<.001
provincial -> ML adoption	-0.067	-0.925	1.981	n.s.
provincial -> NLP adoption	0.034	0.582	1.981	n.s.

The collinearity assessment of the predictor constructs is conducted by examining the variance inflation factors (VIF) values. All predictors and controls for both dependent variables were lower than the conservative threshold of 3, the highest one being 2.137 (Table 5.4). 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 5.4).

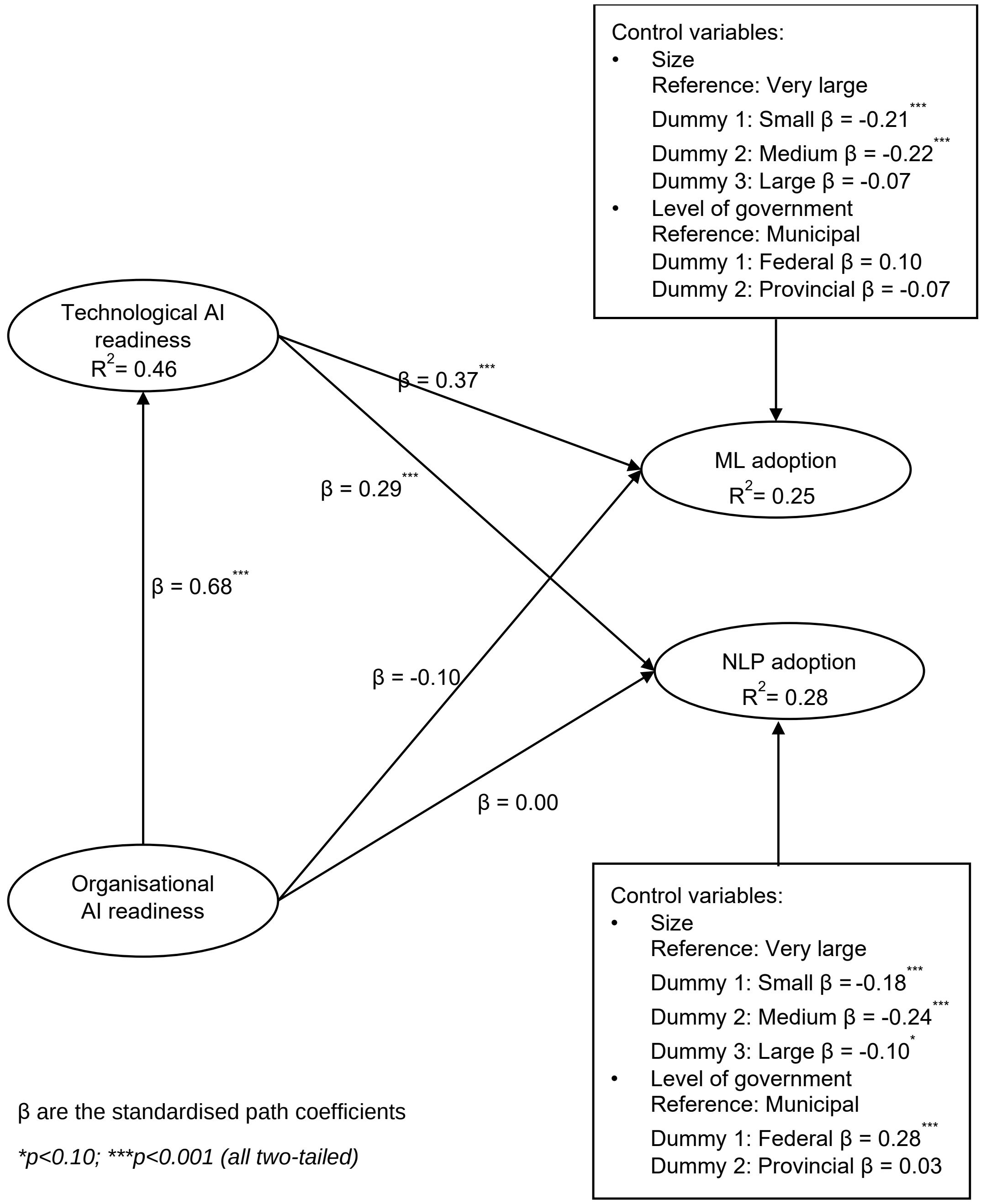

Figure 5.2. Structural model results

Table 5.5 summarises the results of the hypothesis tests, three of the five hypotheses were supported, and two were partially supported. Technological AI readiness has a positively significant effect on both ML adoption ($\beta = 0.375$, $t = 5.193$, $p < 0.001$) and NLP adoption ($\beta = 0.286$, $t = 3.651$, $p < 0.001$), comparing the standardised coefficients the effect is slightly higher on ML adoption than NLP adoption. The effect of organisational AI readiness is not significant on either ML adoption ($\beta = -0.095$, $t = -1.255$, $p > 0.05$) or NLP adoption ($\beta = -0.002$, $t = -0.021$, $p > 0.05$). Organisational AI readiness has a positive significant effect on technological AI readiness ($\beta = 0.675$, $t = 19.506$, $p < 0.001$). Since the direct effect of organisational AI readiness on both dependent variables is non-significant, the effect of organisational AI readiness on ML adoption and NLP adoption is fully mediated by technological AI readiness (Hair et al., 2016). The total effect of organisational AI readiness is significant on both ML adoption ($\beta = 0.157$, $t = 2.781$, $p < 0.01$) and NLP adoption ($\beta = 0.191$, $t = 3.402$, $p < 0.01$).

In terms of organisational size, small and medium size organisations have a negative effect on both ML adoption and NLP adoption when compared to very large organisations; there is no significant difference between large and very large organisations for ML adoption while a weak significant different ($p<0.10$) for NLP adoption. The level of government does not affect ML adoption. For NLP adoption, there is a significant positive effect of the federal government when compared to municipal government and no significant difference between provincial and municipal governments.

There are no major differences between ML adoption and NLP adoption antecedents; a minor difference is observed in terms of the significance of large compared to very large and federal compared to municipal for NLP but not ML adoption.

Table 5.5. Results of hypotheses tests

Research hypotheses	**Supported?**
H1a: Technological AI readiness has a positive effect on ML adoption.	Yes
H1b: Technological AI readiness has a positive effect on NLP adoption.	Yes
H2a: Organisational AI readiness has a positive effect on ML adoption.	Insignificant direct effect Fully mediated
H2b: Organisational AI readiness has a positive effect on NLP adoption.	Insignificant direct effect Fully mediated

H3: Organisational AI readiness has a positive effect on technological AI readiness.	Yes

The model explains 25% of the variance in ML adoption (R^2=0.246) and 28% of the variance in NLP adoption (R^2=0.282) and is deemed to have moderate explanatory power (Hair et al., 2011). The model also explains 46% of the variance in technological AI readiness (R^2=0.455) with a moderate-high explanatory power (Ibid.).

The model was compared with four other models with varying controls and using single dependent variables (Appendix J – Table 7.17). The original model is parsimonious and has the highest predictive power.

5.4 Qualitative Study

The qualitative study is based on the same semi-structured interviews discussed in Chapter 4, Section 4.4 with the exception of one additional one-on-one interview. The part of the interview relevant to this chapter asked for interviewees' opinions on organisational capabilities required for adopting AI and explored the results of the quantitative study. The interview guide is attached in Appendix K.

Chapter 4, Table 4.5 shows the participant profiles and the length of the interviews. This chapter conducted an additional interview as shown in Table 5.6. The interviewee sample consisted of a range of positions at all levels of the government (federal: 41%, provincial: 41%, and municipal: 10%) and industry (8%). 31% of the interviewees were female. 38% of the interviewees also participated in the quantitative study. The length of the interviews ranged from 30 – 170 mins, the section relevant to this chapter is approximately 50% of the interview.

Table 5.6. Interviewee profiles

Interview	Position	Gender	Level of the government / industry	Length of the interview (in min)
I1 – I34	Same as shown in Chapter 4, Table 4.5			
I35	Director	Male	Provincial	30

The coding methodology following template analysis is the same as discussed in Chapter 4, Section 4.4. A priori template was developed using the conceptual model and the results of the quantitative study (Appendix L – Table 7.18). The theoretical saturation for this chapter was achieved at 30 interviews and coding was completed at 35 interviews. The final template is attached in Appendix L – Table 7.19.

The themes of technological and organisational AI readiness are briefly discussed highlighting alignment with the quantitative results. The focus is on a detailed discussion of the results related to the interactions between the constructs and the meta-inferences leading to the development of a novel AI capability development model.

5.4.1 Technological AI readiness

The theme of technological AI readiness includes three sub-themes: data, IT assets, and IT capabilities. These sub-themes are analogous to the first-order items of the reflective construct of technological AI readiness, thus, supporting the measurement model.

5.4.2 Organisational AI readiness

The theme of organisational AI readiness includes seven sub-themes: financial resources, transformational leadership, innovative environment, change capability, acquisition capability, assimilation capability, and workforce acquisition and training. The first six sub-themes are analogous to the first-order items of the reflective construct of organisational AI readiness, thus, supporting the measurement model.

The workforce acquisition and training theme is a new code and is discussed in terms of challenges related to antiquated hiring processes inhibiting the development of data science-specific expertise and the inability to compete with the private sector on salary offerings for attracting new talent. This theme is captured in the following quote:

> *"… our HR policies are not very good … it's hard for us to classify and pay data scientists what they're worth because our classification systems … we're losing out to the private sector in terms of being able to attract … [We do a] terrible job in recruiting data scientists" (I20)*

5.4.3 ML and NLP adoption

The interviewees do not consider any significant difference in terms of resources or capabilities for ML versus NLP adoption, thus, supporting the results of the quantitative analysis. Minor differences in perceptions were discussed. NLP is regarded as more visible, stable, and less threatening in terms of current applications in chatbots, transcription, unstructured data, etc. ML applications need to contend with the negative perceptions of ethical and social issues widely discussed in popular media. The significant positive effect of the Federal government, when compared with municipal, for NLP adoption and not for ML adoption is partly attributed to this perception gap. In addition, the Federal government has been at the frontier of AI adoption developing data strategies and ethical assessment frameworks that are now being used at other governmental levels. This is expressed in the following quote:

> *"… at the Federal level, there is a really good AI and digital strategy coming out. They have done the legwork and I've seen them do the legwork over the last three to five years, like being very intentional about it … So, I would say we [provincial government] are behind in the strategy aspect and we are behind in the implementation aspect" (I3)*

The significant effect of organisational size (very large for NLP and large and very large for ML when compared to other sizes) is attributed to the fact that large organisations have more resources and slack to be able to experiment than seeking funds from central ministries as expressed in this quote:

> *"… there's a bit more success if you funded from within [for innovation] and you don't go cap in hand asking for innovation money" (I3)*

5.4.4 Interaction between Organisation and Technological AI readiness

The resources and capabilities that enable AI adoption are conceptualised across two dimensions of organisational and technological AI readiness as shown in Figure 5.3 and discussed below.

5.4.4.1 Low organisational and low technological AI readiness

Organisations in the low-low quadrant are characterised by first, lacking innovative culture and absorptive capacity that compels them to seek external expertise to help address operational or strategic challenges. And second, lacking internal expertise means the inability to ask the right questions and rely on consultants' analysis. Low maturity on technological assets and data increases reliance on consultants to guide deployments. This is expressed in the following quote:

> *"They didn't have any experts. They didn't have any tools. So, it was much easier to buy something … they didn't really know what questions to ask … [internal] experts will ask too many questions … so they couldn't do it and they didn't have any concerns. They just saw a glossy poster" (I14)*

5.4.4.2 Low organisational and high technological AI readiness

Organisations that are low on organisational AI readiness and high on technological AI readiness have relied on external expertise to acquire appropriate technological artefacts to enable AI adoption. In most cases, such organisations tend to procure AI solutions already embedded in off-the-shelf solutions and rely on technology vendors for customisation and implementation. Interviewees refer to a wild west approach to procuring AI solutions driven by hype rather than strategic problem-solving. This is expressed in the following quotes:

> *"… businesses are looking more to technology. It's the low-hanging fruit at the moment and I think it's ironic in some ways that can quell the real innovation … part of my mandate is to build an innovation management function, but I could tell you that there's a lot less drive for that right now … anything right now it's all just technology side, so we're looking at technical solutions to things" (I12)*

> *"… it feels a bit like the wild west that people, particularly in the procurement space, … are either using AI or procuring AI, but don't have any sort of structures in place … a lack of … central documentation" (I21)*

5.4.4.3 High organisational and low technological AI readiness

Organisations that have high organisational AI readiness but low technological AI readiness are characterised by strong transformational leadership that encourages experimentation and risk-taking. There is an increased focus on building innovative capabilities within the organisation, creating experimental spaces, and gradually increasing data maturity. With higher absorptive capacity, senior leaders are aware of how AI is being piloted and used among their peers. However, they are focused on building internal capability and attracting new talent. The leaders want to encourage bottom-up innovations, both technological and non-technological, to help solve operational and strategic problems. Such themes are expressed in the following quote:

> *"… maturity of systems you would be perhaps shocked and dismayed to see how many things we're doing manually … we've been able to attract … people think [organisation] is cool. And because … we have a startup-type mentality … we have a great deal of innovation in the staff. So, you know right now I'd say we're low tech, high innovative thinking ... aside [from] the technical skills to build systems, I think we need*

> *to have … people who can see the vision of what it is that we're trying to drive and if we can tie them to the results we're hoping to reach …" (I10)*

5.4.4.4 High organisational and high technological AI readiness

Organisations in the high-high quadrant are at the ideal readiness state to be able to adopt AI. They possess sufficient data maturity, and technical skills to scope and evaluate AI for specific business problems and are focused on continuing to build internal AI capabilities. In addition, they possess critical implementation capabilities required to operationalise AI solutions such as agile mentality and project management capabilities. The key concern at this level of maturity is to build trust and confidence in using AI both internally and externally. As well as develop policies and governance on responsible AI development such as a representation of AI ethics and policy experts, AI governance processes, ethical AI development guidelines, policies on risk tolerance from the use of AI, and building mechanisms to resist political pressures generated from hype. These themes are expressed in the following quotes:

> *"… at the end of the day … the moral is really focusing on data maturity, typically building technical capabilities from the beginning with the idea that in the longer run is going to create opportunities for innovation, even if you can't predict what those innovations are going to be. It's really about trying to … build the fundamentals first" (I2)*

5.4.5 AI capability development model

The AI capability development model developed from the qualitative analysis is shown in Figure 5.3. Four distinct capability development paths are identified as a function of maturity on the two dimensions of organisational and technological AI readiness. These are discussed below.

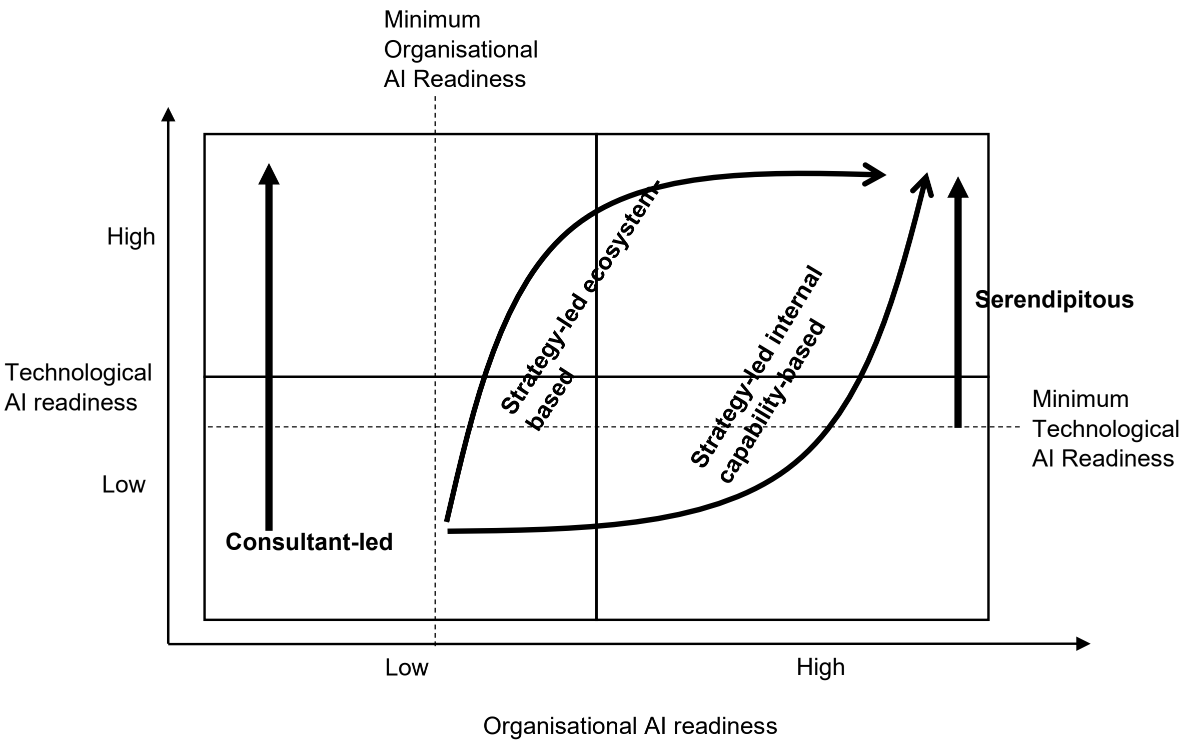

Figure 5.3. AI capability development model
(authors' conceptualisation)

5.4.5.1 Consultant-led

As discussed in the previous section, organisations low on both organisational and technological AI readiness engage external consultants to help address operational and strategic problems. Lacking a digital vision yet aspirations for digital government leadership, senior management tends to follow the hype created by consultants marketing the next big technological solution. The influence of consultants has also been witnessed by several interviewees in previous technological adoptions and is evident from the prevalence of a lucrative government technology sector. This path generally involves high costs and perpetual dependency on consultants. Consultants' motivation is driven by selling the most profitable templated solutions developed in the private sector and generally lacking public administration context. Organisations pursuing this path are less concerned about developing internal capabilities and assume higher technological maturity will lead to higher innovativeness. These themes are expressed in the following quotes:

"… if that expertise [to develop and maintain AI solutions] all sits out in vendors, there's always a little bit of weariness about getting the wool pulled over our eyes" (I7)

> *"… external consultants just don't know enough detail about the internal workings of the department. … a lot of key things they miss … it ends up being more of a waste of time and waste of money … at the end of the day … they [are] … going to try to build something so they can prove value … but it may not necessarily be the right thing … they want to produce a product so that they can justify the cost … they're generally oriented to try to get the next contract … there isn't much incentive … to knowledge transfer, or to basically do the work that government should be doing in the first place, which is building in-house capacity" (I2)*

5.4.5.2 Serendipitous

Organisations high on organisational AI readiness tend to encourage experimentation and bottom-up innovations for solving problems. Once such organisations achieve a minimum level of technological AI readiness, either organically or driven by leadership, employees experiment with AI technologies. This minimum level is characterised by data maturity, in terms of data accessibility, and tools and capabilities for cleaning data and building AI models. These results validate the quantitative results (H3) that organisational AI readiness has a positive effect on technological AI readiness. Through experimentation, once a promising AI solution is demonstrated to show value, it is fast-tracked to operationalisation and in turn necessary technological capabilities are developed. Thus, once a minimum technological AI readiness is achieved, AI adoption becomes serendipitous with a confluence of several factors as expressed in the following quote:

> *"… it seems to be more so like a confluence of factors of the right people on the right time with the right combination with some with the technical skills and the right executive who is willing to support it or ask for it" (I8)*

5.4.5.3 Strategy-led

The strategy-led capability development path can be pursued by organisations with a minimum level of organisational AI readiness that encompasses a strong digital vision and an internal catalyst. Interviewees discussed this catalyst role as a newly hired CIO or CEO who wants to transform and modernise the administration. As well as a leader who is willing to steer high-risk projects and pursue funding. An important component of a strategy-led path is the ability to develop a vision of how AI might be adopted and motivate employees to follow a roadmap. The implementation of this vision can be in the form of developing an ecosystem or a laser focus on developing internal capabilities.

The ecosystem-based strategy for implementing the AI vision is driven by the realisation that AI involves a broad array of skills and not possible for an administrative organisation to develop them internally. Instead, the focus shifts towards utilizing the local ecosystem of private technology companies, consultants, and academic institutions to help solve government problems. This also helps attract new talent to work on government problems. A positive externality of this path is market development attracting new businesses and technology sectors to the jurisdiction. This is expressed in the following quote:

> *".. one of the things that I looked at … very quickly was taking us from last to first when it came to AI … our [local] university … is very well known for its machine learning programme … we have a number of tech startups that are working in the AI space. But the government had done nothing to look at AI and I thought that was quite awful. And so, I met with a couple of people and move forward with doing an RFP … to bring a partnership that would build our AI strategy, as well as looking at responsible AI … so basically, I was the catalyst that brought AI into the Government … I worked with one of the successful proponents [technology vendor] and put together … a proposal to establish a public sector AI lab … it's a way to bring in new graduates as well as undergrads from universities to receive hands-on training and mentorship in AI, as well as an opportunity for the government and municipalities, and not-for-profits, etc., to start bringing their datasets together to see what could be achieved from an AI perspective" (I1)*

The internal capability-based strategy for implementing the AI vision is driven by leaders resolute on building a strong foundation of innovative culture and technological capabilities regardless of time and effort and critical of the technological hype of the moment. This could be partly driven by constraints related to the security clearance of non-governmental employees to access sensitive data, lack of funding to involve consultants or other partners, or a historical context of past failures involving consultants. This development path is a long-term strategy involving several years to develop the right culture and data maturity. Once the minimum technological AI readiness is achieved, AI adoption can be spearheaded though the serendipitous path or an intentional plan to start identifying and experimenting with pilot use cases and demonstrating the value of AI. Consultants might be used to accelerate capability building or support specific project activities. However, the focus remains on forging internal expertise rather than being dependent on consultants to drive digital strategy. This is expressed in the following quotes:

> *"… if we're talking about [capabilities for AI adoption] … going from a core to the outside … core would be data maturity, in-house technical skills, existing infrastructure … you obviously need some infrastructure to be able to work with data and … then you start getting into … innovative culture, transformation leadership … perhaps serving the core" (I2)*

> *"… we started 5-6 years ago with the program … by our … city manager [asking]… is there an opportunity to use AI machine learning within regular operations? … So, we started by building foundational base with resources and technology … the key component on that was how do we reach out to all the operations … and they can come to us with the problems that need … this type of technology to be applied … then we also established … advanced analytics communities of practice" (I24)*

5.5 Discussion

The goal of this chapter was to identify resources and capabilities that enable public administration to adopt AI and explain how those capabilities are developed. The results suggest that technological AI readiness is a necessary condition for AI adoption. Organisational AI readiness, even though an important determinant of technological AI readiness, is not a sufficient condition for AI adoption. These results are further validated through a novel AI capability development model.

The model identifies a minimum technological AI readiness is necessary to experiment and pilot AI supporting hypotheses H1a and H1b. Even when acquiring off-the-shelf AI applications, such as live transcriptions, virtual agents, etc., this minimum level is reflected in capabilities to develop requirements and evaluate vendor solutions for more advanced AI adoption.

Consultants have been shown to influence institutional pressures for AI adoption in public administration (Madan and Ashok, 2023c). Administrative leaders might be influenced by aggressive lobbying by technology vendors and lacking internal expertise unable to test consultants' claims. A consultant-led capability development tends to focus on technological AI readiness and enable AI adoption but will keep the organisation dependent on consultants.

When driven by a leader championing a digital vision, two different strategy-led capability development paths might be pursued. In the ecosystem-based path, the AI strategy is focused on spearheading technological AI readiness through building partnerships with technology vendors and educational institutions. This strategy ensures a constant stream of new talent while staying up-to-date on new developments in the fast-evolving AI space. The external expertise helps fast-track the development of technological AI readiness. This strategy mitigates over-reliance on external expertise and enables building internal capabilities.

The existence of consultant and ecosystem-based paths explains the non-significant effect of organisational AI readiness on AI adoption (H2a and H2b). Organisations circumvent organisational AI readiness in a bid to adopt AI through maturing technological capabilities.

In the internal capability-based path, the digital vision is focused on building the organisational AI readiness organically through innovative culture and achieving data maturity. As this target is reached, adoption could organically be triggered through the serendipitous path or an intentional roadmap. These results also explain the positive significant effect of organisational AI readiness on technological AI readiness (H3). In either case, technological assets to operationalise AI solutions are acquired when potential AI solutions are identified. Thus, a major drawback of this path is the long timeframe towards adoption. The use of consultants can help accelerate this process.

Below the theoretical and managerial implications of our results are summarised and limitations and future research opportunities are discussed.

5.5.1 Theoretical implications

The theoretical contributions of this chapter are in two areas, the RBV and the technology adoption literature.

The RBV has been critiqued for black-box explanations of resource effects on firm outcomes with a lack of resource demarcation (Kraaijenbrink et al., 2010). This chapter showcases how different resource typologies and their interactions can provide novel insights and rich explanations of the phenomena. The study enumerates how different configurations of two resource dimensions (organisation and technological AI readiness) and managerial decisions can lead to four distinct capability development paths. The chapter provides empirical support to the instrumental perspective of public organisations that managerial decisions drive adoption strategy once triggered by institutional pressures. Hence, The chapter forwards a preliminary outline of a theory of capability development with regard to AI adoption grounded in RBV.

The chapter adds to the increasing body of literature on AI capabilities and readiness (Uren and Edwards, 2023; Mikalef et al., 2021; Weber et al., 2022). The construct of AI capability used in literature explains leveraging tangible, intangible, and human resources for generating value from AI use (Mikalef and Gupta, 2021). This chapter takes a step back to explain how AI-specific capabilities on technological and non-technological dimensions are formed in the first place.

Finally, the AI adoption literature lacks empirical evidence on the determinants of AI adoption especially in the public administration context (Madan and Ashok, 2023a). The chapter develops two novel constructs of organisational AI readiness and technological AI readiness and tests their effect on AI adoption.

5.5.2 Managerial implications

The chapter has three managerial implications. First, organisations exploring AI can assess their maturity on the two dimensions of organisational and technological readiness and identify a capability development path. Organisational AI readiness is a critical component for the long-term viability of AI, but in the short-term only relevant when it helps develop technological AI readiness. Hence, public administration leaders who want to adopt AI need to focus on achieving a minimum technological readiness by following one of the capability development paths.

Second, the results show organisations lacking visionary leaders and seeking to adopt AI tend to pursue a consultant-led strategy. This strategy can fast-track AI adoption but is risky with the organisation becoming dependent on external expertise. Organisations should try to achieve a minimum organisational AI readiness by hiring a visionary leader who can develop and steer an AI vision and pursue one of the two strategy-led paths. The use of consultants in a strategy-led path provides optimal returns.

Third, the results highlight a severe lack of resources and expertise in data science and outdated human resource practices for attracting and retaining this expertise. Thus, an ecosystem-based strategy engaging educational institutions is an optimal model to retain a constant stream of new resources. Organisations that are willing to invest time and money and provide digital leadership may consider an internal capability-building strategy. Despite a long arduous journey, the rewards are worthwhile in terms of adopting future technologies and attracting new talent.

5.6 Conclusion

In conclusion, this chapter's objective was to identify resources and capabilities that enable AI adoption in public administration and explain how these capabilities are developed. RBV was used to develop two new constructs of organisational and technological AI readiness. The conceptual model hypothesises a positive effect of both readiness constructs on AI adoption and a positive effect of organisational AI readiness on technological AI readiness. Using a mixed-methods design, the study was conducted in two phases, quantitative (277 survey responses) followed by a qualitative study (39 interviewees). The quantitative testing showed only technological AI readiness was significant in effecting AI adoption and organisational AI readiness was significant in effecting technological AI readiness. The qualitative study was used to explain the results and a novel AI capability development model was developed explicating four capability development paths. Organisations might pursue a consultant-led or ecosystem-based strategy to fast-track developing technological AI readiness and circumventing organisational AI readiness. Or organisations might focus on developing organisational AI readiness in tandem or as a precursor to technological AI readiness through serendipitous or internal-capability development paths. The chapter also provides empirical evidence for an instrumental perspective of public administration showcasing that managerial decisions are important determinants of AI capability development with implications for AI deployment and diffusion.

There are several limitations that provide opportunities for future research. First, as the study was conducted in Canadian public administration, the results have generalisability in similar advanced economies. Replication studies in other nations are suggested to help establish the external validity of the results. Second, the scope of AI was limited to ML and NLP. Future research can explore the adoption phenomenon of other technologies such as computer vision and robotics. Third, more empirical testing is required to test the AI capability development model. Future research can test the effect of capability development paths on AI adoption and deployment outcomes.

The study is based on a cross-sectional survey and the same respondents were used for capturing both dependent and independent variables. Future research can mitigate single-source bias by using different respondents for dependent and independent variables. For the qualitative study, validation of the quantitative results was the main goal. Future research can undertake grounded approaches and in-depth case studies to build the external validity of the results.

6 Conclusion

"When you reach the end of what you should know, you will be at the beginning of what you should sense." (Gibran, 1954: 14)

6.1 Introducing the conclusion

In the quotes at the beginning of the introductory chapter, the thesis introduced the realisation of Turing's dream of intelligent machines being integrated into everyday contemporary life. This was evidenced by the Canadian government's call to use AI to improve service delivery to Canadians. Despite such keen interest, AI adoption remains low in public administration. The goal of this study was to gain greater insights into the Artificial Intelligence (AI) adoption phenomenon in public administration to understand such contradictions in practice. This is an important topic for information systems scholars and public administrators alike. Notwithstanding decades of austerity measures and underfunding, public administration is expected to deliver on substantial political mandates and citizen expectations to remain legitimate and survive (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 to explore the use of emerging technologies such as AI to meet public administration challenges. More recently, there have been technological breakthroughs in generative models leading to mainstream discussions on AI's abilities. However, scholars have also raised alarm about the imminent adverse effects of using biased data and AI for making administrative and policy decisions (Bender et al., 2021). The contemporary rhetoric on the transformational benefits of AI use in public administration is countered by the polar viewpoints of AI's near-term negative externalities on the environment and marginalised populations (Natale and Ballatore, 2020; Ashok et al., 2022; van Noordt and Misuraca, 2020b). This calls for a research agenda to understand the factors driving the AI adoption phenomenon within the public administration. In response to this call, this thesis is comprised of four papers. The first two papers were literature reviews, the third paper explained AI adoption from an outside-in perspective and the last paper explained AI adoption from an inside-out perspective. Apart from the first exploratory review paper where AI was broadly considered to develop an AI use case typology, the scope of AI in the other three papers was limited to two specific technologies, machine learning (ML) and natural language processing (NLP). For brevity, in this chapter the term AI is used to denote both technologies and ML or NLP is discussed separately where variations are relevant.

The discussion synthesising the results of the four papers is presented in this chapter in six sections. In the next section, a summary of key findings from the four papers (Chapters 2-5) is presented. This is followed by a comprehensive discussion section that builds on the four papers and offers new theoretical insights on the AI adoption process synthesising the outside-in and inside-out perspectives. The contribution to literature and theory are discussed next. Following this, the chapter presents key recommendations for public administrators adhering to the pragmatic philosophy adopted for the study and ensuring the utility of the research results by connecting theory with practice. The main limitations of the study and future research opportunities are discussed next. Finally, the chapter is closed with a conclusion section.

6.2 A summary of four papers

The overall research goal of this study was to explain the AI adoption phenomenon in public administration enumerating the antecedents of adoption and their interactions that drive the underlying mechanisms. Thus, the main research questions were formulated as:

RQ1: What are the antecedents of AI adoption in public administration?

RQ2: How is the adoption process shaped by the interaction of these antecedents?

The main research questions were divided into four sets of sub-questions (shown in Table 1.1) that guided the research in the four scholarly papers. The conclusions of these four papers are discussed below.

6.2.1 How is AI being used in governments? What are the factors that impact citizen adoption of AI-driven governmental services?

The first set of research sub-questions was geared towards an exploratory review of how AI was being currently used in governments. And to identify factors that impact citizen adoption of AI-driven governmental services. These questions were addressed through a cross-case analysis of thirty AI implementations in governments. These cases were identified through a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. The qualitative synthesis was accomplished by coding a range of documents related to each case using the template analysis method. Four AI use cases were identified: compliance, organisational management, public service delivery, and regulatory functions. The primary outcomes of AI were captured in the themes of public value creation in duty, social, and service domains. The ethical issues highlighted during these implementations aligned with the AI principles of non-maleficence, autonomy, explicability, beneficence, and justice. The AI use cases were mapped to the occurrence of public values and AI principles themes, and inferences were deduced. The results of this analysis were then synthesised to develop a public value-based adoption model. The model postulates citizens' perceived value of AI-driven governmental service is a key determinant of citizens' adoption intention. The perceived value is affected by public value orientation (as a proxy for benefits) and perception of alignment with AI principles (as a proxy for sacrifices and harms). Perceived usefulness moderates the relationship between public values and perceived value. And effort expediency moderates the relationship between AI principles and perceived value.

Overall, reflecting on the results of the review, several findings are worth noting. First, the use of AI for public service delivery was the most prevalent application at 47% of the cases followed by the regulatory function at 30%. These results concur with the public administration challenges related to resource scarcity to meet service demands. Service delivery is the most labour-intensive function and is deemed suitable for automation. Second, service-related public values were found to be dominant in all the use cases alluding to a strong New Public Management (NPM) driven orientation towards AI adoption. Third, the need for explicability – the ability to provide explanations – is the major concern when designing and implementing AI. This suggests an inward focus for governments to ensure their decisions can be supported when challenged by litigations. There is less focus on societal values associated with beneficence, justice, and non-maleficence. This is a concerning development and presents a higher potential for harm if AI projects fail. Fourth, since citizen adoption of AI was postulated to be a function of AI design decisions, the remaining papers were scoped to focus on how public administration adopts AI. The explanation of organisational adoption of AI was deemed as a precursor before testing the effect of AI design decisions on citizen adoption.

6.2.2 What are the key factors discussed in the literature that influence AI adoption in public administration? What are the key tensions discussed in the literature that might be associated with AI implementation and diffusion in public administration?

The second set of research questions was informed by the previous exploratory review and the typology of AI use cases. The research protocol was developed, and the context was limited to public administration. As well as the scope of research was reduced to two specific AI technologies that were driving the majority of AI applications, ML and NLP. A systematic literature review was conducted to answer the research questions. Following a PRISMA methodology, 73 publications were identified for conducting qualitative synthesis using the template analysis method. Deriving from the Technology-Organisation-Environment (TOE) framework, contextual factors that influence AI adoption in public administration were identified under technology, organisation, and environmental dimensions. Technology contextual factors included IT assets, IT capabilities, and perceived benefits. Organisational contextual factors included organisational culture, leadership, and inertia. Environmental contextual factors included vertical pressures and horizontal pressures. As well as absorptive capacity was identified as a global theme impacting AI adoption. The themes of public values and public administration transformation were identified as the key AI diffusion outcomes. Lending credence to the previous exploratory review, the AI outcomes discussion was focused on achieving service and duty goals. The social goals were discussed in terms of the ethical impacts of AI and as responses to AI principles. Furthermore, five AI tensions resulting from conflicts between competing values during AI implementation and diffusion were identified. These included: automation versus augmentation; nudging versus autonomy; data accessibility versus security and privacy; predictive accuracy versus discrimination, biases, and citizen rights; and predictive accuracy versus transparency and accountability. Finally, a research agenda was developed outlining research questions in AI adoption, implementation, and diffusion phases.

Reflecting on the results of this review and considering the previous exploratory review, several findings are worth noting that were influential in designing the two follow-up empirical studies. First, AI adoption is a complex phenomenon involving several contextual factors across three domains technology, organisation, and environment. To develop parsimonious models that can explain the mechanisms, two empirical studies were envisioned to explain the phenomenon from the outside-in perspective, capturing the influence of environmental factors, and the inside-out perspective, capturing the influence of organisational and technological factors. Second, the AI innovation process was outlined as consisting of three distinct phases, namely, adoption, implementation, and diffusion. To manage the scope of this study within the PhD timelines, the research was limited to explaining AI adoption in-depth. The research agenda on implementation and diffusion will be accomplished in a future research project post-PhD. Third, even though implementation challenges, specifically AI tensions, were identified as prevalent during the implementation and diffusion phases, these themes were omnipresent during AI adoption. They have a significant effect on AI adoption and AI capability building decisions and were included in the respective empirical studies.

6.2.3 What factors affect the perceived benefits of AI use in public administration? How do these factors affect the perceived benefits of AI use in public administration?

The third set of research questions was geared towards the outside-in perspective identifying factors that affect the perceived benefits of AI use in public administration. The scope of AI was limited to two specific AI technologies, ML and NLP. Perceived benefits have been identified as a key determinant of technology adoption in the literature (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012; Rana et al., 2015). Hence, the formation and evolution of perceived AI benefits as AI is adopted and implemented provide a window to explore how external environmental pressures affect organisational members' motivation to adopt AI. Once sensemaking is triggered, it becomes a critical determinant of AI adoption decisions and a facilitator for diffusion. An explanatory sequential mixed-methods research design was undertaken with a quantitative study followed by a qualitative study. The paper drew on institutional theory and sensemaking theory to hypothesise four institutional pressures – vertical coercive, service coercive, mimetic, and normative – and consultant pressures affect perceived AI benefits, the dependent variable. Furthermore, it was hypothesised that consultant pressures affect all four institutional pressures.

The model was tested using a cross-section survey (n=272). The primary data was collected from Canadian public administration at three levels, federal, provincial, and municipal. The results of the quantitative study showed that only service coercive pressures were significant in effecting perceived AI benefits. Consultant pressures were significant in affecting all four institutional pressures but not significant in affecting perceived AI benefits. Hence, the effect of consultant pressures was fully mediated through service coercive pressures. These results were then explored in the follow-up qualitative study consisting of semi-structured interviews (n=34). The results of the qualitative study identified three mechanisms (priming, triggering, and editing) that explained how institutional and consultant pressures affect the sensemaking of AI benefits. Meta-inferences were deduced by reflecting on the quantitative results in light of the sensemaking mechanisms and a processual model of AI sensemaking was developed.

Vertical coercive, normative, and mimetic pressures do not trigger sensemaking and only affect the priming stage providing a social context for the formation of the organising vision of AI. Service coercive pressures are characterised by specific needs and hence trigger sensemaking for identifying solutions to these needs. The organising vision of AI formed during priming affects how AI is perceived as a potential solution and whether a positive piloting decision is made. The editing mechanism provides social feedback during piloting and plays a pivotal role in the final adoption decision. The consultants' positive narratives and hype contribute to institutional pressures, but they fail to manifest any direct effect on AI perceived benefits unless associated with a value proposition that is site-specific during the triggering or editing stages. The cognitive constraints provided by the institutional structures and administrative laws shield public administrators from undue pressures from consultants. Hence, vertical coercive, normative, and mimetic pressures are weak in terms of having a direct effect on perceived AI benefits and hence, insignificant. Thus, the key conclusion was summarised as in the earlier stages of adoption, demand pull rather than technology push is a key driver of AI adoption.

6.2.4 What resources and capabilities enable AI adoption within the public administration? How are the capabilities that enable AI adoption within the public administration developed?

The last set of questions was geared towards explaining the inside-out perspective of AI adoption identifying resources and capabilities that enable AI adoption within the public administration. And explaining how these capabilities are developed. The scope of AI was limited to two specific AI technologies, ML and NLP. An explanatory sequential mixed-methods research design was undertaken with a quantitative study followed by a qualitative study. The paper developed two new constructs of technological AI readiness and organisational AI readiness. These constructs measure the level of maturity of a public administration on the technological and non-technological dimensions that enable AI adoption. The paper drew on the resource-based view (RBV) of the firms to hypothesise that both technological AI readiness and organisational AI readiness have a positive effect on AI adoption. Furthermore, it was hypothesised that organisational AI readiness has a positive effect on technological AI readiness. AI adoption is measured using two dependent variables for ML adoption and NLP adoption.

The model was tested using a cross-section survey (n=277). The primary data was collected from Canadian public administration at three levels, federal, provincial, and municipal. The results of the quantitative study support the hypothesis that technological AI readiness has a significant effect on AI adoption. However, organisational AI readiness was found to be insignificant in effecting AI adoption and significant in effecting technological AI readiness. This suggested a fully mediated relationship between organisational AI readiness and AI adoption through technological AI readiness. Thus, although organisational AI readiness is an important determinant of technological AI readiness, it is not a sufficient condition for AI adoption. These results were then explored in the follow-up qualitative study consisting of semi-structured interviews (n=35). The results of the qualitative study suggested different configurations of technological and organisational dimensions led to four maturity levels that were mapped on a two-by-two grid. These included: low organisational and low technological AI readiness, low organisational and high technological AI readiness, high organisational and low technological AI readiness, and high organisational and high technological AI readiness. Meta-inferences were deduced by reflecting on the quantitative results in light of the four maturity levels and an AI capability development model was developed.

The model identifies four AI capability paths undertaken by public administration: consultant-led, strategy-led ecosystem-based, strategy-led internal capability-based, and serendipitous. The minimum threshold of organisational AI readiness is assessed by the existence of a technological vision. The minimum threshold of technological AI readiness is assessed by the data maturity needed to pilot AI solutions. Public administration that follows consultant-led or strategy-led ecosystem-based paths can circumvent maturity on organisational AI readiness in pursuit of technological maturity. Hence, technological AI readiness is a necessary condition for AI adoption and has been pursued in the absence of organisational AI readiness.

6.3 Discussion

The previous section summarised the main conclusions of the four papers. This section discusses the overall findings moving beyond individual studies and linking the conclusions to theory and practice.

6.3.1 A detailed view of the AI innovation process

The results of the study concur with the literature that experimentation and piloting are essential components of the AI adoption process (Desouza et al., 2020; van Veenstra and Kotterink, 2017). The quality and quantity of data impact the accuracy of AI models. Even when high-quality data is accessible, AI-driven applications are characterised by probabilistic and uncertain outcomes. AI is a general-purpose technology (GPT) whose fitness in specific application areas needs to be experimented with and generally involves a lag before its potential can be realised (Crafts, 2021). This necessitates an assessment of AI fitness for a site-specific problem. In recent years, there has been an increased focus on agile practices as a way to deal with changing requirements during the development and implementation phases (Mergel, 2016). Agile approaches, both for AI development and procurement, are the preferred methodologies for AI projects (Desouza et al., 2020). An AI fitness assessment is characterised by an additional pilot or sprint even prior to an adoption decision.

Diffusion of Innovation (DOI)'s five stages of the innovation process in organisations include agenda-setting, matching, redefining/restructuring, clarifying, and routinising (Rogers, 2003). Agenda-setting and matching comprise the initiation phase that leads to the adoption decision (Ibid.). The remaining three stages comprise the implementation phase (Ibid.). This conceptualisation of the innovation process has been dominant in innovation and technology adoption literature (Hameed et al., 2012; Damanpour and Schneider, 2006). The need for an AI fitness assessment before an adoption decision suggests a two-step matching process during the initiation process. This expanded AI innovation process is shown in Figure 6.1 and discussed below.

Cognitive constraints are characterised by institutional structure, values, and administrative law. Cognitive constraints limit the decision choices and provide boundaries as to where AI can be used or not.

The agenda-setting stage is characterised by triggering events resulting from a crisis, specific business problems, or gradual performance gaps. This stage can vary from days, in response to a crisis, to several months or years for other triggers. The output of this stage is a clear definition or scope of a site-specific problem. Agenda-setting could also involve prioritising a portfolio of problems.

In the first-stage matching, public administration engages with the organising vision of AI[18] in its search for potential solutions to the site-specific problem(s) identified and prioritised during agenda-setting. Swanson and Ramiller (2004) term this stage as the conceptualisation stage. If AI shows potential, a more thorough exploration of AI's suitability is considered leading to a piloting decision. The piloting decision commits the public administration to invest resources in exploring AI's potential within the context of the specific problem(s). The piloting decision also communicates administrative leaders' support for using AI. This stage might involve evaluating the accessibility of available datasets to ensure AI can be piloted.

[18] As discussed in Chapter 4, the organising vision of AI is the output of the priming sensemaking mechanisms that comprises of a broad outlook on AI benefits effected by the exogenous factors of media influences and consultants and institutional pressures related to mimetic, vertical coercive, and normative.

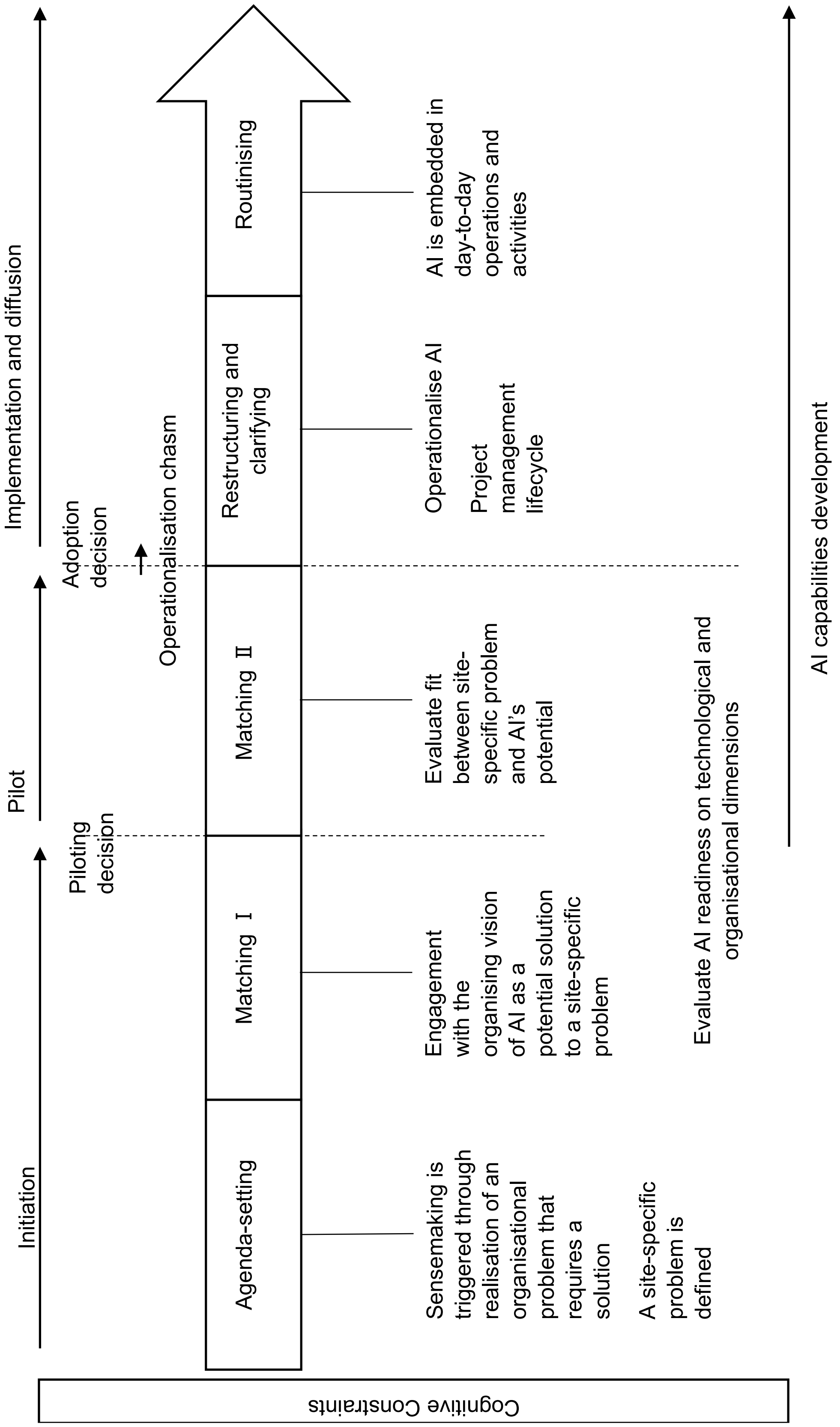

Figure 6.1. AI innovation process

(author's conceptualisation adapted from Rogers (2003: 420))

In the second-stage matching, AI is piloted to test its feasibility and fit for the site-specific problem(s). The piloting stage will involve the acquisition of suitable infrastructure and tools and the development of internal capabilities in data science and AI, or the acquisition of external expertise. This stage involves exploration and cleaning of the available datasets, training and testing of the AI models, and validation of the results. The results and AI's fitness for the business problem are demonstrated horizontally and vertically within the organisation and externally to political leadership and peer organisations. A suitable buy-in from organisational and political leaders and positive feedback from peers encourages public administration to operationalise the AI solution.

An important component during both the matching stages is not only AI fitness but also a fit between the required capabilities for operationalising AI and the current state. A close alignment between these two aspects, or organisational commitment to invest resources in developing required capabilities, will lead to an adoption decision.

The implementation steps following an adoption decision are similar to previous technology projects. AI projects are generally implemented using agile methodology and sprints involving iterative development. The implementation involves redefining/restructuring and clarifying stages as the AI solution is adapted to the organisation and changes are made to the organisational processes (Rogers, 2003). Prior to these stages, operationalisation may also involve developing technological and organisational capabilities required to implement AI identified in the matching stages. The implementation will be followed by the routinisation stage where AI becomes embedded in the day-to-day operations and activities and benefits can be realised (Rogers, 2003). This will eventually lead to the diffusion of the AI solution to other parts of the organisation and peer administrative organisations.

6.3.2 AI capabilities development and the AI innovation process

AI capabilities development is on a continuum and starts with the second-stage matching as shown in Figure 6.1. To enable experimentation and piloting, capabilities development initially focuses on a minimum technological AI readiness characterised by data maturity and tools needed for piloting. Following an adoption decision and assessment of the current technological gaps, capabilities development effort shifts towards ensuring technological maturity to operationalise AI. In addition, there is an increased focus on ensuring responsible AI development practices and guidelines from central Ministries are followed. As part of these guidelines, public administration needs to ensure appropriate governance to resolve AI tensions (as discussed in Chapter 4) that may arise during the operationalisation process.

As implementation proceeds, capabilities development pivots toward building processes and internal expertise to manage AI solutions in production. A post-implementation organisational unit or team needs to be created to manage audits and ongoing development of AI as new data emerge and models need to be retrained.

The four AI capability development paths (as discussed in Chapter 5) provide deeper insights into how the AI innovation process unfolds based on different configurations of resources, actors, and managerial decisions.

Consultants are influential in effecting agenda-setting and first-stage matching by highlighting service-related needs and offering potential solutions in the form of AI. Public administration that lacks technological vision is prone to be influenced by consultant pitches. Consultants might be engaged to demonstrate AI's fitness through a pilot project. A successful demonstration showcasing AI's potential in addressing an urgent need and the promise to establish the organisation as a leader in emerging technologies motivates adoption. Thus, AI adoption and technological maturity are spearheaded by consultants without a plan for the development of internal expertise. This adoption path led by consultants will lead to a perpetual dependence on external expertise for ongoing updates and maintenance through long-term service contracts.

Public administration with a minimum level of organisational AI readiness, reflected in strong leadership, and a technological vision is open to consultants' pitches as a means of keeping up-to-date on the developments in the industry and the peers. This is evident through the active participation of consultants in first-stage matching. However, the piloting decision is driven by the organisation's strategic posture on technology and its assessment of its current capabilities. Public administration may decide to focus on internal capabilities, both technological and organisational, building before pursuing AI. The strategy could include an active role of consultants to help build internal capabilities. However, this internal capability-based path presents significant challenges in terms of lengthy timelines for AI adoption and the scarcity of AI expertise. Such organisations have a formidable challenge to compete for resources with technology companies that can pay much higher salaries and benefits than public administration. There is also a risk of losing internally trained employees to the private sector in a hot labour market.

To mitigate resource challenges and accelerate AI adoption, public administration might pursue an ecosystem-based approach by creating partnerships with the private sector and educational institutions. This route ensures a consistent supply of new graduates from industry-leading educational programmes supported by private-sector mentorship. The full AI innovation process is transformed into one large sprint. Pilot project candidates are identified during agenda-setting and first-stage matching. The selected projects are developed and tested by a cohort of graduates supported by private sector expertise. Pilots that show promise are greenlighted for an adoption decision and the follow-up implementation steps by transferring the pilot to an operationalisation team. The cohort may become part of the support structure as applications are routinised rather than relying on consultants.

Some organisations with high organisational AI readiness, particularly leadership and innovativeness, might lack a technological vision or a specific vision for AI adoption. Leaders in such organisations encourage innovation and experimentation to help solve business problems. High organisational AI readiness is also characterised by a high absorptive capacity to keep up to date on industry and peers. Thus, the innovative and open culture will lead to an organic growth of internal expertise in data science and AI. Once a minimum level of data maturity is achieved, internal experts will start experimenting with AI to solve business problems identified in the agenda-setting stage. In essence, such organisations will skip the first-stage matching since they would have already been engaging informally with the organising vision of AI for a long time during internal expertise building. Once piloting shows promise, it is demonstrated to leadership and external peers. If the AI solution is supported by the management, the same operationalisation process ensues as described previously.

It is worth noting that the operationalisation of AI presents significant challenges regardless of the capability development path. This is discussed in the next subsection.

6.3.3 AI operationalisation chasm

As discussed in Chapters 4 and 5, public administration has several pilot projects underway within the second-stage matching. However, there is a low transition rate from pilot to production AI solutions. This is also confirmed by literature (Daly, 2023). The study's results suggest the reason for this low transition rate is the existence of significant inertia resulting from technical debt, lack of processes and guidelines to manage AI tensions, and silos between data science and operationalisation teams. This study terms this inertia as AI operationalisation chasm.

The primary goal of the piloting stage is to demonstrate AI fitness for a site-specific problem. During pilots, the training and validation of AI models are conducted in isolated environments. There is minimal consideration of technical requirements for operationalising AI following the pilot. These requirements could include infrastructure upgrades, acquiring cloud-based solutions, bandwidth requirements, procurements, legal requirements regarding the use of personal information, privacy risk assessments, cyber security requirements, and consideration of organisational structures and expertise for maintaining AI solutions. The data science team leading the pilot works in silos from the operationalisation team that will assume the lead once a pilot is signed off for implementation. A soft adoption decision on the solution is generally the trigger for engaging the operationalisation team to assess readiness and document technical requirements for final approval. This engagement unravels legal and policy issues with the use of datasets, lengthy timelines for conducting privacy and security assessments, investments in infrastructure, and lengthy procurements.

A significant challenge contributing to AI operationalisation chasm is being able to manage AI tensions that might emerge during AI development and implementation. There are several high-level guidelines on responsible AI development from central digital offices such as Canada's directive on automated decision-making (Government of Canada, 2023a) and Ontario's AI guidance (Ontario Government, 2023). Such high-level guidelines are policy-driven and suggest overall principles such as a need for autonomy, transparency, accountability, justice, beneficence, and non-maleficence. However, several implementation-level decisions are left for the adopting administration. During readiness assessment a lack of processes and governance mechanisms required to manage AI tensions becomes evident. Such as the Ontario Government's AI guidance principles stipulate "there must be transparent use and responsible disclosure around data enhanced technology like AI, automated decisions and machine learning systems to ensure that people understand outcomes and can discuss, challenge and improve them" (Ontario Government, 2023). However, the implementing administration needs to decide how to manage consent on using citizen data collected for different purposes, how accountability and delegation will work within the organisation, and what comprises acceptable risk in terms of error rates that can be legally supported. Thus, even if organisations achieve the desired level of maturity in organisational and technological readiness, they will still need to develop project specific governance structures and mechanisms for making such decisions, especially for high-risk public facing applications. The study reveals a low level of maturity and work in defining these governance processes during piloting.

The technical debt is evident in public administration resulting from the last wave of technology implementations and contributes towards the AI operationalisation chasm. Even to this date, there are large infrastructure projects underway to replace legacy systems within the public administration (Ottawa Civic Tech, n.d.). Several challenges hinder AI operationalisation due to this technical debt. First, lack of motivation from the leadership to invest resources in adopting AI when large information technology (IT) projects are already underway, and in several instances delayed and over budget. If an AI solution is implemented in parallel to these upgrades, another project might be required at the end of the legacy upgrades to update the production AI solution. Second, the employees are already under pressure to balance their day-to-day operational tasks while supporting these upgrades, training on the new system, and preparing for organisational changes resulting from these implementations. The organisation is already under digital transformation fatigue which makes organisational change resulting from AI even more challenging to manage. Third, the use of legacy data introduces new technological challenges. On one hand, public administration has vast amounts of data collected from this first wave of technological artefacts. However, the quality and compatibility of this data are questionable and need custom applications to extract and clean this data on an ongoing basis.

Hence, pilots are abandoned after readiness assessment reveals that the size of the AI operationalisation chasm is too big to cross. There might be a need for significant investments, the timeline for adoption too early within the current portfolio of IT projects, and a lack of political or administrative will to assume the political risk associated with uncertainty on resolving AI tensions.

6.3.4 Identifying the drivers of AI adoption

The results of this study provide insights into the AI adoption phenomenon within the public administration identifying key drivers and actors. Plagued by systemic resource deficits, made worse following the COVID-19 mass resignations, public administration is under extreme pressure to deliver on political mandates and demonstrate its commitment to “doing more with less.” No surprise, the driving force behind the adoption of AI is a promise to help address these challenges. Marketing and policy literature talks about the transformative benefits of AI through increasing citizen engagement, enhancing democratic values, and making government decisions more rational. However, such drivers are absent or considered marginal side benefits in pursuit of operational performance. The study finds service demands rather than technology push are driving AI adoption in public administration. Once more large-scale AI use cases are implemented and show the value of AI at scale, it is expected normative and mimetic pressures will become significant drivers and part of the agenda-setting stage of AI innovation.

The use of consultants and their influence is also no surprise in public administration. The study shows consultants affect all four institutional pressures, service coercive, vertical coercive, normative, and mimetic. Consultants help outline service-related demands and deficiencies that need a solution, lobby political leadership to adopt AI, and generate peer pressure by marketing AI successes. Consultants are embedded in every aspect of administrative decision making and the government technology industry is characterised by former administrators joining consulting companies. This fluid exchange initiates professionalisation pressures. The cognitive constraints established through institutional structures and administrative law tend to act as a barrier towards consultants having a direct influence on AI decisions. Furthermore, previous technology implementations have increased the maturity of organisations to be able to question and challenge consultants' claims.

6.3.5 The role of media debates and science fiction

The contemporary media debate is characterised by the cultural myths and science fiction narratives of super-intelligent machines posing existential risks to human existence (Natale and Ballatore, 2020). Other scholars stress the near-term risk of AI as a means for maintaining power and controlling citizens as discussed in Chapter 2. The debates on the power of generative models have entered the mainstream with the rollout of ChatGPT and similar applications. It remains to be seen whether this is another hype cycle in AI development with heightened expectations (Floridi, 2023). Such debates do impact how AI is perceived and adopted in public administration. The study shows exogenous signals affect the priming mechanisms where an overall perception of AI is formed by public administrators. This organising vision of AI, even though not a trigger, impacts how AI is viewed as a possible solution during the first-stage matching and affects the piloting decision. Furthermore, this organising vision also plays a role in contributing to the AI operationalisation chasm introducing political risks and influencing how much risk public administration can assume when making the AI adoption decision.

6.3.6 New Public Management (NPM) driven AI adoption

The first wave of technology in public administration was driven by goals of efficiency and cost savings spearheaded by the NPM reforms (Djellal et al., 2013). Technology was considered an enabler of a specific set of NPM values towards achieving decentralisation and managerial rigour (Dunleavy et al., 2005). However, NPM has performed poorly, and the technology has had lukewarm success in bringing about digital transformations seen elsewhere in the private sector (Coursey and Norris, 2008; Savoldelli et al., 2012; Hung et al., 2006; Dunleavy et al., 2005). Some of the common challenges include compatibility and interoperability of systems, lack of internal expertise, data governance, inertia to change, weak leadership and political support, management of varied stakeholder demands, and poor project management practices (Zhang et al., 2014; Kumar et al., 2002; Alshehri and Drew, 2010).

The results of the study suggest a similar NPM-driven agenda for AI adoption. In Chapter 2, the study found that service-related goals were the most dominant AI use case. This was empirically confirmed in Chapter 3 with service coercive pressure being the sole institutional pressure affecting perceived AI benefits and thus, AI adoption. Furthermore, consultants were shown as influential in effecting all institutional pressures and forwarding private sector successes of AI similar to previous implementations. However, the institutional structures have been successful in shielding direct consultant influence.

The study lends credence to the continuation of the same digital transformation agenda as the previous wave. The duty and social public values goals have taken a back seat and are generally viewed as challenges. This perspective calls into question whether the current AI solutions might be able to bring about any significant transformational impact. Or will AI end up being another tool for achieving efficiency and cost savings and becoming technical debt a few decades later?

6.3.7 Size matters

Both empirical studies find support for the hypothesis that large organisations are associated with higher technology adoption. This supports public sector innovation literature that organisational size is positively associated with innovation given higher economies of scale, slack resources, and financial resources for experimentation (Walker, 2006; Walker, 2014; Damanpour and Schneider, 2006; Damanpour and Schneider, 2009; Bernier et al., 2015). After controlling for the organisational size, the level of government was not a significant factor in determining adoption. Thus, AI adoption can be pursued at any level of government but is generally associated with larger public administration organisations that have resources to support experimentation and wherewithal to cross the AI operationalisation chasm.

6.4 Contributions

The overall contributions of the study to theory and methodology and managerial recommendations are discussed below.

6.4.1 Theoretical contributions

This study is multi-disciplinary and contributes to three bodies of literature, public administration, technology adoption, and strategic management.

6.4.1.1 Developing an updated view of the AI adoption process in public administration

The literature reviews in Chapters 2 and 3 synthesised current scholarship on the AI adoption phenomenon in public administration. The reviews highlighted a paucity of empirical research on understanding the antecedents of AI adoption. A critical gap relates to testing the antecedents derived from public sector innovation and e-government literature (Alsheibani et al., 2018; Jankin et al., 2018; Misuraca et al., 2020; van Noordt and Misuraca, 2020b; Valle-Cruz et al., 2019). Furthermore, an in-depth knowledge of the mechanisms driving the AI adoption process was identified as essential to guiding public administration transformation and enabling public value creation (Hung et al., 2006; Criado and Gil-Garcia, 2019). The study addresses these critical gaps in the e-government focused technology adoption literature. Through a systematic literature review, Chapter 3 identified a comprehensive list of technological, organisational, and environmental antecedents of AI adoption. Chapter 4 tests the environmental antecedents of perceived AI benefits, a critical determinant of AI adoption decisions and facilitator for AI diffusion. Chapter 5 tests the organisational and technological antecedents of AI adoption. Furthermore, the qualitative components of both empirical studies explain the underlying mechanisms. Thus, the empirical studies provide rich insights into the AI adoption phenomenon in public administration and its contextual nature.

With respect to the environmental antecedents, the study deviates from the current e-government literature that suggests a strong influence of vertical coercive pressures on technology adoption (Mergel, 2018; Walker et al., 2011; Desouza et al., 2020; Walker, 2006; Korac et al., 2017). The study finds vertical coercive pressures are insignificant in affecting AI adoption. The effect of the other three pressures – service coercive, mimetic, and normative – aligns with the literature. Literature has mixed results on the effects of mimetic and normative pressures and the positive effect of service coercive pressures on technology adoption (Desouza, 2014; Korac et al., 2017; Damanpour and Schneider, 2006; Walker, 2006; Hong et al., 2022; Walker et al., 2011; Berry and Berry, 1999). The qualitative study explains these contrary results by elucidating the underlying sensemaking mechanisms driving the AI adoption process. The negative perceptions associated with AI represent a significant political risk and there is a lack of demonstrable AI benefits at scale in production solutions. Thus, vertical coercive, mimetic, and normative pressures are not significant in triggering agenda-setting. Agenda-setting is only influenced by service demands for meeting productivity and efficiency goals.

From a technology lens, the study provides empirical support and explanations for DiMaggio and Powell's (1983) and Tolbert and Zucker's (1983) suppositions that during the early stages of technology innovation, efficiency and performance rather than legitimacy concerns are the main drivers of innovation adoption. In the earlier stages of technology evolution characterised by uncertainty and risks, external pressures are only relevant as priming influencers. External pressures are not strong enough to trigger a need via technology push. Only demand pull triggers a search for technology to meet efficiency and productivity needs. When the technology becomes diffused and more widely accepted, isomorphism and the pursuit of legitimacy becomes dominant. All external pressures will start to play the role of triggers and the technology push becomes strong. This contingent view extends the current technology adoption theory and explains how political and media rhetoric interacts with the operational concerns of an administration at different levels of technological maturity.

With respect to the technological and organisational antecedents, the study also deviates from the current e-government literature that emphasises the role of innovation, change capabilities, and transformational leadership as determinants of technology adoption (Kim and Yoon, 2015; Kim and Chang, 2009; Agolla Joseph, 2016; Arundel et al., 2015; Bugge and Bloch, 2016; De Vries et al., 2016; Yu et al., 2023; Reddick, 2009; Holden et al., 2003; Wang and Feeney, 2016; Zhang et al., 2014). The empirical evidence from this study suggests only an indirect relationship between innovativeness and leadership, measured as organisational AI readiness, and AI adoption. This relationship is fully mediated by technological maturity, measured as technological AI readiness. An explanation of this interaction through the qualitative study reveals important insights into capability development paths being pursued by public administration. Public administration can pursue technological maturity and adopt AI without a high level of innovativeness and leadership capabilities by engaging consultants or through an ecosystem. These results shed light on the influential role of consultants in shaping the AI adoption process.

The results of both empirical studies informed the new AI innovation process model in public administration as discussed in the previous section. The model highlights the existence of an AI operationalisation chasm as a significant barrier to transitioning pilot AI projects to production solutions. This expanded AI innovation model showcases the application of diffusion of innovation theory to the specific context of AI innovation in public administration.

6.4.1.2 Contributing to the public organisation debate on institutionalism versus instrumentalism

This study contributes to the debate on whether public organisations are driven by institutional logic or rational choice logic (Christensen et al., 2007). The results of the study provide empirical evidence for Oliver's (1997) propositions that these two positions are in practice complementary. The sensemaking mechanisms in Chapter 4 and the AI innovation process model in this chapter show institutional logic is evident through cognitive constraints that provide boundaries on what is legitimate and limit strategic choices by providing institutional roles, structures, and a requirement for conformance with the administrative law. However, managerial assessment of resources in meeting political mandates and administrative service demands is shown to drive AI adoption. This conclusion is further strengthened by the AI capability development model in Chapter 5 which shows how managerial decisions on different configurations of two dimensions can lead to four distinct capability development paths in pursuit of similar goals and within the same institutional logic. Thus, the results of the study provide credence to the rational choice perspective of public organisations and the role of leadership and managerial decisions in innovation and organisational outcomes. However, the evidence also recognises that institutional logic plays a significant role in limiting the available strategic options and defines hard boundaries within which organisational decisions should be situated.

6.4.1.3 Opening the black-box of institutional theory and RBV

The widespread usage of institutional theory in information systems research has followed the empirical institutionalism approach testing the effects of institutional pressures on organisational outcomes (Altayar, 2018; Savoldelli et al., 2014; Sherer et al., 2016; Pina et al., 2010; Peters, 2000). This application provides a black-box explanation assuming organisational members are passive recipients of institutional logic (Jensen et al., 2009a). Such explanations have garnered significant critique for only focusing on the structuration aspects of institutions while ignoring organisational members' motivations in pursuing specific strategic choices (Suddaby, 2010). To overcome this limitation, the study showcases how sensemaking theory can complement the institutional theory to explain how organisational members engage with the macro-level institutional logic forming preferences and driving strategic decisions. Chapter 4's results provide empirical support to Weber and Glynn's (2006) proposition of cognitive constraints and three contextual mechanisms operating within the black-box. Chapter 4 also adds a temporal dimension to these mechanisms. This magnified view of the underlying sensemaking mechanisms showcases the original propositions of institutionalism comprising both structuration and meaning systems forwarded by Zucker (1977) and Meyer and Rowan (1977).

The use of RBV has also been critiqued for providing black-box explanations of the effect of resources on organisational outcomes (Kraaijenbrink et al., 2010). Chapter 5 addresses this critique by first, providing resource demarcation between two types of resources and capabilities, and second, explaining how interactions between these two resource dimensions and managerial decisions lead to distinct organisational capability development paths. The novel AI capability model developed in Chapter 5 extends the current AI capability literature (Uren and Edwards, 2023; Mikalef et al., 2021; Weber et al., 2022) by explaining how AI capabilities are developed in the first place. This also serves as a preliminary sketch for a capability development theory extending the RBV theory.

The expanded view of institutionalism and RBV also lends credence to the complementarity of institutional logic, through structuration, and rational choice logic, through meaning systems and resource configuration choices, as discussed in the last sub-section.

6.4.2 Methodological contributions

This study contributes to methodology in two main areas.

First, the study develops and tests two novel constructs of organisational AI readiness and technological AI readiness. Technological AI readiness measures the degree of maturity in technological resources and capabilities that enable AI adoption. Organisational AI readiness measures the degree of maturity in organisational innovative resources and capabilities that enable AI adoption. The study provides an associated scale for each of the constructs. These scales can be adapted to different contexts, within public or private sector implementations, to test the AI adoption and diffusion phenomena.

Second, the study demonstrates the use of a mixed-methods approach in providing rich explanations of a phenomenon. The use of a mixed-methods approach in Information systems (IS) research has been critiqued for lacking meta-inferences and thus, deficient in substantive theoretical contributions (Venkatesh et al., 2013). The study showcases two examples of sequential explanatory mixed-methods research design. An important exemplar relates to developing meta-inferences that provide a higher level of abstraction of the phenomenon and an outline for future theory development work (Venkatesh et al., 2013). This meta-inference is showcased in Chapter 4 through the elucidation of AI’s perceived benefits and sensemaking mechanisms and in Chapter 5 through the development of an AI capability development model. The study illustrates how a mix of quantitative and qualitative studies can address the limitations of established theoretical frameworks such as institutional theory and RBV. Thus, by addressing these critiques, the study provides insights into expanding the established theories.

6.4.3 Managerial contributions and recommendations

The overall managerial contributions in terms of practical recommendations are discussed below.

6.4.3.1 Assessing organisational and technological AI readiness

The study develops and tests two constructs to measure public administration's maturity that enables AI adoption. Organisational AI readiness is reflected in the level of maturity of transformational leadership, innovative culture, financial resources, change capabilities, and acquisition and assimilation capabilities. Technological AI readiness is reflected in the level of maturity of IT assets, data, and IT capabilities. These two readiness dimensions can be measured using the questionnaire developed for this study (Chapter 5 – Appendix I). The organisational AI readiness questionnaire should elicit responses from across the organisation. The technological AI readiness questionnaire should be limited to departments with knowledge of the organisation's technological capabilities, assets, and strategic plans. For simplicity, summated means can be used to determine the level of maturity for each of the readiness scale constructs. Using these construct measures, a qualitative assessment should be conducted by the leadership teams to assign high, medium, or low scores on organisational AI readiness and technological AI readiness dimensions. Furthermore, the leadership team should judge whether the organisation possesses minimum organisational AI readiness determined by the leadership construct and the existence of a technological vision. As well as judge whether the organisation has minimum technological AI readiness based on the data construct.

The scores should be plotted on a two-by-two grid (similar to Figure 5.3) consisting of organisational AI readiness and technological AI readiness dimensions. The position on this grid will help determine the current state and guide the capabilities development path as discussed next.

6.4.3.2 Developing AI capabilities

When an organisation lacks the minimum organisational AI readiness, the focus of the organisation should be on hiring a technological leader, or promoting from within, who can develop and steer an AI vision. There might be instances where external consultants are engaged to develop a technological strategy and AI vision. The study cautions that the role of consultants should be limited to supporting the development of the strategy through engagement with organisational leaders. The ownership of this vision should be assumed by an internal technological leader and not led by consultants. Organisations might find themselves in the high technological and low organisational AI readiness grid. In this instance, the leadership needs to evaluate the role of consultants in leading technological maturity. Is there an internal lead steering the enterprise vision? If the current AI initiatives are led by consultants, is there a transition plan to build internal organisational capabilities? A consultant-led strategy with a lack of a transition plan or enterprise vision is an indication of the influential role of consultants in steering AI adoption. There is a high risk the organisation will be reliant on consultants for ongoing maintenance and development post-implementation.

An organisation with a technological vision and leadership, thus above the minimum organisational AI readiness, should determine the AI capability development path. Is there a specific AI vision being pursued? Or is the current vision geared towards innovative capabilities regardless of specific technological artefacts? If former, the next question to consider is whether the current plan focuses on building internal capabilities to experiment and pilot with AI technologies. Or does the current strategy involve an ecosystem of educational institutes and private sector firms? Both are viable capability development paths with different time goals. An internal capability development path is a long-term investment through hiring new expertise or training existing employees, establishing digital offices, and encouraging experimentation with AI. If the organisation is struggling with attracting suitable resources to help build internal capabilities, the ecosystem-based path can propel AI adoption and ensure a consistent flow of new talent.

On the other hand, if the strategy is broadly geared towards building innovative capabilities, organisations should focus on achieving minimal data maturity. This will help encourage bottom-up innovations and experimentation with AI. And can position the organisation on the serendipitous path.

Regardless of the AI capability development path, a formidable challenge for AI adoption is crossing the operationalisation chasm as discussed next.

6.4.3.3 Crossing the operationalisation chasm

Operationalism chasm is characterised by the existence of technical debt, a lack of policies and guidelines for managing AI tensions, and a lack of engagement with the operational teams – IT, privacy, procurement, policy, legal, and cybersecurity – during the piloting stage. To cross the operationalisation chasm effectively, the study provides three recommendations. First, once the technological vision enumerates the organisational intent to adopt AI, sufficient resources and effort should be dedicated to developing processes and guidelines for managing AI tensions. These could build on central ministries' guidelines adapted to the specific project governance structures of the organisation. The critical starting point should be the development of a data governance framework.

Second, the scope of piloting should not only include AI fitness but also consider operationalisation fitness. This can be pursued in two ways. The piloting team need to demonstrate an operationalisation plan in consultation with other operational teams. The pilot should consider documenting technical requirements for operationalisation, associated budget, and work breakdown structure of the activities. In essence, the output of second-stage matching should be an AI fitness demonstration accompanied by a robust business case ready for the executive team approval and resource assignment. Alternatively, if organisations find this process cumbersome and time-consuming, they will benefit from building a cross-functional piloting team. This will ensure implicit consideration of technical requirements during piloting and demonstrating AI fitness.

Third, the persistence of technical debt is an unavoidable dimension of the operationalisation chasm. Organisations that have already upgraded their platforms are in an opportune position to start pursuing AI and will only need to manage the other two dimensions of the chasm. Organisations in the midst of platform upgrades are already subsumed with large IT projects and will need a strong business case to be able to pursue AI adoption. A better proposition would be to focus on the process dimension of building data maturity and governance processes until platform upgrades are near completion. If an organisational need dictates an AI-based solution, it should be considered as a scope change to the existing project and managed accordingly. Organisations planning to undertake platform upgrades in the future will be hesitant to attempt AI adoption until such legacy systems have been replaced. If the business need dictates AI adoption, the first consideration should be ensuring the data can be ingested from disparate systems and cleaned and processed into a data lake. And ensure that data governance processes have been developed. If the platform upgrade project emerges during or after the AI project, the needed upgrades to the AI solution should be planned and managed within the scope of the larger IT project. In short, the management of technical debt needs strong project management practices, enterprise architecture capabilities, and a technological vision.

6.4.3.4 Managing media and negative perceptions of AI

As discussed previously, the negative perceptions related to AI are commonplace in media and inflamed by high-profile failures such as the use of Clearview AI facial recognition technology by Canadian law enforcement and Australia's Robodebt case (Robodebt Royal Commission, 2023; Office of the Privacy Commissioner of Canada, 2021). The current debate on AI's existential risk increases the political risk of pursuing AI-driven solutions. To manage these negative perceptions, a two-pronged approach is recommended. First, the government learning units need to educate political and administrative leadership on what is AI, its current capabilities, and its potential. A clear distinction needs to be established between the current AI use cases and future scenarios regarding artificial general intelligence (AGI) that drives the hype and mainstream rhetoric. Consultants can play a major role in this space through knowledge and marketing campaigns dedicated to understanding AI. Second, benefits realisation from AI at scale needs to be demonstrated. Leaders need evidence that AI can be used at scale and in a production environment. The pilot demonstrations only show potential capabilities but get overshadowed by the effort required to cross the operationalisation chasm. Thus, as discussed previously, a robust business case should be developed and accompany pilot demonstrations.

6.4.3.5 Public administration's enviable position – blessing or curse

Public administration possesses a treasure trove of administrative and citizen data. This positions public administration in an enviable spot compared to private sector data and its applications. The public administration AI agenda will dictate whether this data becomes a blessing or a curse. Public administration can use this data and AI capabilities towards meeting duty and social goals. The government-citizen relationship can be transformed by envisioning a smart, lean, personalised, and transparent government as touted by several scholars (Dunleavy et al., 2005; Wirtz and Müller, 2019; Criado and Gil-Garcia, 2019; Schedler et al., 2019). However, with the current drivers being service-related goals, there is a risk the use of AI will be geared towards economic goals of efficiency and cost savings resulting in only marginal gains over previous technological implementations. A lack of a transformational agenda driven by AI will be a missed opportunity at a critical juncture in AI's development and global events mired by wicked problems. Public administration needs to engage a broader community of public administration, legal, and philosophy scholars and technologists to envision AI-driven government. The efforts in responsible AI development have been commendable and need to continue. However, similar efforts are also required to develop a transformational government AI agenda. So far, the focus has been trying to regulate the curse of data rather than rejoice in its blessing.

6.5 Limitations of the study and future research

This study suffers from several limitations in terms of context, scope, and methodology. This study provides empirical evidence and in-depth insights into the AI adoption phenomenon in public administration. Nonetheless, future research is needed to further validate and extend the results of this study. These are discussed below.

6.5.1 Contextual and scope limitations

First, the study was conducted in the Canadian context. Canada is characterised by the Anglo-Saxon context and a Westminster-style government. The historical context of Canada is unique and includes several public administration reforms, the political ideologies of the government in power, and a vibrant AI research environment. The models and results of this study have generalisability in similar advanced economies with Westminster-style governments characterised by similar reform movements. However, external validity needs to be established through similar studies in other countries such as the UK and Australia. Future research should also test the models and results in emerging economies, such as India, and provide additional insights on the institutional path dependence of AI adoption through cross-national comparisons.

Second, the research sample is limited to public administration and excludes a large sector of public organisations in health, law enforcement, emergency services, etc. The results of the study should be used cautiously in these contexts. Future research in other public sector organisations is needed to establish external validity. A cross-sector comparison can help enumerate the contextual role of the institutional environment and further strengthen the results.

Third, the study was limited to two specific AI technologies, ML and NLP. The results of the study might not apply to other AI technologies such as robotics, computer vision, etc. Future research on these technologies can shed light on the technology-specific variations in the adoption process.

Fourth, the AI sensemaking mechanisms developed in Chapter 4 and the expanded AI innovation process developed in this chapter need empirical testing. A cross-case analysis of AI implementations can help strengthen the results. Furthermore, a longitudinal study of the full AI innovation process can validate and further develop the AI innovation process model. A future study can test the supposition that once AI is widely diffused, service coercive, mimetic, and normative pressures will also act as triggers rather than just priming forces. Furthermore, the concept of operationalisation chasm needs validation through case studies and action research.

Fifth, the AI capability development model developed in Chapter 5 needs empirical testing. Future research can use case studies and qualitative research to further develop the model and theory of AI capability development. A future quantitative study can test for the effect of different capability paths on AI adoption outcomes.

Sixth, to manage the scope of this thesis within PhD timelines, the focus of the papers was on AI adoption. The public values adoption model developed in Chapter 2 to test determinants of citizen adoption of AI needs to be tested in future research. Furthermore, the AI implementation and diffusion agenda developed in Chapter 3 needs to be researched in a future study. The five AI tensions need to be explored in-depth through case studies or ethnographic studies of AI implementations. A quantitative study can test the effect of decisions on AI tensions on public value creation with AI.

6.5.2 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. Thus, the issue of single-source bias associated with self-reported survey data cannot be ruled out (Favero and Bullock, 2015). Methodological and statistical measures were undertaken to reduce this bias as discussed in the respective chapters. A future study can mitigate single-source bias by using different respondents for dependent and independent variables. Furthermore, a longitudinal study using panel data can be used to test the AI innovation model at various stages of AI adoption.

Partial least squares structured equation modelling (PLS-SEM) strengths are in estimating complex models with smaller sample sizes and do not require distributional assumptions over parameter specifications (Chin, 2009). However, there are several limitations in using PLS estimates. First, a major limitation of PLS path modelling relates to PLS bias. Wold's (1982) seminal work states PLS estimates are consistent for large samples and thus, unrealistic in social science research with limited sample sizes. Gefen et al. (2011: vi) state PLS estimates “for paths between observed variables and latent variable proxies are biased upward in PLS (away from zero), while parameter estimates for paths between proxies are attenuated.” The cause of this bias is accounted to PLS’s adherence to composite-based measurement model estimation for both formative and reflective constructs (Sarstedt et al., 2016). Thus, PLS produces bias estimates when the measurement model is reflective, i.e. based on a common factor model (Yıldız, 2022). However, Sarstedt et al. (2016) show that PLS bias when estimating common factor models is small as long as the measurement model meets the minimum thresholds. Furthermore, Sarstedt et al. (2016) find the bias associated with sample sizes over 250 is small and declines further with larger sample sizes of common factor populations. The conceptual models and measurement data for this study are based on a common factor population and hence suffer from PLS estimation bias. Steps taken to minimise this bias include ensuring the measurement model meets the suggested thresholds and the sample size is greater than 250. Second, another limitation of PLS is a lack of goodness of model fit and thus, limited applicability for theory testing and confirmation. As discussed in the introduction, the objectives of this study are aligned with theory development and have a predictive orientation. Hence, a lack of goodness of model fit was not a concern. A future research design can consider parameters specific based on the composite model population. After future theory development efforts in different contexts, as discussed in the previous sub-section, covariance based structured equation modelling (CB-SEM) can be considered for quantitative testing.

As with all social science research based on non-experimental methods, the presence of endogeneity is inevitable. Endogeneity is caused when a predictor variable is correlated to the error term and may result from omitted variable bias, simultaneity, and measurement error (Antonakis et al., 2014). This is a common issue with cross-sectional data used for this analysis. Hence, this study is subject to issues of endogeneity. The study followed the criteria suggested by Hult et al. (2018) for addressing endogeneity in PLS-SEM. The conceptual models relied on established theoretical frameworks to handle omitted variable bias and the control variables approach was adopted based on robust testing in prior literature. The problem with simultaneity may exist. Such as in the conceptual model in Chapter 5, it is expected organisational AI readiness is a precursor for AI adoption. AI adoption can also influence organisational AI readiness, especially if the organisation pursues a consultant-led or ecosystem-based approach to develop capabilities. Similar to omitted variable bias, simultaneity was handled by relying on theory and validation through the qualitative component of the studies. The measurement error can affect the measurement model introducing PLS bias. The use of multiple-indicator reflective measures helps minimise measurement error (Saris and Revilla, 2016). As well as non-response and sample selection bias can contribute to the measurement error (Jackman, 1999). To minimise measurement error, the study used reflective measures and tested for non-response bias. The pilot study ensured any item ambiguity was addressed before the main survey was rolled out. Sample selection was based on purposive sampling and the identification of experts by the author following suggested literature guidelines. Future research can consider more robust econometric and statical techniques for addressing endogeneity such as using instrumental variables in general and Gaussian Copula approaches specifically for PLS-SEM (Hult et al., 2018).

For the qualitative study, an explanation of the quantitative results was the main goal. The rigour and trustworthiness of the qualitative study were established by showcasing credibility, transferability, and confirmability (Lincoln and Guba, 1985). However, there is a chance of researcher bias during interviews and coding that was focussed on validating the quantitative model using an a priori template rather than following a grounded approach. Future research can undertake grounded approaches, ethnomethodology, and in-depth case studies of AI adoption and implementation to build external validity of the results.

6.6 Conclusions

In conclusion, the goal of this study was to identify antecedents of AI adoption in public administration and explain the underlying mechanisms. This was achieved through a mixed-methods research design and four scholarly papers that explained AI adoption from outside-in and inside-out perspectives. This chapter synthesised the results of the individual papers to answer the two primary research questions and discussed the theoretical and practical implications of the findings. For the first research question, the study identified internal and external antecedents of AI adoption and deviated from prior e-government literature. This led to the proposition that the current state of AI adoption is in the early stages of technological innovation where demand pull rather than technology push is influential. As well as the influential role of consultants and the propensity of public administration to focus on technological maturity rather than organisational innovativeness when pursuing AI adoption. This conclusion had implications suggesting an NPM-driven technological innovation agenda. Such agenda risks only realising marginal gains over previous technological implementations despite the immense potential of transformative opportunities from using AI.

For the second research question regarding the underlying mechanisms, the study developed a detailed view of the AI innovation process building on DOI and introducing a two-stage matching process. The study identified the existence of inertial forces in the form of the AI operationalisation chasm responsible for a low rate of transition from pilot AI applications to production solutions. Furthermore, the study enumerated AI capabilities development paths and priorities during various stages of the AI innovation process. The study also highlighted the role of exogenous signals affecting AI adoption priming stages when the organising vision of AI is formed by organisational decision-makers and thus, affects their perceptions. In addition to extending DOI in the context of AI innovation, these findings have two other theoretical implications. First, the findings provide support for the complementary view of institutionalism and instrumentalism perspectives of public organisations. Second, the findings enumerate the mechanisms that operate the assumptions from the institutional theory and RBV.

Finally, the study provided several practitioner recommendations on assessing organisational and technological AI readiness, developing AI capabilities, crossing the operationalisation chasm, and effectively managing media and negative perceptions of AI.

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Appendices

Appendix A. AI Adoption Survey and Consent Form

Dear participant,

You are being asked to take part in a research study that aims to investigate Artificial Intelligence (AI) adoption and diffusion in public sector organisations. This study is part of a PhD research by Rohit Madan at Henley Business School, University of Reading, UK. The research has received favourable review by the Business Informatics, Systems and Accounting ethics office, Henley Business School, University of Reading, UK.

Your participation
In this study, you will be asked to complete an online questionnaire. Please follow the instructions carefully. You participation should not take longer than 10 minutes.

Data Storage
All data is stored securely on Qualtrics. Backup copies are made on a local drive, stored securely, and never shared with anyone outside the research team. Data is destroyed after five years as part of the International Data Protection Act.

Right to withdraw
You can stop being a part of the research study at any time with no need for an explanation. You have the right to ask that any data you have supplied to that point be withdrawn or destroyed, you also have the right to omit or refuse to answer or respond to any question that is asked of you. You have the right to have your questions about the procedures answered, before, or after the questionnaire.

Risks
There are no foreseeable risks.

Cost, reimbursement, and compensation
Your participation in this study is voluntary and no monetary compensation will be given for this study.

Confidentiality/anonymity
The records of this study (either hard copy or electronic) will be kept private. In any sort of report we make public we will not include any information that will make it possible to identify you. Research records will be accessed only by the research team. We anticipate to use the research findings to produce outputs like academic papers, book chapters, etc.

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CONSENT I confirm I'm aged 18 year or over and that I have read and understood the information sheet for the above study. I have had the opportunity to consider the information, ask questions, and have had these answered satisfactorily. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason. I agree to take part in the above study.

○ Agree

○ Disagree

Please assess the following statements at the organisational level. If you are a consultant, contractor, or advisor, please respond to the questions from the perspective of a single public administration organisation where you have recently worked within the last 2 years.

To what extent **natural language processing** applications are being used in your organisation?
Common examples include intelligent text or voice interaction with citizens; analysing unstructured data such as citizen and stakeholder feedback through topic modelling, text categorisation, informational extraction, relationship extraction; sentiment analysis

- We do not use or plan to use it
- We anticipate using it in the next 2 years
- We have plans to start using it in the next 6-12 months
- We are in the process of piloting and testing
- We are currently using it

To what extent **machine learning** applications are being used in your organisation?
Common examples include predictive analytics for decision support and policy development; anomaly detection; process automation such as HR management, case management, financial management; optimisation of resource allocations; automation of public services.

- We do not use or plan to use it
- We anticipate using it in the next 2 years
- We have plans to start using it in the next 6-12 months
- We are in the process of piloting and testing
- We are currently using it

Please assess the following statements at the organisational level. If you are a consultant, contractor, or advisor, please respond to the questions from the perspective of a single public administration organisation where you have recently worked in the last 2 years.

Please assess the citizen pressures on your organisation.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Citizen demands drive the adoption of new technologies	○	○	○	○	○	○	○
Citizen expectations drive the adoption of new technologies	○	○	○	○	○	○	○
Traditional and social media, as distinct sources of information, drive the adoption of new technologies	○	○	○	○	○	○	○

Please assess your organisation's leadership and culture.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Senior leadership in my organisation has a clear understanding of where we are going	○	○	○	○	○	○	○
Senior leadership in my organisation is always seeking new opportunities for the organisation	○	○	○	○	○	○	○
Senior leadership in my organisation are able to get others committed to organisational vision	○	○	○	○	○	○	○
Senior leadership in my organisation lead by “doing” rather than simply “telling”	○	○	○	○	○	○	○
Senior leadership in my organisation encourage employees to be “team players”	○	○	○	○	○	○	○
Senior leadership in my organisation have stimulated others to rethink the way they do things	○	○	○	○	○	○	○
The organisational culture of my organisation is innovative	○	○	○	○	○	○	○
My organisation is quick to take advantage of opportunities	○	○	○	○	○	○	○

My organisation accepts taking risks	○	○	○	○	○	○	○
My organisation expects taking individual responsibility	○	○	○	○	○	○	○
New technologies are adequately funded	○	○	○	○	○	○	○
My organisation is able to anticipate and plan for the organizational resistance to change	○	○	○	○	○	○	○
My organisation acknowledges the need for managing change	○	○	○	○	○	○	○
My organisation is capable of communicating the reasons for change to the members of our organization	○	○	○	○	○	○	○
My organisation is able to make the necessary changes in human resource policies for process re-engineering	○	○	○	○	○	○	○

Please assess your organisation's technology and infrastructure. AI refers to natural language processing and/or machine learning applications.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
My organisation has adopted/in the process of adopting cloud-based services for processing data	○	○	○	○	○	○	○
My organisation has invested/ in the process of investing in scalable data storage infrastructures	○	○	○	○	○	○	○
My organisation has invested/ in the process of investing in the necessary processing power (on premise or cloud) to support high intensity applications (e.g. CPUs, GPUs)	○	○	○	○	○	○	○
My organisation has invested/ in the process of investing in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)	○	○	○	○	○	○	○
My organisation has implemented/ in the process of implementation of information security and privacy protocols for storage and use of personal and sensitive data	○	○	○	○	○	○	○
My organisation has access to large, unstructured, or fast-moving data for analysis	○	○	○	○	○	○	○
My organisation can integrate data from multiple internal sources into a data warehouse or mart for easy access	○	○	○	○	○	○	○
My organisation can integrate external data with internal to facilitate high-value analysis of our business environment	○	○	○	○	○	○	○

My organisation has the capacity to share our data across organizational units and organizational boundaries.	○	○	○	○	○	○	○
My organisation can prepare and cleanse data efficiently and assess data for errors	○	○	○	○	○	○	○
My organisation can obtain data at the right level of granularity to produce meaningful insights	○	○	○	○	○	○	○
My organisation has access to internal or external talent with the right technical skills to support new technologies implementations	○	○	○	○	○	○	○
My organisation has access to IS staff (internal or external) who can support IT infrastructure and security	○	○	○	○	○	○	○
My organisation has access to internal or external data scientists capable of using new technologies such as machine learning or natural language processing	○	○	○	○	○	○	○
My organisation has access to internal or external data scientists capable of cleaning and processing big data	○	○	○	○	○	○	○
The use of AI will help my organisation to make better decisions	○	○	○	○	○	○	○
The use of AI will help my organisation to improve operational efficiency	○	○	○	○	○	○	○
The use of AI will help my organisation to speed up processing applications	○	○	○	○	○	○	○

The use of AI will help my organisation to reduce clerical errors (e.g. duplicate data sets)	○	○	○	○	○	○	○
The use of AI will help my organisation to improve citizen engagement	○	○	○	○	○	○	○
The use of AI will help my organisation to improve service delivery and customer satisfaction	○	○	○	○	○	○	○

Please assess your organisation's external environment.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Competition with other peer governmental organisations drive the adoption of new technologies in our organisation	○	○	○	○	○	○	○
External consultants/ advisors drive the adoption of new technologies in our organisation	○	○	○	○	○	○	○
Head of departments drive adoption of new technologies in our organisation	○	○	○	○	○	○	○
Political changes drive the adoption of new technologies	○	○	○	○	○	○	○
Economical changes drive adoption of new technologies	○	○	○	○	○	○	○
Citizen demographical changes drive adoption of new technologies	○	○	○	○	○	○	○
Political leadership and central ministry mandates/requirements drive the adoption of new technologies	○	○	○	○	○	○	○
There are enough financial incentives available from central ministries to ensure that new technologies can be implemented	○	○	○	○	○	○	○

Audits, reports, or pressures from oversight bodies drive the adoption of new technologies	○	○	○	○	○	○	○

Please assess your organisation's absorptive capacity.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Our organisation has frequent interactions with Ministers' office to acquire new knowledge	◯	◯	◯	◯	◯	◯	◯
Employees of our organisation regularly visit other governmental organisations/departments.	◯	◯	◯	◯	◯	◯	◯
We collect industry information through informal means (e.g. lunch with industry friends, talks with governmental associations)	◯	◯	◯	◯	◯	◯	◯
Our organisation periodically organises special meetings with citizens, industry associations or third parties to acquire new knowledge.	◯	◯	◯	◯	◯	◯	◯
Employees regularly approach third parties such as consultants, technology vendors, industry associations	◯	◯	◯	◯	◯	◯	◯
We are slow to recognise shifts in citizen demands or political mandates	◯	◯	◯	◯	◯	◯	◯
New opportunities to serve our citizens are quickly understood	◯	◯	◯	◯	◯	◯	◯
We quickly analyse and interpret changing citizen or political demands	◯	◯	◯	◯	◯	◯	◯

Please answer the following demographical questions.

COUNTRY In which country is your organisation located?

▼ Afghanistan ... Zimbabwe

At what level of government is your organisation?

- ○ National - Central/Federal
- ○ Regional - State/Provincial/County
- ○ Local - City/Municipal/Borough
- ○ Public body/ Arm's length agency

What is the size of your organisation based on the number of employees?

- ○ Fewer than 50
- ○ 50-99
- ○ 100-249
- ○ 250-499
- ○ 500-749
- ○ 750-999
- ○ 1,000 or more

What is your position within the organisation?

- ○ Executive
- ○ Senior Director/Head of Department
- ○ Director
- ○ Senior Manager
- ○ Functional Manager/Project Manager
- ○ Team Lead
- ○ Consultant/ Advisor
- ○ Other (please specify) ____

What is your gender?

- ○ Male
- ○ Female
- ○ Other

What is your age group?

- ○ 24 years and under
- ○ 25 to 29 years
- ○ 30 to 34 years
- ○ 35 to 39 years
- ○ 40 to 44 years
- ○ 45 to 49 years
- ○ 50 to 54 years
- ○ 55 to 59 years
- ○ 60 years and over

What is your highest level of education?

- Diploma/ certificate or below
- Bachelor’s degree
- Professional degree
- Master’s degree
- Doctoral degree

Will you be willing to participate in an interview for a follow-up study on AI adoption and diffusion within public administration?

- Yes
- No

Are you interested to receive a summary report of this research project?

- Yes
- No

If yes to above, please provide your contact information.

- Name ____
- Email ____

Name of your organisation ____

Appendix B. Interview Consent Form and Information Sheet

Information sheet

Title: Artificial Intelligence adoption and diffusion in public administration

You are being asked to take part in a research study that aims to investigate Artificial Intelligence (AI) adoption and diffusion in public organisations at the national, regional, and municipal levels in Canada. This study is part of a PhD research by Rohit Madan at Henley Business School, University of Reading, UK. The research has received favourable review by the Business Informatics, Systems and Accounting ethics office, Henley Business School, University of Reading, UK.

Your participation

This qualitative part of the study involves interviews with senior leaders involved in digital transformations and those involved in a consulting capacity for implementing AI solutions. The interview will explore AI adoption and diffusion within your or client's public organisation. In the first part of the interview, I will explore how AI adoption decisions are made and get your feedback on the results of the survey recently conducted. In the second part, I will explore in-depth the AI design and implementation process and how ethical tensions are resolved.

Data Storage

With your permission, I would like to record and take notes for later analysis. All data and recordings will be secured safely on a local drive and never shared with anyone outside the research team. Data is destroyed after five years as part of the International Data Protection Act.

Right to withdraw

You can stop being a part of the research study at any time with no need for an explanation. You have the right to ask that any data you have supplied to that point be withdrawn or destroyed, you also have the right to omit or refuse to answer or respond to any question that is asked of you. You have the right to have your questions about the procedures answered, before, or after the interview.

Risks

There are no foreseeable risks.

Cost, reimbursement, and compensation

Your participation in this study is voluntary and no monetary compensation will be given for this study.

Confidentiality/anonymity

The records of this study (either hard copy or electronic) will be kept private. In any sort of report we make public we will not include any information that will make it possible to identify you or your organisation. Research records will be accessed only by the research team listed below. We anticipate using the research findings to produce outputs like academic papers, book chapters, etc.

For further information:

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Consent form

Title: Artificial Intelligence adoption and diffusion in public administration

1. I have read and had explained to me by Rohit Madan the information sheet relating to the project and any questions have been answered to my satisfaction.
2. I agree to the arrangements described in the information sheet insofar as they relate to my participation.
3. I understand that my participation is entirely voluntary and that I may withdraw from the project at any time.
4. I agree to the interview being *audio* recorded.
5. I agree to the primary data being used in publications directly related to this research. I understand that data will be retained securely for this purpose.
6. I have received a copy of this consent form and of the accompanying information sheet.
7. I am aged 18 or older.

Name of participant: ....

Signed: ....

Date: ....

Contact details of Researcher:

Name of researcher: Rohit Madan

Email address: r.madan@pgr.reading.ac.uk

Appendix C. List of publications included in the review in Chapter 3

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Appendix D. Final template from qualitative analysis in Chapter 3

1. Technology Context
   - 1.1. IT assets
     - 1.1.1. Cloud computing capabilities
     - 1.1.2. Current digital infrastructure
       - 1.1.2.1. High connectivity and bandwidth
       - 1.1.2.2. Processing power and server hardware
       - 1.1.2.3. Networks
       - 1.1.2.4. System integration
     - 1.1.3. Data
       - 1.1.3.1. Data quality, availability, accessibility
       - 1.1.3.2. Database management infrastructure
       - 1.1.3.3. Data ownership and sharing
       - 1.1.3.4. Storage – cloud or on-premises
       - 1.1.3.5. Data governance maturity
   - 1.2. IT capabilities
     - 1.2.1. Current capabilities in managing IT assets
     - 1.2.2. Staff's knowledge of AI and big data
     - 1.2.3. Data oriented culture
     - 1.2.4. Big data and analytics specialists and experts
     - 1.2.5. Ecosystem of commercial partners and experts
   - 1.3. Perceived benefits
     - 1.3.1. Expected benefits
     - 1.3.2. Simple intuitive design
     - 1.3.3. Meets users' needs
2. Organisational Context
   - 2.1. Organisational culture
     - 2.1.1. Innovativeness
     - 2.1.2. Institutional arrangements
     - 2.1.3. Technology and strategy alignment
   - 2.2. Leadership
     - 2.2.1. Transformational leadership
     - 2.2.2. CIO's leadership and technical expertise
   - 2.3. Inertia
     - 2.3.1. Routine rigidity
       - 2.3.1.1. Bureaucracy, centralised decision making

2.3.1.2. Status quo and resistance to change

2.3.2. Resource rigidity

2.3.2.1. Resource scarcity

2.3.2.2. Costs versus benefits for experimental projects

2.3.3. Union resistance

3. Environmental Context

3.1. Vertical pressures

3.1.1. Political environment, election cycles

3.1.2. Policy signals, directives, mandates

3.1.3. Regulations, laws, procurement practices

3.1.4. National AI guidelines

3.2. Horizontal pressures

3.2.1. Citizen demands

3.2.2. Inter-governmental competitive pressures

3.2.3. Media scrutiny and oversight

4. Absorptive capacity

4.1. Path-dependency

4.2. Knowledge management practices

4.3. Dynamic capabilities

5. Implementation strategies

5.1. Experimentation

5.2. Innovative procurement

5.3. Collaboration and co-creation

5.4. Project management

6. Outcomes

6.1. Public values

6.1.1. Duty

6.1.2. Service

6.1.3. Social

6.2. Public sector transformation

7. AI Tensions

7.1. Automation versus augmentation

7.2. Nudging versus autonomy

7.3. Data accessibility versus security and privacy

7.4. Predictive accuracy versus discrimination, biases, citizen rights

7.5. Predictive accuracy versus transparency and accountability versus gaming the system

8. Data Governance

Appendix E. Survey instrument used in Chapter 4

Construct	Item	References
Service coercive pressures	SC1. Citizen demands drive the adoption of new technologies	(Korac et al., 2017; Walker, 2006; Walker et al., 2011)
	SC2. Citizen expectations drive the adoption of new technologies	
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	
Perceived benefits	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 F. Measurement and structural analysis for Chapter 4

Table 7.1. Cross loadings for the measurement model in Chapter 4

	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**

Table 7.2. Fornell Locker Criteria analysis for the measurement model in Chapter 4

	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

Table 7.3. HTMT ratios for the measurement model in Chapter 4

	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 7.4. Confidence intervals for HTMT ratios for the measurement model in Chapter 4

	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

Table 7.5. PLS predict for the structural model in Chapter 4

	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 7.6. Model comparisons for structural models in Chapter 4

	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 level 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 G. Interview Guide for Chapter 4

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 AI benefits. What is your opinion on the extent of these pressures effecting perception of AI benefits and driving AI adoption and use?

Appendix H. Templates for the qualitative analysis in Chapter 4

Table 7.7. A priori template for Chapter 4

1. Consultant pressures
2. Institutional pressures
    2.1. Mimetic pressures
        2.1.1. Competition with peers
        2.1.2. Economic changes
        2.1.3. Citizen demographic changes
    2.2. Normative pressures
        2.2.1. Networking
            2.2.1.1. Internal government
            2.2.1.2. Industry
        2.2.2. Professional organisations
    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. Oversight bodies
3. Perceived benefits
    3.1. Make better decisions
    3.2. Improve efficiency
    3.3. Improve processing
    3.4. Reduce errors
    3.5. Improve citizen engagement
    3.6. Improve service delivery
4. Sensemaking mechanisms
    4.1. Cognitive constraints
    4.2. Priming
    4.3. Triggering
    4.4. Editing

Table 7.8. Final template for Chapter 4

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
    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 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 from 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

Appendix I. Survey instrument used in Chapter 5

Construct	Item	Scale	References
IT assets	ITA1: My organisation has adopted/in the process of adopting cloud-based services for processing data	7-point Likert-type scale	(Mikalef et al., 2021)
	ITA2: My organisation has invested/ in the process of investing in scalable data storage infrastructures		
	ITA3: My organisation has invested/ in the process of investing in the necessary processing power (on premise or cloud) to support high intensity applications (e.g. CPUs, GPUs)		
	ITA4: My organisation has invested/ in the process of investing in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)		
	ITA5: My organisation has implemented/ in the process of implementation of information security and privacy protocols for storage and use of personal and sensitive data		
Data	ITD1: My organisation has access to large, unstructured, or fast-moving data for analysis	7-point Likert-type scale	(Mikalef et al., 2021)
	ITD2: My organisation can integrate data from multiple internal sources into a data warehouse or mart for easy access		
	ITD3: My organisation can integrate external data with internal to facilitate high-value analysis of our business environment		
	ITD4: My organisation has the capacity to share our data across organizational units and organizational boundaries		

Construct	Item	Scale	References
	ITD5: My organisation can prepare and cleanse data efficiently and assess data for errors		
	ITD6: My organisation can obtain data at the right level of granularity to produce meaningful insights		
IT capability	ITC1: My organisation has access to internal or external talent with the right technical skills to support new technologies implementations	7-point Likert-type scale	(Mikalef et al., 2021)
	ITC2: My organisation has access to IS staff (internal or external) who can support IT infrastructure and security		
	ITC3: My organisation has access to internal or external data scientists capable of using new technologies such as machine learning or natural language processing		
	ITC4: My organisation has access to internal or external data scientists capable of cleaning and processing big data		
Leadership	LED1: Senior leadership in my organisation has a clear understanding of where we are going	7-point Likert-type scale	(Podsakoff et al., 1990; Kim and Yoon, 2015)
	LED2: Senior leadership in my organisation is always seeking new opportunities for the organisation		
	LED3: Senior leadership in my organisation are able to get others committed to organisational vision		
	LED4: Senior leadership in my organisation lead by “doing” rather than simply “telling”		
	LED5: Senior leadership in my organisation encourage employees to be “team players”		
	LED6: Senior leadership in my organisation have stimulated others to rethink the way they do things		
Innovative culture	CUL1: The organisational culture of my organisation is innovative	7-point Likert-type scale	(Sarros et al., 2005)

Construct	Item	Scale	References
	CUL2: My organisation is quick to take advantage of opportunities		
	CUL3: My organisation accepts taking risks		
Financial resources	FIN1: There are enough financial incentives available from central ministries to ensure that new technologies can be implemented	7-point Likert-type scale	(Mikalef et al., 2021)
	FIN2: New technologies are adequately funded		
Change capability	CNG1: My organisation is able to anticipate and plan for the organizational resistance to change	7-point Likert-type scale	(Mikalef et al., 2021)
	CNG2: My organisation acknowledges the need for managing change		
	CNG3: My organisation is capable of communicating the reasons for change to the members of our organization		
	CNG4: My organisation is able to make the necessary changes in human resource policies for process re-engineering		
Acquisition capability	AQC1: Employees of our organisation regularly visit other governmental organisations/ departments.	7-point Likert-type scale	(Jansen et al., 2005; Cepeda-Carrion et al., 2012)
	AQC2: We collect industry information through informal means (e.g. lunch with industry friends, talks with governmental associations)		
	AQC3: Our organisation periodically organises special meetings with citizens, industry associations or third parties to acquire new knowledge		
	AQC4: Employees regularly approach third parties such as consultants, technology vendors, industry associations		
Assimilation capability	ASC1: We are slow to recognise shifts in citizen demands or political mandates - reverse coded	7-point Likert-type scale	(Jansen et al., 2005; Cepeda-Carrion et al., 2012)
	ASC2: New opportunities to serve our citizens are quickly understood		

Construct	Item	Scale	References
	ASC3: We quickly analyse and interpret changing citizen or political demands		
ML adoption	MLA1: To what extent **machine learning** applications are being used in your organisation? Common examples include predictive analytics for decision support and policy development; anomaly detection; process automation such as HR management, case management, financial management; optimisation of resource allocations; automation of public services.	• We do not use or plan to use it • We anticipate using it in the next 2 years • We have plans to start using it in the next 6-12 months • We are in the process of piloting and testing • We are currently using it	
NLP adoption	NLPA1: To what extent **natural language processing** applications are being used in your organisation? Common examples include intelligent text or voice interaction with citizens; analysing unstructured data such as citizen and stakeholder feedback through topic modelling, text categorisation, informational extraction, relationship extraction; sentiment analysis	• We do not use or plan to use it • We anticipate using it in the next 2 years • We have plans to start using it in the next 6-12 months • We are in the process of piloting and testing • We are currently using it	

Appendix J. Measurement model and structural analysis in Chapter 5

Table 7.9. Lower order constructs cross loadings for the measurement model in Chapter 5

	LED	CUL	FIN	CNG	AQC	ASC	ITA	ITD	ITC
LED1	**0.877**	0.682	0.406	0.662	0.347	0.508	0.364	0.400	0.426
LED2	**0.878**	0.691	0.418	0.674	0.399	0.521	0.356	0.422	0.385
LED3	**0.884**	0.690	0.433	0.712	0.367	0.547	0.321	0.442	0.409
LED4	**0.881**	0.723	0.398	0.687	0.350	0.496	0.336	0.338	0.327
LED5	**0.702**	0.558	0.277	0.561	0.273	0.425	0.231	0.315	0.300
LED6	**0.853**	0.725	0.403	0.678	0.357	0.573	0.413	0.458	0.420
CUL1	0.788	**0.922**	0.470	0.683	0.336	0.586	0.428	0.438	0.450
CUL2	0.742	**0.926**	0.479	0.636	0.330	0.600	0.397	0.421	0.390
CUL3	0.659	**0.892**	0.431	0.562	0.250	0.484	0.344	0.420	0.371
FIN1	0.258	0.297	**0.868**	0.387	0.176	0.345	0.301	0.369	0.436
FIN2	0.542	0.576	**0.911**	0.610	0.328	0.518	0.442	0.468	0.457
CNG1	0.700	0.650	0.522	**0.874**	0.323	0.531	0.386	0.459	0.463
CNG2	0.626	0.526	0.382	**0.842**	0.313	0.453	0.412	0.404	0.429
CNG3	0.705	0.574	0.451	**0.860**	0.343	0.475	0.414	0.476	0.442
CNG4	0.614	0.582	0.574	**0.805**	0.247	0.524	0.326	0.503	0.488
AQC1	0.324	0.271	0.229	0.329	**0.754**	0.315	0.212	0.262	0.199
AQC2	0.309	0.283	0.083	0.208	**0.691**	0.273	0.211	0.165	0.145
AQC3	0.348	0.280	0.238	0.305	**0.825**	0.378	0.265	0.293	0.247
AQC4	0.278	0.204	0.277	0.240	**0.744**	0.374	0.271	0.291	0.235
ASC1	0.433	0.401	0.230	0.363	0.280	**0.718**	0.251	0.302	0.288
ASC2	0.615	0.608	0.516	0.605	0.428	**0.923**	0.407	0.491	0.440
ASC3	0.501	0.541	0.470	0.509	0.430	**0.914**	0.384	0.487	0.432
ITA1	0.237	0.260	0.337	0.258	0.261	0.242	**0.777**	0.285	0.338
ITA2	0.321	0.336	0.362	0.372	0.301	0.322	**0.838**	0.440	0.379
ITA3	0.321	0.379	0.411	0.367	0.282	0.351	**0.852**	0.464	0.393
ITA4	0.366	0.438	0.323	0.425	0.205	0.394	**0.804**	0.451	0.355
ITA5	0.364	0.277	0.214	0.388	0.206	0.336	**0.661**	0.405	0.437
ITD1	0.308	0.318	0.378	0.381	0.280	0.363	0.468	**0.691**	0.494
ITD2	0.340	0.379	0.367	0.400	0.260	0.391	0.452	**0.849**	0.567
ITD3	0.392	0.391	0.360	0.435	0.353	0.438	0.411	**0.842**	0.505
ITD4	0.461	0.395	0.376	0.482	0.312	0.419	0.370	**0.751**	0.472
ITD5	0.403	0.415	0.411	0.475	0.260	0.445	0.390	**0.869**	0.655
ITD6	0.384	0.352	0.399	0.462	0.199	0.401	0.405	**0.815**	0.621
ITC1	0.434	0.452	0.533	0.567	0.290	0.489	0.450	0.625	**0.790**
ITC2	0.420	0.388	0.337	0.485	0.278	0.380	0.485	0.457	**0.706**
ITC3	0.372	0.355	0.389	0.409	0.211	0.342	0.360	0.591	**0.892**
ITC4	0.308	0.314	0.414	0.378	0.190	0.347	0.347	0.598	**0.903**

Table 7.10. Lower order constructs Fornell Locker Criteria analysis for the measurement model in Chapter 5

	LED	CUL	FIN	CNG	AQC	ASC	ITA	ITD	ITC
LED	**0.848**								
CUL	0.802	**0.913**							
FIN	0.463	0.504	**0.890**						
CNG	0.783	0.690	0.571	**0.846**					
AQC	0.414	0.336	0.290	0.362	**0.755**				
ASC	0.607	0.612	0.493	0.587	0.451	**0.857**			
ITA	0.403	0.429	0.424	0.455	0.321	0.414	**0.789**		
ITD	0.472	0.467	0.475	0.545	0.346	0.510	0.518	**0.805**	
ITC	0.450	0.444	0.502	0.539	0.282	0.460	0.478	0.688	**0.827**

Table 7.11. Lower order constructs HTMT ratios for the measurement model in Chapter 5

	LED	CUL	FIN	CNG	AQC	ASC	ITA	ITD	ITC
LED									
CUL	0.876								
FIN	0.540	0.600							
CNG	0.875	0.777	0.698						
AQC	0.496	0.413	0.360	0.442					
ASC	0.693	0.701	0.598	0.683	0.553				
ITA	0.457	0.489	0.520	0.537	0.394	0.493			
ITD	0.519	0.521	0.580	0.622	0.407	0.585	0.599		
ITC	0.521	0.520	0.639	0.650	0.357	0.557	0.594	0.792	

Table 7.12. Lower order constructs confidence intervals for HTMT ratios for the measurement model in Chapter 5

	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI
LED -> CUL	0.876	0.877	0.021	41.293	0.841	0.910
LED -> FIN	0.540	0.541	0.057	9.419	0.444	0.633
LED -> CNG	0.875	0.876	0.029	30.639	0.827	0.920
LED -> AQC	0.496	0.494	0.060	8.286	0.393	0.590
LED -> ASC	0.693	0.692	0.047	14.760	0.614	0.766
LED -> ITA	0.457	0.457	0.063	7.285	0.350	0.558
LED -> ITD	0.519	0.520	0.052	9.996	0.432	0.603
LED -> ITC	0.521	0.522	0.058	8.940	0.424	0.616
CUL -> FIN	0.600	0.600	0.054	11.196	0.510	0.686
CUL -> CNG	0.777	0.777	0.036	21.825	0.715	0.833
CUL -> AQC	0.413	0.412	0.072	5.738	0.291	0.526
CUL -> ASC	0.701	0.701	0.048	14.677	0.619	0.776
CUL -> ITA	0.489	0.490	0.053	9.315	0.401	0.575
CUL -> ITD	0.521	0.521	0.050	10.528	0.436	0.600
CUL -> ITC	0.520	0.521	0.051	10.119	0.434	0.601
FIN -> CNG	0.698	0.699	0.055	12.797	0.607	0.786
FIN -> AQC	0.360	0.370	0.070	5.121	0.258	0.490
FIN -> ASC	0.598	0.599	0.062	9.662	0.495	0.698
FIN -> ITA	0.520	0.523	0.062	8.406	0.417	0.621

	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI
FIN -> ITD	0.580	0.581	0.057	10.260	0.484	0.670
FIN -> ITC	0.639	0.640	0.057	11.143	0.543	0.732
CNG -> AQC	0.442	0.440	0.068	6.481	0.323	0.552
CNG -> ASC	0.683	0.684	0.062	11.103	0.579	0.779
CNG -> ITA	0.537	0.537	0.061	8.833	0.433	0.632
CNG -> ITD	0.622	0.623	0.047	13.292	0.542	0.697
CNG -> ITC	0.650	0.650	0.051	12.696	0.561	0.731
AQC -> ASC	0.553	0.554	0.062	8.985	0.450	0.653
AQC -> ITA	0.394	0.394	0.069	5.676	0.280	0.509
AQC -> ITD	0.407	0.409	0.065	6.280	0.300	0.512
AQC -> ITC	0.357	0.359	0.070	5.122	0.244	0.473
ASC -> ITA	0.493	0.493	0.064	7.688	0.384	0.594
ASC -> ITD	0.585	0.587	0.060	9.758	0.483	0.681
ASC -> ITC	0.557	0.558	0.060	9.268	0.457	0.654
ITA -> ITD	0.599	0.599	0.048	12.547	0.516	0.674
ITA -> ITC	0.594	0.595	0.057	10.397	0.497	0.684
ITD -> ITC	0.792	0.793	0.038	21.083	0.730	0.852

Table 7.13. Cross loadings for the measurement model in Chapter 5

	ORG	TECH	MLA	NLPA
LED	**0.872**	0.525	0.094	0.087
CUL	**0.846**	0.529	0.070	0.078
FIN	**0.722**	0.556	0.122	0.124
CNG	**0.868**	0.611	0.111	0.133
ACQ	**0.571**	0.372	0.122	0.181
ASC	**0.799**	0.548	0.051	0.104
ITA	0.523	**0.759**	0.226	0.175
ITD	0.604	**0.880**	0.218	0.263
ITC	0.577	**0.881**	0.384	0.351
MLA1	0.120	0.335	**1.000**	0.600
NLAPA1	0.147	0.320	0.600	**1.000**

Table 7.14. Fornell Locker Criteria analysis for the measurement model in Chapter 5

	ORG	TECH	MLA	NLPA
ORG	**0.787**			
TECH	0.675	**0.842**		
MLA	0.120	0.335	Single-item	
NLPA	0.147	0.320	0.600	Single-item

Table 7.15. HTMT ratios for the measurement model in Chapter 5

	ORG	TECH	MLA	NLPA
ORG				
TECH	0.808			
MLA	0.130	0.369		
NLPA	0.162	0.351	0.600	

Table 7.16. Confidence intervals for HTMT ratios for the measurement model in Chapter 5

	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	5% CI	95% CI
ORG -> TECH	0.808	0.812	0.038	21.032	0.747	0.874
ORG -> MLA	0.130	0.140	0.055	2.356	0.060	0.239
ORG -> NLPA	0.162	0.167	0.059	2.747	0.076	0.268
TECH -> MLA	0.369	0.370	0.060	6.133	0.269	0.464
TECH -> NLPA	0.351	0.353	0.067	5.233	0.240	0.463
MLA -> NLPA	0.600	0.599	0.048	12.530	0.519	0.676

Table 7.17. Model comparisons for the structural model in Chapter 5

	ML Adoption			NLP Adoption		
	BIC	R^2	Adj R^2	BIC	R^2	Adj R^2
Model 1	-34.175	0.246	0.226	-47.845	0.282	0.263
Model 2	-23.533	0.133	0.126	-16.847	0.111	0.105
Model 3	-27.73	0.18	0.168	-38.984	0.212	0.201
Model 4	-32.444	0.241	0.221	-	-	-
Model 5	-	-	-	-46.621	0.279	0.26

All models are based on the same measurement model.

Model 1 – original model

Model 2 – original model with no controls

Model 3 – original model with only fixed effects of the level of government as controls

Model 4 – original model with one dependent variable of ML adoption

Model 5 – original model with one dependent variable of NLP adoption

Appendix K. Interview guide for Chapter 5

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. Can you discuss some current use cases of AI within your organisation?
4. What do you think are some of the key capabilities required to adopt and implement machine learning and/or natural language processing solutions within the public administration?
5. What do you think is the relationship between organisational readiness in terms of leadership and innovation and technological readiness in terms of IT infrastructure, data maturity and governance, and technical skills?
6. How are AI projects started and by whom?
7. How do you see AI projects relative to the previous technological implementations within the public administration?
8. What is the governance structure for making decisions on the design and implementation of AI projects?
9. Any closing thoughts on AI adoption within the public administration?

Appendix L. Templates for qualitative analysis in Chapter 5

Table 7.18. A priori template for Chapter 5

1. Organisational AI readiness
    1.1. Financial resources
    1.2. Transformational leadership
    1.3. Innovative culture
    1.4. Change capability
    1.5. Acquisition capability
    1.6. Assimilation capability
2. Technological AI readiness
    2.1. Data
    2.2. IT assets
    2.3. IT capability
3. ML adoption
4. NLP adoption

Table 7.19. Final template for Chapter 5

1. Organisational AI readiness
    1.1. Financial resources
    1.2. Transformational leadership
        1.2.1. Leaders' comfort with technology
        1.2.2. Long-term commitment
        1.2.3. Ability to navigate challenges
        1.2.4. Provide a vision for AI adoption and use
        1.2.5. Risk tolerance
        1.2.6. Transformation leadership
    1.3. Innovative environment
        1.3.1. Experimentation
        1.3.2. Attitudes towards use of new technologies
        1.3.3. Innovation department/team
        1.3.4. Innovative culture
        1.3.5. Modernisation agenda
    1.4. Change capability
        1.4.1. Change management processes

1.4.1.1. Change management
1.4.1.2. Education and awareness
1.4.1.3. Engagement with users and citizens
1.4.1.4. Openness to adopt and adapt
1.4.2. Changing roles and identity
1.4.3. Multiple stakeholder voices
1.5. Acquisition capability
1.5.1. Engagement with consultants
1.5.2. Participation in demonstrations
1.5.3. Awareness of public/citizen perceptions and media narratives on AI
1.6. Assimilation capability
1.6.1. Evaluate AI capabilities and limitations
1.6.2. Managing AI projects and its challenges
1.7. Workforce acquisition and training
1.7.1. Challenges with antiquated human resources processes
1.7.2. Attract new talent
1.7.3. Develop multi-disciplinary teams
1.7.4. Training
1.7.4.1. Invest in building internal resources
1.7.4.2. Public sector specific training
1.7.4.3. Skills shift and need more training
2. Technological AI readiness
2.1. Data
2.1.1. Data availability and quality
2.1.1.1. Availability of extensive data
2.1.1.2. Good quality and appropriate data
2.1.1.3. Data as a feature of an organisation
2.1.1.4. Data lakes
2.1.1.5. Strategic value of datasets
2.1.2. Data maturity
2.1.2.1. Data culture
2.1.2.2. Data literacy
2.1.2.3. Need for data maturity, currently low maturity
2.1.3. Data governance
2.1.3.1. Central data office and strategy
2.1.3.2. Data accessibility and right to use
2.1.3.3. Data dictionaries
2.1.3.4. Data separation and anonymity
2.1.3.5. Data stewardship

2.1.3.6. Data security

2.1.3.7. Tools for managing data

2.1.3.8. Need for data governance

2.1.4. Data science and AI development skills

2.1.4.1. Business analyst skills to bridge business users and AI development

2.1.4.2. Building internal capabilities in data science and AI development

2.1.4.3. Prepare data for multiple uses

2.2. IT Assets

2.2.1. Cloud based technology

2.2.1.1. Building cloud based infrastructure

2.2.1.2. Challenges of transitioning to cloud

2.2.1.2.1. Geolocation of data centres

2.2.1.2.2. Procurement

2.2.1.3. Hybrid model of cloud and on-premise infrastructure

2.2.2. Legacy systems

2.2.2.1. Platform upgrades

2.2.2.2. Technical debt

2.2.3. Technical infrastructure

2.2.3.1. Path of least resistance, acquiring off-the-shelf applications from existing vendor

2.2.3.2. Open-source tools for AI development

2.2.3.2.1. Open source and accessible

2.2.3.2.2. Challenges of adopting to existing infrastructure

2.2.3.3. Upgrade existing technology stack

2.3. IT Capabilities

2.3.1. Capabilities in deploying AI solutions

2.3.2. Supporting IT assets

2.3.3. Supporting applications when operational

3. ML vs NLP adoption

4. Interactions between Organisational and Technological readiness

4.1. Low organisational and low technological readiness

4.1.1. Lack of expertise to scope and ask the right questions

4.1.2. Seek external consulting

4.2. Low organisation and high technological readiness

4.2.1. Acquire AI embedded in off-the-shelf solutions

4.2.2. Technological maturity will lead to innovation and new ideas

4.2.3. Wild west on adopting and procuring AI solutions

4.3. High organisational and low technological readiness

4.3.1. Encourage internal AI capability building and bottom up innovation

4.3.2. Experimental spaces
4.3.3. Increasing data maturity
4.3.4. Leadership encourages experimentation and risk taking
4.4. High organisational and high technological readiness
4.4.1. Ability to scope and evaluate AI
4.4.2. Build trust and confidence in using AI operationally
4.4.3. Focus on building AI capabilities internally
4.4.4. Implementation capabilities
4.4.4.1. Agile project management capabilities
4.4.4.2. Pilot projects to demonstrate value
4.4.4.3. Technology project management capabilities
4.4.4.3.1. Collaborative design
4.4.4.3.2. Process for operationalisation, handover to IT
4.4.4.3.3. Project governance
4.4.4.3.4. Risk management
4.4.4.3.5. Software project management
4.4.4.3.6. Stakeholder management
4.4.5. Internal development of AI
4.4.6. Responsible AI development
4.4.6.1. AI ethics and policy experts in the team
4.4.6.2. AI governance processes
4.4.6.3. AI project candidate identification process
4.4.6.4. Ethical AI development guidelines
4.4.6.5. Policy on risk tolerance with AI use
4.4.6.6. Resistance to political pressures embedded in the policy
5. AI capability development paths
5.1. Consultant-led
5.1.1. Consultant driven adoption with no internal capability building
5.1.2. Driven by hype
5.1.3. Prevalence of consultants in public administration
5.1.4. Risks
5.1.4.1. High costs
5.1.4.2. Lack of understanding of the public sector context
5.1.4.3. Selling templated high margin solutions and looking for next contract
5.2. Strategy-led
5.2.1. Leadership driven
5.2.2. Developing strategy and roadmap for AI adoption
5.2.3. Types
5.2.3.1. Ecosystem-based

5.2.3.2. Internal capability-based

5.3. Serendipitous

5.3.1. Bottom-up innovation

5.3.2. Confluence of a number of factors, right environment, leadership, resources, idea

5.3.3. Showing value from AI