Artificial Intelligence (AI) Adoption in Canadian Local Governments: Opportunities, Challenges and Factors of Innovation

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Abstract

Artificial Intelligence (AI) has become increasingly prevalent in local governments worldwide, contributing to improved internal administrative processes and service delivery. Local governments serve as the frontline of citizen interactions and are vital to economic development and sustainability, whereas they face resource limitations and struggle to manage AI's high risks. Canada presents an interesting case study, as it is recognized as a leader in AI and invested heavily in AI firms, whereas Canadian governments are generally considered risk-averse. In this thesis, I empirically investigate AI adoption in Canadian local governments with the aim of understanding the aspects that play a crucial role in the successful adoption of AI.

I begin by comparing and contrasting Information Technology (IT) and AI adoption in local governments, providing an opportunity to identify whether IT adoption can provide insights into AI adoption. I conclude that although AI presents unique issues, AI and IT adoption share similarities in their promises to local governments and pitfalls around their resource requirements and political influence. In Chapter 3, I present a survey of 28 representatives directly involved in AI projects in Canadian local governments. I highlight positive perceptions of the benefits of AI but also identify challenges related to resources, training, expertise, data and computing infrastructure. In Chapter 4, I examine the innovation factors that contribute to the success of AI adoption in the City of Edmonton, Alberta, Canada, a leader in AI among Canadian cities. I develop a framework that consists of internal and external factors specific to AI innovation in local governments then I apply these factors to Edmonton. The study highlights six internal factors, including AI-specific resources, internal needs, risk-taking culture, collaboration and knowledge sharing, upper management support, and AI process fit, and three external factors encompassing the innovation ecosystem, environmental drivers, and AI regulation and ethics.

This thesis contributes to the research on and praxis of local government adoption of AI in several ways. First, it uncovers differences and similarities between traditional IT systems and AI systems in local governments, providing lessons for AI adoption. Second, the thesis offers the first empirical investigation on the current practice of AI in Canadian local government and identifies the challenges they face in adopting AI, providing insights for informed policy decisions and responsible AI implementation. Third, it introduces a framework for measuring AI innovation in the public sector, which aids future analysis of AI innovation and helps local

governments understand the necessary conditions for AI innovation. Last, the thesis provides empirical evidence by analyzing AI practices in the City of Edmonton, showcasing how these innovation factors manifest in practice. These findings should guide future AI implementation in other local governments and contribute to research on AI adoption in the public sector.

Résumé

L'intelligence artificielle (IA) est de plus en plus répandue dans les gouvernements locaux du monde entier, contribuant à l'amélioration des processus administratifs internes et de la prestation de services. Les gouvernements locaux sont en première ligne des interactions avec les citoyens et sont essentielles au développement économique et à la durabilité, alors qu'ils sont confrontés à des limitations de ressources limitées et peinent à gérer les risques élevés de l'IA. Le Canada constitue une étude de cas intéressante, car il est reconnu comme un leader en matière d'IA et a investi massivement dans des entreprises d'IA, alors que les gouvernements canadiens sont généralement considérés comme peu enclins à prendre des risques. Dans cette thèse, j'investigue empiriquement l'adoption de l'IA dans les gouvernements locaux canadiennes afin de comprendre les aspects qui jouent un rôle crucial dans l'adoption réussie de l'IA.

Je commence par comparer et mettre en parallèle les technologies de l'information (TI) et l'IA dans les gouvernements locaux, permettant ainsi de déterminer si l'adoption des TI peut donner des indications sur l'adoption de l'IA. Je conclus que, bien que l'IA présente des problèmes uniques, l'adoption de l'IA et des TI présentent des similitudes en ce qui concerne les promesses faites aux gouvernements locaux et les pièges liés aux ressources nécessaires et à l'influence politique. Au chapitre 3, je présente un sondage mené auprès de 28 représentants directement impliqués dans des projets d'IA au sein des gouvernements locaux canadiens. Je souligne les perceptions positives des avantages de l'IA, mais j'identifie également les défis liés aux ressources, à la formation, à l'expertise, aux données et à l'infrastructure informatique. Dans le chapitre 4, j'examine les facteurs d'innovation qui contribuent au succès de l'adoption de l'IA dans la ville d'Edmonton, Alberta, Canada, un chef de file en matière d'IA parmi les villes canadiennes. J'élabore un cadre composé de facteurs internes et externes propres à l'innovation en matière d'IA dans les gouvernements locaux, puis j'applique ces facteurs à la ville d'Edmonton. L'étude met en évidence six facteurs internes, dont les ressources spécifiques à l'IA, les besoins internes, la culture de prise de risque, la collaboration et le partage des connaissances, le soutien de la haute direction et l'adaptation du processus d'IA, ainsi que trois facteurs externes englobant l'écosystème d'innovation, les facteurs environnementaux et la réglementation et l'éthique de l'IA.

Cette thèse contribue à la recherche et à la pratique de l'adoption de l'IA par les gouvernements locaux de plusieurs manières. Tout d'abord, elle met en évidence les différences et les similitudes entre les systèmes d'TI traditionnels et les systèmes d'IA dans les gouvernements locaux, ce qui permet de tirer des leçons pour l'adoption de l'IA. Deuxièmement, la thèse offre le premier sondage empirique sur la pratique actuelle de l'IA dans les gouvernements locaux au Canada et identifie les défis auxquels ils sont confrontés dans l'adoption de l'IA, permettant ainsi de prendre des décisions politiques éclairées et de mettre en œuvre l'IA de manière responsable. Troisièmement, elle présente un cadre de mesure de l'innovation en matière d'IA dans le secteur public, qui facilite l'analyse future de l'innovation en matière d'IA et aide les gouvernements locaux à comprendre les conditions nécessaires à l'innovation en matière d'IA. Enfin, la thèse fournit des preuves empiriques en analysant les pratiques d'IA dans la ville d'Edmonton, montrant comment ces facteurs d'innovation se manifestent dans la pratique. Ces résultats devraient guider la mise en œuvre future de l'IA dans d'autres gouvernements locaux et contribuer à la recherche sur l'adoption de l'IA dans le secteur public.

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List of Abbreviations

Abbreviation	Definition
ADM	Automated Decision-Making
AI	Artificial Intelligence
AI COP	AI Municipal Government Community of Practice
AIA	Algorithmic Impact Assessment
IT	Information Technology
PIA	Privacy Impact Assessment

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Contribution of Authors

Contributions to Chapters 1, 2 and 5:

Sichen wrote the introduction, literature review and conclusion chapters. My supervisor, Dr. Renee Sieber provided comments, feedback, and suggestions on the writing. My supervisory committee member, Dr. Grant McKenzie provided feedback on drafts of these chapters.

Contribution of Chapters 3 and 4:

These chapters were co-authored with my supervisor, Dr. Renee Sieber, as peer-reviewed journal articles. I am the primary author and I conducted the research, including question formulation, planning, data collection, analysis, and writing. Dr. Sieber provided guidance on the research direction, literature to examine, research methodology, and writing. My supervisory committee member, Dr. Grant McKenzie provided feedback on drafts of these chapters.

Chapter 1. Introduction

1.1 Introduction

With the rapid advancement of technology, the explosion of big data, and the significant progress in computing power, Artificial Intelligence (AI) has emerged as one of the most popular and transformative innovations of the 21st Century. From smart city initiatives to data-driven governance, AI appears to be transforming how local governments operate and interact with their communities. AI poses a set of unique and powerful characteristics that set AI apart from traditional Information Technology (IT). One of its defining features is the ability to learn and adapt from data, a concept known as machine learning (Goodfellow, 2016; Fomin, 2020).

These abilities hold immense promise for local governments. AI promises to enhance service delivery, making it more efficient and personalized for citizens (Misuraca et al.; 2020; de Sousa et al., 2019). AI can optimize operations and automate administrative tasks and resource allocation, leading to streamlined processes and cost savings (Valle-Cruz et al., 2019; Zuiderwijk et al., 2021). AI's analytics capabilities may enable data-driven decision-making, providing insights and patterns to guide policy formulation (McEvoy, 2019; Misuraca & Noordt, 2020). AI promises to strengthen democratic governance by promoting citizen engagement and participation, allowing residents to have a more active role in decision-making processes (Darmon, 2019; Karanasiou, 2019).

Accompanying the promises of AI in local governments are the significant barriers governments face in implementing the technology. AI is opaque, which presents a challenge for local governments, making it difficult for them to comprehend the systems and assess their performance (Burrell, 2016; Hayes et al., 2023). This lack of transparency raises concerns about the legitimacy and accountability of AI-assisted decision-making processes (Mittelstadt et al., 2019). AI is prone to bias, influenced by biases in data, algorithm design, and learning processes, which can lead to unjust decisions and potential discrimination (Mittelstadt et al., 2016). Within local government, regulating AI can prove onerous, as it involves numerous components, such as data, training algorithms, and auxiliary algorithms (Ip et al., 2022). The current regulatory landscape at both federal and local levels is lacking, resulting in an accountability gap (Katyal, 2019). Implementing AI requires substantial resources in terms of AI personnel, funding, and infrastructure (Vogl, 2021; Yigitcanlar et al., 2022). Further, AI introduces ethical concerns, such as inequity and privacy (Mittelstadt et al., 2016).

Many challenges faced by AI in local governments are not new; they have persisted since the adoption of IT in local governments in the 1970s. The opacity of AI systems echoes the difficulties encountered with early computer systems, where understanding and assessing performance were also challenging due to limited system transparency (Weizenbaum, 1972). Bias in AI was present in early information systems and automated processes (Friedman and Nissenbaum, 1996). Recognizing the historical continuity of these challenges allows us to draw from past experiences and lessons learned to approach today's AI adoption in local governments. The extent to which AI differs from its predecessors and how it may influence future local government requires thorough examination and understanding.

While there has been considerable research on AI adoption in the public sector at the national level, its implementation in local governments has received relatively limited attention. Local governments play a critical role as the frontline of interactions with citizens, responsible for promoting economic development and sustainability within the city (Streib & Willoughby, 2005). Compared to national governments, local governments often face resource constraints (Shearmur, 2016) and AI can be resource-intensive (e.g., hiring data scientists and investing in AI infrastructure) (Vogl, 2021; Yigitcanlar et al., 2022). Managing the risks associated with AI is also crucial for local governments, as AI sometimes promises more than it can deliver. Local governments must ensure that they make well-informed decisions, especially when taxpayers expect their money to be spent wisely. Moreover, local governments have competing priorities, and AI adoption may not always be a top priority. They must allocate funds to maintain underfunded physical infrastructure, such as bridges and roads, which directly impact citizens' daily lives. As a result, finding the right balance between investing in AI and addressing essential infrastructure needs becomes a complex undertaking for local governments.

The country of Canada stands out as a compelling case for studying the integration of AI in local government due to its prominent role as an AI leader, as evidenced by its Directive on Automated Decision-Making (ADM) (Government of Canada, 2019) and Algorithmic Impact Assessment (AIA) (Government of Canada, 2020). Notably, significant investments in AI have been made by governments at all levels of jurisdiction (Brandusescu, 2021). However, it is intriguing to observe that Canadian governments exhibit a more risk-averse nature compared to the United States when it comes to implementing AI solutions (Crane & Meyer, 2006), so it is interesting to investigate more cautious implementation. Despite these factors, there is currently no empirical research that has examined the adoption of AI in Canadian local governments.

1.2 Research Questions

The objective of this thesis is to critically examine what contributes to the success of AI adoption in local governments. In this thesis, I define AI adoption as the process of integrating AI technologies, including decision-making on adoption, planning to build, buy or collaborate, and deployment and maintenance of AI systems. I use local government to refer to government organizations operating at a regional or municipal level. I define success as balancing the opportunities with the challenges imposed by AI and compliance with factors of innovation.

I examine the following research questions:

1. How does AI adoption differ from or is similar to IT adoption in local governments?
2. What and how is AI being adopted in Canadian local governments?
3. What are the opportunities and challenges of AI perceived by individuals involved in local government AI projects?
4. What factors of innovation contribute to the success of local government AI adoption?

1.3 Methodology

In Chapter 2, the first question is addressed through a literature review that tracks the evolution of IT use in local governments from the 1960s and compares it with AI. This chapter conceptualizes IT and AI, introduces the history of IT adoption in government, and compares the promises and pitfalls of IT with AI. This literature review provides a historical context and understanding of the progression of technology adoption in government settings, highlighting the challenges and opportunities faced in the past. By comparing the promises and pitfalls of IT with AI, the literature review offers insights into the potential advantages and challenges that local governments may encounter while adopting AI, highlighting a lack of empirical research on Ai adoption in local governments.

In Chapter 3, the second and third research questions are addressed through a survey conducted with 28 representatives who have direct involvement in the design, development, or deployment of AI systems in Canadian local governments. The chapter provides an overview of the various types of AI technologies adopted by local governments, shedding light on the extent of AI implementation in Canadian local governments. Additionally, the background and expertise of the surveyed individuals are characterized. By examining the approaches taken in AI development, the chapter delves into the reasons for the approaches taken and the costs and benefits of each approach. Furthermore, the perceptions of the surveyed representatives regarding the opportunities and challenges posed by AI adoption in local governments are critically examined. This chapter contributes essential knowledge on AI adoption in local governments. The finding of this chapter can help in recognizing the benefits and challenges and aid in identifying effective strategies of AI adoption in local governments.

In Chapter 4, the last research question is addressed through an examination of a best practice case of AI adoption in the City of Edmonton, Canada. Despite historical perceptions of Edmonton as non-innovative (Jones et al., 2019), the city has emerged as a leading developer of AI among Canadian cities. The chapter develops and tests a comprehensive framework comprising various success factors that are instrumental in local governments' successful adoption of AI. To construct this framework, the chapter draws from existing literature across multiple disciplines, including organizational innovation, smart cities, algorithmic governance, and public sector AI adoption. By synthesizing insights from these diverse fields, the chapter identifies key internal and external elements that should contribute to the effective integration of AI technologies in municipal governance. To illustrate the practical application of the identified success factors, the City of Edmonton is used as a case study. The chapter analyses various data sources, including interviews, presentations, news articles, and government documents related to Edmonton's AI innovation. These various sources serve to triangulate the findings, reduce biases, and uncover internal and external perspectives. This chapter provides a comprehensive framework, outlining essential factors for AI innovation in local governments, which can be utilized in future research. The findings offer valuable insights that may assist other local governments in understanding the crucial conditions and considerations for successful AI adoption

Chapter 5 concludes the thesis findings, shedding light on the current state of AI adoption. The chapter also acts as a launching point for future research directions, emphasizing the need for ongoing investigations in this domain. It is hoped that this thesis and continued research will facilitate informed decision-making, effective policy formulation, and the maximization of AI's potential in local governments.

Chapter 2. Literature Review: From Local Government Information Technology in the 1970s to Artificial Intelligence in the 2020s: Promises and Pitfalls

2.1 Introduction

Over the past decade, there has been a rising interest in the use of Artificial Intelligence (AI) by local governments. Reasons include reducing time routine tasks, responding to reduced government revenue as well as taxpayer demands for efficiency, and improving administration inside local governments (Bullock, 2019; Ojo et al., 2019; Toll et al., 2019; Valle-Cruz et al., 2019; Zuiderwijk et al., 2021).

AI does not represent a new introduction of computing systems to the government. Since the 1960s, computers - the hardware, software and digital data, have been used to automate aspects of government. Many information technologies (IT) were used to support policy making, perform routine tasks, policy analysis, decision-making, and strategic planning (Geertman & Stillwell, 2004; Kraemer, 1969, Maguire, 1991; Ventura, 1995). Since the early 1990s, there have been efforts to incorporate AI in government such as the use of expert systems (Berry et al., 1998) and agent-based models (Wolpert et al., 1999) and machine learning (Fischer, 1994).

It is yet unclear how today's AI compares to traditional IT used in local governments. Without that knowledge, it is unclear whether AI is dramatically different from traditional IT in terms of new opportunities or challenges or whether it is merely an extension of IT. I suspect that we may learn much from examining the history of IT adoption, which can provide valuable lessons for understanding potential opportunities, challenges and risks of AI adoption. Given the significant investment in AI at all levels of government (Brandusescu, 2021) and the newness of AI adoption in local governments, a comparison of IT and AI may provide hints of the promises as well as the problems of AI.

In this chapter, I will first introduce IT and AI and discuss how AI is different from IT and the issues introduced by AI including overfitting, bias and opacity. Next, I will cover the brief history of the evolution of IT in local government, leading up to AI. Then I will extract themes on the promises and pitfalls of IT and compare them to AI. The literature review highlights both the similarities and differences between IT and AI in local government adoption. We conclude that AI differs from IT in terms of learning ability and AI exacerbates opacity and biases compared to IT, whereas, AI shares many commonalities with IT in terms of the promises and challenges related to resources and staff. By recognizing the parallels and differences between IT and AI, policymakers and practitioners can draw upon the lessons learned from past experiences to inform their approach to AI implementation. Furthermore, the review underscores the need for a critical examination of the challenges specific to government AI adoption.

2.2 Introduction to IT and AI

In this section, I first introduce IT and AI, in terms of their definition, components and similarities. Next, I examine the fundamental differences between AI and traditional IT systems, showing the unique characteristics of AI. Next, I discuss how the unique characteristics of AI may result in issues relating to overfitting, bias and opacity.

2.2.1 What is IT and AI

Prior to discussing the introduction of IT and AI in local government, it is useful to define both. King (1982) provided a comprehensive description of the components of IT, including hardware (i.e., central processor unit (CPU), main memory unit, secondary storage devices), system software, and application software. Interestingly, the emphasis was originally on hardware/software and not data. IT covers a wide range of systems used by governments including information systems (IS) (Dickson, 1981), planning support systems (Geertman & Stillwell, 2004) and decision support systems (McGowan & Lombardo, 1986). With the introduction of the Internet, IT also includes websites, cloud infrastructures, server-side applications, smartphone applications, and Internet of Things sensors (Berisha-Shaqiri, 2015).

There has been no consensus on the definition of AI, especially as AI covers a wide range of tasks such as classification, regression, transcription, machine translation, and anomaly detection (Goodfellow 2016). Scholars may also distinguish between deep learning (i.e., neural networks) and traditional machine learning (e.g., random forest, decision trees) (Goodfellow 2016). Many define it not as a set of mathematical algorithms but as machines that can simulate humans. Russell and Norvig (1995) identified four categories of AI definitions: systems that think like humans, act like humans, think rationally, or act rationally. Hutton (2011) provided a broad definition, stating that AI is the activity dedicated to making machines intelligent, where intelligence enables entities to function appropriately and foreseeably in their environment. The lack of consensus and the multifaceted nature of AI indicate that it is a complex and evolving field.

AI and IT share similarities in the sense that both of them involve input, processing and output. Although we generally think of AI as algorithms, it also requires hardware infrastructure to function, such as processors, memory, and storage devices. In addition, AI and IT both possess the ability to process data. In Sections 5 and 6, you will see how the same arguments used for IT in government persist for AI in government.

To navigate the conceptual difficulties of IT and AI, in this chapter, I use the term IT to describe computational systems with explicit program instructions and the term AI to refer to systems utilizing machine learning or deep learning.

2.2.2 Fundamental Difference Between AI Systems and Traditional IT Systems

Fomin (2020) provided a clear explanation of the distinction between traditional IT systems and AI, stating that "If traditional (algorithmic) computational systems were built on the foundation of strict control over the system, then ML algorithms, which power AI, are radically different, in that they do not receive explicit programming instructions (p323)". Instead of these explicit instructions, AI can learn and adapt from the data. While traditional IT systems follow predefined rules, AI systems learn from the data and output a program to make future predictions. Domingos (2012) provides a clear explanation of the essential process of "learning", including representation, evaluation, and optimization. Representation involves expressing a classifier in a language that a computer can understand, and determining the set of classifiers that can be learned. Evaluation involves using an evaluation function to differentiate between good and bad classifiers. Optimization focuses on searching for the best classifier by selecting an appropriate optimization technique.

The adaptive and learning ability of AI offers significant benefits to local governments because of its ability to process big data, handle complex scenarios, and automate decision-making. However, these abilities introduce unique challenges related to overfitting, bias and opacity.

2.2.3 Issue of Overfitting

The “learning” aspect of AI renders it susceptible to overfitting. Domingos (2012) emphasized that the ultimate goal of machine learning is to go beyond the training data and accurately predict outcomes for unseen data. This assumes that a sufficient amount of training data is available, the parameterization is appropriate, and past data reflects present reality in both time and space. In reality, algorithms are trained on limited data and are typically claimed to be generalizable based on certain theoretical assumptions. This leads to unintended predictions by AI systems when confronted with unseen scenarios, resulting from a phenomenon called shortcut learning (Mitchell, 2021). Shortcut learning involves developing decision rules that only fit the training data but fail to generalize to real-world situations (Geirhos et al., 2020). Consequently, machine learning can be overfitted, wherein the model achieves perfect performance on the training data but exhibits significantly lower performance in real-life situations (Domingos, 2012).

2.2.4 AI is More Bias Prone Than IT

All computer systems can contain the assumptions of their developers and users but AI is arguably more susceptible to bias than traditional IT systems. The issue of bias in computer technology has long been recognized. Friedman and Nissenbaum (1996) defined computer systems as biased if they “systematically and unfairly discriminate against certain individuals or groups of individuals in favour of others”. The authors identified three types of biases in computer systems: preexisting, technical, and emergent. Pre-existing bias refers to the biases that stem from societal institutions, practices, and attitudes, either consciously or unconsciously, introduced by individuals or embedded within the broader social context. Technical bias encompasses biases that arise from technical limitations in computer systems, including hardware and software constraints, decontextualized algorithms that fail to treat all groups fairly, flawed random number generation, and attempts to formalize human constructs into computer systems. Emergent bias occurs after completion of design and during the interaction with users, due to changes in societal knowledge, user population, or cultural values.

Numerous studies have recognized the biases in AI systems that resemble biases in IT. Several scholars point out how biases are rooted in data because the AI systems trained from that data tend to reflect the characteristics of a particular group at a specific time (Barocas & Selbst, 2016;

Janssen & Kuk, 2016; Fomin, 2020). Fomin (2010) suggests that bias may be introduced during data collection due to historical, political, or technical factors, and the utilization of third-party or repurposed data can amplify the bias. Mittelstadt et al. (2016) argue that bias is inevitably embedded in the design of the algorithms because the process of algorithm development involves subjective choices at each stage, rather than objective decisions. Consequently, the algorithms reflect the values of their creators and the intended purposes for which they are developed. Diakopoulos (2015) discusses how bias manifests in different types of automated decisions made by algorithms, including prioritization, classification, association and filtering.

Further, Fomin (2020) argues that AI is more prone to bias resulting from the learning process. The author suggests that the learning process involves optimization and adaptation based on data and experiences, which is different than IT systems. AI systems cannot be easily controlled for bias in the process of learning. This is because the rapid pace at which the algorithm learn makes it difficult for users to understand algorithmic logic, as it may diverge from the initial guidelines set by programmers (Burrell, 2016). This lack of control and unknown technical properties of learning contribute to the increased bias vulnerability of AI systems. As a consequence, the biases resulting from the use of AI may lead to discrimination to a much greater extent than with IT (Mittelstadt et al., 2016).

2.2.5 AI is More Opaque Than IT

The historical concern regarding the opacity of computing systems and its implications has been well-documented. Wiener (1960) has raised concerns about the incomprehensibility of automated machines, stating that we might not fully grasp how machines work until long after they have completed their assigned tasks. The author further pointed out that though machines can theoretically be subject to human criticism, such criticism may lack effectiveness until a considerable amount of time has passed. Weizenbaum (1972) emphasizes the risks associated with increasing complexity and decreasing understanding of computer systems. They argued that this lack of comprehensibility can lead to decision-making being shifted to technologies that policymakers may not fully grasp, ultimately creating a society where crucial questions are addressed by anonymous and unaccountable actors.

Opacity in AI has raised growing concerns today. Burrell (2016) synthesizes three forms of opacity in machine learning algorithms. First, there is intentional opacity resulting from corporate or state secrecy. Second, there is opacity stemming from technical illiteracy, where individuals lack the necessary knowledge to understand the algorithms. Lastly, there is an inherent opacity arising from the characteristics of machine learning algorithms and the scale needed to effectively apply them.

The third point shows the distinction between machine learning and traditional IT. Burrell (2016) argues that machine learning algorithms face challenges of scale and complexity that transcend the number of lines of code or the size of the team. First, machine learning models often possess a degree of complexity that is necessary for their usefulness, particularly in terms of classification accuracy. Second, machine learning deals with the "curse of dimensionality" in analyzing vast amounts of data with numerous properties or features, which adds further complexity to the code. Ultimately, the complexity arising from the interaction between large datasets and the mechanisms of machine learning algorithms contributes to their distinct nature and opacity. This complexity of machine learning can render an algorithm opaque even to domain experts or programmers themselves (Etzioni and Etzioni, 2016; Hayes et al., 2023). Consequently, it is difficult, if not impossible for humans to fully understand the comprehensive criteria or reasoning behind the decisions they generate. (Mittelstadt et al., 2019) As stated by Fomin (2020, p236), “black box or algorithmic opacity of AI implies not only the non-transparency of algorithmic logic but also the inability of system users to trace the reasons for certain decisions of the system”.

2.3 A Brief History of IT in Local Government

With the stage set, I investigate the history of computing in government. Computing, regardless of jurisdictional level, dates back to the late 1950s when digital computers first emerged. A review by Bauer et al. (1961) revealed that the US government utilized computers for various purposes, including simulating the emergency duties of the US president, election forecasting, census data management, and evaluating government contract bids. These applications were primarily at the national level due to the high cost of computers and hardware (Kraemer & King, 1982).

Smaller-size governments began to adopt IT in the late 1960s because of the decrease in the costs of hardware (Kraemer & King, 1982). From the 1960s to the 1980s, the use of computers within government agencies expanded primarily for administrative tasks. This mirrored the adoption of computer technology in the private sector, particularly in budget management (Danziger, 1977), human resources and payroll management (Beadles et al., 2015; King, 1982). Governments also began adopting IT to meet analytical needs, such as data handling, storage, modelling, and process control (Kraemer, 1969). Similar to more resourced governmental levels, local governments started to adopt information systems for urban management, planning and decision-making (Kraemer & King, 1982). One example is the Geographic Information Systems (GIS), which found wide adoption in local governments for purposes such as spatial data analysis, record management, map production, natural resource management, and planning (Maguire, 1991; Ventura, 1995). Decision support systems also were incorporated in government to assist managers in decision-making and policy formulation (McGowan & Lombardo, 1986), as well as in urban planning (Geertman & Stillwell, 2004). The increased adoption of IT in local governments signifies the increasing role of technology across various domains of governance and public administration.

Despite the widespread use of computers in governments, IT primarily served internal goals until the 1980s. The advent of the Internet in the 1990s introduced concepts like e-government, shifting the focus towards government interaction with external agencies such as citizens and businesses (Reece, 2006). The goal of e-government was to improve access to government services and promote civic participation (Fang, 2002), aiming to enhance digital democracy or e-democracy (Van Dijk, 2012). This period also saw the development of participatory approaches utilizing IT, such as Public Participation Geographic Information Systems (PPGIS) (Sieber, 2006). An example that integrates citizen participation into e-government is the Public Electronic Network (PEN) system launched by Santa Monica in 1989 (Rogers et al., 1994). This open-access system allowed citizens to access information, exchange information, and participate in political discussions. Unlike many other e-government systems that widened the information gap, PEN engaged citizens with diverse backgrounds, including disadvantaged groups like women and the homeless, by providing free public access terminals and interactive public conferences. This transition away from a technocratic approach towards a participatory approach marked a significant step towards the use of IT in promoting accessibility, and active citizen involvement in shaping government policies and services.

There have been historical attempts to incorporate AI in governments' IT practices in the 1980s and 90s, although AI back then differs from today's AI. The origin of AI can be found in expert systems, which involved humans building systems to store knowledge and rules in specific domains. Examples include a system created to assist government document retrieval in 1988 and a Supervisor Assistance System developed in 1992 by a Florida government agency to assess employee disciplinary procedures (Berry et al., 1998).

Expert systems' limitations in generalizing under complex circumstances led to a decline in their popularity. The next generation of AI applications emerged, focusing on fields such as linguistics and neural science. With advances in computing power, the late 1980s and 1990s saw the development of key components of modern AI, including the backpropagation algorithm for neural networks (LeCun et al., 1989), the first chatbot (Wallace, 2009), and Long Short-Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997).

In the 2010s, AI research and applications encompassed a multitude of functions within the public sector, spanning various local government domains such as health, transportation and safety (Sousa et al., 2019). More recently, the use of AI has exploded in local governments, transforming numerous government functions, with promises of making government more efficient and effective and improving service delivery.

2.4 Promises and Pitfalls of IT for Government

In this section, I examine early studies on computer and computing systems since the 1970s. These early studies on IT were primarily conducted by a research group at the University of California, Irvine (UCI) in the United States, providing the earliest empirical studies of computers and computing systems in local governments. I also examine more recent literature on e-government. I discuss the promises and challenges associated with IT adoption in local government and compare them with AI in the next section.

IT can assist local government in delivering services to citizens, either directly to the public or indirectly by enhancing governmental administration (Kraemer and Kling, 1983). The authors also found that the use of computing tools has primarily focused on supporting essential government services such as the police, fire departments, highways, and sanitation. The improvement of services became particularly prominent in discussions surrounding e-government, highlighting the potential for electronic service delivery through e-government portals. These portals allow citizens to access a wide range of government services and interact with local governments (Beynon-Davies & Martin, 2004).

Efficiency and productivity also have been crucial factors driving governments to adopt IT. Numerous studies have demonstrated that integrating IT can generate efficiencies by increasing productivity, reducing staff, saving time, and improving managerial control over employees and processes (Danziger and Andersen, 2002; Kraemer & Danziger, 1990). IT also offers a significant promise in terms of facilitating decision-making. IT has been attributed with several benefits, including the ability to identify or anticipate problems, evaluate different scenarios, and compare alternative solutions to problems (Kling, 1978; McGowan and Lombardo, 1986). These capabilities have led to the belief that IT and data utilization can result in more rational decisions. Consequently, the concept of urban information systems emerged to formalize and rationalize informal activities (Kraemer, 1969) and provide neutral and optimized planning decisions (Langendorf, 1985). In the realm of policy-making, IT has been seen as a tool to enhance the rationality of policy decisions by offering a range of policy options (Kling, 1978).

Another promise of IT is its potential to enhance accessibility and thereby foster a more citizen-oriented or democratic form of governance. The visions towards the role of IT in enhancing democracy have been through waves of public sector IT revolutions (Van Dijk, 2012), starting with the early view that IT would promote direct democracy (e.g. Barber, 2004; Malina, 1999), followed by the expectation that e-platforms would enable mass participation and online deliberation (e.g., Froomkin, 2004; Norris & Jones, 1998; Wright & Street, 2007), to the Web 2.0 generation (O'Reilly, 2005) that emphasizes citizens co-creation and user-generated contents (e.g. Chadwick, 2008; Leadbeater and Cottam, 2008).

Despite these promises, local governments face significant challenges in implementing IT, whether it is incorporating information technology before the 1980s or implementing e-government starting from the 1990s. The most commonly mentioned challenge relates to resource requirements for IT implementation in local governments. With advancements in software and hardware in the 1980s, local governments experienced a surge in demand for IT personnel. King (1982) predicted that "a chronic shortage of good technical personnel will be a serious impediment to the use of information technology." Danziger et al. (1978) pointed out the difficulties faced by cities to account for the high costs associated with IT development, including the costs of developing the technology itself and supporting resources and staff. The authors further suggest that there may be costs induced by changes in operations, such as management or system upgrades. Similar issues were observed in e-government studies, highlighting the need for skilled staff and sufficient resources in incorporating e-government (Andersen et al., 2010; Beaumaster, 2002; Streib & Willoughby, 2005). The resource and staff requirements for IT implementation pose greater challenges for smaller local governments. Numerous studies have shown that larger governments were able to adopt these innovative technologies more rapidly, leaving behind those who cannot afford them (Brudney, 1988; Brudney and Seldon, 1995; Danziger et al., 1978; King, 1982; Moon, 2002).

In addition to implementation challenges, local governments also face challenges in achieving their desired outcomes--those bolded items above--from IT implementation. Despite the commonly cited justifications of enhancing efficiency and reducing costs, many IT systems have failed to deliver their intended benefits, such as increasing government revenue (Brudney, 1988; Danziger et al., 1978; Dutton, 1982; Kraemer, 2001; Norris & Kraemer, 1996). Kraemer (2001) highlighted a "productivity paradox." He stated that, despite massive investments in IT, the productivity gains or payoffs from its use were found to be insignificant. It has been suggested that the use of IT in enhancing productivity in local governments faces multiple barriers related to politics, managerial practices, organizational culture, the type of system implemented, and users' characteristics (Ammons, 1985; Danziger, 1979; Danziger & Kraemer 1985; Kraemer; 2001). Similarly, Moon (2002), through an analysis of a 2000 e-government survey, found that e-government initiatives were often over-promised, as only a small percentage of cities were able to achieve cost savings and revenue generation. Although e-government often promises improvements in service delivery and democratic governance, some scholars have noted the danger of these initiatives in creating power imbalances and inequity (Mossberger et al., 2003; Norris, 2001; Helbig et al., 2009). For example, Helbig et al. (2009) argue that individuals or groups lacking Internet access or sufficient technical skills may be unable to participate in governance initiatives, such as smart cities. As a result, decisions arising from these initiatives may exclude the perspectives of these marginalized groups.

While IT holds the promise of aiding decision-making, it is crucial to acknowledge the influence of politics on IT implementation and day-to-day usage. Scholars have increasingly recognized the intertwining of IT and the political nature of decision-making (Allison, 1967; Kling, 1978; McGowan and Lombardo, 1986; Welch, 1992). Kling (1978) argued that computer tools possess a significant social influence by not only aiding in acquiring new insights but also reinforcing the political perspectives and initiatives of municipal officials. Kraemer and Kling (1983) noted that the use of computing tools in local government often prioritizes bureaucratic activities and control, rather than directly serving citizens. This may lead to the use of IT to orient toward efficiency rather than equity. Arguably seeking efficiency is far easier than more complex urban problems like ensuring equity. It is hardly surprising that Rittel and Webbers's (1973) article on Wicked Problems emerged during this time. They argue that urban problems are complex and possess fundamental characteristics that prevent quantification, among them, wicked problems do not have a "definitive formulation"; problems lack an inherent logic as to when problems are finally solved; solutions are not "true-or-false, but good-or-bad"; and, because there are waves of potential consequences, there is no clear way to assess the wicked problem's solution (pp. 161-3). Then, as now, authors argued that government decision-making could probably never be fully or even mostly automated (Harris, 1968; Guszcza et al., 2017).

2.5 Promises and Pitfalls of AI in Government

In this section, I review literature on local government AI adoption, in terms of its promises and challenges. I examine whether the promises and pitfalls of AI adoption in local government are similar to IT or if they present new challenges.

Like IT, the use of AI is often intended to enhance the delivery of public services. Misuraca and van Noordt (2020) proposed a typology of AI applications that can support public services, while de Sousa et al. (2019) synthesized the types of services that AI can assist with (Table 2.1). However, in their review of 85 AI applications in European countries, Misuraca et al. (2020) pointed out that, although more than half of these AI initiatives aim to provide or improve public services for citizens, in reality, they primarily contribute to the administrative work itself, echoing the observations made by Kraemer and Kling (1983).

Table 2.1. AI in supporting Public Services (modified from Misuraca & Noordt, 2020 and de Sousa et al., 2019)

Typology of AI	Example of Services	
Audio Processing	Knowledge Management and Data Processing Automation	Measurement and Optimization of Consumption and Water Quality
Chatbots, Intelligent Digital Assistants, Virtual Agents and Recommendation Systems	Identification of Fraud	Traffic Analysis
Cognitive Robotics, Process Automation and Connected and Automated Vehicles	Analysis of Work Effectiveness	Measurement and Optimization of Public Transport
Computer Vision and Identity Recognition	Support for Decisions and Prioritization	Prediction of Behaviour and Needs
Expert and Rule based Systems, Algorithmic Decision Making	Organizational Performance Measurement	Disaster Preparedness and Response
AI-empowered Knowledge Management	Organizational Credit Risks Analysis	Digital Security
Natural Language Processing, Text Mining and Speech Analytics:	Optimization of Irrigation	Crime Prediction and Assessment
Predictive Analytics, Simulation and Data Visualisation	Identification of Sustainable Areas	Construction Performance Measurement
Security Analytics and Threat Intelligence	Identification of Pollution	Identification of Risk in Birth
Other Machine Learning or Deep Learning	Improvement of Agriculture and Analysis of Fertilizer Use	Disease Prediction
	Measurement and Optimization of Energy Consumption	Learning Development

Similar to IT, AI is considered to hold great potential for enhancing efficiency. Allam and Dhunny (2019) believe that AI can significantly improve efficiency in city governance and operations by enabling real-time analysis of big data and providing insights into challenging urban issues. Additionally, AI has the potential to enhance the efficiency of administrative processes and routine tasks (Bullock, 2019; Kuziemski & Misuraca, 2020; Sousa et al., 2019;

Valle-Cruz et al., 2019; Zuiderwijk et al., 2021). However, limited empirical research has examined the extent to which AI can enhance efficiency. Vogl et al. (2020) shed some light on this by examining the use of AI in UK local government, suggesting that AI can free workers from routine tasks, allowing them to allocate more time to complex and sophisticated tasks.

The discussion on rationality extends to AI systems. Misuraca & Noordt, (2020) suggest that AI may facilitate the identification of social issues or citizen concerns, providing timely and accurate policy decisions in response to these problems. McEvoy (2019) further argues that governments have a moral obligation to use AI systems in political decision-making because of AI's ability to provide rational policy options.

Similar to the promises of e-government, AI shows potential in improving accessibility and providing more direct forms of citizens governance (e.g., Darmon, 2019; Karanasiou, 2019) for example through the use of AI-powered chatbot (Androutsopoulou et al., 2019) or through the use of AI in enhancing accessibility of decision-making process (Havrda, 2020).

The concept of environmental sustainability in relation to AI is a relatively new aspect discussed in scholarly literature, particularly in relation to the discussion of smart cities. Previous research on IT did not extensively explore the sustainability dimension, likely because sustainability has gained attention in recent decades. AI shows potential in waste management, energy efficiency, and natural resource management, contributing to sustainability efforts (Allam & Dhunny, 2019; Ben Rjab & Mellouli, 2019; Höjer & Wangel, 2015; Kramers et al., 2014).

Though AI shows a number of similar promises to IT, it is conceivable that local governments face great challenges in implementing AI. The fast-growing demand for AI specialists is likely to be a challenge faced by local governments, similar to the challenge we have seen in the 1980s. While the empirical research is still limited, it has been observed that there is a lack of AI knowledge and data literacy among government employees (Campion, 2020; Yigitcanlar et al., 2022). To implement AI, local governments also need to leverage funds in hiring expensive AI personnel (Bright et al., 2019; Campion et al., 2020; Vogl., 2021; Yigitcanlar et al., 2022). In addition to the financial costs, the environmental costs of AI and its infrastructure have been noted by scholars. Robbins and van Wynsberghe, (2022) pointed out that the proliferation of AI and IoT devices leads to increased consumption of materials and production of e-waste. The training and constant updates of learning algorithms require high computational power, resulting in substantial energy consumption and carbon emission (Henderson et al., 2022; Strubell et al., 2019). Interestingly, we see that the challenges of high costs and staffing issues faced by AI mirror those encountered by IT in the 1970s.

The effectiveness of AI is highly dependent on the data quality (Desouza et al., 2020), whereas local governments face the issues of inaccurate, incomplete (Volg, 2021) and biased data (Yigitcanlar et al., 2022). Local governments also struggled in dealing with the inconsistent data format due to a siloed organizational structure and a lack of consensus on data collection methods (Volg, 2021). Additionally, AI implementation requires challenges in hardware and software, such as servers, cloud computing, and data science software (Bright et al., 2019; Desouza, 2018). However, the siloed IT practices may prevent local governments from incorporating changes at a system level (Desouza, 2018).

Whether the promises of efficiency enhancement, cost saving and better service delivery can be achieved remained to be under-discussed in the literature. Among the limited empirical research, Misuraca et al., (2020) in reviewing 85 AI applications in European countries, discovered that the majority of AI projects focus on enhancing efficiency, while only a small number of projects aim to promote service delivery inclusion or increase the openness of local governments to the public. Yigitcanlar et al., (2022) pointed out the potential of AI adoption in creating inequity, as only the cities with sufficient resources can afford to implement AI, resulting in a widened knowledge gap. Further, because of the heuristic, opaque, biased-prone nature of AI, scholars raised concerns were raised on the transparency, legitimacy, fairness and accountability of AI-generated decisions (e.g., Brauneis & Goodman, 2018; Burrell, 2016; de Fine Licht & de Fine Licht, 2020; Mittelstadt et al., 2016). Additionally, regulations to date are immature in handling the potential ethical and legal issues resulting from the use of AI (Ip et al., 2022). How these concerns and issues manifest in local government and how they may be mitigated or addressed is yet to be studied.

2.6 Conclusion

I present an overview of the history of IT adoption within governments and compare the similarities and differences between AI and IT. I argue that AI is different than IT because it does not follow predefined algorithms and it is able to learn and adapt from data. I point out the issue of overfitting and argue that AI exacerbates the issue of bias and opacity previously recognized in IT studies.

Despite these differences between AI and IT, it is evident that both technologies share similar promises to local governments. Both AI and IT offer potential benefits to governments, both internally and externally. Internally, they promise to enhance administration processes, streamline operations, and improve efficiency. Externally, they hold the promise of delivering better public services, facilitating decision-making with more options and insights, and enhancing accessibility for citizens to engage with government services and participate in governance. They also share the very same pitfalls in terms of the resource and staff requirements for implementation. Despite the limited empirical research on the adoption of AI by local governments, it is plausible to anticipate that AI may encounter challenges as witnessed in IT adoption in effectively achieving its objectives. It is also reasonable to assume that AI is also susceptible to similar types of political influence and power dynamics.

I would like to end with an insightful statement by Kling (1973, p28), "As we AI researchers separate ourselves from the larger computing community, we easily indulge in the fantasy that our impacts will be of a different order than related technologies. This is a very tenuous assumption. For example, to the extent that AI-based artifacts are costly and require sophisticated environments for use, they will be used by organizations and groups with substantial power. To the extent that these technologies are 'intrinsically' influence-enhancing", they will increase the gap between the weak and the powerful, the rich and the poor." I contend that it is, therefore, crucial to critically examine the current practices, motivations, and challenges associated with AI adoption in the local government context.

Preface to Chapter 3

The goal of the thesis is to identify what constitutes successful local government adoption of AI. Chapter 3 presents a survey to assess the second and third research questions: What and how is AI being adopted in Canadian local governments? What are the opportunities and challenges of AI perceived by individuals involved in local government AI projects? This study was motivated by the literature review presented in Chapter 2, which revealed research gaps in understanding the benefits, challenges and pitfalls of AI adoption in local governments.

As an article manuscript, this chapter was co-authored with my supervisor, Dr. Renee Sieber. We plan to submit the manuscript to

- *Government Information Quarterly*
- *Public Administration Review*
- *Social Science Computer Review*
- *International Journal of Public Administration*
- *AI & Society*

Chapter 3. Smart AI for Smart Cities: Opportunities and Challenges of AI Adoption in Canadian Local Governments

Abstract:

There has been considerable rhetoric on the potential of artificial intelligence (AI) in city operations, management and service delivery; whereas, local governments face numerous challenges in AI adoption. This study examines AI projects within Canadian local governments and perceptions of opportunities and challenges associated with the adoption of AI in Canadian local governments. We surveyed 28 individuals across Canada, who were directly involved in AI system design, development, or deployment. The study reveals diverse backgrounds, expertise levels, and varied approaches to AI development among individuals involved in AI within Canadian local governments. We find positive perceptions of the potential benefits of AI, that AI can offer new insights, potentials for automation, efficiencies, problem-solving, and community benefits. Debates exist regarding labour cost reduction and decision-making. Balancing those potential benefits, results highlight significant organizational and technical challenges faced by local governments in adopting AI, including insufficient staff training and awareness and funding constraints. Technical challenges include a lack of in-house expertise, challenges in outsourced AI systems, data availability and access issues and the integration of computing infrastructure and software utilization. Societal concerns are expressed regarding risks to privacy and security, transparency of AI systems, and the reliability of AI models. These findings contribute to a better understanding of AI adoption in Canadian local governments, which helps inform policy decisions, address challenges, and promote responsible and effective governance practices in AI implementation.

3.1 Introduction

In the past decade, cities worldwide have increasingly embraced technologies to enhance internal operations and provide digital services to their citizens. This aligns with the contemporary notion of smart cities, where the adoption of technologies like AI plays a central role (Albino et al., 2015; Yigitcanlar et al., 2021; Luusua et al., 2023). As an indication of that desire to foster innovation and global competitiveness, the Canadian federal government launched the Smart

City Challenge grant competition (2017-2018), pledging millions of dollars to develop technologically advanced cities in Canada. Canada also has made substantial investments in the AI sector, amounting to billions of dollars as of 2020 (Brandusescu, 2021).

AI is a popular “smart” technology in cities due to its perceived benefits of automation, efficiency, objectivity, fairness and better service delivery (Bullock, 2019; Misuraca & van Noordt, 2020; Misuraca et al., 2020; Ojo et al., 2019; de Sousa et al., 2019; Toll et al., 2019; Valle-Cruz et al., 2019; Yigitcanlar et al., 2020; Zuiderwijk et al., 2021). Governments promote AI because it offers real-time analysis of large volumes of data (Allam & Dhunny, 2019; Kitchin, 2014; Rjab & Mellouli, 2019), enabling cities to collect and analyze big data by prioritizing, classifying, associating, and filtering information (Goodfellow, 2016). AI is believed to provide solutions to various urban issues concerning the environment, society, and health (Allam and Dhunny, 2019; Dirks & Keeling, 2009; Yigitcanlar et al., 2020).

Researchers in the field of AI have argued that AI systems differ from traditional computing, for example, in smart cities, due to their opaque nature, heuristic capacity, and biased potential (Burrell, 2016, Fomin, 2020). Although limited, previous studies on AI adoption in government have highlighted a number of adoption challenges related to a lack of internal capacity such as funding and expertise (Bright et al., 2019; Campion et al., 2020; Vogl, 2021; Wirtz et al., 2019; Yigitcanlar et al., 2022), issues of data quality (Desouza et al., 2020; Vogl, 2021; Yigitcanlar et al., 2022), computing infrastructure (Bright et al., 2019; Desouza, 2018), deficient policy or managerial support (Bright et al., 2019; Campion et al., 2020, 2022), a need for cross-sectoral collaboration (Campion et al., 2020, 2022; Desouza, 2018; Vogl, 2021; Mikhaylov et al., 2018), possible resistance (Yigitcanlar et al., 2022), and impacts of AI regulation and policy (Dickinson & Yates, 2023; Hickok, 2022).

Despite challenges, cities in Canada are adopting AI. For example, the City of London, Ontario adopted AI to predict chronic homelessness (Lamberink, 2020). The City of Edmonton, Alberta adopted AI to enhance the efficiency of building inspections (Pica-Alfano, n.d.). The City of Laval, Quebec harnessed AI in dealing with non-emergency service requests (Cann, 2021). Nonetheless, it is difficult to understand what challenges these and other local governments faced in AI adoption; it is also difficult to assess if the benefits of AI adoption outweigh the costs.

The objective of this paper is to assess how representatives of Canadian local governments perceive AI in terms of motivations, opportunities and challenges in the adoption of AI. We surveyed 28 individuals across Canada, who were directly involved in AI system design, development, or deployment. The study reveals diverse backgrounds, expertise levels, and varied approaches to AI development among individuals involved in AI within Canadian local governments. The survey focused on individuals directly involved in the design, development, or deployment of AI systems, including data scientists, consultants, and external stakeholders. We first explored respondents' backgrounds and knowledge of AI, which helped us understand AI expertise and skills and knowledge required for AI adoption. Then we examined respondents' perception of the benefits and challenges associated with AI adoption, which is important to develop effective strategies to maximize the benefits while addressing the challenges. Next, we assessed their understanding of the costs and other concerns related to AI. The concerns can inform the development of governance frameworks, policies, and regulations and can ensure responsible and ethical AI deployment in local governments. Finally, we gathered respondents' suggestions regarding government use of AI-based on their experiences, which may guide other local governments in their AI adoption. Overall, this study's importance lies in its contribution to the understanding of AI adoption within Canadian local governments, which we hope may inform policy decisions, help address challenges, and promote responsible and effective AI governance practices.

3.2 AI Adoption in Local Governments

This section reviews the literature on AI adoption in local governments. The literature comes from multiple disciplines, including smart cities, AI and algorithmic governance and public sector AI adoption. It begins by examining the hype surrounding smart cities since that promise grounds AI adoption. The motivations of local governments in adopting AI are then explored, followed by an analysis of the challenges local governments face in implementing AI. This will shed light on the practical realities of AI adoption in the public sector.

When we talk of AI, we generally refer to machine learning and deep learning. AI systems differ from traditional computing systems, in the ways that 1) as opposed to IT, AI algorithms do not receive explicit programmed instructions and 2) AI algorithms are heuristic in that they learn from the data (Fomin, 2020). Because of the ability to extract insights and acquire knowledge from data, AI offers significant advantages to local governments in data analysis and modelling. As suggested by Openshaw (1992), traditional modelling approaches are limited in application areas and often lack practical performance due to their theoretical optimization.

The fundamental goal of AI is to generalize beyond the examples it has seen (Domingos, 2012). However, AI systems can produce unintended outcomes. This emergent behaviour can result from model design or from overfitting, in which the decision rules are developed to fit only the training data, but fail to generalize in real-world scenarios (Mitchell, 2021; Geirhos et al., 2020).

AI systems, particularly deep learning, also are more opaque. Fomin (2020) argued that the "black box or the algorithmic opacity of AI implies not only the non-transparency of algorithmic logic, but also the inability of system users to trace the reasons for certain decisions of the system" (p. 326). Opacity also can result from the proprietary nature of AI algorithms, in which vendors prevent users from accessing the algorithms (Burrell, 2016; Brauneis & Goodman, 2018; Mittelstadt et al., 2016). Because of the opacity, local governments might struggle to comprehend AI systems fully: to assess their performance and trace their reasoning. Assessment and traceability are crucial because democratic governments have a greater responsibility to be transparent and explainable. It is possible that local governments may approach the procurement, development, or implementation of AI as if they were dealing with conventional software, overlooking the fundamentally different nature of AI. Consequently, local government may not have the necessary expertise or resources to address issues when the AI system malfunctions.

3.2.1 The Promise of the Smart City: Hype Meets Reality

AI is often considered a part of a suite of smart city technologies, which include smart interface (e.g. city dashboards), smart control systems (e.g., traffic control system), and Internet of Things (e.g., smart lamp posts) (Al-Hader et al., Allam and Dhunny, 2019). Like other smart city rhetoric, visions of AI are often idealized. In such visions, AI systems and other smart technology are ofen considered a 'magic solution' to many urban issues (Allam and Dhunny, 2019), and because of adoption, a city becomes smarter, more efficient, citizen-oriented and sustainable, solving issues related to numerous disciplines (e.g. Dirks & Keeling, 2009). The assumption is that "all aspects of a city can be measured and monitored and treated as technical problems which can be addressed through technical solutions" (Kitchin, 2014, p. 9). Under this technology-centred approach to governance, AI and their metrics become the experts that rule decision-making within the cities.

The hype of smart cities can be driven by corporations, which see the city as a potential market for promoting their products (Shearmur, 2016). This is supported by Söderström et al., (2014), arguing that the essence of "corporate storytelling" ties municipal goals of fairness, sustainability and accountability to a market orientation of city management. The market orientation of smart cities become part of a neoliberal turn in cities, which has increasingly been critiqued in the literature for being overly simplistic and failing to account for the numerous perspectives, such as culture and politics, that shape the city (e.g., Kitchin, 2014; León and Rosen, 2020; Shelton et al., 2014; Söderström et al., 2014).

Shelton et al. (2014) discussed a gap between rhetoric and reality in the smart city, stressing the importance of understanding the "actually existing smart city". This is important for AI, in which hype is pervasive. Through case studies in two cities, the authors demonstrated the complex, political nature of the smart city initiatives and how they shaped the political outcome and created inequality. The authors critiqued the market rhetoric as well as an imaginary that considered a smart city an idealized, depoliticized, and decontextualized project, in which data and technology are utilized without an understanding of the actual geographical and historical context.

Although there have been criticisms of the smart city as a neoliberal and technocratic system, there has been little account of organizational and technological issues of AI implementation within local governments. In the next sections, we discussed the AI hype and challenges of adopting AI within local governments.

3.2.2 The Rhetoric of AI

The hype for AI originated before the concept of smart cities, dating back to the early 1960s when there was an over-optimistic belief that AI could achieve human-level intelligence. For instance, Simon (1960) famously predicted that machines would attain human-like abilities. However, as time passed, it became evident that these early hypes were overly optimistic. In the 1990s, expert systems emerged as a means to make judgments based on domain-specific knowledge (Jackson, 1986). Expert systems soon lost their popularity because of the inability to cope with complex problems and adapt to different scenarios (Mitchell, 2021).

AI hype continues. Mitchell (2021) has argued that the AI field today is infused with “wishful mnemonics ”, as first used by McDermott (1976) to describe the misleading terms that are used to describe AI systems. The author states that terms that are broadly used to describe AI today, whether in the media or research community, such as learn, read, understand and think, do not resemble human intelligence, leading to public misconceptions of over-optimistic understandings and on the ability of AI systems. Therefore, it is crucial to foster a balanced understanding of AI's capabilities and limitations, grounding local government AI adoption practices in reality.

In need of being “smarter”, local governments face the pressure to adopt new technologies like AI systems (Dirks & Keeling, 2009) in enhancing their internal operations and service delivery (e.g. Bullock, 2019; Misuraca et al., 2020; Ojo et al., 2019; de Sousa et al., 2019; Toll et al., 2019). This is part of the tension within smart cities to compete with each other to demonstrate which is smarter, and which can attract tech employees (e.g., Kitchin, 2014; Monfaredzadeh & Berardi, 2015). As an example, Brandusescu (2021) has discussed the enormous investment by the City of Montreal and the Province of Quebec in AI to establish Montreal as a leader in AI. Montreal has developed an advanced AI ecosystem, encompassing AI research communities, experts, and businesses, which has drawn in prominent players in the field of AI (Montréal International, 2022).

One motivation for local governments lies in the hope that AI will enhance efficiency (Bullock, 2019; Ojo et al., 2019; Valle-Cruz et al., 2019). Efficiency is considered to result from the automation of an existing task (Toll et al., 2019; Valle-Cruz et al., 2019; Zuiderwijk et al., 2021). One example is from a recent empirical study conducted by Vogl et al. (2020) on UK local government. The authors suggest that within organizations, AI can free workers from routine work, providing the workers with more free time on more sophisticated tasks. Greater efficiency from the use of technology is usually associated with the potential to reduce labour costs (Pinsonneault & Kraemer, 1997). Although there has been little empirical research on the impact of AI on labour cost reduction within government organizations, several organizational studies from the 70s to 80s have suggested the labour-saving potential through automation (e.g., Kraemer & Danziger, 1990; Pinsonneault & Kraemer, 1993; Sulek & Marucheck, 1992).

The second motivation is the potential of AI in making better policy decisions. McEvoy (2019) argues that AI systems allow governments to make more reliable decisions by providing a wider range of policy options. Therefore, it is considered by the author a moral imperative to incorporate AI in decision-making. This is not a novel argument. Indeed, there have been historical debates on the role of computing systems in policymaking. As concluded by Kling (1978), automated computing systems were perceived as an instrument to enhance the rationality of policymaking as it is capable of providing alternative policy options, which underscores the political influence of the decision-making process. The historical perspective underscores the ongoing issue of political influence in decision-making processes, as well as the tendency of policymakers to use technology, including AI, as a means to justify decisions.

While the aforementioned two motivations are related to the improvement of governments' internal work, the third and fourth motivations concern the external factors – service delivery and civic engagement. Some scholars have argued that AI can help facilitate government improvement of citizen service delivery (e.g., de Sousa et al., 2019; Misuraca et al., 2020; Yigitcanlar et al., 2023). Local governments, as service providers (Streib & Willoughby, 2005), interact frequently with citizens due to their proximity to citizens, which poses a substantial impact on citizens' daily life (Beaumaster, 2002). For example, Mehr et al. (2017) identified five types of AI use cases for citizen inquiries, including answering citizens' questions, document processing, routine requests handling, translation and document drafting. Al-Mushayt (2019) proposed that deep learning models can be integrated into the existing e-government platform to automate government digital services. AI promises quicker responses to citizen inquiries, transforming the way citizens and local governments interact.

Finally, cities may be motivated to adopt AI because they believe it can improve civic engagement. Havrda (2020) presented the method through which AI can help enable greater participation in decisions impacting community well-being. This can be achieved by using AI to produce community well-being impact assessments, by providing multiple solutions to citizens' questions, assessing these solutions, and summarizing and presenting the impacts to the community members. The author promoted AI as a tool to handle large numbers of variables and assess complex scenarios. Second, AI can enhance public participation by adding channels of communication between citizens and the government. For example, Androutsopoulou et al.

(2019) suggested that AI-enabled chatbots would allow a wider range of citizen interaction. Therefore, AI can support motivations to enhance the accessibility of decision-making processes.

3.2.3 The Reality: AI Implementation Challenges in Local Government

There has been considerable rhetoric on the potential of AI; whereas actual AI adoption is complicated, especially for local governments. Some of the literature on the challenges of AI adoption discussed challenges at any level of government and others examined local governments explicitly. We identified seven challenges from the literature. A summary of all the challenges we identified is presented in Table 1.

The most mentioned challenge is the lack of internal capacity, including financial feasibility and technical skills. A lack of internal capacity to develop, deploy or even procure the technology presents challenges for local governments as they often have limited resources (Shearmur, 2019; Bright et al., 2019; Campion et al., 2020; Vogl., 2021). With limited budgets and uncertainty of return on investment, local governments face the risks of wasting money if unsuccessful (Yigitcanlar et al., 2022). To remedy the deficiency, local governments would have to leverage funds to hire a range of costly AI personnel, such as consultants, AI analysts, business intelligence specialists and domain specialists (Jöhnk et al., 2021; Vogl, 2021; Wirtz et al., 2019).

AI is generally data intensive so local government needs quality data to train and implement the AI models. Desouza et al. (2020) argue that, as AI models learn from data, it is important to assess the data quality and examine the potential bias before developing the AI systems. AI systems based on inaccurate data may lead to poor performance and biased decisions (Vogl, 2021). Vogl (2021) surveyed UK local authorities and found them concerned about incomplete and inaccurate data, as well as difficulties in preprocessing data from various sources and with different formats. Data quality is also linked to a lack of data standards and synchronized efforts in data collection. Yigitcanlar et al. (2022) identified challenges related to data bias through interviews with city managers in Australia and US, suggesting that local governments struggle to remove bias in training data.

Another challenge is the insufficient data and AI literacy among local government employees, which hampers AI projects in local government. Campion (2020) found deficiencies in data literacy and a lack of understanding on the types of questions that can be addressed by AI.

Yigitcanlar et al., (2022) suggested that insufficient AI knowledge at the council was due to the lack of awareness and training, which prevented councils' ability to plan, develop and manage AI systems.

In addition to the data required to train the AI models, local governments need appropriate computing infrastructures to support AI. Desouza et al. (2018) found outdated IT infrastructures and siloed IT practices ill-suited to AI; it may be necessary for the public sector to leverage cloud computing and open-source solutions to allow the deployment of AI at the system level. Bright et al., (2019) discussed computing infrastructures in terms of software and pointed out local government needs for data science tools, whether off-the-shelf analytics software or the open source packages. Although the off-the-shelf software is easier to use, it often lacks flexibility and poses risks should the supplier withdraw support for the product. Additionally, local governments may face challenges in procuring these tools considering their complexity and skill requirements.

As AI is new to most local governments as well as non-mission critical, elected officials and senior management must be willing to allocate time and resources to support AI adoption. Nili et al., (2022) suggested the key challenge at the early stage of AI adoption lies in effectively handling differing perspectives among stakeholders. Bright et al. (2019) pointed out that a major challenge to AI adoption in local government is convincing senior management of the potential of AI so that they will fund risky AI projects. Campion et al., (2020) found that AI initiatives often were driven by policy from a higher level, in which case there would be proactive effort internally to encourage AI adoption.

In certain cases, local governments may choose to outsource their AI projects or partner with other organizations to develop AI systems, whether with universities, research agencies, or/and private sectors (Campion et al., 2020; 2022; Desouza et al., 2018; Vogl, 2021; Mikhaylov et al., 2018). Desouza et al. (2018) suggested external collaborations were essential for the public sector, particularly with academia to initiate AI projects, as the public sector often lacked the ability to manage large IT projects. The authors further suggested that collaboration on AI requires a long-term agile approach because AI systems and tools evolve continuously. Mikhaylov et al. (2018) provided a cautionary note for collaborations with the private sector as a result of competing institutional logic. The authors argued that, while government employees prioritize serving the public, private sector employees would strive to promote their market-oriented goals. An additional challenge referenced the unbalanced AI skill level between governments and private sectors: governments usually lacked the personnel with adequate AI knowledge to participate in the collaboration effectively.

While Mikhaylov et al. (2018) discussed the challenges of collaboration with the private sector, Campion et al. (2022) uncovered challenges in collaboration by examining collaboration between local governments and universities. The authors found that privacy mandates might prohibit or restrict public sector organizations' sharing of data, including how data might be repurposed. Also, they saw misalignments in the expectation for AI projects, not only between the university and public sector but also between the top and bottom levels of an individual organization.

Local governments face significant regulatory challenges in outsourced AI projects. It is extremely challenging to regulate AI when different parts of AI (i.e., AI models, learning algorithms, axillary algorithms, data inputs and data outputs) are owned by multiple parties and are outside municipal jurisdiction (Ip et al., 2022). Lack of regulation holds important implications for private sector AI contracts. Regulations often specify intellectual property (i.e., ownership) and access. When it is not required by the contract (Hickok, 2022) or for the protection of trade secrets (Burrell, 2016; Katyal, 2019), the public sector may not have access to proprietary algorithms or the design of AI systems, which makes it impossible for the public sector to assess how well systems perform (Dickinson & Yates, 2023; Hickok, 2022). Regulations often include accountability measures. When AI is outsourced to the private sector, the responsibility normally attributed to the public sector may be partially transferred to the private sector (Hickok, 2022; Dickinson & Yates, 2023). This creates an accountability gap, which is a growing concern pointed out by many scholars: when an AI system fails to perform, it is impossible to determine who should be held accountable (e.g., Diakopoulos, 2015; Matthias, 2004; Mittelstadt et al., 2016).

Lastly and under-discussed in the literature is user acceptance of AI. User acceptance can be difficult because of the opaque nature of AI, which means that users may be unable to evaluate the performance of the system (Dickinson & Yates, 2023) or trace the reasons for AI decisions (Fomin, 2020). Users also may resist using AI systems because of their unwillingness to change organizational practices. Yigitcanlar et al., (2022) briefly described the issue related to user acceptance of AI systems that are intended for the public. For example, senior citizens may be reluctant or unable to use the new technology. Strategies to reduce user resistance and enhance the usability of the AI interface may be of great importance. We also are interested in internal users of the technology, for example resistance of staff to change their routines.

Table 3.1. Local Governments AI Adoption Challenges

Challenges	Authors
Lack of Internal Capacity (i.e., funding and technical expertise)	Bright et al., 2019; Campion et al., 2020; Vogl, 2021; Wirtz et al., 2019; Yigitcanlar et al., 2022
Lack of Quality Data	Desouza et al., 2020; Vogl, 2021; Yigitcanlar et al., 2022
Insufficient Data Literacy or AI Literacy	Campion et al.; 2022; Desouza, 2018; Yigitcanlar et al., 2022; Vogl, 2021
Insufficient or Incompatible Computing Infrastructure	Bright et al., 2019; Desouza, 2018
Lack of Stakeholders Buy In	Bright et al., 2019; Campion et al., 2020, 2022; Nili et al.,2022
Challenges in Collaboration (i.e., resistance in collaborating, divergent organizational value and practice, skill imbalance)	Campion et al., 2020; 2022; Desouza, 2018; Vogl, 2021; Mikhaylov et al., 2018
Regulatory Challenges	Dickinson & Yates, 2023; Hickok, 2022
User Resistance	Yigitcanlar et al., 2022

3.3 Methodology

To better understand the use of AI in local governments, we developed a survey to understand their perceptions of opportunities and challenges of AI. In this section, we discuss the target population, method of recruitment and the content of the survey instrument.

3.3.1 Recruitment of Participants

We wanted to identify the cities that seek to adopt or have adopted AI and to identify the potential respondents for the survey. The target population are individuals who have a direct role in the adoption of AI systems. We define "direct" as those working closely to the design, development or deployment of AI systems, which include, but are not limited to government employees, data scientists, consultants, and external stakeholders.

We targeted two pools of potential respondents. The first consisted of applicants to the Canadian Smart Cities Challenge. The Smart City Challenge (2018-2019) was launched to promote innovation in Canadian cities and garnered 130 eligible submissions, 20 finalists and 4 winners (Infrastructure Canada, 2018). We reviewed the original applications of the Challenge to determine which communities proposed to use AI and to determine the contact people for those applications. We assumed that if a community application mentioned AI or AI-related terms then it may have begun AI adoption (where adoption might include in-house development or outsourcing). In total, 25 respondents were selected from this process. Our second pool of respondents included 94 individuals who had attended monthly meetings called AI Municipal Government Community of Practice (AI COP). These meetings have gathered Municipal IT managers, directors, chief technology officers, data scientists, and academics. They share projects, best practices and collaborate around AI deployment in municipal government. In total, we selected 119 individuals to survey.

We obtained research ethics approval by the McGill Research Ethics Board Office before initiating the survey (Appendix A). We sent out customized recruitment emails based on where they were identified, their job titles and the projects that they were involved in. The potential participants were given the option to fill out the survey by email, by LimeSurvey platform or through an online interview. The interviews were conducted via video or phone calls, through a platform preferred by the respondents. To increase the response rate, we sent out follow-up emails to non-respondents and made a poster announcement at the AICOP conference. We provided no monetary compensation; instead, the motivation for their participation relied on goodwill and we promised to offer them a copy of the research report.

We obtained a total of 28 responses, two from the Smart Cities Challenge pool and 26 from the AI COP pool. Our suspicion for the low number from the Smart Cities Challenge pool is that respondents' AI adoption depends on receiving grants. Additionally, some contacts no longer worked for the local governments. We participate in the AI COP on a monthly basis so our participation was a likely inducement for them to participate.

3.3.2 Survey

A survey instrument (Appendix B) was created to understand respondents' backgrounds, the extent of AI use in governments, motivations for their adoption, the perceived opportunities and challenges and the impact of AI projects. The instrument contained a total of 18 open and closed-ended questions. We anticipated that our respondents might have different levels of skill in AI and might be in different stages of the AI project so we design questions that everyone could answer. For example, we asked "How is the AI project developed or intended to be developed?".

We first asked respondents about their backgrounds and to describe their current or anticipated AI projects within the organization. We then provided respondents with three sets of Likert scale questions on opportunities, organizational, and technical challenges that were previously identified from the literature. At the end of each session, respondents were given the chance to provide additional comments on a specific question or supplement the list of opportunities and challenges. Next, we asked the respondents to choose one project that they were most familiar with and discuss their perception of motivations and impacts of AI adoption. Finally, we asked for their suggestions on the government's use of AI based on their experience. With the permission of the respondents, we recorded the interviews for the analysis.

3.3.3 Data Analysis

We transcribed the recordings so we could combine the interviews and the surveys. To analyze the qualitative data, we conducted a content analysis using thematic coding following an inductive approach. First, we read through the transcript to discover the emerging themes. Then we labelled content with the themes we identified. Next, we grouped similar themes into categories. Finally, we applied these categories to the entire transcript. We also pulled representative quotes related to the key themes for illustrative purposes. For the Likert scale questions, we calculate their summary statistics including the mean, medium and variance.

3.4 Results and Discussion

In this section, we discuss the results of our survey. We first discuss the respondents' background in terms of their job titles, type of organization and level of AI knowledge. Then we discuss their AI projects, how they developed or intended to develop their AI projects and the main reasons for the approach they chose. Lastly, we examine their perception of opportunities, challenges and concerns in AI adoption.

3.4.1 Respondent Background

The respondents in the study represent a diverse range of backgrounds and roles, with varying levels of knowledge in AI. Job titles include data scientist, data storyteller, manager, chief information officer, project manager, consultant, planner, and professor. The majority of the respondents are employees of local governments, indicating their direct involvement in AI initiatives within the public sector. Ten percent of the respondents are from universities or colleges, working collaboratively with local governments on project delivery. Two respondents are from other government organizations that oversee multiple municipalities within a region.

In terms of their knowledge of AI (Figure 1), close to a half of the respondents have an academic background related to AI. Among those individuals, only a small portion (17.9%) are formally trained as a data/AI scientist. Approximately one-third (34.6%) come from related fields such as information science. A few of the respondents (11.5%) are not in the field related to AI but are self-taught or trained by their organization. In terms of their roles, almost half of the respondents have jobs that do not require technical knowledge of AI. Instead, they serve in managerial positions or contribute domain knowledge to AI projects.

This composition of respondents reflects a diverse range of expertise and perspectives, encompassing individuals with deep technical knowledge of AI as well as those with broader roles and domain-specific knowledge.

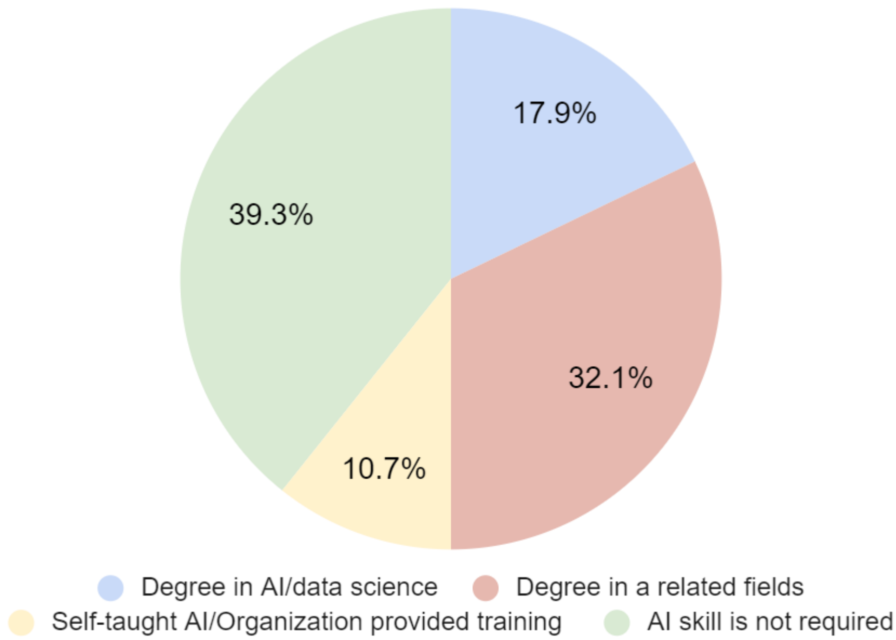

Figure 3.1. Respondents' Knowledge of AI

3.4.2 What are Their AI Projects?

We asked respondents to describe the AI project they have or intend to initiate. According to the responses provided by the participants, the AI projects consisted of a combination of less complex machine learning techniques such as logistic regression naive Bayes, and random forest, as well as a few deep learning projects involving tasks like image recognition and natural language processing.

In terms of the stage of adoption, the majority of respondents (64%) stated that their AI projects were in the early stages, either not started or at the pilot stage. This suggests that these projects were still in the experimental or developmental phase, with limited implementation or operationalization. The remaining respondents (36%) indicated that their AI projects had already been operationalized, meaning they were actively used or integrated into their existing systems or processes.

Table 3.2 presents some examples of the areas in which the AI projects are being implemented. These examples demonstrate the diverse range of AI applications within different domains of city governance, indicating the potential for AI to address various challenges and improve efficiency, decision-making, and service delivery in cities.

Table 3.2. Examples of AI Projects within Canadian local governments

Building risk assessment	AI is used to analyze building data, predict the risks of building types and determine whether a city could drop certain inspections.
Citizen service	AI technologies are implemented to improve citizen services, such as chatbots for customer support.
Community safety	AI is employed to enhance community safety by finding patterns to identify potential crime hotspots, predict crime trends, and optimize service and resource allocation.
Detection of road deficiencies	AI algorithms are employed to analyze road conditions, detect potholes or other road deficiencies, and prioritize maintenance and repair efforts.
Environmental and weather analysis	AI is employed to analyze environmental data such as rainfall data to support environmental monitoring and planning.
Internal document analysis	AI is utilized to process large volumes of internal documents, automate information retrieval, or extract relevant insights to support decision-making and knowledge management.
Labour trends	AI is used to analyze labour market trends, predict job demand, identify skills gaps, or facilitate workforce planning and development initiatives.
Real estate price prediction	AI algorithms are used to analyze satellite imagery, real estate data, and other factors to predict property prices.
Retirement prediction	AI is used in predict the number of employees retiring to plan recruitment.
Smart home	AI is integrated into smart home systems to provide another channel of accessibility to city services.
Traffic monitoring	AI is utilized to monitor and analyze traffic patterns.
Wildlife detection	AI is applied to detect wildlife in images and identify species at urban-rural fringe.
Water billing analysis	AI is applied to analyze water usage patterns, detect anomalies or

	leaks, optimize billing processes, or identify areas for water conservation.

3.4.3 How Local Governments Developed or Plan to Develop Their AI Projects

Respondents were asked how they chose to adopt AI. We derived these categories from discussions during the AI COP. This was actually a "who" question, as in who would develop the system, whether it was internal or external to the government. This included in-house development, purchase of an existing product, outsourced to an external company/team for development, or done in collaboration with an external entity. Done in collaboration refers to working with colleges and universities, collaborating informally with medium-sized firms, engaging student interns, as well as working with AI research institutes. Respondents also could answer that they had yet to decide who would develop it.

Figure 3.2 shows that most respondents reported they would develop AI in-house. This was closely followed by "Done in collaboration". Instances of collaboration included working with Durham College in Ontario and engaging student interns from Quebec AI Institute (MILA).

Respondents reported that most collaborations were built upon existing relationships. One respondent recommended to "Elaborate [rely on] partnerships, whether or not it is university or private sectors, whoever that you can find." Collaboration could encompass considerable informality in relation to formal Requests for Proposals (RFPs). We found that two cities had thresholds of between $10,000 and $100,000 before a formal RFP needed to be generated for AI. We speculate that the informality of relationships (cf., formal procurement processes) may result from most local governments being at an early stage of AI adoption or not yet in production. Campion et al. (2022) noted that informal collaboration allows organizations to develop trust. One respondent pointed out that they worked with interns to develop proof of concepts for AI. This could serve as a prelude to an RFP or to absorbing a project in-house.

The way in which AI projects are carried out may not depend exclusively on the options given. For example, one respondent reported that they switched to in-house development because the consultant failed to provide the desired solution. This confirms a brief mention in Vogl (2021) in which "local authorities have had to modify, build upon, or take over from suppliers" (p. 11).

Vogl et al. (2020) pointed out that this may be related to vendors' lack of contextual knowledge in designing the AI system. This mention of contextual knowledge could be of the local area; it could be of a specific application domain like ecology. However, when a vendor focuses only on technological development, the AI systems may not fulfil the actual expectations of local governments.

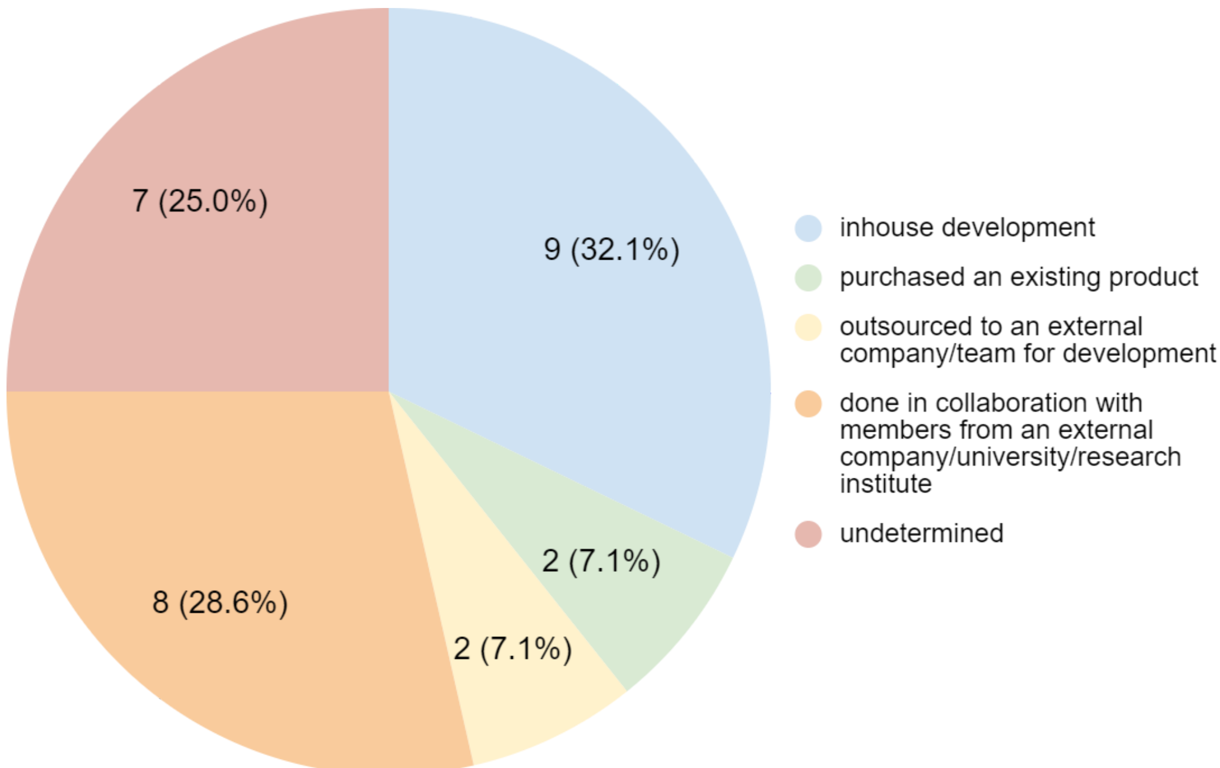

Figure 3.2. Ways AI is Developed or Intended to be Developed

3.4.4 Why the Above Choice?

In an open-ended question, we asked respondents why they made the above choice. They offered two primary reasons but we found that the responses differ depending on whether or not they chose to develop the AI fully in-house. Therefore, we aggregated the responses into two groups, in-house development and outsourcing.

3.4.4.1. In-house AI Expertise as a Difference between In-house and Outsourcing

Whether or not a local government chooses in-house or outsourcing, possessing in-house AI expertise was the most common consideration (53%). Those who chose to develop their project fully in-house possessed in-house staff with technical skills in AI, with two data scientists minimum a common characteristic for those local governments. Among the individuals who were outsourcing or planned to outsource, the majority (64%) acknowledged that they had "zero in-house expertise" for in-house AI development. For local governments, outsourcing appeared an obvious and sometimes the only option as they had little knowledge of how to initiate the AI project. Dickinson and Yates (2023) noted the importance of retaining some in-house AI capacity even if outsourced, to support system operation and respond to system failure.

3.4.4.2. Financial Considerations when Choosing Whether to Develop In-house or to Outsource

Financial consideration emerged as another reason for choosing in-house development or outsourcing. Of those who chose to outsource, 50 percent suggested that they had insufficient funds to develop AI and hire AI-related staff. Of those who were driven to develop in-house, almost half reported they could not afford to outsource a project even if that would gain them external resources such as consultants and cloud computing infrastructure. One respondent suggested that a lack of funding irrespective of in-house/outsourcing may respond to how budgets are allocated in the local governments. Funding for hiring permanent local governmental employees might be separated from hiring consultants.

In addition, for two respondents, outsourcing allowed them to leverage funds from external institutions such as universities, in the form of research grants. In these cases, respondents also would gain access to professorial expertise. One respondent suggested that they were able to obtain skilled student interns at lower salary rates. Financial considerations largely drove collaboration by local governments with educational institutions.

3.4.5. Perception of Opportunities

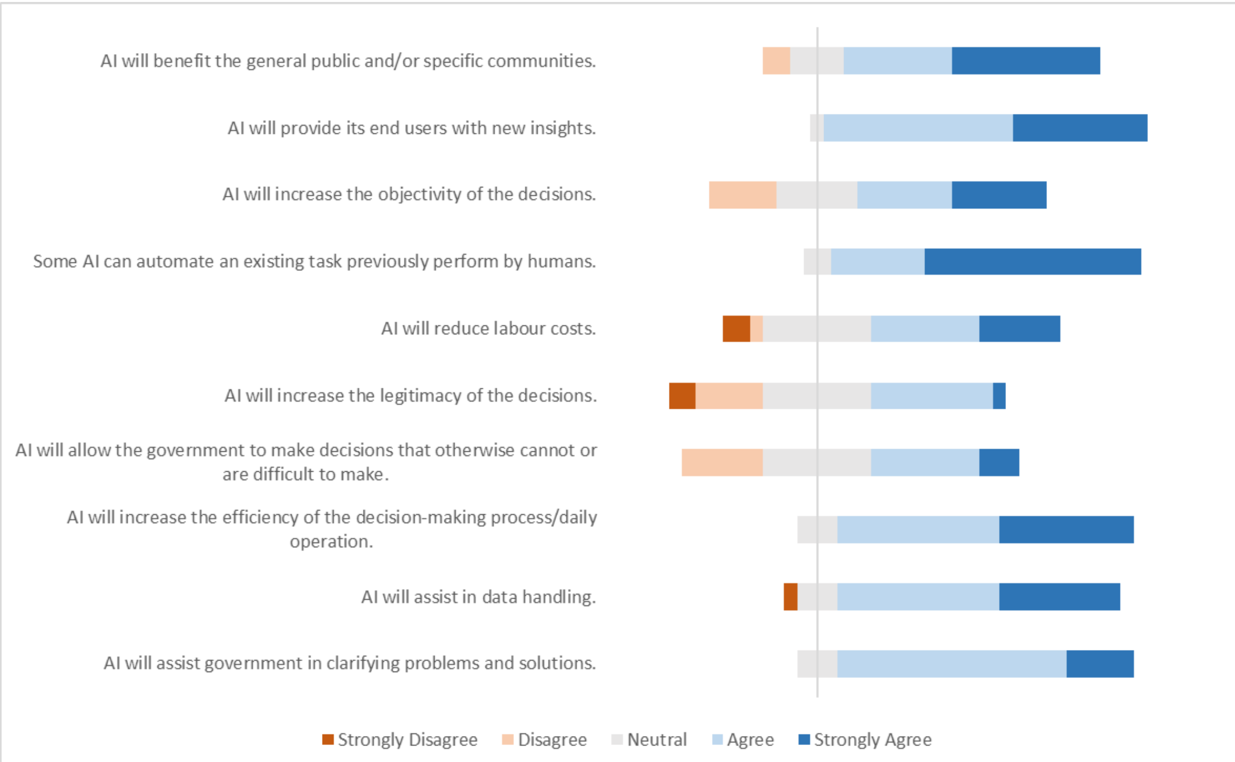

Figure 3.3. Perception of Opportunities

Table 3.3. Summary Statistics of Perception of Opportunities

	mean	median	std
Problems and solutions identification	4.2	4.0	0.5
Data handling	4.0	4.0	1.1
Efficiency	4.3	4.0	0.7
Decision making	3.5	3.5	1.1
Legitimacy	3.2	3.0	1.0
Labour saving	3.5	3.5	1.2
Automation	4.6	5.0	0.6
Objectivity	3.7	4.0	1.1
New insights	4.4	4.0	0.6
Community benefits	4.2	4.5	1.0

We asked respondents to rate their perception of various opportunities presented by AI on a scale of 1 to 5 (see Appendix B for specific wording). In addition, we invited them to provide comments on the opportunities listed and suggest any additional opportunities we may have missed. Figure 3.3 illustrates the responses, with each bar representing the total number of respondents in each rating category. The results indicate an overall positive opinion towards almost all of the opportunities. From a statistical standpoint, all of the opportunities have a mean and median value equal to or greater than 3 (Table 3.3).

Among the listed opportunities, automation received the highest level of agreement, with a mean rating of 4.6. This was closely followed by AI's potential to enhance new insights, improve efficiency, clarify problem-solving processes and provide community benefits, all of which had mean ratings higher than 4. Additionally, some opportunities were found to be interconnected. For instance, three respondents highlighted AI's ability to assist in routine processes, which in turn improves efficiency and reduces costs. Interestingly, survey findings indicate a strong consensus among respondents regarding the potential of AI in local governments, even though a number of respondents have yet to implement AI initiatives or were at an early stage of adoption. Their perceptions appear to align with the rhetoric of AI (Bullock, 2019; Ojo et al., 2019; Toll et al., 2019; Valle-Cruz et al., 2019; Zuiderwijk et al., 2021) whether or not AI can deliver its promise.

Three of the opportunities are much debated among respondents, including the role of AI in labour cost reduction, the objectivity of AI decisions, and the legitimacy of AI decisions. We discuss them in the following subsections.

3.4.5.1 AI in Labour Cost Reduction as an Opportunity

We found that the potential of AI to reduce labour costs sparks the most significant debate among respondents. It also exhibits the highest standard deviation (Table 3.3). Approximately half of the respondents agree or strongly agree that AI can reduce labour costs. However, two respondents hold a different perspective, disagreeing with the notion that AI saves labour costs. They argue that AI brings additional work to local governments as employees must dedicate time to tasks created by AI. One respondent acknowledges the potential of AI in reducing labour costs but expresses the hope that labour will transition to higher-value areas. Conversely, two respondents highlight the potential risk of job loss due to the impact of AI. One respondent specifically states, "I do not hope AI will reduce labour costs because that means we are using AI to hire fewer people." This viewpoint aligns with Vogl et al. (2020), who suggest that AI has the potential to reduce repetitive administrative processes, allowing staff to focus on more complex work rather than replacing workers entirely.

3.4.5.2 Objectivity of AI Decisions as an Opportunity

As seen in Figure 3.3, respondents expressed that AI would increase objectivity. One respondent strongly believed that AI increases objectivity, despite acknowledging the presence of algorithmic biases. That individual argued that AI is “inherently more objective” than human decision-making. A different respondent disagreed that AI would enhance objectivity, highlighting that major decisions are often influenced by political considerations rather than sound business or technical reasoning. According to this view, while AI outcomes may be taken into account, political factors tend to override other considerations. This discussion echoes the early work of Kling (1978) on information technology implementation in local government, who argued that computing systems were initially seen as tools to enhance the rationality of decision-making and policy formulation by providing a variety of alternate policy options. The realization that AI-related decision-making is inherently influenced by political factors indicates that AI’s impact on decision-making may be more complex and nuanced than initially anticipated.

3.4.5.3 Legitimacy of AI Decisions as an Opportunity

Related to the concept of objectivity is the legitimacy of the output. Though definitions vary, legitimacy of AI generally concerns the effectiveness, credibility, fairness, and trustworthiness of the decision (Starke & Lünich, 2020). Like objectivity, there were differences of opinion, with this opportunity rated the lowest on average (3.2, and a median of 3.0). One respondent suggested that legitimacy concerns the notion of what constitutes a "good decision" and suggested that AI does not necessarily lead to better decisions but rather faster ones. They argued that the legitimacy of a decision depends on how it is defined and that AI should not be relied upon solely to make decisions legitimate. Five respondents emphasized the importance of human involvement in the decision-making process. AI could aid decision-making but human judgment necessary to reach the final decision.

3.4.6 Perception of Organizational Challenges

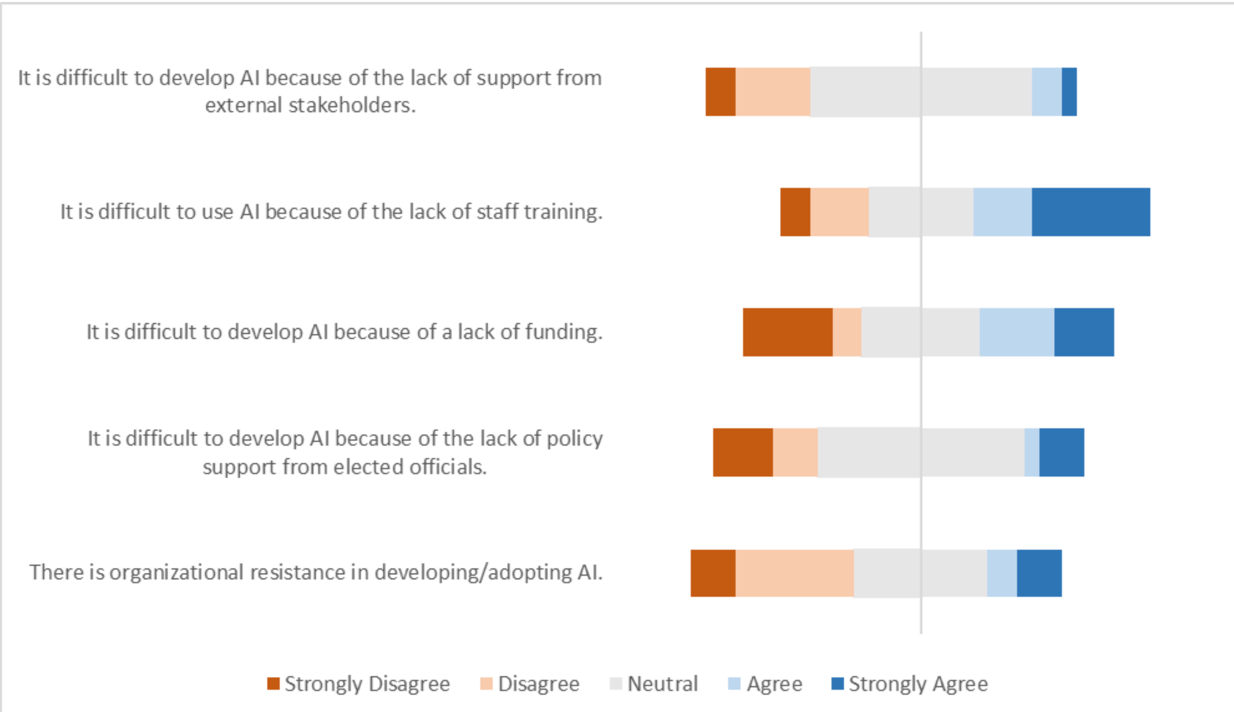

Figure 3.4. Perception of Organizational Challenges

Table 3.4. Summary Statistics of Perception of Organizational Challenges

	mean	median	std
Organizational resistance	2.7	3.0	1.2
Policy support	2.8	3.0	1.1
Funding	2.9	3.0	1.4
Training	3.5	3.5	1.3
External stakeholder support	2.8	3.0	1.0

We asked respondents to rate their perception of various organizational challenges related to AI adoption on a scale of 1 to 5 and we invited them to provide comments on the listed challenges and any additional challenges we may have missed. Compared to the opportunities in the prior section, respondents rated organizational challenges as a relatively low barrier to adoption (neutral to strongly disagree) or they were neutral, as indicated by median values equal to or close to 3 (Table 3.4).

3.4.6.1 AI Awareness and Training as a Challenge

The most commonly agreed-upon challenge was the lack of staff training, which received the highest number of agree and strongly agree responses (Figure 3.4) and had the highest median and mean values (Table 3.4). Seven respondents mentioned a general lack of awareness and understanding of AI among their staff and elected officials. One of the respondents explained that: “There is … a lot of confusion about AI in general. Maybe this is a part of the difficulty of using AI, but it is about even understanding it and knowing what is possible is a challenge.” Respondents highlighted the absence of training programs to help internal staff understand AI, as well as the difficulty in interpreting and comprehending AI results. Our findings align with Campion (2020) and Yigitcanlar et al. (2022), which found a lack of AI knowledge and training, as well as an understanding of the potential questions to be addressed by AI.

3.4.6.2 Funding for Development and Maintenance as a Challenge

Another significant challenge reported by almost half of the respondents was the lack of funding, which is consistent with the literature (Vogl, 2021; Wirtz et al., 2019; Yigitcanlar et al., 2022) and was echoed in the finding about the choice over outsourcing. One respondent mentioned the challenge of justifying AI investment due to its technical debt. Technical debt means “the increasing software development costs over time” especially when that cost is not anticipated and fixed early (Tom et al., 2013, p. 1498). This respondent stated that the technical debt from prior IT “generated a lack of investment [in AI] and our priority is more focused on managing this technical debt.” The influence of existing technical debt on AI adoption in local governments is under-discussed in the literature. The only one we found was Desouza (2018), who highlighted the issue of high maintenance costs associated with legacy IT systems in the public sector, which constrain the budget that can be allocated to emerging technologies such as AI.

Not only must local governments manage costs in legacy IT systems, they need to leverage funding to develop and maintain AI systems. One respondent expressed that funding may not be allocated to AI because AI does not represent a priority for local governments, stating that “Municipal government's main focus is to provide core services, like fixing sidewalks.” Two respondents mentioned that maintaining AI systems is costly, while the development phase may be budgeted for, ongoing maintenance requires additional spending on data storage, project management, training, and operational support. These discussions speak to the importance of budget planning and allocation in AI adoption.

3.4.6.3 Support From External Stakeholders as a Challenge

External stakeholders are any actor outside of the local government, which may include citizens, vendors, and universities. Respondents generally considered external stakeholders as universities and vendors, that is potential external developers. As mentioned above, support from external stakeholders was emphasized by respondents, as it allows access to expertise and external resources. One respondent pointed out that obtaining external support can be a way to gain expertise rapidly and on an as-needed basis (e.g., a city hires a consultant who works at the city during the duration of AI development), in line with Mikhaylov et al. (2018) who suggested that collaboration with external entities can be a way to gain expertise.

However, one respondent pointed out that the lack of communication and understanding with stakeholders hinders effective collaboration with university student interns. As stated by this respondent, “We have a project where the data science student provides an algorithm but it wasn’t useful for the city”. A similar challenge was observed by Campion et al. (2022), who noted that a lack of alignment between project interests and expectations has hindered the successful collaboration between entities.

Nevertheless, more than half of the respondents remained neutral or disagreed with the notion that the lack of support from external stakeholders posed a challenge. We speculate that this is because they either had not encountered this issue yet or were able to gain support when needed.

3.4.6.4 Policy Support and Guidance as a Challenge

As can be seen in Figure 3.4 on organizational challenge of a lack of policy support, more than half of the respondents remained neutral. For example, one respondent believed that elected officials were interested in AI but not actively pushing for it. Conversely, two respondents agreed that the lack of existing policies and guidelines on AI development posed a challenge. They interpreted policy support as best practices and noted an absence of established AI projects within Canadian cities. Consequently, local governments had to pilot their own projects rather than learning from existing ones. Concerns also were raised about the lack of appropriate policy guidelines in AI procurement and contracts. One respondent stated that “although we already have certain control on…those traditional IT contacts, like dealing with those legislations, accessibility, PCI [Payment Card Industry systems], privacy, and consent, there is no policy on how we do AI.” This affects policies governing outsourcing contracts. The complexity of AI outsourcing contracts has been recognized in the literature (Hickok, 2022; Katyal, 2019).

3.4.6.5 Organizational Resistance as a Challenge

“There is organizational resistance in developing/adopting AI:” was the challenge that received the most disagreement. with the majority of respondents choosing to disagree or strongly disagree (Figure 3.4). Likely this was a consequence of our selection of respondents. Several respondents stated that respondents within organizations actually expressed enthusiasm about AI. However, one respondent mentioned resistance from frontline workers in a specific AI project, driven by fears of job displacement. To address this resistance, the respondent reportedly reduced it by engaging users, enhancing trust, and assuring them that AI would not replace their jobs. User engagement involved brainstorming feature variables with users and explaining AI concepts in non-technical terms. This is consistent with the literature that suggests face-to-face interaction and learning activities are important in developing trust and reducing resistance (Campion et al., 2022, Mikhaylov et al., 2018).

3.4.7 Perception of Technical Challenges

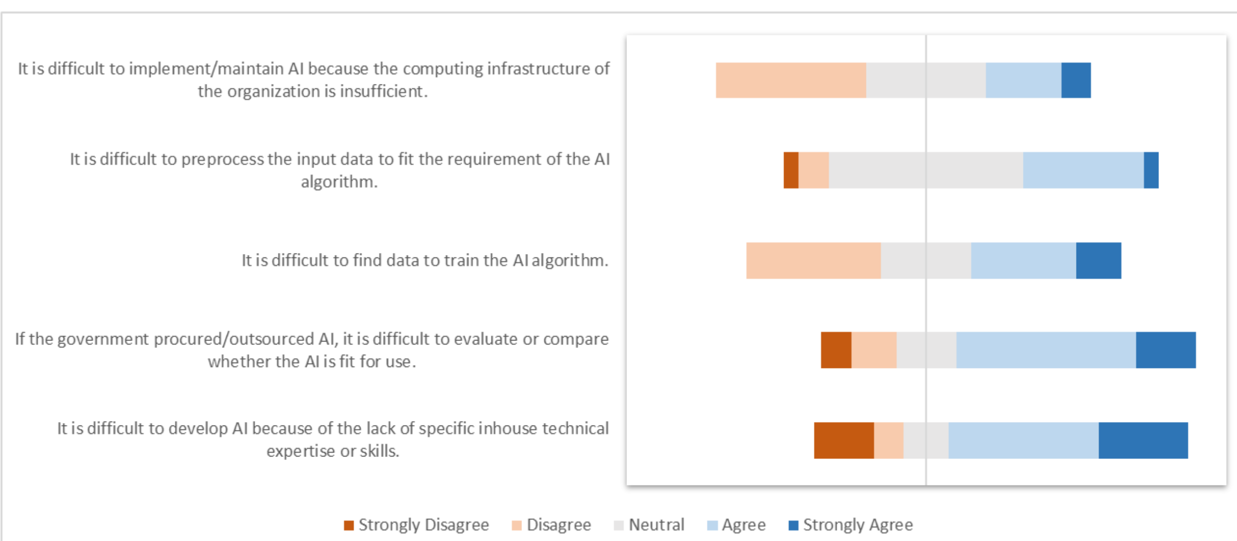

Figure 3.5. Perception of Technical Challenges

Table 3.5. Summary Statistics of Perception of Technical Challenges

	mean	median	std
In-house expertise	3.5	4.0	1.3
Evaluate fitness for use	3.5	4.0	1.2
Data availability	3.3	3.0	1.1
Data preprocessing	3.3	3.0	1.0
Computing Infrastructure	3.0	3.0	1.0

Similar to organizational challenges, we asked respondents to rate their perception of various technical challenges related to AI adoption and provide additional comments. Some respondents pointed out additional technical challenges that were not covered in the Likert scale questions. Figure 3.5 shows respondents' perception of technical challenges. Overall, we found a greater level of agreement on the technical challenges compared to organizational challenges (Figure 3.4), indicating that the technical challenges are considered more significant.

3.4.7.1 Inhouse AI Expertise as a Challenge

Section 3.4.4.1 is about the choice to in-house or outsource development; here we elaborate on how expertise challenges AI adoption. The majority of people (11 respondents) agreed or strongly agreed that the most significant technical challenge to AI adoption consisted of a lack of in-house expertise or skills (Figure 3.5). A rare case in terms of in-house expertise is the City of Edmonton, which staffs a seven-person data science team consisting of a project manager, three data scientists, a data storyteller, a data architect and a strategic foresight analyst. Cities may have IT specialists but most respondents replied that they had no in-house AI expert.

One respondent noted that “The technical gap is large between the current status and AI initiatives. Most of the time, the best return on investment comes from a "SELECT * GROUP BY" sentence as the city comes from far behind.” That person is suggesting that most cities don’t have the needed expertise so the best they should do is data management and analysis methods, via in this case a Structured Query Language statement. That may not prevent policymakers and elected officials from requesting more advanced AI-driven analytics.

The challenge lies in not only the lack of expertise but also the difficulty in hiring and retaining expertise. Hiring and retaining AI-related staff also were identified, with three respondents reporting difficulties in finding suitable AI staff. As stated by one, "I am not sure if our remuneration can match some of the private sector offerings for these skills….We see that across our IT group."

In addition to computational expertise, the study highlights the significance of subject matter expertise in effectively utilizing AI. The recognition that AI alone cannot fully comprehend data and its implications underscores the need for understanding the specific context and purpose of data collection and usage, particularly in planning. This aspect of subject expertise is often overlooked in the literature, as noted by Vogl (2021), who highlighted the challenges arising from a lack of contextual knowledge in suppliers when developing AI systems.

3.4.7.2 Outsourced AI Systems as a Challenge for Fitness of Use

An equally significant challenge is the difficulty in evaluating fitness for use for outsourced AI systems, with a similar number agreeing and strongly agreeing (Figure 3.5). One respondent believed that it is difficult to evaluate fitness for use if outsourced because the development process is opaque, complex and context-dependent. According to respondents, fitness for use includes several aspects, including data pre-processing, algorithm training and parameter tuning. Outsourcing also makes it difficult to evaluate the results, as stated by one respondent "If you know the technique you should know when it fails and why it fails and really be able to explain that to people whereas if a product just starts to give you weird answers it is gonna be a lot harder to say why." Hickok (2022) argued that an outsourced system can obscure potential AI ethics violations around fairness, accountability and transparency.

One respondent brought up maintenance by vendors of outsourced AI systems. This type of concern may only increase. As AI systems become more opaque and complex, local governments may face increasing difficulties in maintaining them effectively over time. Examining and addressing these maintenance challenges is crucial to ensure the long-term success and sustainability of AI initiatives in the public sector. The point raised by Hickok (2022) about the public sector's limited ability to independently monitor AI system performance is supported by these findings.

3.4.7.3 Data Availability, Data Quality and Data Sharing as Challenges

Respondents expressed significant AI adoption challenges related to data, including availability, quality, and sharing. The importance of data in AI development has been emphasized by Desouza et al. (2020) and Vogl (2021). Respondents had mixed opinions about data availability, with nearly half of them believing they have sufficient data; whereas others felt they lacked the necessary data for their AI projects.

Two data scientists mentioned instances where AI initiatives were launched without adequate data support, leading to difficulties in AI development. One respondent highlighted the issue, stating that: “The data to support the development of AI solutions are many times missing and the stakeholder does not realize it prior to launching an initiative”. Another concern raised was the manual entry of data, which could result in incomplete datasets. In such cases, employees tend to substitute missing values with default values, introducing errors and biases into the data. Vogl (2021) also noted similar challenges, such as incomplete, inaccurate, or inconsistent data, which can negatively impact model performance and prediction accuracy in AI models.

Even when data is available, accessing it can be problematic due to the absence of data-sharing protocols and siloed local government departments. AI development often necessitates internal and external data-sharing. However, respondents mentioned the time-consuming process of waiting for memoranda of understanding to be signed before they could access and work on each dataset. In other cases, data-sharing protocols may not exist and government departments may operate in silos, making it difficult to access the necessary data. The challenge of internal data sharing in AI is identical to the struggles faced by spatial data-sharing agreements in the 1990s (Onsrud & Rushton, 1995).

3.4.7.4 Computing Infrastructure: Hardware and Software as a Challenge

Last, respondents reported that a mismatch regarding computing infrastructure, both in terms of hardware and software, hampered AI adoption. A lack of computing infrastructure received the least disagreement among the challenges and the specific issues raised shed light on significant obstacles faced by the respondents.

Regarding hardware, one respondent mentioned the absence of a dedicated server in their city, which forced them to rely on running AI programs in their local environment, leading to crashes and limitations in processing power. As stated by the respondent “Building up our infrastructure has been difficult at the time because it is a very different technology stack compared to traditional IT… Because it's the city and everything is very rigid. We don't have any ability to go in there and make adjustments ourselves.” This highlights the need for adequate hardware infrastructure to support AI initiatives effectively. The expressed need for cloud computing infrastructure was raised by three respondents, even when they owned a server in house. One respondent pointed out a general lack of understanding of cloud computing; while another emphasized the difficulty of integrating cloud infrastructure into the existing system and the rigidity of organizational processes. These observations align with Desouza's (2018) argument that outdated IT infrastructure and siloed IT practices are not well-suited for AI adoption in the public sector.

The difficulty in integrating and accessing necessary software within the organizational process was highlighted by two respondents. One respondent mentioned the challenges of installing software, which may be hindered by the need for testing and approvals within the city. Bureaucratic processes and protocols can create obstacles when it comes to implementing new software tools for AI. Another respondent stressed the technical difficulty of aligning software within existing organizational processes, stating that “It is hard to integrate AI tooling [softwares], …using specific languages like R or python is not supported… so that handoff is gonna be difficult unless we are building a lot of the pipeline…It would need a lot of help to make that part of an existing process internally.” This highlights the importance of not only selecting appropriate software tools but also ensuring compatibility and integration with the existing IT practices. Bright et al. (2019) noted a similar challenge related to the adoption and acquisition of data science tools. They highlight the complexities faced by organizations when using and procuring such tools, whether through purchasing off-the-shelf analytics software like Microsoft Power BI or Tableau, or by installing open-source software packages like R and Python.

Overall, findings demonstrated the need for local governments to develop strategies for evaluating and procuring software tools that align with their existing IT infrastructure and processes, considering the compatibility of languages and platforms, streamlining approval processes and creating guidelines for software installation and integration.

3.4.8 Societal Concerns on AI Projects

We inquired about respondents' societal, legal or ethical concerns regarding their AI projects. A notable number of participants (6) indicated that they had no concerns, primarily because they were still in the experimental phase of AI adoption or were not utilizing confidential data. As one respondent stated, their current implementations or proof of concepts had not encountered any legal, ethical, or transparency issues, as they were primarily focused on assisting existing workflows. The remaining respondents expressed concerns related to privacy, the risk of failure, reliability, and explainability.

Privacy was a major concern raised by five respondents, particularly regarding the privacy and security risks associated with sharing data with vendors. This consideration becomes crucial when deciding whether to develop an AI project in-house or involve external vendors. As one respondent emphasized, privacy is a constant worry when making decisions driven by AI. This concern aligns with the findings of Campion et al. (2022), who observed resistance to data sharing from government agencies to third parties due to privacy considerations and regulatory constraints. The authors suggested that fostering trust through active engagement with third-party providers and ensuring robust data security measures are ways to mitigate the resistance.

Transparency was perceived as important for developing trust among users, whether they were internal to the local governments or external stakeholders such as residents and local businesses. Four respondents mentioned the need for transparency, both in terms of AI models and the disclosure of AI usage by local governments. Ensuring transparency of AI models was highlighted as challenging, as many models struggle to provide detailed explanations for their decision-making process. This limitation has implications for trust and understanding. One respondent mentioned that the necessity of transparency had led them to choose logistic regression, as it could provide clearer explanations for decisions, such as tax calculations. Two respondents stressed the importance of transparency regarding AI usage by local governments. One respondent suggested integrating transparency into AI procurement processes, while another proposed the creation of an AI registry as a means to enhance transparency.

The risk of failure associated with implementing AI was another concern mentioned by multiple respondents. Three participants reported that AI implementation involved significant costs and uncertainties, which presented a considerable opportunity cost when experimenting with AI. Demonstrating the value of AI to elected officials was seen as a prerequisite before proceeding further with AI initiatives. One respondent was concerned that if their first project fails then they will not be able to gain support from councils for future AI projects. This finding aligns with existing literature emphasizing the importance of senior management buy-in and policy support of AI in the local governments' AI adoption process (Bright et al., 2019; Campion et al., 2020, 2022).

Last, the reliability of AI models was a concern raised by three respondents. Two proposed measures to ensure reliability, such as triangulating results from different algorithms to validate their consistency. Another respondent emphasized the importance of training and validating models on different data sets over extended periods to ensure reliable performance. These measures aimed to address concerns regarding the dependability of AI outcomes.

3.5 Conclusion and Recommendation

This paper examined the practice of AI projects within Canadian local governments and assessed how local governments develop and perceive AI. The findings revealed a diverse range of backgrounds and levels of expertise among the respondents. AI systems spanned a variety of applications, indicating the broad scope of AI adoption within local governments. Development approaches employed by the respondents also varied, reflecting the flexibility and informality of AI implementation within local governments. Respondents' responses differ based on whether the project is fully in-house. Their decision on in-house versus outsourcing is based on whether they have in-house AI expertise and financial considerations. This diversity in backgrounds, expertise, applications, and development approaches underscores the multifaceted nature of AI adoption.

In terms of perceptions of AI adoption, we found there are overall positive views on the opportunities of AI, such as its ability to provide new insights, automate, increase efficiency, clarify problems and solutions and provide community benefits. There are varying opinions on the cost reduction potential of AI, with concerns about job displacement as well as the need for employees that can transition to newer tasks. Discussions around the objectivity of AI in decision-making reveal contrasting views, highlighting the political nature of decision-making processes. The concept of decision legitimacy is also a point of consideration, with an emphasis on human involvement and judgment.

We found local governments face significant organizational and technical challenges in AI adoption. A lack of staff training and awareness represents significant challenges, emphasizing the need for comprehensive training programs. Funding constraints also pose a considerable challenge, although collaborations with external institutions offer potential solutions. Support from external stakeholders and the development of clear policies and guidelines for AI implementation were emphasized. While organizational resistance to AI adoption was not considered a major concern, local governments need to attend to job displacement fears and need to engage frontline workers.

We found that the most significant challenge is the lack of in-house technical expertise and skills, with respondents acknowledging a large technical gap between their current capabilities and AI initiatives. Hiring and retaining AI-related staff also are reported as difficult, particularly due to competition with the private sector. Evaluating the fitness for use of outsourced AI systems shows that the complex and context-dependent AI development process makes it difficult to assess the results and understand the decision-making process. Maintaining AI systems in-house is viewed as resource-intensive, requiring additional spending on data storage, project management, training, and operational support. Concerns over the availability, quality, and access of data are mixed and reflect an absence of data-sharing protocols and siloed government departments. Computing infrastructure, including hardware and software highlights misalignments due to limited server capacity, a lack of cloud computing infrastructure, and difficulties in integrating AI tools and scripts into existing organizational processes.

Finally, the findings highlighted several key concerns in AI adoption for local governments. These included privacy and security risks associated with data sharing, the need for transparency in AI models and usage by local governments, the risk of failure and the importance of demonstrating value, and the reliability of AI models.

Our results show a gap and a paradox between AI promises and reality. For example, one motivation for local government AI adoption is to reduce costs, whereas in many cases, AI project implementation requires intensive resources and time, which poses a financial burden to the organization. Even though AI promises to improve services, paradoxically cities may be unable to invest in AI, because they have to focus on their core services. It is unclear whether AI adoption would provide a significant return on investment or whether it would result in greater costs.

Because of the time constraints, this study did not explore how perceptions may vary based on different factors, such as the stage of AI projects, the individual backgrounds of respondents, and the specific methods used to develop AI solutions. Understanding these nuances could provide valuable insights into the factors influencing AI adoption. For instance, local governments in the early planning stages might have different concerns than those experiencing the actual implementation phase. Investigating these distinctions could help tailor strategies to address specific challenges at each stage of AI adoption.

Nonetheless, this study highlights the challenges Canadian and other local governments need to address to successfully adopt AI. First, local governments need to prioritize internal AI education and training, secure adequate funding, foster collaboration, and establish supportive policies to navigate the organizational challenges in AI adoption. Second, local governments need to address technical skill gaps, invest in infrastructure, establish data foundation and data-sharing protocols, and ensure ongoing maintenance and support for AI systems to overcome the technical challenges in AI adoption. Last, local governments need to establish robust privacy protocols, build transparent AI models, ensure reliable outcomes, and develop effective ways of communication to gain trust to address the concerns on AI adoption. We hope these findings help local governments in understanding the challenges and guide local governments in AI adoption and inform better AI governance practices.

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3.7 Appendices

Appendix A. Research Ethics Approval Certificate

McGill

Research Ethics Board Office
James Administration Bldg.
845 Sherbrooke Street West. Rm 325
Montreal, QC H3A 0G4

Website: www.mcgill.ca/research/research/compliance/human/

Research Ethics Board 1
Certificate of Ethical Acceptability of Research Involving Humans

REB File #: 21-03-096

Project Title: Adoption of Automated Decision-Making Tools in Smart Cities

Principal Investigator: Sichen Wan

Status: Master's Student

Dept: Geography

Supervisor: Professor Renee Sieber

Funding: SSHRC (PI Prof. R. Sieber)

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The REB-1 reviewed and approved this project by delegated review in accordance with the requirements of the McGill University Policy on the Ethical Conduct of Research Involving Human Participants and the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans.

Deanna Collin
Research Ethics Officer

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* Approval is granted only for the research and purposes described.
* Modifications to the approved research must be reviewed and approved by the REB before they can be implemented.
* A Request for Renewal form must be submitted before the above expiry date. Research cannot be conducted without a current ethics approval. Submit 2-3 weeks ahead of the expiry date.
* When a project has been completed or terminated, a Study Closure form must be submitted.
* Unanticipated issues that may increase the risk level to participants or that may have other ethical implications must be promptly reported to the REB. Serious adverse events experienced by a participant in conjunction with the research must be reported to the REB without delay.
* The REB must be promptly notified of any new information that may affect the welfare or consent of participants.
* The REB must be notified of any suspension or cancellation imposed by a funding agency or regulatory body that is related to this study.
* The REB must be notified of any findings that may have ethical implications or may affect the decision of the REB.

Appendix B. Survey Instrument

Opportunities and Challenges of AI Adoption in Municipal Governments

A. Your Background
1. Could you tell me your job title? ____________________
2. Could you tell me what department or unit you are in? ________________________
3. What best describes your organization?
    1. Local government
    2. Other government
    3. Product supplier to city
    4. Private sector consultant
    5. Academic institution
    6. Other (please specify): ___________________
4. Check one that best describes your own knowledge of AI/ML.
    a. I'm formally trained as a data/AI scientist (e.g., I have a degree in computer science that specialize in data science).
    b. My academic background included learning statistical and computer programming techniques that prepared me for working in AI/ML (e.g., I have a degree in a field that had many courses in statistics/mathematics/information science, without learning AI/ML).
    c. I was not in the field related to AI/ML/statistics/data. I am self-taught or my organization provided training.
    d. My role in an AI project does not require technical knowledge in AI/ML (e.g., I serve in a project management role or I bring to the AI project skills in a specific domain like transportation or ecology).
    e. Other (please specify). ________________________
5. Within your organization, could you describe your current or anticipated AI-related projects?

____
____
____

6. Which of the following best represents how the AI project is developed/intended to be developed?
a. Inhouse by government employees.
b. Purchased an existing product.
c. Outsourced to an external company/team for development
d. Done in collaboration with members from an external company/university/research institute.
e. We haven't determined who will develop it yet.
f. Other
7. Can you describe why you choose the development in Question 6

B. Perception of Opportunities and Challenges of AI in Your Cities

7. On a scale of 1 to 5 *, when thinking about your own city (or the city that you work with) what do you hope your city's current or anticipated AI project(s) accomplishes?	
AI will assist government in clarifying problems and solutions.	
AI will assist in data handling.	

AI will increase the efficiency of the decision-making process/daily operation.	
AI will allow the government to make decisions that otherwise cannot or are difficult to make.	
AI will increase the legitimacy of the decisions.	
AI will reduce labour costs.	
Some AI can automate an existing task previously done by humans.	
AI will increase the objectivity of the decisions.	
AI will provide its end users with new insights.	
AI will benefit the general public and/or specific communities.	
Is there any opportunity I missed, or would you like to talk about any of these at length? ______________________________	
8. On a scale of 1 to 5 *, when thinking about your own city (or the city that you work with) what might be the organizational challenges of your city's current or anticipated AI project(s)?	
There is organizational resistance in developing/adopting AI.	
It is difficult to develop AI because of the lack of policy support from elected officials.	
It is difficult to develop AI because of a lack of funding.	
It is difficult to use AI because of the lack of staff training.	
It is difficult to develop AI because of the lack of support from external stakeholders.	
Is there any organizational challenge I missed, or would you like to talk about any of these at length? ______________________________	
9. On a scale of 1 to 5 *, when thinking about your own city (or the city that you work with) what might be the technical challenges of your city's current or anticipated AI project(s)?	
It is difficult to develop AI because of the lack of available expertise/technical skills.	
If the government procured/outsourced AI, it is difficult to evaluate or compare whether the AI is fit for use.	
It is difficult to find data to train the AI algorithm.	

It is difficult to implement/maintain AI because the computing infrastructure of the organization is insufficient.	
It is difficult to assess if the training data is usable.	
It is difficult to preprocess the input data to fit the requirement of the AI algorithm.	
Is there any technical challenge I missed, or would you like to talk about any of these at length?	

C. Perception of AI Project in Your City (or a city you work with)

10. Within your organization, could you describe the AI-related projects in which you've been involved, or you are contemplating to initiate? Don't feel the need to be exhaustive in your list.

11. Please mention one AI project that you are most familiar with or most likely to initiate.

12. What do you think motivates your city to choose to initiate the project mentioned in Q10? Feel free to rely on the table above in your answer.

13. What do you think are the "costs" in your city choosing to initiate the project mentioned in Q10? Feel free to rely on the table above in your answer.

15. Do you have any concerns on your city's current or anticipated AI project (e.g.,related to reliability, transparency, legal issue, privacy, biases)?

16. We are curious whether the AI project mentioned above is part of a smart city initiative? If so, can you describe how this tool contributes to the achievement of that initiative?

D. Comments & Recommendations

17. Do you have any recommendations on governments in their adoption of AI?

18. Do you have any comments/ recommendations that you would like to share about this study?

Preface to Chapter 4

The goal of the thesis is to identify what constitutes successful local government adoption of AI. Chapter 4 presents a case study of successful AI adoption in the City of Edmonton to assess the research question: “What factors of innovation contribute to the success of local government AI adoption?” This study was motivated by the findings in Chapter 2, which suggests that Edmonton is a leading city in AI adoption. This chapter uses part of the survey results from the previous chapter with additional data sources. As an article manuscript, this chapter was co-authored with my supervisor, Dr. Renee Sieber. We plan to submit the manuscript to

- *Urban Studies*
- *Journal of Open Innovation: Technology, Market, and Complexity*
- *Public Management Review*

Chapter 4. Factors for AI Innovation in Local Government: AI in the City of Edmonton

Abstract:

Artificial Intelligence (AI) plays an increasingly important role in local government. Whereas extensive research has examined factors for successful innovation in the public sector, little is known about what factors influence AI innovation in local governments. In this paper, we proposed a framework consisting of internal and external factors particular to AI innovation by examining the literature on innovation, smart cities, and public sector AI adoption. We applied these factors to the City of Edmonton. The Edmonton local government is considered an exemplar in information and technologies innovation and the city is host to one of the three main AI research centres in Canada. We analyzed various sources of data, including interviews, presentations, news articles and gray literature. We found six internal factors, encompassing AI-specific resources, internal needs, risk-taking culture, collaboration and knowledge sharing, upper management support and AI 'process fit'. We found three external factors, which cover the exogenous innovation environment, environmental drivers, and AI regulation and ethics. The factors can assist future analysis of AI innovation in other cities and the findings can aid cities in understanding the necessary conditions for implementing AI innovation.

4.1 Introduction

New digital technologies such as the Internet of Things (IoT), big data analytics, and computing platforms are increasingly incorporated in cities (Kandt and Batty 2021). These technologies may be used by local governments[1] to improve public services and enhance cities' problem-solving abilities (Allam & Dhunny, 2019). Artificial Intelligence (AI) is part of a bundle of smart city innovations (Yigitcanlar et al., 2021) that offers greater efficiency (e.g., Kuziemski & Misuraca, 2020; Valle-Cruz et al., 2019; Zuiderwijk et al., 2021), better decision-making capacity (e.g., McEvoy, 2019) and improved citizen services (e.g., Al-Mushayt, 2019; de Sousa et al., 2019; Mehr, 2017; Misuraca et al., 2020).

[1] We distinguish between government within cities and the spatial extent of cities because innovation can occur internally to the government (e.g., by government employees) and externally (e.g., by universities within or near the boundaries of the city).

AI has been used by city governments in numerous specific ways. For example, chatbots have been deployed to provide citizens with customized and up-to-date information because of chatbots' ability to process and filter information (e.g., Androutsopoulou et al., 2019). Urban AI promises to make cities safer through, for example, predictive policing by learning from past data (e.g., Alves et al., 2018; Yadav et al., 2020). AI supposedly enhances internal efficiencies ("business intelligence") by automating repetitive tasks (e.g., Misuraca & Noordt, 2020). Because cities and their governments have long been considered engines of innovation and development (Molotch, 1976), the use of AI can be viewed as the next step in cities' attempts to become creative economies (Florida, 2003), which seek competitive advantage (Kitchin, 2014; Monfaredzadeh & Berardi, 2014).

Even as cities are 'hotbeds' of development, local governments can find developing and implementing AI quite daunting. City governments, as compared to higher levels of government, usually possess limited resources. AI adoption is resource intensive, in terms of both the financial costs and technical skills needed for development (Campion et al., 2020; Vogl, 2021). Complexity can be further exacerbated by a lack of AI-specific regulations and guidelines (e.g., procurement) (Ip et al., 2022; Katyal, 2019).

Risk is yet another challenge. What sets Canada apart is its risk-averse culture (Crane & Meyer, 2006). AI, because of its opacity, resource-intensiveness and difficult-to-anticipate impacts, is a risky proposition. Despite risks, the Canadian government has invested billions of dollars in AI, including in cities (Brandusescu, 2021), making Canadian local governments an intriguing case for examining AI adoption. We focus on the City of Edmonton, Alberta, which has not always been perceived as a competitive and innovative city compared to other Canadian cities (Jones et al., 2019). However, Edmonton has gained recognition as a leading smart city and has demonstrated innovation in open data and data analytics (Carruthers, 2014). It has also emerged as a prominent hub for AI, hosting the Alberta Machine Intelligence Institute and the University of Alberta, one of the top five AI universities globally (Edmonton Global, n.d.). Notably, the Edmonton city government has developed and deployed its own AI systems, establishing itself as one of the pioneering local governments in this field (Pica-Alfano, n.d.). Part of our research is to explore these contrasting perceptions of innovation in Edmonton.

Our interest lies in understanding the conflicting image of Edmonton as an innovative city and uncovering the factors that contribute to its leading role in AI. To achieve this, we comprehensively reviewed how researchers have studied innovation in the public sector to create a framework for evaluating urban AI systems. To put the framework into practice, we reviewed the grey literature of newspapers and government documents, interviewed the local government AI team, and analyzed their project presentations. Our goal is to assess the internal and external factors contributing to the city government's leadership in AI innovation.

We first review the literature on internal and external drivers of innovations reported in the literature (Sections 2, 3), including our innovation factors assessment framework specific to AI. Section 4 covers the methodology, including the selection of Edmonton and our varied sources of material. Section 5 details the results of internal and external factors we found. Ultimately this research addresses a theoretical gap by proposing an internal and external factors framework tailored for measuring AI innovation. Furthermore, it fills an empirical gap by investigating the factors that facilitate AI adoption in local government, focusing on a best practices case, the City of Edmonton.

4.2 Innovation: Moving from the Private to the Public Sector

A body of literature has emerged that examines the factors influencing innovation. The research has focussed the factors that facilitate innovation in the private sector, but the public sector has distinct characteristics that impact its ability to innovate. In this section, I first introduce the definition of innovation and its various types. Next, I examine the similarities and differences between innovation in the public and private sectors. Last, I discuss the internal and external factors that influence innovation in the public sector.

4.2.1 Public and Private Sectors Innovation

Defining innovation can be challenging, despite extensive research in the field. An innovation can be understood as any idea, practice, or object that is perceived as new by an individual or another adopting entity (Rogers, 2003). The Organisation for Economic Co-operation and Development (OECD) succinctly defines innovation as the introduction of a new or improved product that becomes available to potential users, or the implementation of a new process within an organization (OECD & Eurostat, 2018). We often think of innovation as a new technology (e.g., AI) but the concept of innovation can apply to any modification of standard operating procedure.

Numerous research studies in the past have focused on measuring innovation in the private-sector organizations (e.g., Cooper & Kleinschmidt, 1987; Frambach & Schillewaert 2002). The most complete guideline for this purpose is the Oslo Manual (OECD/Eurostat, 2018), which offers a uniform framework to define and measure innovation, enabling consistent comparisons of innovation activities across different organizations. It covers both internal factors (i.e., general resources, management capabilities, human resources and skills, and technological capabilities) and external factors (i.e., location, market, public policy, and society) that influence innovation in firms. Although initially intended for the private sector, the Oslo Manual has been adapted and utilized extensively to measure innovation in the public sector as well (Arundel et al., 2019).

The public sector and the private sector innovation share numerous commonalities. Both sectors require an organizational culture that fosters innovation (e.g., Asgari et al., 2013; Dobni, 2018; Kiefer et al., 2021). According to Dobni (2008, p. 544), “a culture supporting innovation engages in behaviors that would value creativity, risk-taking, freedom, teamwork, be value seeking and solutions-oriented, communicative, instill trust and respect, and be quick on the uptake in making decisions”. General resources, including staff, funding, and time, are essential for innovation in both sectors. Success is also influenced by the management style and the level of support from upper management (Arundel et al., 2019; Damanpour & Schneider, 2006). Both sectors are driven by internal problems or motivations for improvement (Borins, 2001; Demircioglu & Audretsch, 2017). Finally, knowledge sharing and collaboration play a central role in innovation regardless of the type of organization (Cinar et al., 2019; Kiefer et al., 2021), as innovation thrives on collective sharing and learning, facilitated by interactions among participating entities.

Given these shared characteristics, some scholars have attempted to adapt existing innovation measurement approaches from the private sector to measure public sector innovation (e.g., Walker et al., 2002). Concerns have been raised by Bloch and Bugge (2013) about potentially undermining the unique characteristics of the public sector when directly transferring measurement frameworks developed for the private sector. This is because the public and private sectors have fundamentally different objectives (Bloch and Bugge, 2013; De Vries et al., 2016) and incentive structures (Potts & Kastelle, 2010). Unlike the private sector, public sector innovation typically has a non-market orientation, driven by the responsibility to citizens rather than profit (Bloch and Bugge, 2013; Shearmur, 2019). Therefore, it is crucial to carefully tailor innovation indicators specifically for the public sector.

To measure public sector innovation, several empirical studies have been conducted. The Measuring Public Innovation in the Nordic Countries (MEPIN) survey by Bloch (2011) was the first large-scale survey on public sector innovation. It collected responses from over 2,000 individuals in central and local governments across Denmark, Finland, Iceland, Norway, and Sweden, identifying drivers and barriers to innovation in the public sector. The Innobarometer survey conducted by the European Commission (2010) further contributed to the understanding of public sector innovation, collecting data from 3,272 European public sector agencies. Numerous publications based on this survey focused on topics such as measurement methods for innovation, the impact of governance forms on innovation, the role of managers, the influence of external information sources, and examples of good practices (e.g., Arundel et al., 2015, 2019; Arundel & Hollanders, 2011; Arundel & Huber, 2013; Petkovšek & Cankar, 2013). Some of these studies examine the drivers of and barriers to innovation in the public sector. We will discuss them in the next section.

One comprehensive review of public sector innovation is by De Vries et al. (2016), which examined 181 articles on the subject. This review provides valuable insights into critical factors for innovation in the public sector. In the following section, we will elaborate on these factors in greater detail.

4.2.2 Internal and External Factors for Public Sector Innovation

Literature on innovation often classifies innovation factors as internal and external (Bugge et al., 2011). Internal factors reflect the cultural and structural characteristics of an organization; whereas, external factors describe the greater environmental context, for example, nearby research universities (De Vries et al., 2016). Factors that are shared by both the public and private sectors are mostly internal ones, such as innovation culture, resources, internal problems or motivations, and knowledge sharing. In this section, we will examine internal and external factors that are particularly important for the success of public sector innovation. We summarize internal and external factors in Table 4.1 and Table 4.2, respectively and elaborate on key factors below.

The first internal factor is a culture of risk-taking within the organization, which represents a significant difference between the public and private sectors. Relative to the private sector for which risk-taking is frequently the key to firms' competitive advantage, the public sector is risk-averse, posing an important barrier to public innovation (e.g., Albury, 2005; Arundel et al., 2019; Mulgan & Albury, 2003). Public sector organizations may have less to gain and face a greater cost if they fail from innovation compared to the private sector (Bloch and Bugge, 2013). Key individuals who initiate innovations risk their reputation and government agencies bear the risk of unpredictable outcomes that may influence citizens (Shearmur, 2019). There is also the risk of a negative media image if the innovation is unsuccessful (Borins, 2001). However, Shearmur (2019) argued that an environment that encourages risk-taking is vital for innovation in the public sector.

Second, a major challenge for the public sector is measuring the concrete economic outcome of an innovation. Whereas the private sector can measure products by revenues; the public sector provides services that often cannot be measured with a single indicator (Albury, 2005; Arundel et al., 2019; Bloch and Bugge, 2013; OECD & Eurostat, 2018). Evaluating innovation outcomes often relies on subjective indicators such as increased effectiveness or enhanced citizen satisfaction (Arundel et al., 2019; Bloch and Bugge, 2013). Lacking concrete measurements of costs and benefits, there may be less incentive for the government to innovate. Therefore, it is important for the public sector to have metrics that also serve to encourage innovation.

Public sector innovation is also influenced by external factors as the public sector operates within an interconnected environment. Scholars have identified a set of environmental drivers of innovation, including competition between similar institutions or their tendency to become similar (e.g., Andersen & Jakobsen, 2018; Borins, 2001; De Vries et al., 2016), political drivers such as new laws and regulations (e.g., Andersen & Jakobsen, 2018; Arundel et al., 2019; Borins, 2001; De Vries et al., 2016; Walker, 2006), and public pressure such as citizen demand or media attention (e.g., Borins, 2001; De Vries et al., 2016; Walker, 2006).

Regulation is often mentioned as an important external factor that may drive or prevent innovation. Public sectors are bound by regulations and have a duty of care to citizens so the rigidity of regulation may be considered a barrier to innovation (Bugge et al., 2013; Johns et al., 2006). However, De Vries et al. (2016) pointed out that, in certain cases, regulation may facilitate innovation by providing guidance to and establishing boundaries for innovators.

It is important to consider the place in which innovation is located. As suggested by De Vries et al., (2016), "innovations are locally embedded and the result of co-evolution between different demands and pressures that stem from different but closely related (public, political and media) environments (p. 156)" Asheim & Gertler (2009) add the importance of spatial closeness in innovation. The authors argue that, first, new knowledge production and sharing are core for innovation, where knowledge is specific to the local contexts and difficult to exchange over long physical distances. Actors in the same geographic region likely share conventions and norms developed in the shared environment and they have personal knowledge of each other through past collaboration and informal interactions. Innovation is driven by collective learning, which is spatially dependent as it requires a shared understanding of "local codes". Second, innovations are geographically clustered since skilled workers are attracted to places that offer the best employment environment and the highest quality of life. Therefore, we look to exogenous innovation environment as an indicator of innovation.

Table 4.1. Internal Factors Influencing Public Sector Innovation

Source	Factors
Albury (2005)	● short-term budgets and planning horizons ● insufficient skills in active risk or change management ● few rewards or incentives to innovate or adopt innovations ● technologies available but accompanied by constraining cultural or organizational arrangements ● reluctance to close down failing programmes or organizations ● culture of risk aversion ● delivery pressures and administrative burdens

Arundel, Bloch, & Ferguson (2019)	• entrepreneurial mindset of managers • motivation for senior and middle managers to innovate) • organizational support for innovation • degree of risk aversion
Bugge, Mortensen, & Bloch (2011); Bloch & Bugge (2013)	• internal management • internal staff • lack of incentives for staff • lack of funding • inadequate time • resistant users
Borins (2001)	• internal problems (e.g., inability to reach target population, inability to meet demand for program, resource constraints, or inability to coordinate policies) • support coming from the top • rewards and awards for innovation • resources
Cinar, Trott, & Simms (2019)	• ineffective administration of process activities • resistance or lack of support from specific actor(s) • lack of available resources • rigid organizational structure/culture • lack of skills/knowledge/expertise • a lack of shared understanding • a lack of effective network governance • inadequate communication and knowledge sharing • lack of involvement by essential organizations • inappropriate accountability between public sector organizations
Demircioglu & Audretsch (2017)	• experimentation • responding to low performers • the existence of feedback loops • motivation to make improvements
De Vries, Bekkers, & Tummers (2016)	• slack resources (time, money, information and communications technologies equipment) • leadership styles • degree of risk aversion/room for learning • incentives/rewards • conflicts • organizational structures

Mulgan & Albury (2003)	● culture of risk aversion ● reluctance to close down failing programmes or organizations ● over-reliance on high performers as sources of innovation ● technologies available but constraining cultural or organizational arrangements ● no rewards or incentives to innovate or adopt innovations ● short-term budgets and planning horizons ● delivery pressures and administrative burdens
Walker (2014)	● organizational size ● administrative capacity ● organizational learning

Table 4.2. External Factors Influencing Public Sector Innovation

Source	Factors
Andersen & Jakobsen (2018)	● political pressure ● conformity pressure
Arundel, Bloch, & Ferguson (2019)	● form of governance ● political driving forces (i.e., budget changes, new laws or regulations and new policy priorities
Asheim & Gertler (2009)	● location ● spatial clossness of innovation ● geographic clusters of innovation ● new knowledge production and sharing
Borins (2001)	● initiatives coming from the political system ● new opportunities created either by technology or other factors ● a crisis, defined as a current or anticipated publicly visible failure or problem
Bugge, Mortensen, & Bloch (2011)	● budget ● consideration to citizens ● lack of political incentives ● lack of flexibility in law ● rules hinder collaboration ● lack of innovative suppliers

De Vries, Bekkers, & Tummers (2016)	● environmental pressures (media attention, political demands, public demands) ● participation in networks and inter-organizational relationships ● regulatory aspects ● compatible agencies/organizations/states adopting the same innovation ● competition with other organizations
Cinar, Trott, & Simms (2019)	● laws and regulations ● lack of standardisation ● geography
Walker (2006)	● public pressure from external sources (e.g. media) ● public pressure from users and citizen demand ● changes in the social, political and economic context

4.3 AI as an Example of Public Sector Innovation

According to the definition provided by De Vries et al. (2016), AI best fits into the category of technological process innovation, which is defined as "the creation or use of new technologies introduced in an organization to render services to users and citizens" (p 153). We see a similar definition in the smart city literature, where AI is often labelled as an integral part of urban technology innovation (e.g., Allam and Dhunny, 2019; Nam & Pardo, 2011; Yigitcanlar et al., 2021). AI is an increasingly essential component of smart cities, enabling efficient service delivery and routine management in local governments (Yigitcanlar et al., 2021). The concept of a smart city itself can be considered an urban innovation when it is envisioned as "a city's effort to make itself smart" (Nam & Pardo, 2011, p. 185). The importance of the smart city literature in the discussion of AI lies in its connection to a specific jurisdictional level, namely cities. The literature on public sector AI adoption often presents factors without differentiating among different levels of government; whereas, city government innovation poses unique challenges that are often overlooked. In the following sections, we will examine prevalent factors in AI adoption literature in the public sector and discuss how innovation plays out in the context of city government.

4.3.1 Public Sector AI Adoption Factors

Our ultimate goal is to create a set of factors specific to local governments' openness and readiness to adopt AI, that is their ability to innovate regarding AI. As of this writing, the only study that explicitly examined the factors for AI innovation in the public sector is by van Noordt & Misuraca (2022). The authors pointed out that, in addition to previously identified factors in the public sector innovation literature, there are factors unique to AI innovation, particularly related to data governance. We look to the literature on public sector AI adoption, which primarily focuses on implementation opportunities and challenges, to identify factors important for AI innovation.

As pointed out above, public sector innovation is driven by a set of internal motivations or needs. Abundant research in the AI adoption literature has highlighted the potential for AI to address needs such as efficiency enhancement in daily operations (de Sousa et al., 2019; Kuziemski & Misuraca, 2020; Valle-Cruz et al., 2019; Zuiderwijk et al., 2021), data and information processing capability (Rjab & Mellouli, 2019; Wirtz & Müller, 2019), and policy-making support (Alexopoulos et al., 2019; Kuziemski & Misuraca, 2020; Rjab & Mellouli, 2019; Valle-Cruz et al., 2019).

Despite motivations to adopt AI, the technology is resource-intensive (Wirtz et al., 2019). This speaks to one of the internal innovation factors, adequate internal capacity. In large part, this reflects the need for resources mentioned earlier, such as funding (Yigitcanlar et al., 2021), infrastructure (Toll et al., 2019), and staff (Campion et al., 2020; Vogl, 2021). Some resource requirements are specific to AI. For example, one needs to have quality data available for training AI models, which are generally data-intensive (Jöhnk et al., 2021). Implementing AI at scale may require cloud infrastructure and a software stack (Bright et al., 2019; Desouza, 2018), necessitating greater organizational capacity and expertise.

The public sector must be willing to accept the risks associated with AI innovation. Scherer (2015) argues that AI is high-risk due to its unique characteristics, including unpredictability, opacity, automation that can seek to eliminate the human from the loop, and difficulty in control. The opacity of AI makes it challenging to predict outcomes and may result in behaviour that is beyond human control (Burrell, 2016), creating an accountability gap (e.g., de Fine Licht & de

Fine Licht, 2020; Burrell, 2016; Mittelstadt et al., 2016). This poses a significant challenge for the public sector concerning the governance of AI, for example determining legal responsibility for the consequences of AI (Wirtz et al., 2019). Another substantial risk for the public sector is the issue of biases (de Sousa et al., 2019; Mikhaylov et al., 2018). Many scholars have highlighted the problem of bias in AI algorithms and the resulting social discrimination (e.g., Diakopoulos, 2013; Mittelstadt et al., 2016; Zarsky, 2016). Fostering a culture of risk-taking is vital for AI-related innovations but that suggests a conflict when governments also need to frame AI innovation in an ethical regime.

Regulating AI is considerably more complex due to the high risks associated with AI and its potential impact on citizens. Boyd & Wilson (2017) argue that, for the public sector and citizens to benefit from AI, policies and regulations must be established based on societal values. Wirtz et al. (2019) discuss three key challenges to creating a regulatory and governance framework for public sector AI: 1) Accommodating AI's black box properties and incomprehensible nature; 2) Delineating responsibility and accountability as it is difficult to determine who is in charge and responsible for decisions made by AI; and 3) Addressing individual privacy, for example protection from security threats and handling concerns over surveillance. Regulation presents an intriguing paradox, as regulations can be seen as both a barrier to innovation and a necessity to ensure the ethical and safe adoption of AI. Finding the right balance between regulation and fostering innovation is a critical challenge for entities that wish to govern AI.

An alternate form of regulating AI is the "soft law" approach (Marchant, 2019). Whereas "hard law" refers to a set of government rules and regulations that are established through standardized procedures; soft law can be defined as a collection of non-enforceable norms or principles (Marchant, 2019). Many scholars have argued that the traditional regulatory approach is no longer suitable for AI (Hagemann et al., 2018; Marchant, 2019). Traditional regulatory systems are unable to match the rapid pace of emerging technologies (Hagemann et al., 2018), like AI (Marchant, 2019). Rigid and inflexible traditional regulations may hinder innovation (Hagemann et al., 2018). Federal governments may be hesitant to introduce regulations that could prevent innovation in AI for global competitiveness (Marchant, 2019). Additionally, the application of AI may involve multiple government agencies, levels of government, and stakeholders, making it challenging to develop a synchronized regulatory approach (Hagemann et al., 2018; Marchant, 2019), and the risks imposed by AI may influence far beyond a jurisdictional boundary (Marchant, 2019). Last, regulators and policymakers often lack knowledge of rapidly developing technologies. The "soft law" approach may be better suited for AI. The existence of not only hard law, but also "soft law" should be considered a factor for innovation.

Successful public sector AI adoption is influenced by various external 'environmental' drivers, including competitive pressure, public demands, and political demands. Citizen demands for AI services take the form of requests for faster service delivery (Toll et al., 2019), improved service quality (Kuziemski & Misuraca, 2020), and better communication with the government (Mehr et al., 2017). Additionally, political leaders, under constant global competitive pressure, are likely to adopt policies that support advanced technologies, such as AI (Kuziemski & Misuraca, 2020). These external drivers are essential for public sector organizations to navigate AI innovation.

AI 'process fit' has not been extensively discussed in the innovation literature, although it is significant in the implementation of AI (Jöhnk et al., 2021). AI process fit refers to the alignment between an organization's AI strategy and its practical application. Although the authors did not provide further details, it appears to involve the strategic alignment of promises, standard operating procedures, divisions of labour, and resources for AI. The level of process fit can impact the successful operationalization of AI. In the public sector, AI is still a relatively new innovation (Wirtz, 2019). Moving AI from pilot projects to full-scale implementation can be challenging due to difficulties in integrating AI with existing organizational structures and ensuring satisfactory performance in real-world scenarios, as observed by Gonfalonieri (2019). Whereas, discussions of process fit have mainly focused on private firms; it is plausible that this factor holds importance for the public sector as well.

4.3.2 Local Government AI Adoption that Complicates Innovation Factors

Local governments face unique opportunities and challenges in adopting AI compared to other levels of government, which have implications for the innovation factors we choose. Localities directly interact with citizens and can use AI to engage publics in decision-making. However, they face limited resources and greater flexibility in problem-solving. Close collaboration with local partners and regular citizen interactions will influence their ability to adopt and innovate with AI. In this section, we discuss these characteristics and examine how these may influence local government innovation.

As mentioned, local governments have a unique advantage in their direct interaction with citizens, making them more accessible compared to state/provincial or federal governments. With the utilization of AI tools, cities are increasingly leveraging technology to engage citizens in decision-making processes, provide access to information and services, and enhance public participation (Yigitcanlar et al., 2021). This direct engagement also means that local governments bear the direct impact of AI technologies on their communities. Recognizing the significance of responsible AI innovation, Yigitcanlar et al. (2021) emphasize the importance of engaging citizens in AI planning processes at the local government level. By involving citizens in discussions and decision-making related to AI, local governments can ensure that the technology is deployed in a manner that aligns with the needs, values, and concerns of their communities and presumably ensure greater public trust in the technology. Trustworthy AI has emerged as an important concept in AI ethics (Kaur et al., 2022) so capturing this engagement as a factor is important.

Compared to state or federal governments, local governments often face resource constraints, both in terms of financial and human resources, which can limit their capacity for innovation (Shearmur, 2019; Yigitcanlar et al., 2022; Vogl, 2021). Conversely, due to their decentralized structure, local governments may be able to respond more quickly to problems and make more daring decisions relative to larger organizations (Gabris, 1999). This challenges the notion that the public sector is inherently risk-averse (Arundel et al., 2019; Mulgan & Albury, 2003), as local governments may exhibit a greater willingness to risk adopting AI. This risk-taking is paired with concerns about local governments becoming live urban laboratories for testing new products, services, and technologies, where the risks and costs of innovation are disproportionately borne by citizens (Zygiaris, 2013; Shearmur, 2016). These dynamics reflect the complex interplay between resource limitations, risk-taking tendencies, and the potential ethical implications of AI innovation at the local government level.

With the lack of local resources and expertise, Campion et al. (2022) suggested that there will be increased reliance on collaborative approaches to AI in cities, particularly collaboration among local partners. For instance, they found that “the collaboration also strengthened the university’s relationship with local communities through its work to increase volunteering opportunities for students" (p. 466). Conversely, a lack of effective cooperation would prevent local governments from adopting AI, as pointed out by city managers (Yigitcanlar et al., 2022). Mikhaylov et al. (2018) summarized the conditions for successful collaboration in AI, including facilitative leadership, shared objectives, knowledge gathering and sharing, communication, socializing, expertise, and sense-making. The need for local partners such as industry and academia strengthens the importance of spatial closeness for effective innovation.

Despite the importance of external factors, studies have highlighted the significance of internal factors over external factors for local governments. Walker (2006) conducted an empirical test of innovation factors and found that different types of innovation are influenced by distinct determinants. Technological innovations were associated with internal determinants (e.g., service needs) and diffusion determinants (e.g., public pressure from external sources or citizens). Organizational innovations were influenced by both internal and environmental determinants (e.g., service needs, changes in social, political, and economic contexts). In a more recent review, Walker (2014) emphasized the importance of internal factors, such as organizational size and administrative capacity, over external factors like societal need, wealth, and urbanization in local government service innovation. These findings align with the results of a large-scale questionnaire conducted by Borins (2001), which concluded that internal challenges (e.g., resource constraints and the need to meet internal demands) are the primary drivers of public sector innovation.

Given the distinctive attributes of local governments and the complexity of AI, there is a need to customize the factors identified in innovation literature to assess AI innovation within this context. By integrating findings from innovation literature and AI adoption literature, we summarize internal and external factors that play a crucial role in evaluating AI innovation in local governments (Table 4.3).To identify these factors in our case study, we listed potential wording related to each factor.

Table 4.3. Internal and External Factors that Derive From the AI Adoption Literature and the Public Sector Innovation Literature

Factor	Innovation Literature	AI Adoption Literature	Description
Internal Factors			
AI-specific Resources (funding, infrastructure and expertise)	Arundel et al., 2019; Asgari et al., 2013; De Vries et al., 2016; Dobni, 2008;	Jöhnk et al., 2021; Kiefer et al., 2021; Vogl, 2021	Ensuring sufficient time to develop or procure AI, money, funding, data and computing infrastructures; hiring a data scientist(s); accessing AI-related infrastructures
Risk-Taking Culture	Arundel et al., 2019; Dobni, 2008;	Scherer, 2015; Shearmur, 2019; Zygiaris, 2013	Embracing risk, taking a chance, trying something new; coping with failure; having a legacy/history of risk taking
Internal need	Demircioglu & Audretsch, 2017	Ben Rjab & Mellouli, 2019; Bullock, 2019; Kuziemski & Misuraca, 2020; de Sousa et al., 2019; Valle-Cruz et al., 2019; Wirtz & Müller, 2019; Zuiderwijk et al., 2021	Improving efficiency, automation, responses to internal problems; seeing AI as solution to reducing labour costs, better handling of data, insights and decision-making
AI Process Fit	N/A	Jöhnk et al., 2021; Vogl, 2021	Aligning AI strategies and action; establishing organizational structure that allows AI innovation and adoption; aligning policies to implement AI and organizational ability to move project from AI proof of concept to implementation.

Collaboration and Knowledge Sharing	Cinar et al., 2019; Kiefer et al., 2021	Campion et al., 2020; Mikhaylov et al., 2018	Referencing AI-related education, collaborating with other units/departments, Engaging in AI training, workshops
Manager/Councils Support and Involvement	Arundel et al., 2019; Bugge et al., 2011	Campion et al., 2020; Yigitcanlar et al., 2022	Supporting/involving/sponsoring AI projects coming from managers/councils
Reward Mechanisms	Borins, 2001; Mulgan & Albury, 2003	N/A	Rewarding new ideas/entrepreneurs within organization
External factors			
Exogenous Innovation Environment	Asheim & Gertler, 2009; De Vries et al., 2016	N/A	Referencing external organizations researching, developing, adopting AI (e.g., local universities, startups); finding other organizations doing AI innovation within or geographically close to city
Environmental Drivers (e.g., competition, media attention, political demands, public demands)	Andersen & Jakobsen, 2018, Borins, 2001; De Vries et al., 2016, Walker, 2006, 2014	Kuziemski & Misuraca, 2020; Mehr et al., 2017; Toll et al., 2019	Appreciating a need to adopt AI (e.g., service to citizens;communication with citizens, societal benefit); improving competition with other organizations/cities
Regulations and AI Ethics	De Vries et al., 2016; Jöhnk et al., 2021;	Boyd & Wilson, 2017; Marchant, 2019; Wirtz et al., 2019	Enacting regulations on procurement or adoption of AI; adopting regulations on privacy, similar technology, open data; adopting a ‘soft law’ approach in regulating AI

4.4 Methodology

This section outlines the methods we used to examine the factors that may influence AI innovation in a particular city government, Edmonton, Alberta, Canada. We first describe why we selected the City of Edmonton as a case study. Next, we look for instances of these factors in several sources of data, for better coverage for both internal and external factors. Our data sources include web-based content related to Edmonton's AI innovation (i.e., newspaper articles, podcasts, websites, government strategic plans and reports), Edmonton's presentations on their AI projects, and interviews with Edmonton's employees who worked with AI projects. We assume that external factors will be identified in the web-based content; whereas internal ones will be observed in the presentation and interview data. Recognizing that every source of data has its biases, the various sources of data help reduce biases. For example, a newspaper might be biased in favour of innovation or critical of government action, while the government's publication may be biased in promoting the city's achievements.

4.4.1 Selecting Edmonton

Before selecting the City of Edmonton, we conducted an analysis of 18 cities in Canada. We looked for indicators of a 'good' AI city, including 1) The extent to which AI systems have been adopted within the city governments; 2) The presence of an innovation ecosystem within the city; and 3) A city strategy that supports innovation and adoption of AI. We selected the City of Edmonton because the City of Edmonton has the most AI deployment among all Canadian cities, with an innovative ecosystem including leading AI institutions, innovation community and start-ups clearly present. Also, we looked for city plans indicating the intentions for promoting technological innovations. It is worth noting that Edmonton has not always been viewed as an innovative city. Jones (2017) highlighted a public perception of Edmonton that was less favorable in terms of its aesthetic and cultural appeal when compared to other cities. Their focus group expressed a city that was characterized as "ugly, cheap, homogeneous, blue-collar, industrial, cold, non-collaborative, isolated and shortsighted" (ibid., p. 56). We are interested in unravelling the contradictory image of Edmonton being an innovative city and understanding the key factors that establish Edmonton as a leader in AI.

What constitutes the "city" of Edmonton may involve multiple units of analysis. There is the city as a spatial extent, the local government, individual departments within the local government, individual AI applications, and developer teams and users. We do some homogenizing across these different internal levels and, for example, police departments (one of the applications below) have wildly different organizational structures from other departmental units in a local government. We follow other studies (e.g., Campion et al., 2022), which treat city governments as a single unit of study.

Identifying internal and external factors demands precision in what we call the City of Edmonton, that is the employees and the governance of the city. From now on, we will call it the city government. According to the innovation literature, innovative city governments exist within a regional ecosystem, which may include surrounding suburbs. For this paper, we restrict this region by looking at the jurisdictional boundary of the City of Edmonton and nearby suburbs. We will call that ecosystem the Edmonton region.

4.4.2 Data Collection and Analysis

We conducted a content analysis of several data sources, including interviews, presentations and news articles, AICOP presentations and gray literature. Descriptions of all the sources are shown in Appendix A. In the next subsections, we describe the data and method for searching the gray literature and news articles related to Edmonton's innovation and AI.

4.4.2.1 Interviews

In total, the first author conducted four interviews with employees of their AI projects, including two data scientist, one manager, and one planner. Each interview lasted 45 minutes and was conducted through the platform preferred by the participants (e.g., Zoom, Skype). I asked about their background, the AI project they were involved in and their perception of challenges in Al.

4.4.2.2 AI Community of Practice Conference (AICOP) Presentations

Additional to the interviews, we analyzed the AI project presentations from Edmonton local government employees from the AICOP to understand the context and details of AI projects. The authors regularly attend these meetings; the second author is the co-host. AICOP is a monthly meeting that gathers local governments' Information Technology (IT) Managers, Directors, Chief

Technology Officers, data scientists, and academics, who share projects, and best practices, and collaborate around AI deployment in local government. Edmonton to date has done the most presentations of any city. Their presentations include the Safety Code Inspection Project (Gready, 2020), Text Depo Application (City of Edmonton, 2021), Wildlife Monitoring Project (Rizwan & Shier, 2020), and the Community Safety Deployment Model (Data Science and Research, 2021). (PowerPoint slides and/or audio recordings are available on request from second author.)

4.4.2.3 News Article and Gray Literature

To identify the news article and gray literature related to Edmonton's innovation in AI, we adapted our search method from Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), a method predominantly used for conducting systematic reviews (Page et al., 2021). The first phase was defining the search terms that may be able to identify the records that are relevant to Edmonton's innovation and AI. Then the records were screened and evaluated to determine whether these articles were eligible for our purpose. The final output is the records that would be included in the study (Appendix B). Figure 4.1 shows our flow diagram suggested by PRISMA to outline the process.

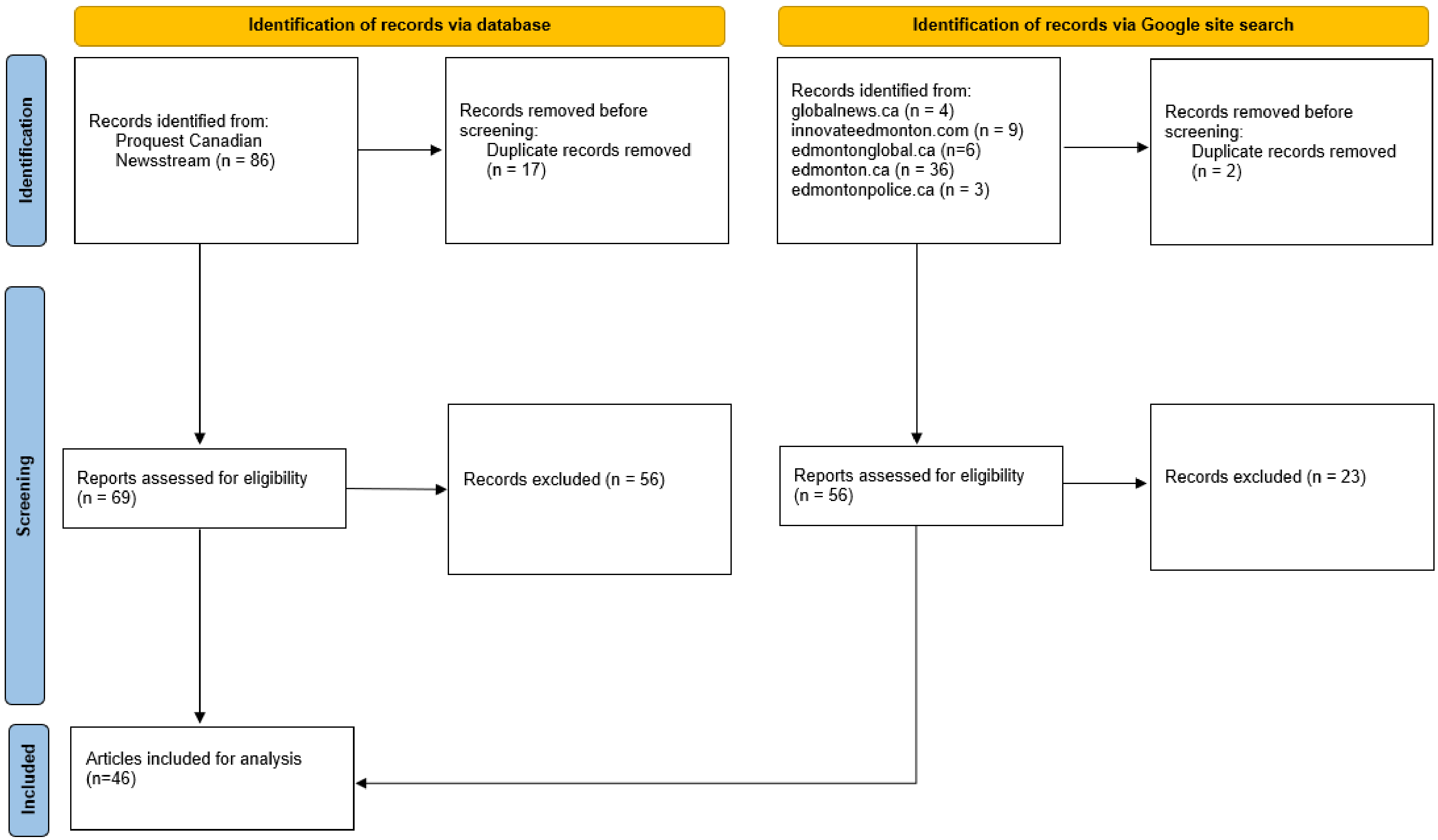

Figure 4.1. Flow Diagram of Document Search Process

We were interested in specific AI and innovation-related documents from the City of Edmonton. The key search terms were Artificial Intelligence, Edmonton, and Innovation. AI may be referred to in various ways. For example, in the cities, AI might be referred to as the actual algorithms or methods such as machine learning or deep learning, or it might be referenced in relation to the actual application such as predictive policing and smart traffic. This challenge was recognized by Trielli et al., (2011) when attempting to search the use of algorithms in government. We followed the authors' recommendation by brainstorming a list of AI-related terms we used for searching. The terms we used are presented in Table 4.4.

Table 4.4. AI-Related Terms (Grayed terms are found to produce no record in the search)

Terms Related to or Types of Algorithms	Terms Related to AI Application in Cities
Machine learning Deep learning Supervised learning Unsupervised learning Reinforcement learning Natural language processing Sentiment Analysis Text Classification Computer vision Object recognition Object detection Object classification Image recognition Pattern recognition Predictive Modelling Advanced modelling Predictive analytics Smart analytics Automated Automation	Predictive policing Smart policing Crime prediction Facial recognition Smart light Smart traffic Smart bin Chatbot

We sought two types of documents: news articles (e.g, newspaper, blog, podcasts) and gray literature published by the Edmonton city government. To find news articles, we used Proquest Canadian Newasstrem, a database that offers access to over 400 news sources within Canada. We started with an individual search to determine AI-related terms useful for our search. Throughout this process, we eliminated terms that did not return relevant results. We looked for patterns of irrelevant search results. For instance, we chose not to include a number of articles related to AI innovation in agriculture. Our final search of the news database was constructed as follows, where TIABSU searches for the exact phrase in the Title, Abstract, and Subject data:

[AI-related terms] AND TIABSU(Edmonton) AND Innovati* NOT agricultur*

To look for gray literature published by Edmonton governments, we used a directed Google site search. We found that the City of Edmonton uses edmonton.ca as their website and domain. The search was conducted as followed:

[AI related terms] AND Edmonton AND Innovati* NOT agricultur* site: edmonton.ca

We used LinkClump, a Chrome plugin that allows us to copy all the links and titles on a web page. We then exported all of the records we identified to a spreadsheet. We removed all the duplicate results and ineligible records. We define our eligibility criteria as follow:

1. Be available in English
2. Published within the past three years
3. Mention Edmonton in the title, abstract or subject data.
4. Mention Innovation anywhere.
5. Mention AI or any AI-related terms
6. Content is relevant to Edmonton city or governments

Table 4.5 shows examples of included and excluded records.

Table 4.5. Examples of Eligible and Ineligible Records

Title	Decision	Reason
Edmonton, AB builds AI framework to deliver smarter projects	Included	Explicitly mention AI projects in Edmonton and relevant to innovation
Innovate Edmonton Funds, Launches and Lands Accelerators, Benefiting Edmonton Tech Companies	Included	Explicitly mentions Edmonton and Innovation and may be relevant to AI

Edmonton explores 5G network potential as experts warn to be careful where it comes from	Excluded	Irrelevant to AI
Predictmedix announces technology deployment at Long Term Care residence in Edmonton, in partnership with Optima Living	Excluded	Too specific to a private company deployment. Not related to the City of Edmonton or the Edmonton government.
Cities leverage new technology to find & fill potholes	Excluded	Too broad. Not talking about Edmonton specifically.

4.4.2.4 Data Analysis

We list all the data (i.e., interviews, AICOP presentations, news articles and gray literature) in a spreadsheet for analysis. We searched through each of the samples and looked for the occurrence of the phrases listed in Table 4.3, which describes the factors. We counted the number of records that contain at minimum one phrase and collected representative quotes for each factor.

4.5 Results and Discussion

We observed the presence of various internal factors within the local government of the City of Edmonton, as outlined in Table 4.1. Overall, there were more occurrences of internal factors compared to external factors, aligning with the findings in innovation literature that emphasize the significance of internal factors for technological innovation in local government (Borins, 2001; Walker, 2006). The two most frequently mentioned internal factors were AI-specific resources and internal needs, followed by a risk-taking culture. Conversely, AI knowledge sharing, upper management support, and AI process fit were mentioned relatively infrequently. Among the external factors, an innovative environment was the most commonly mentioned, followed by environmental drivers. AI regulation and ethics were mentioned the least. Notably, we did not find instances of a reward mechanism. Instead, city government employees appeared to be driven by intrinsic motivation, deriving satisfaction from witnessing the impact of AI projects. In the subsequent sections, we discuss each factor that emerged in the records in greater detail.

Table 4.6. Presence of Internal and External Factors

Factor	Number of Records
Internal Factors	
AI-specific Resources (expertise, time, funding)	32
Internal Need	32
Error Culture and Risk-Taking	10
Collaboration and Knowledge Sharing	2
Upper Management Support	3
AI Process Fit	3
Reward Mechanisms	0
External Factors	
Innovative Environment	24
Environmental Drivers (e.g., media attention, political demands, public demands, competitive pressure)	16
AI Regulations (hard law) AI Ethics (soft law)	7

4.5.1 Internal Factors

4.5.1.1 AI-Specific Resources

Employees of the City of Edmonton recognized the importance of dedicated resources to ensure the success of AI projects. Initially, data science-related staff were dispersed across different departments, leading to an informal internal collaboration (Respondent 2). It became evident that a more structured internal approach was needed to disseminate information on AI usage and connect individuals with internal AI experts (Respondent 4). In response, the city reorganized and established a "data science and research" team. This team, led by a manager and comprising three data scientists, a data storyteller, a data architect, and a strategic foresight analyst, now provides centralized service and support for AI projects across various city departments. Approximately 95 percent of the city's AI projects are developed by this team (Respondent 2), with around 20 projects deployed annually (Respondent 1).

The team operates in a consulting capacity, interacting with clients and formalizing requests from other city units (Figure 4.2). To effectively manage these requests, they have implemented an "intake assessment form" and referred to the requesting entities as "business areas" (see Appendix C). The intake assessment form serves as a tool to evaluate the problem, discuss potential approaches, determine resource requirements, ensure commitment from the business area, and obtain support and sponsorship from managers. Respondent 1 emphasized the importance of the business area prioritizing the project and providing the necessary time and resources to support its implementation.

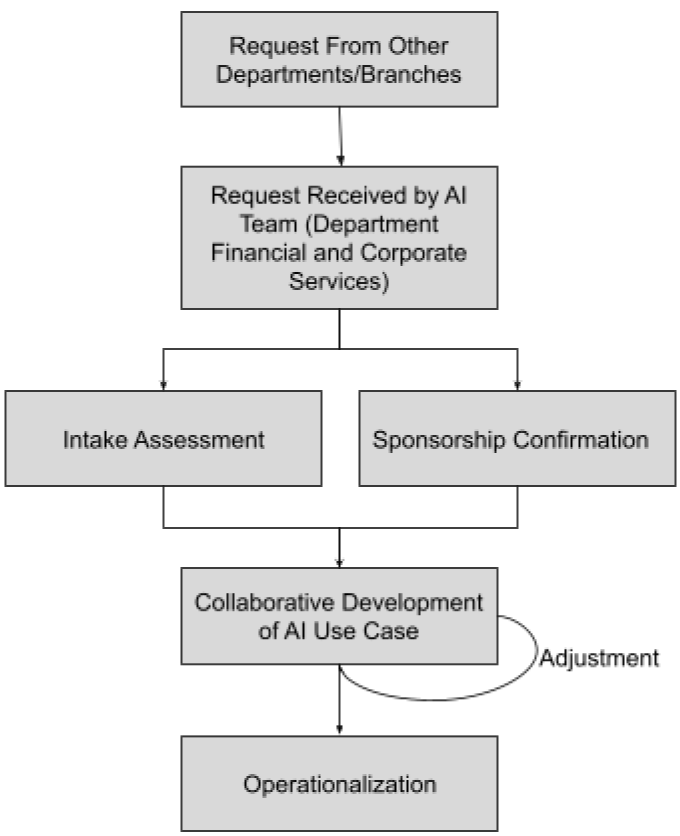

Figure 4.2. Edmonton Data Science Team AI Development Model

The team actively works on developing a reusable software stack consisting of reliable tools like Shiny and Docker that, according to them, facilitates the swift deployment of applications.

Additionally, they have created user-friendly dashboards for users they hope will be able to conveniently access and view these applications (Data Science and Research, 2021).

The City of Edmonton benefits from the presence of pre-existing internal data, as highlighted by Respondent 2, *"*There is a whole spectrum of things that organizations need to be ready. One is having good data management and data governance in place such that there is data available to use for projects*."*

The importance of pre-existing usable data is shown in the Safety Code Inspection Efficiency project. Also according to Respondent 2, Edmonton successfully developed an AI system by leveraging ten years' worth of safety inspection data to identify low-risk inspections. Similarly, in the Community Safety Deployment Model project, data from multiple partner organizations across the city were utilized to deploy services based on various types of requests (Respondent 3).

Edmonton's AI initiatives also benefit from the presence of an existing open data portal. The city has recognized the importance of open data in its Edmonton Economic Action Plan, highlighting its significance for current AI projects (City of Edmonton, 2021b, p. 20). According to Respondent 2, "We were lucky enough to have a direction of open data already at the city, so this function complements the AI projects very well."

Overall, the findings suggest that Edmonton's local government possesses sufficient AI personnel, funding, and data, which are essential factors for AI innovation. This aligns with the broader innovation literature that emphasizes the importance of resources for innovation (Arundel et al., 2019; Asgari et al., 2013; De Vries et al., 2016; Dobni, 2008). It is also consistent with the AI adoption literature, which identifies resource limitations as barriers to AI adoption (Jöhnk et al., 2021; Kiefer et al., 2021; Vogl, 2021).

4.5.1.2 Internal Needs

Innovation in Edmonton appears driven by internal needs, including the need for efficiency enhancement, prediction, decision-making, and cost and labour reduction. Internal needs are discussed in two parts, from potential or current AI projects and expressed by the potential AI users within the department.

First, efficiency enhancement is mentioned in nine instances including an interview of one respondent, the intake assessment form, two presentations and five external records (Edmonton Police Service, n.d.-a; City of Edmonton, n.d.-f; Johnston, S., 2018; Pica-Alfano, n.d.-a, n.d.-b). AI applications within the city, such as facial recognition software used by the Edmonton Police Service and AI-assisted prediction of building inspection risks by the Edmonton Codes and Inspections project, aim to improve operational efficiency. Other examples include the incorporation of AI in urban planning and economy for faster wildlife image analysis and the adoption of smart traffic signals for efficient traffic management. On the most mentioned case, Edmonton Safety Code Inspection Project, Pica-Alfano (n.d.-b) commented, "The use of this AI model and the new inspection process in Edmonton has resulted in a 37% decrease in eligible inspections – a staggering efficiency pickup – and an economic boost from faster development with fewer roadblocks." Another example is the text depot project, for which the data science team saw an internal need to search city data more efficiently. The emphasis on efficiency aligns with the literature, which highlights efficiency enhancement as a common driver for AI adoption (de Sousa et al., 2019; Kuziemski & Misuraca, 2020; Valle-Cruz et al., 2019; Zuiderwijk et al., 2021).

Second, the need to reduce costs is found in four records including one interview and three external documents (City of Edmonton, n.d.-e, n.d.-f; City of Edmonton, 2020). According to the Edmonton Business Technology Strategy (City of Edmonton, 2020), AI and IoT technologies are considered a "cost-effective" way to improve public services that require extensive human labour, allowing "staff to be refocused from repetitive tasks to activities providing increased value to citizens." This should not be construed that employees support the replacement of workers by AI. As emphasized by Respondent 1, "I think AI can reduce labour costs. My hope is that labour can move to a higher value. Our help allows them to offer better value to citizens because they are less constrained by these processes and doing unnecessary tasks." This finding is consistent with research that suggests AI can free workers from routine municipal tasks (Vogl et al., 2020).

Third, the city believes that data and AI enables Edmonton to make evidence-based, smarter or quality decision-making, as mentioned in ten records, including two presentations and eight external documents (City of Edmonton, n.d.-e, n.d.-f, n.d.-g; 2019a, 2020; 2022; Stolte, 2019;

Edmonton City Council, 2022; Edmonton Police Service, 2022, n.d.-a; Pica-Alfano, L. n.d.-a, n.d.-b). The need for "smarter" decision-making that drives AI innovation is indicated in various applications within the city. An example is the Edmonton Police Department, which procured facial recognition software to assist identification of crime to enhance community safety and preserve time and resources. It is also mentioned in its 2023-2026 Strategic Plan that Edmonton Police Service will improve predictive policing with the use of data, with the goal of "better predict policing needs and effectively re-direct resources to where they are most needed." (Edmonton Police Service, n.d.-b, p. 10). Additionally, Edmonton waste service has proposed to leverage smart technology to make decisions on routing design (City of Edmonton, n.d.-g), with 200 sensors installed on 50 collection bins to determine the types of waste in the bin (City of Edmonton, 2022). The is agreeing on the decision-making aspect mentioned in the literature (e.g., Alexopoulos et al., 2019; Ben Rjab & Mellouli, 2019).

Internal needs are also reflected from the (internal) client's perspective. The intake assessment form used by the city asks clients to evaluate the value brought by AI projects, including financial gains, time savings, risk reduction, and aesthetics ("looks good"). The emphasis on aesthetics is seen in the visualization of projects, such as user interfaces, dashboards, and maps (Figure 4.3 and Figure 4.4). While efficiency, cost savings, and decision-making have been well-established drivers in the literature (Ben Rjab & Mellouli, 2019; de Sousa et al., 2019; Valle-Cruz et al., 2019), the importance of a user-friendly interface for AI tools and user acceptance is a unique aspect that deserves attention.

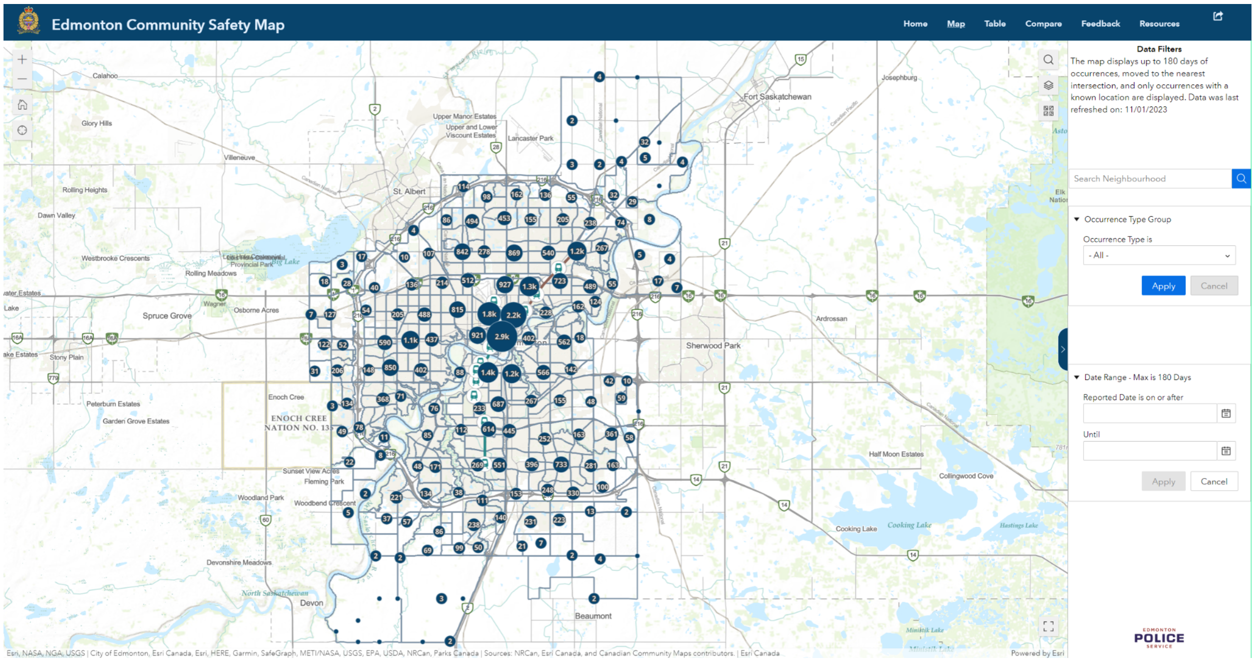

Figure 4.3. Edmonton Community Safety Map, created as a part of the Community Safety Deployment Project.
(https://experience.arcgis.com/experience/8e2c6c41933e48a79faa90048d9a459d/)

4.5.1.3 Collaboration and Knowledge Sharing

Collaboration and knowledge sharing is considered critical for innovation (Cinar et al., 2019; Kiefer et al., 2021). In the case of Edmonton, the city recognizes the significance of internal knowledge sharing and collaboration, through the establishment of an "analytics special interest group" and regular meetings hosted by the Data Science and Research Team.

The "analytics special interest group" serves as a platform for individuals interested in data and analytics projects within the city to exchange knowledge. These bi-monthly meetings not only help staff gain awareness and understanding of AI but also facilitate the promotion of the Data Science and Research Team's work to other departments. By actively engaging employees and promoting AI awareness, the city hopes to further an environment conducive to collaboration and knowledge sharing.

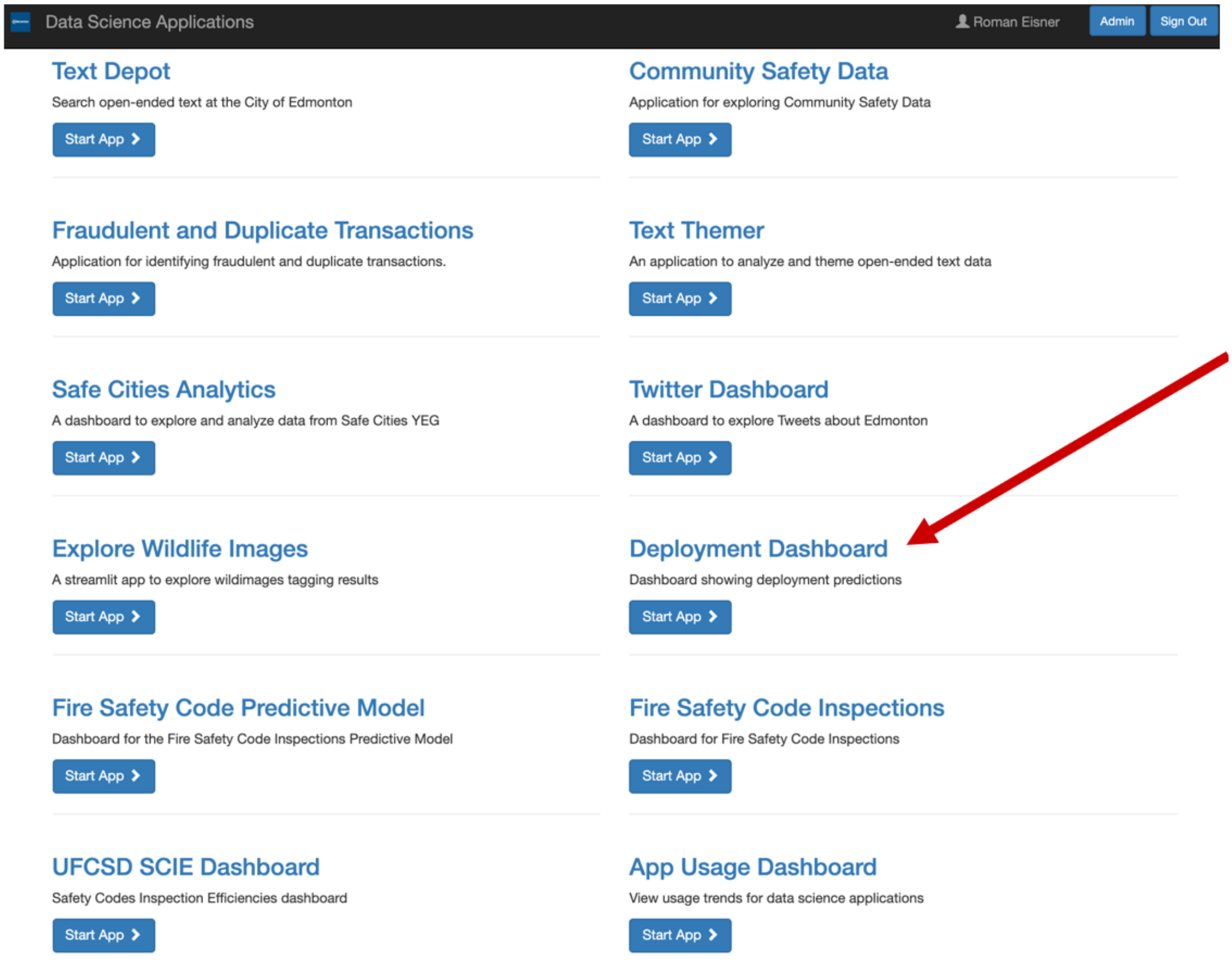

Figure 4.4. Edmonton Data Science Project Application Portal

The Data Science and Research Team also conducts AI knowledge workshops specifically tailored for staff from other city departments with which they are collaborating. Given that many departments in the city have limited experience with AI and may have concerns about job displacement, these workshops may play a crucial role in reducing frontline staff's resistance to AI implementation. By explaining AI models in a language that staff can understand and addressing their concerns, the team hopes to build trust and alleviate resistance to change. As stated by Respondent 2 in response to its residential building inspection application:

> We use an analogy like the "fishing net". The bigger your fishing nets are, the more inspections you drop. The more types of fish you don't want to catch, you will also catch along fish you want to catch…So basically you can decide how many inspections you

want to drop by the size of your fishing net and that place off against the number of the inspection that would have failed if you had inspected them.

Internal knowledge sharing also allows the Data Science and Research Team to gain trust from other departments by involving them in the process of building AI systems. For instance, the team collaborates with staff in respective departments to brainstorm feature variables for AI models. The team provides feedback on the importance of these variables, fostering an interactive and collaborative relationship. Like the workshops, this collaboration presumably builds trust and ensures that the AI systems align with the needs and requirements of the departments they are working with. As suggested by Respondent 2, *“* If you just go away for three months and come with a blackbox model they won't feel very much invested versus if you meet with them every two weeks and allow them to ask questions then they feel invested in it.”

In summary, findings indicate that collaboration and knowledge sharing within internal departments are vital for reducing resistance to change, enhancing trust, and facilitating AI implementation. The interactive relationship between internal users and AI developers, supported by collaboration, allows for knowledge exchange and ensures the implementation process is aligned with the organization's needs. These results align with the innovation literature emphasizing the importance of external collaboration (Cinar et al., 2019; Kiefer et al., 2021; Campion et al., 2022). However, our finding highlights that internal collaboration and interactions are equally important for successful local AI adoption.

4.5.1.4 Risk-Taking Culture

Ten records suggest that the City of Edmonton has an overall culture of risk-taking, which is reflected in both internal and external sources. Half of the records are internal, including information from the city's website and interviews, while the other half are external, primarily from local newspapers. This triangulation of information provides further evidence of the city's willingness to take risks.

The mayor of Edmonton has expressed a positive attitude toward risk-taking and emphasized the importance of governments being open to innovation and accepting failure. This attitude was demonstrated in the mayor's statement during the SingularityU Canada summit, where he highlighted the need for courageous decision-making with AI in the face of technological and other disruptions (Parsons, 2019b).

The city's plans and strategies also repeatedly mention the embrace of change and new opportunities, indicating a recognition of the importance of risk-taking in the context of disruptive technologies. This was repeated, with minor word changes, in three articles published by the government (City of Edmonton., 2019; City of Edmonton., 2020; City of Edmonton, n.d.-d).

Additionally, the core AI development team within the city considers risk-taking to be an inherent part of AI innovation. Their intake assessment form includes a commitment to being comfortable with the unpredictable results of innovation. The team acknowledges that asking city departments to take risks associated with AI/ML projects involves some level of uncertainty. Respondent 1 stated that *"Developing in-house with an agile development methodology poses very little overhead. We are asking business areas to take some risks associated with AI/ML projects, and there's some risk in those decisions."*

These findings challenge the general belief in the literature that the public sector is risk-averse (Arundel et al., 2019; Mulgan & Albury, 2003). Despite the high-risk nature of AI, the City of Edmonton demonstrates a culture of willingness to take risks. Our findings indicate that the city government recognizes the need for risk-taking to drive AI innovation and is willing to accept the associated uncertainties and challenges.

4.5.1.5 Upper Management Support

The result suggests a degree of policy support in AI innovation, which aligns with the existing literature (Arundel et al., 2019; Bugge et al., 2011; Campion et al., 2020; Yigitcanlar et al., 2022). The previous mayor of Edmonton has expressed support for AI innovation and the use of data for evidence-based decision-making (Pica-Alfano, n.d.-b). The city's action plans and strategies also indicate a commitment to innovation and technology development (City of Edmonton, 2021a, 2021b, 2021c).

However, obtaining initial and ongoing support from upper management for AI projects required effort from the Edmonton Data Science and Research team. While the consolidation of data scientist-related staff into one unit demonstrated support, the team had to actively promote themselves and present to leaders of other departments. They also needed to demonstrate success from their initial AI projects, as not all AI projects turned out to be successful. “First, you need to get a couple of projects with some success as you know many AI projects don’t turn into successful projects and you kind of need to know when to drop the project as well.”(Respondent 2)

After some promotion and success, the team started receiving numerous requests from other departments. Prior to the development of a new AI system, the team ensures that the departmental manager is committed to the project and that responsibilities and directions are clearly delineated. The commitment and support from other departments within the city government are crucial for the operationalization of the AI systems. As stated by Respondent 1, “It is very important for us to develop things that are useful for the team, and it is extremely important for our team, gratifying that they actually see their work having an impact. Not just resulting in a white paper or an application that is developed but never used.”

Overall, while there is some policy support for AI innovation in Edmonton, obtaining support for implementation required active promotion, demonstration of success, and commitment from internal stakeholders. This highlights the importance of garnering support from upper management and ensuring that AI projects have tangible impacts and are valued by the organization.

4.5.1.6 AI Process Fit

The concept of AI process fit, as described by Jöhnk et al. (2017), refers to the alignment between an organization's AI strategy--its plan for implementation and the goals for its AI systems--and its operationalization. While the City of Edmonton may not have a specific AI strategy, there are strategic plans and initiatives that demonstrate an alignment with the development and implementation of AI projects.

The Digital Action Plan (City of Edmonton, n.d.-d) and Business Technology Strategy (City of Edmonton, 2020) emphasize the need to embrace new technologies and use data to make what they consider evidence-based decisions. In relation to this strategy, as mentioned before, the city has consolidated a data science team and created a business model to take in AI project requests from other city units. This alignment between strategic goals and AI initiatives contributes to the AI process fit.

The ability to move from pilot projects to operationalization is another aspect of AI process fit. It has been our experience in the AICOP, supported by literature in the private sector (Sjödin et al., 2021), that many AI projects fail to move beyond proof-of-concept. Respondent 1 suggested that it is rare for the AI projects developed by the Edmonton Data Science and Research team to not be operationalized. This suggests a strong alignment between AI process fit and the above-mentioned factor - upper management support. The creation of the business model and ensuring the support from the top has enabled a process fit.

There remain challenges to achieving a complete AI process fit within the City of Edmonton. One challenge relates to computing infrastructure and organizational processes. Respondent 1 mentioned that AI systems require a different technology stack compared to traditional IT systems as well as cloud computing, the expertise, which limits the scalability of systems. In line with Desouza (2018), the rigidity of city processes also can hinder timely adjustments and changes when requests are made, creating a barrier to achieving a seamless AI process fit. T

Respondent 4 highlighted limitations in organizational processes that affect system-wide communication and data exchange, particularly for individuals without IT expertise. As stated by this respondent: “For those who are not in the IT department, for me to actually access the data that I've collected, now they are reinstituted in AI process, I do not get it back as efficiently as if is actually on my hard drives, so we have this extra level of administrative details to do in order to get appropriate accesses involved.” This interconnection between AI expertise and AI process fit means that accessing and exchanging data efficiently becomes a challenge when there are administrative details and restrictions involved.

These challenges highlight the need for further improvement in computing infrastructure, organizational processes, and communication channels to enhance the overall AI process fit within the City of Edmonton. Overcoming these obstacles would enable a smoother integration of AI innovation in existing workflows and processes.

4.5.2 External Factors

4.5.2.1 Exogenous Innovation Environment

The results suggest the presence of an innovation network in and around the City of Edmonton that contributes to municipal AI development. The literature emphasizes the importance of location and spatial proximity to innovation in fostering innovation activities (e.g., Asheim & Gertler, 2009; De Vries et al., 2016). The City of Edmonton benefits from the innovation culture in direct and non-direct ways, facilitated by an established innovation ecosystem, partnerships, talent attraction, and external recognition and investments.

The innovation ecosystem in the Edmonton region includes key entities such as the University of Alberta, Alberta Machine Intelligence Institute (Amii), Innovate Edmonton (a funding agency), and a cluster of 160 AI companies. The City of Edmonton government actively collaborates with these external entities, as indicated in various government records (City of Edmonton, n.d.-a, n.d.-b) and external sources (Innovate Edmonton funds, 2021, Innovate Edmonton, 2022b, n.d.; Rock & Watson, 2019; Unique business accelerator, 2021). The Edmonton Strategic Plan highlights the city's participation in regional innovation to promote economic diversity and competitiveness. Alberta is known for the predominance of the oil industry (Jones et al., 2019) so diversification is considered a priority in its capital city and beyond.

One example of collaboration is the public-private partnership involving the Edmonton Police Foundation, Amii, the University of Alberta, and ATB Financial Motorola. They established the Community Safety & Wellness Accelerator powered by Alchemist, which supports local companies using AI systems to provide societal benefits and improve community wellness (Innovate Edmonton, 2021). The accelerator is funded by government agencies at all three levels, city, provincial, and federal.

The innovative ecosystem in Edmonton also has attracted an increasing number of skilled talents and entrepreneurs. News articles highlight job growth and the city's ability to attract tech talents (Agrba, 2019; Cook, 2019). The city government does what it can to foster an innovative ecosystem that promotes creativity and innovation (City of Edmonton., n.d.-b, n.d.-c, n.d.-d).

The Edmonton region has received global recognition for its innovation ecosystem, including hosting the SingularityU summit (Kornik, 2019; Parsons, 2019b) and receiving the Smart 50 Award for its Open Space Autonomous and Electronic Equipment Pilot (Johnston, 2019). The city has also attracted investments in AI and other tech companies (Hicks, 2019; Innovate Edmonton, 2022). These adulations are tempered by mixed opinions about the competitiveness of Edmonton's innovation ecosystem, which compared to other cities, reveals some doubts about the region's ability to match more advanced markets (Parsons, 2019a).

Overall, the presence of an innovation ecosystem, partnerships, talent attraction, and external investments indicate the importance of the exogenous innovation environment in supporting AI innovation in the City of Edmonton.

4.5.2.2 Environmental Drivers

Our findings indicate that the primary environmental drivers influencing AI innovation in the City of Edmonton are public demands and competitive pressure. Most of this is expressed by the city itself, although we did not observe much documentation externally that captures these environmental drivers.

The city government recognizes the importance of meeting the needs and expectations of its citizens, as evinced by plans to implement chatbot technology for improved communication and service delivery (City of Edmonton., 2019a). AI is also seen as a means to address social issues, such as crime prevention (Stolte, 2019), greenhouse gas emission reduction (City of Edmonton., n.d.-e), and waste management (City of Edmonton., n.d.-g), with the ultimate goal of creating a more resilient and livable city (City of Edmonton, 2020). Our findings align with the existing literature, which suggests that numerous public demands drive innovation (Walker, 2006; Borin, 2001; De Vires et al., 2016) and AI is perceived as a way to meet these demands (Toll et al., 2019; Kuziemski & Misuraca, 2020; Mehr et al., 2017).

In addition to meeting public demands, the city government views AI adoption as a way to enhance economic competitiveness (City of Edmonton, 2020). Recognizing the importance of talent and demographics in supporting new and emerging economies, the city aims to provide opportunities for employment, entrepreneurship, and creativity to stay relevant in a changing global world. This focus on competitiveness is reflected in investments made to support high-growth firms and capitalize on global market opportunities (“Innovative, High-Growth Edmonton Companies”, 2022). These examples align with the existing literature, which suggests that competitive pressure is a significant factor influencing innovation (Andersen & Jakobsen, 2018; Borins, 2001; De Vires et al., 2016).

4.5.2.3 AI Regulations and AI Ethics

AI governance can be influenced by both hard law and soft law (Hagemann et al., 2018). In the context of AI governance in cities, certain aspects such as Algorithmic Impact Assessments (AIA) and calls for Responsible AI are considered soft law. At the federal level in Canada, there are recognized gaps in the laws and regulations pertaining to AI (Ip et al., 2022), but efforts are being made in the development of soft law governance tools like the AIA Tool by the Government of Canada (2021).

The City of Edmonton is predominantly guided by norms and demands for responsible and ethical AI, which resonates with the literature highlighting the challenges of a hard-law approach and the advantages of a soft-law approach (Hagemann et al., 2018; Marchant, 2019). An example of the city's commitment to responsible AI is its participation in the AI, Ethics and Society Conference (2019) at the University of Alberta. The city government also responds to initiatives at the provincial level, such as the requirement from the Privacy Commissioner of Alberta for custodians to conduct privacy impact assessments (PIA) to address privacy risks in projects involving personal or health information. Although not mandatory, the city government conducted a PIA for their Community Safety Model project, which involves sensitive data from the police department (Respondent 1).

The city government has taken steps to incorporate ethics into its AI projects. They hired a data ethicist who provides project evaluations and works with the AI team throughout the project's life cycle. The discussions on AI ethics primarily revolve around transparency and biases. Transparency is challenging, especially in individual AI models, as Respondent 2 noted, "It is quite difficult for many models to show exactly why a particular one came up with the answer." Developing AI systems internally allows for a certain level of transparency through open communication and close collaboration with partners, highlighting the interdependence of collaboration and transparency.

Bias in AI models has been addressed through measures to ensure reliability. For example, in the safety codes and inspection project, Respondent 2 mentioned simulating the model's performance on historical data for multiple years to test its reliability. By running the model on different time periods and analyzing the results, they hope to ensure the model's consistent and reliable performance.

Overall, the City of Edmonton demonstrates a commitment to responsible and ethical AI practices, incorporating soft-law approaches, conducting assessments, and addressing transparency and bias concerns to ensure the reliability and ethical use of AI technologies.

4.6 Conclusion

Previous research has primarily focused on investigating factors that enable or hinder innovation in firms and public sectors, with limited literature specifically examining AI innovation in local governments. Given the unique characteristics of AI, a distinct framework is necessary to examine AI innovation in local government. We developed such a framework that integrates factors from organizational studies, public sector innovation, smart cities, and AI adoption literature. We applied this framework to the City of Edmonton and identified internal and external factors that may influence AI innovation in the city government.

Our findings indicate that the most prevalent internal factors are AI-specific resources and internal needs. Internal needs driving innovation include efficiency enhancement, prediction, decision-making, and labour-saving. The availability of sufficient time and resources is also crucial for AI innovation. It is important to acknowledge that the size of the city plays a role in resource abundance. Compared to many other Canadian cities, Edmonton is a large city with a high population density that provides greater access to resources. It also is the capital of the Province of Alberta, which provides it access to over levels of government. The limitation of resources for AI innovation has implications for task prioritization, resource allocation, and risk mitigation by governments. As suggested by Shearmur (2016), the cost of AI investments is borne by citizens, but the returns on AI innovation are high-risk and uncertain. However, Edmonton appears to be sufficiently resourced.

Despite the significance of resources, they are not the sole determinant of AI innovation in the Edmonton city government, especially when compared to larger cities (e.g., the City of Toronto).

Edmonton's relatively fewer resources highlight the importance of a risk-taking culture in fostering AI innovation.

The most important external factors identified are the exogenous innovation environment and environmental drivers. The exogenous innovation environment includes institutions such as universities, startups, and financial and research institutes. Although we did not directly observe interactions with the AI development team, we argue that closeness to these innovation institutions is crucial for AI innovation within the city government. We found that environmental drivers predominantly consist of public demands and competitive pressure. We noticed that the demands were expressed from the government's perspective rather than directly reflecting citizen input. This may be attributed to the types of records included in our study. Incorporating other data sources such as social media posts could provide a better understanding of actual public demands.

External innovation factors primarily focus on innovation dynamics within the Edmonton region. Our results indicate interactions beyond the region as well, as documents revealed Edmonton's efforts to brand itself as an innovative city to attract global investment. Cook (2001) argues that, while innovation systems are typically located in specific regions, non-regional interactions also can play a role. Although our focus is on the Edmonton region, considering the city's interactions with federal and international actors is important for a comprehensive examination of innovation.

It is crucial to recognize the interdependence of some of these factors. For instance, we found that upper management support positively contributes to AI process fit; whereas, a lack of AI expertise is negatively associated with process fit. This highlights the interconnectedness of factors within the framework and the need to consider their combined effects on AI innovation in the City of Edmonton.

One surprising finding unique to Edmonton is that economic diversification is mentioned as a driver of technology-related innovation. This is situated in the city's context, considering its economy is largely based on the oil and gas industry (Jones et al., 2017). This aligns with the findings of Jones et al. (2017), who identified Edmonton's investment in the nanotechnology industry as a means to diversify the economy, attract talent, and position the city as a world-class hub. With AI, economic diversification continues to serve as a driver of technological innovation and, converse to nanotechnology, the process fit appears to have been achieved. Diversification has not been extensively discussed in the literature on public sector innovation but it may have implications for other cities with resource-based economies.

The emphasis on economic diversification aligns with the Edmonton city government's desire to function like the private sector. The city government’s “corporate business plan” reflects this perspective, stating that

> The City fosters new approaches and develops new business models that provide effective services and improve the resident experience. The City embraces disruptive technology as an opportunity to future-proof and enable the digital transformation of Edmonton (City of Edmonton, 2019a).

This business movement aligns with neoliberal assumptions underpinning innovation, which externally focuses on goals and tools that advance economic progress; internally, it advocates for government functioning like the private sector that prioritizes efficiency (Schnellenbach, 2007). The danger of this approach is the potential of the city government to prioritize efficiency rather than equity. This challenge has been recognized since the early days of IT in municipal governments (Kraemer and Kling, 1983).

Several factors that can be considered barriers to AI innovation are particularly relevant to local governments, especially in the context of AI. One such factor is regulation, which has been under-discussed in the innovation literature but is crucial for the responsible development and deployment of AI. Adopting a soft law approach for regulating AI may help address the challenges associated with hard-law regulation. Further, some factors necessary for innovation may conflict with the mandate of the public sector. For instance, AI innovation often prioritizes efficiency and cost-saving but, in a vast country like Canada with a significant population gradient (Statistic Canada, n.d.), remote and rural areas may be excluded from accessing AI-based services due to cost considerations.

One limitation of this study is the lack of exploration of personal-level factors that may influence innovation, such as the entrepreneurial traits of individuals driving innovation and the management style of leaders (Liddle, 2013). These factors have been identified as important in the innovation literature (De Vries et al., 2016). Moreover, the study did not delve into the roles and interactions of various actors within the innovation system, which could provide a more comprehensive understanding of the influence of external factors on AI innovation in the city government. For example, previous research has highlighted the role of universities in fostering innovation in the public sector (Demircioglu & Audretsch, 2019).

The contribution of this paper lies in three aspects. First, it fills the theoretical gap by providing a framework for measuring AI innovation in the public sector, addressing the lack of such frameworks in the existing literature. Second, the study presents a methodological approach for searching diverse sources of documents, which can be valuable for future studies relying on the content of gray literature. Last, empirical evidence is provided by analyzing how these factors manifest in the City of Edmonton's AI innovation practices, both internally and externally. The findings of this study can inform other cities about the important factors to consider when initiating AI-related innovations.

4.7 References

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4.8 Appendices

Appendix A. Descriptions of Secondary Data Sources

Sources	Description
Proquest Canadian Newsstrem	This database offers unparalleled access to the full text of over 400 Canadian news sources from Canada's leading publishers. This full text database includes the complete available electronic backfile for most newspapers, providing full access to the articles, columns, editorials and features published in each.

globalnews.ca	A supplementary news source as it is not covered by the Proquest Canadian Newsstream
edmonton.ca	City of Edmonton main site
innovateedmonton.com	Innovate Edmonton unites and promotes home-grown innovation as a gateway to solving the world's most pressing problems. We harness the power of the public and private sectors, ground-breaking academic research, and purpose-driven investment to build a shared prosperity and open international markets. From sustainable climate solutions to public health and digital inclusion, Edmonton is a leading global centre for inspiration, ingenuity and inclusion.
edmontonglobal.ca:	Edmonton Global is a foreign direct investment (FDI) and international business development agency. We're a hub that represents 14 municipalities in our region.
govlaunch.com:	Wiki for local government innovation. It provides podcasts, case studies and solutions towards local government innovation worldwide.
AICOP presentation: Safety Code Inspection Efficiencies	"The Safety Code Inspection project aims to enhance inspection efficiency by using a predictive model to determine whether an inspection can be dropped. The model is trained based on the historical building inspection data and attributes. Four types of attributes were included: building attributes (i.e., permit class, floor area, home design, infill location, secondary suite, lot area, and construction value); geographical information (i.e., neighbourhood classification; contractor attributes (i.e., contractor/builder/applicant 12 and 3-month inspection volume and first-time pass rate); and inspection attributes (Inspection type, date, time between permit submission and inspection."
AICOP presentation: Community Safety Deployment Model	"This model brings together data from the Edmonton Police Service, the City of Edmonton and REACH Edmonton -- a local non-profit who provide crisis diversion support. This common operating picture positions the agencies to deploy the right resource, at the right place, at the right time, with the right information for a safer city. The triaging function is supported by a model developed by the City of Edmonton's Analytics Centre of Excellence that predicts both the probability and the severity of incidents up to two weeks in advance. Built with data ethics and privacy in mind, the Community Safety Deployment Model leverages data void of personally identifiable information — focusing exclusively on the time, location and incident type."
AICOP presentation: Wildlife Monitoring Project	This project uses object detection algorithm to assist and speed up the analysis of wildlife images. The images were collected

	from millions of images collected by the cameras that were previously deployed.
AICOP presentation: Text Depot applications	This project offers internal government staffs a user-friendly interface to search and analyze an enormous amount of text-based data using natural language processing (NLP) algorithms. Such data include council reports, media monitoring, meeting minutes, 311 engagement notes, policies, urban plans, bylaws, etc. "Council reports, media monitoring, meeting minutes, 311 engagement notes, policies, urban plans, bylaws... the City of Edmonton has, and continues to collect, an enormous volume of text based data. However, without a centralized location, and a user friendly mechanism to access these sources, we have not realized the potential that this information presents. Until now. Offering a user-friendly searchable interface, Text Depot offers a solution through its ability to centralize, search across text data sets, and uncover insights through the application of AI models."

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Appendix C. Intake Assessment Form

Intake Assessment			
Project			
<Type in Project Name>			
What we understand the problem to be			
[Include brief description]			
What we think our solution could look like			
[Include brief description]			
Intake recap	**Yes**	**No**	
We are measuring our success	☐	☐	Add comments
We have additional partners	☐	☐	Add comments
We need to buy data	☐	☐	Add comments
We need to collect data	☐	☐	Add comments
We need personal information	☐	☐	Add comments
GBA+ has been considered	☐	☐	Add comments
We are adding the data to the IDP	☐	☐	Add comments
This is a one time analysis	☐	☐	Add comments
This is a repeated analysis	☐	☐	Add comments
We will adopt or reuse a solution	☐	☐	Add comments
We will buy a solution	☐	☐	Add comments
We will build a solution	☐	☐	Add comments
We have decided on a distribution method	☐	☐	Add comments
Training is required	☐	☐	Add comments
A team approach			
In order to get results, we'll need to work together as a team. Our ability to support you with effective innovation and strategic advice hinges on your commit on work related to:			
1. Prioritizing this project and supporting it with time and resources			
2. Obtaining the support of your Branch Manager			
3. Change management related to people and processes			
4. Law Branch, the Office of the City Clerk, Information Security and Data and Analytics Ethics requirements			
5. The interface with Mayor, Council and ELT			
6. Communications and Engagement requirements			
7. Being comfortable with the unpredictable results of innovation			
8. Being comfortable with sharing the results of our work together under the MIT License			
9. And most importantly, taking what we build together and moving it to action			
Are you ready to be a partner? (Select from responses below)			
Where do we sit?			
Strategic Alignment (Select from response below)			***Points (Auto-populates)***

Intake Assessment			
Project			
<Type in Project Name>			
Strategic Objective: Make transformational impacts in our community			3
Is project funding available?			
Yes/No (Select from responses below)			***Points (Auto-populates)***
Yes			2
What value do we bring?			
	Yes	**No**	
Makes money	☐	☐	Add comments
Saves money	☐	☐	Add comments
Looks good	☐	☐	Add comments
Reduces risk	☐	☐	Add comments
Saves time	☐	☐	Add comments
		Points	0
		Total Points:	**5**
		Queue Placement:	
		Anticipated Start Date:	
		Anticipated End Date:	
Partnership agreement			
The parties signed here agree to the scope and conditions reflected in this assessment			
Name, Title	**Branch**		**Signature**
Content	Content		
Content	Content		
Content	Content		
Content	Content		
Project Cancellation			
Complete only if decision has been made to no longer proceed with project . This can be completed at any stage of the project.			
Cancellation Justification	**Name** Replace with name below		**Signature**
	Project Sponsor		
	ACE Project Manager		
	ACE Director		

Chapter 5. Discussion and Conclusion

5.1 Discussion of Findings

This thesis sought to examine what contributes to the success of AI adoption in local governments. Canada serves as a compelling case for studying AI integration in local government due to its AI leadership and significant AI investments. Whereas, Canada exhibits a more cautious approach compared to the United States in adopting AI solutions.

The following research questions are addressed:

1. How does AI adoption differ from or is similar to IT adoption in local governments?
2. What and how is AI being adopted in Canadian local governments?
3. What are the opportunities and challenges of AI perceived by individuals involved in local government AI projects?
4. What factors of innovation contribute to the success of local government AI adoption?

Chapter 2 contextualized the thesis with an overview of the history of IT adoption within governments and addresses Research Question 1. I decided to compare current AI adoption as proposed today with traditional IT adoption as proposed in the 1970s to see similarities and differences in terms of promises and pitfalls. I found that AI distinguishes itself from IT by its ability to learn and adapt from data rather than relying on predefined algorithms. However, this learning capability raises concerns about overfitting and exacerbates the issue of bias and opacity, which have been previously identified in IT studies. Despite these differences, I saw that both AI and IT share numerous promises for local governments, including enhancing administration processes, improving public services, and facilitating data-driven decision-making through automation. Both AI and traditional IT face challenges, such as resource and staff requirements. I anticipate that AI will encounter similar challenges seen in IT adoption, including potential political influence and power dynamics, which are often overlooked. Understanding these aspects can aid responsible and effective AI implementation in municipal governance.

Chapter 3 addresses Research Questions 2 and 3 with a survey that examined AI projects within Canadian municipalities and assessed their development and perception of AI. It first addressed What and how is AI being adopted in Canadian local governments? AI projects included less complex machine learning alongside some deep learning, spanning a diverse range of applications. The survey showed diverse backgrounds and expertise of respondents, ranging from managerial roles to formally-trained AI specialists. Since AI and data science are emerging municipal practices, it is unsurprising that some employees would need to "learn on the job". Development approaches also varied, including in-house development, collaboration and purchasing. Research Question 3 was What are the opportunities and challenges of AI perceived by individuals involved in local government AI projects? The survey revealed respondents' positive views on AI opportunities. However, some did question the promise of cost reduction and the objectivity of decision-making. AI adoption presented a number of organizational and technical challenges to local governments. Organizational challenges included a lack of staff training, funding constraints, and the need for external support and clear policies. Technical challenges involved a lack of in-house expertise, difficulty in hiring and retaining AI staff, data availability and quality issues, and computing infrastructure limitations. Privacy, security, transparency, reliability, and risk of failure were key concerns in AI adoption. The study emphasizes the need for staff, education, funding, collaboration, policies, and technical investments to address these challenges and ensure successful AI adoption in municipalities.

Chapter 4 asked Research Question 4: What factors contribute to the success of local government AI adoption? To assess factors, I developed an innovation framework by examining literature on the public sector innovation and AI adoption. The framework was tailored to address three components: (a) AI specifically, differentiating it from other forms of innovation, (b) the public sector, setting it apart from the private sector, and (c) local governments, distinguishing them from other levels of government. I discovered that AI stands apart from other forms of innovation due to its need for a suitable process fit to accommodate the special properties such as increased opacity, reduced traceability in terms of reasoning, and new technical needs (e.g., new software stack, cloud computing). I included factors that would emphasize the significance of cultivating a culture of risk-taking and stress regulations that foster innovation in the public sector. In the context of local government, I underscored the increased resource constraints and inability to create regulations because of their jurisdictional level. Furthermore, due to limited municipal resources, we highlighted the value of collaboration. We also highlighted the interplay among resource constraints, a culture for risk-taking, and the ethical considerations associated with AI innovation. I tested the framework in the City of Edmonton by examining interviews, presentations, news articles and grey literature on AI innovation in Edmonton. Edmonton is an chosen because they have the most internal capacity with a leading number of AI projects. Edmonton also is interesting because of countervailing evidence that suggests Edmonton is unable to be innovative (Jones, 2019). The framework highlighted the importance of internal factors such as AI-specific resources, internal needs and risk-taking culture in driving innovation. External factors include the exogenous innovation environment and environmental drivers, with proximity to innovation institutions and public demands playing significant roles. The interdependence of factors is recognized and economic diversification emerges as a unique driver in Edmonton. The emphasis on efficiency and cost-saving raises concerns about potential equity issues. Barriers to regulation and conflict between innovation and public sector mandates present a dilemma in AI innovation. We find this framework useful in assessing internal factors. One exception is that we included the reward mechanism as a factor in our framework but did not identify it in our data. This omission could be attributed to the way the interview question was formulated, as we did not explicitly explore this aspect. Alternately, it might be due to a lack of reward mechanisms in local governments. External factors presented greater challenges to find and required greater inference (e.g., from the choice of words in newspapers or the number of startups in the region). Perhaps the data sources used were not optimal for capturing these complexities. Considering including social media data to gain insights into citizens' perspectives would be beneficial. Overall, as much as we desire innovation factors to be predictive, they will always lack causality. The best practices can only be synthesized after the fact, with the hope that factors found in a successful city can be applied more broadly elsewhere.

This thesis provides a comprehensive exploration of AI adoption and innovation in local governments and contrasts the considerable rhetoric on AI capability with the extensive challenges faced by local governments in adopting AI. Many of these challenges are projected to persist as local governments continue to navigate AI adoption. AI may bring new challenges to local governments compared to traditional IT adoption. The learning, adaptive, and unpredictability nature of AI can lead to difficulties in ensuring transparency, accountability, and fairness in decision-making processes, which are essential for local government. Surprisingly, many of the concerns about societal, organizational, and technical promises and pitfalls in municipalities were expressed with IT adoption since the 1970s (Andersen et al., 2010; King, 1982; Kraemer & Kling, 1983; Streib & Willoughby, 2005).

Further, it is important to recognize the unique demographic characteristics of Canada. Canada's vast geographical and demographic diversity poses unique challenges to AI adoption. Striving for efficiency in this context might inadvertently neglect fairness considerations. For example, designing systems that serve the greatest number of residents in Canada will privilege dense urban areas at the expense of the needs in rural and remote communities, which comprise the majority of the land mass of Canada. Additionally, it is crucial to acknowledge the multifaceted challenges inherent to local governments as they struggle to manage various responsibilities ranging from infrastructure management to essential services delivery. The non mission-critical nature of AI places pressure on local governments to ensure the responsible and efficient use of taxpayer funds. While taxpayers might advocate for enhanced efficiency, municipalities could struggle to manage the risk of AI and keep up with the swift pace of technological transformation.

The rapid pace of technological change in AI can outpace the ability of local governments to adapt. Local governments are likely to lag behind in adopting AI. This delay may exacerbate the concern of falling behind in competitiveness. Like IT outsourcing, local governments may be incentified to outsource AI developments to the private sector to catch up with the pace (Gantman & Fedorowicz, 2020; Moon et al., 2010). However, it is critical to recognize the danger of cities being transformed into testbeds for innovation. As suggested by Shearmur (2016), the city may risk being "tie[d] into proprietary technologies, updates and long-term service contracts that will divert funds from the spending and investment the population may desire or need" (p. 808).

Research on local government AI adoption continues to evolve during the period of this research. For example, Rjab et al., (2023) examined the barriers of AI adoption in cities through a literature review. The United Nations conducted a global survey to evaluate the opportunity and challenges faced by local governments in responsibly utilizing and governing AI systems across cities worldwide (United Nation University, Forthcoming). It is interesting to note that many of the opportunities and challenges uncovered in these studies confirmed the findings of this thesis.

Despite this progress, there is still much to uncover about how local governments can effectively navigate these challenges and ensure that the anticipated benefits of AI materialize; there remains an immature understanding of how the AI systems will be used and its political characteristics as stressed in IT studies almost 50 years ago (e.g, Kling, 1978; Kraemer & Kling, 1983). Addressing the complexities of AI implementation and its implications for local governments will pose a challenge for researchers in the field. Long-term studies will need to move beyond rhetoric to ground the research in actual adoption to be able to capture the reality of the dynamic and evolving nature of AI adoption and its impact on governance.

5.2 Future Research Directions

If time permitted I could have conducted additional research. This would have included an in-depth investigation into the technical specifics of the AI algorithms employed in local governments. Access to code and technical documents on AI systems was restricted, possibly due to the early stage of AI adoption in local governments and a lack of openness in sharing such information. Greater transparency and openness in AI initiatives would facilitate comprehensive research and understanding in the future. The establishment of a comprehensive AI registry could be a viable solution, serving as a centralized repository where local governments can voluntarily disclose information about their AI projects, including technical details, algorithms used, data sources, and objectives (Brandusescu and Reia, 2022). This registry would not only facilitate research efforts but also foster knowledge sharing among local governments and encourage the responsible and ethical development of AI systems. By making relevant information publicly available, the registry could promote accountability and build trust between governments and their citizens.

This thesis primarily involves actors within local governments, whereas it is important to acknowledge the role of a multitude of actors, such as elected officials, city managers, university researchers and private sector partners, in this dynamic landscape (e.g., Campion et al., 2022; Yigitcanlar et al., 2022). As local governments increasingly rely on collaborations with universities or the private sector to develop AI systems (e.g., Campion et al., 2022; Mikhaylov et al., 2018), understanding the dynamics and implications of these partnerships becomes crucial, as collaborations offer valuable expertise, resources, and technological advancements that can accelerate AI adoption and innovation in the public sector. Future research may examine the roles and contributions of various stakeholders and their interactions. This may involve case studies and interviews with stakeholders involved in collaborative AI projects on the collaborative process. Additionally, comparative studies across different municipalities with varying levels of collaboration would help identify best practices and potential areas for improvement.

Whereas the thesis examines the development approach of AI in local governments, such as in-house development, purchasing, and collaboration; a comprehensive investigation into the specific differences in benefits, challenges, and adoption conditions for each approach could be conducted. It is vital to acknowledge that local governments may encounter distinct challenges depending on their chosen approach and location, as evidenced by past IT studies (e.g., Gantman & Fedorowicz, 2020). Understanding the unique advantages, potential obstacles, and necessary prerequisites associated with each development approach can play a pivotal role in guiding local governments toward selecting the most suitable approach for their specific needs and circumstances. Further research in this area would contribute valuable insights, enabling local governments to navigate the complexities of AI adoption more effectively and aligning their choices with their organizational goals and capabilities.

5.3 Final Conclusion and Summary

The objective of this thesis was to examine what constitutes successful AI adoption in local governments. Our investigation revealed that, while AI offers substantial opportunities, its adoption by local governments is impeded by significant technical and organizational challenges. Additionally, we pinpointed key innovative factors that influence local government AI adoption. Successful AI adoption demands local governments find an equilibrium between the benefits it offers and the challenges it presents. Achieving successful AI integration further hinges on the readiness and willingness of local governments to embrace this particular innovation, while managing the interplay of innovation factors such as risk-taking and efficiency with AI ethics and the public sector mandate of fairness.

This thesis contributes significantly to academic knowledge, policy making, and city planning. This thesis contributes to academic knowledge by uncovering differences and similarities between traditional IT systems and AI systems within local governments. This exploration fills a gap in existing literature, providing a foundation for further scholarly inquiry into AI implementation in local government contexts. The emprcial findings of this thesis further augment academic knowledge in this field. In addition, the thesis provides importance for policymaking as it presents the first empirical investigation into the current practices of AI adoption in Canadian local governments. By identifying opportunities and challenges face, the thesis offers insights crucial for informed policy decisions. Further, the introduced framework for measuring AI innovation in the public sector serves as a practical tool for local governments. It enables systematic analysis of AI practices and offers a structured approach to understanding the conditions necessary for successful AI innovation. This contributes to more informed and strategic planning processes, enableing local governments to navigate challenges and optimize their approaches to AI implementation. The empirical evidence from the analysis of AI practices in the City of Edmonton provides a tangible guide for other local governments, facilitating more effective and context-aware planning for AI integration

Overall, while providing a preliminary understanding, this thesis lays the foundation for further exploration in local government AI adoption. The findings can aid local governments in their future AI adoption, guiding them toward responsible and equitable AI governance practices and policies. As the study represents just the initial step, there is still much more to be explored and researched in the dynamic landscape of AI adoption in local governance.

Chapter 6. Bibliography

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