LUISS

Department of Business and Management
Master of Science (MSc) in Strategic Management

Course Digital and Organizational Innovation

Artificial Intelligence and Public Sector Transformation:
Conditions for Successful Implementation

Prof. Federici Tommaso

SUPERVISOR

Prof. Balestrieri Luca

CO-SUPERVISOR

Alberto Cervelli - 787221

CANDIDATE

Academic Year 2024/2025

Table of Contents

Purpose

Public administrations worldwide are exploring Artificial Intelligence (AI) to improve governance and service delivery. Yet, many AI initiatives face significant hurdles, and not all deliver on their promise. This study aims to identify what factors lead to successful AI-based projects in public administration and what obstacles hinder AI adoption. In particular, the research focuses on key success factors (e.g. governance, resources, skills) that enable AI initiatives to thrive, and the regulatory, economic, and organizational barriers that often cause such projects to stall. By examining both enablers and impediments, the study seeks to provide a holistic understanding of how governments can better implement AI for the public good. Prior work notes that AI adoption in the public sector remains under-studied and lacks extensive empirical insights (Madan & Ashok, 2023), making this investigation both timely and necessary. Ultimately, the purpose is to generate evidence-based recommendations on overcoming challenges and creating conditions for successful AI integration in government.

1. Introduction

1.1 Context and motivation

Public administrations are increasingly faced with the challenge of providing services that are faster, more responsive, and more predictable, and all this within structural constraints such as complex boundaries, limited resources, and high accountability demands. In this context, Artificial Intelligence (AI) is often cited as a promising enabler: it could help with the automation of repetitive tasks, enhance analytical power, and facilitate new interaction patterns between governments and citizens. Nevertheless, the role of AI in the public sector cannot be considered solely in terms of its enabling potential. Public administrations are subject to legal, procedural, and public observation requirements, and they are also tasked with achieving outcomes that go beyond efficiency, such as equity, transparency, and legitimacy.

These institutional features make AI implementation in public administration particularly demanding. Even when AI solutions are technically available, public organizations must translate ambitions into initiatives that are feasible within administrative procedures and acceptable within a democratic setting. This translation involves decisions about responsibilities and ownership, coordination across functions and units, relationships with external suppliers, and the design of safeguards that preserve trust and accountability over time. As a result, the relevance of studying AI in government lies not only in what the technology can do, but in how public administrations can integrate it responsibly within their organizational and institutional constraints.

In this context, the present thesis focuses on AI implementation in public administration as an organizational and governance challenge, setting the stage for the research aim and question introduced in the next section.

1.2 Research aim and positioning of the study

The aim of this thesis is to explore the factors that enable the successful implementation of AI projects in public administration and the factors that impede such implementation. As such, the thesis takes an implementation focus: it is interested in how AI projects are made operational in public sector organizations, rather than in comparing particular algorithms.

The thesis is informed by the following Research Question:

"Which organizational, technical and governance-related conditions most strongly influence the successful implementation and stabilization of AI-based projects in public administrations, and through which mechanisms do they enable (or obstruct) the transition from pilot initiatives to routine operational use under public-sector accountability constraints?"

This question fills a gap in the literature and the debate on public sector AI. While the literature has grown rapidly, much of the work that has been done has been either normative or high-level, often focusing on principles, opportunities, and risks. When implementation is considered, the evidence is often piecemeal and presented in the form of lists of drivers and barriers. It is therefore still not clear which factors and barriers are most important in practice and how they interact to influence implementation outcomes, especially when projects seek to move from pilots to implementation.

Within the context of this thesis, "implementation success" is a multidimensional concept. It is not simply the generic promise of innovation or the technical correctness of an AI system when viewed in a vacuum. Rather, it is the ability of an AI project to move from promise to stable operationalization within a public administration, which is to say that the project becomes institutionalized within the administration's workflows and managed in a way that preserves accountability and legitimacy. This is particularly important in the public sector, where procedural and legal requirements can have a significant impact on implementation decisions and the ability of AI projects to be successfully institutionalized.

Therefore, the thesis proposes an organizational and governance perspective and a socio-technical and institutional approach to the implementation of AI in public administration. In this respect, implementation is contingent on three interconnected areas: organizational readiness (ranging from data availability and accessibility, integration capacity, internal capabilities, and leadership support); implementation and delivery options (encompassing pilot and scaling approaches, change management, adoption by organizational members, and coordination among organizational units); and governance structures (encompassing accountability allocation, compliance and risk management, transparency and oversight structures, and monitoring and evaluation processes). These areas do not function in isolation. For example, limitations in internal capacity may raise the importance of external sources; procurement and contracting decisions may inform solution design, flexibility, and long-term maintainability; and governance needs may shape the acceptability of a project and the rate and sustainability of implementation. In this respect, one of the main assumptions of this thesis is that the outcomes of implementation are seldom the result of single-factor determinism, but rather may be better accounted for by the interplay of multiple factors and the trade-offs that arise as AI projects transition from experimentation to operationalization.

Another reason for conducting the research is the gap that may be observed between high-level expectations about AI in the government and the reality of public administration. Even if AI is often linked to efficiency and better decision-making, public administrations face a “translation challenge” because they have to define use cases, ensure that data and technology infrastructure are able to support delivery, gain internal ownership, coordinate stakeholders, and develop safeguards that are still operational in everyday life. It is necessary to understand the frictions and how they are viewed by the actors who are working in or around public administration initiatives about AI in order to determine which factors are most important and which barriers have the most impact.

In this context, the thesis fills the gap in the literature by providing a comprehensive framework of implementation determinants based on a concept-centric synthesis of the literature and qualitative insights from the public sector ecosystem. The aim is not only to replicate existing lists of drivers and barriers, but rather to shed light on the relative importance of recurring factors and to link literature-based expectations with practice-based evidence. In this process, the thesis seeks to improve the empirical foundation of implementation-focused debates on public sector AI and to offer a structured reflection space for both academics and practitioners on how AI initiatives can become operational, sustainable, and aligned with public accountability.

1.3 Structure of the thesis

This thesis is structured into six chapters. Chapter 1 sets out the context of the study and presents the research aim and research question, clarifying the scope and positioning of the inquiry. Chapter 2 synthesizes academic and institutional contributions on AI in public administration through a concept-centric review, establishing the conceptual foundation for the study. Chapter 3 outlines the methodological approach adopted to address the research question. Chapter 4 reports the empirical findings emerging from the interview analysis. Chapter 5 interprets these findings in light of the literature and develops the main implications of the study. Chapter 6 concludes by summarizing the key insights, acknowledging limitations, and indicating directions for future research and practice.

Building on this positioning, the next chapter consolidates the relevant literature and provides the conceptual background that informs the empirical chapters that follow.

2. Literature review

2.1 Positioning AI within Digital Government and Public Value Debates

Artificial Intelligence has become a central component of contemporary digital government agendas. However, the adoption in public administration differs from technology uptake in private organizations since AI systems are embedded in a distinctive institutional environment shaped by legal mandates, democratic accountability, and expectations of fairness, transparency, and equal treatment. Thus, the literature increasingly frames AI adoption as part of broader processes of digital transformation, rather than as a purely technical upgrade. Digital transformation in government was defined as the reconfiguration of public organizations, processes and service delivery through digital technologies, often entailing capabilities, governance arrangements, and organizational culture change (Mergel et al., 2019).

Within this broader transformation, AI appears as an enabler of more anticipatory data-driven, and personalized services, as well as of improved analytical capacity for policy design and operational decision support. Meanwhile, AI raises governance and legitimacy questions that are comparatively more salient for public organizations than for private firms-particularly when algorithmic tools influence eligibility decisions, enforcement priorities, or the allocation of public resources (Margetts & Dorobantu, 2019; Young et al., 2019). Research has hence moved from early descriptive mapping of applications to analytical work on the conditions under which AI can produce public value while respecting democratic, legal, and ethical constraints (Mikhaylov et al., 2018a; Wirtz et al., 2019; Criado & Gil-García, 2019).

A highly influential framing is that of "artificial discretion", which draws attention to how algorithmic systems may redesign the discretionary space classically wielded by street-level bureaucrats and public managers. This perspective focuses on the fact that algorithmic tools contain assumptions, proxies, and policy trade-offs, rather than framing AI as a neutral automation of tasks. Consequently, AI adoption needs examination through organizational lenses, such as capabilities, resources, processes, and implementation pathways, and through governance lenses, such as accountability, oversight, legality, and public trust.

2.2 Thematic Framework and Concept-Centric Synthesis

The literature is synthesized in line with the concept-centric approach outlined in the Methodology chapter, around the second-level thematic framework derived from inductive coding of the review corpus. Evidence has been organized hence around five macro-themes:(i) adoption factors and organizational readiness; (ii) implementation strategies and operational pathways; (iii) benefits and public value opportunities; (iv) ethical and social challenges; and (v) governance and accountability mechanisms. Where relevant, illustrative cases are integrated within each theme in order to clarify how the same conceptual issues materialize in practice across different administrative settings, rather than being treated as a separate, stand-alone section.

2.2.1 Adoption Factors and Organizational Readiness

Throughout the literature, AI adoption is repeatedly conceptualized as contingent on a mix of technological readiness, organizational capacity, and an enabling policy environment. Comparative and case-based studies underlined how public organizations differ substantially in digital maturity and absorptive capacity, thereby shaping the feasibility of AI initiatives and the likelihood of scaling beyond pilots (Neumann et al., 2022a).

Technological readiness is most often operationalized through the availability of high-quality, interoperable data and the presence of scalable infrastructure. Data silos, fragmented ownership, and legacy systems are recurring barriers because they put constraints on both the training of machine-learning models and the integration of AI tools into existing information systems and workflows (Mikhaylov et al., 2018a; Pencheva et al., 2020). Public sector institutional fragmentation and legal and organizational obstacles to sharing data across units and agencies run the risk of amplifying issues.

This encompasses both human and structural dimensions of organizational capacity. Skill shortages-particularly in data science, machine learning engineering, and AI governance-are often considered one of the major bottlenecks, frequently leading agencies to rely on external vendors and consultants (Wirtz et al., 2019; NAPA, 2019). However, capacity also depends on leadership sponsorship and strategic direction: this means that visible top-management commitment and a clear articulation of how AI supports organizational missions go along with more coherent portfolios of initiatives, which are more likely to be institutionalized (Criado & Gil-García, 2019; Neumann et al., 2022a).

The policy and regulatory environment further shapes the risk calculus of public organizations. Unlike private firms, public administrations operate under strict administrative law, procurement rules, and sectoral regulations. Legal uncertainty-especially regarding automated decision-making, data protection, and issues of liability-can lead to slower adoption or to guide it toward low-risk uses (Kuziemski & Misuraca, 2020). Similarly, institutional guidance underlines that lawful and trusted AI demands clarity on responsibilities, data governance, compliance mechanisms, and the conditions under which automation is permissible (European Commission, 2019; OECD, 2021a). Illustrative cases reinforce how readiness constraints manifest operationally. For instance, OECD case material portrays how AI-related initiatives by Transport Canada required the collation of dispersed records into machine-consumable formats and relied upon sustained senior management sponsorship, two conditions which map directly onto data readiness and leadership capacity, respectively. In the Italian context, recent sectoral analyzes likewise emphasize uneven data infrastructures and capability distribution across administrations as structural constraints shaping which agencies can move beyond experimentation (Ambrosetti, 2024; Osservatorio AI4PA, 2025).

2.2.2 Implementation Strategies and Operational Pathways

The literature differentiates between the adoption 'readiness' of the concrete pathways through which AI initiatives are implemented, integrated into workflows, and institutionalized. Indeed, one recurring pattern relates to the role of pilots and proofs of concept in testing feasibility, building internal confidence, and clarifying data requirements before scaling (Wirtz et al. 2019; Ambrosetti 2024). Pilot-based approaches are often joined by incremental scaling strategies whereby administrations progress the scope once performance, legitimacy, and organizational fit have been validated.

Implementation strategies are shaped by the public procurement context. Procurement processes can be long and rule-bound, limiting agile iteration and making it difficult to specify requirements for rapidly evolving AI solutions. Academic and policy sources therefore emphasize the importance of procurement capability, vendor governance, and contractual arrangements that preserve transparency and auditability throughout the system life cycle (OECD, 2021a; Government of Canada, 2024). This in practice often motivates the creation of cross-functional roles or task forces that bridge technical, legal, and operational expertise.

Another prominent strategy is cross-organizational collaboration, reflecting the fact that many AI use cases depend on data and processes distributed across agencies. Collaboration may involve inter-agency coordination mechanisms, shared data infrastructures, or public–private partnerships that provide technical capabilities and implementation support (Mikhaylov et al., 2018b; OECD, 2021a; Formit & Trilateral Research, 2024). However, these arrangements raise governance questions of model ownership, data sovereignty, and accountability when decisions rely on vendor-provided systems (Kuziemski & Misuraca, 2020).

Policy and practice-oriented sources increasingly recognize that implementation requires organizational learning and capability building, not only technical deployment. Training progra**m**s, communities of practice, and experimentation environments - such as innovation labs and sandboxes - are discussed as mechanisms to reduce capability gaps, align stakeholders and support responsible experimentation Ambrosetti, 2024; OECD 2021.

Illustrative cases indicate that pathways to implementation are often designed around service delivery constraints. For example, the OECD documentation on Finland's AuroraAI initiative points out the human-centered approach taken to develop services centered around life events experienced by citizens. Such an approach necessitates both the coordination among agencies and careful design to ensure usability and legitimacy in many respects. In Italy, the diffusion of pilots reported by Ambrosetti (2024) and Osservatorio AI4PA suggests that, especially within administrations, implementation often tends to start with bounded use cases, usually in support functions or information services, before scaling to sensitive decision contexts.

2.2.3 Benefits and Public Value Opportunities

The potential benefits of AI in public administration are often framed in terms of efficiency and service quality gains with improved decision support. Early reviews and mappings emphasize such applications as service triage, fraud detection, predictive analytics, and administrative automation (Mikhaylov et al., 2018a; Wirtz et al., 2019).

From a public value perspective, AI is expected to improve outcomes by enabling more timely and accurate decisions, lessening the burdens on citizens and civil servants, and improving access to services (Criado & Gil-García, 2019; Pencheva et al., 2020).
At the same time, the literature cautions that 'value' in the public sector is multi-dimensional. Beyond efficiency, public value encompasses fairness, responsiveness, legitimacy, and trust. Accordingly, authors argue that success of AI initiatives should be gauged not only by technical performance metrics but also by their impact on public values and the acceptability of new decision-making arrangements (Young et al., 2019; Margetts & Dorobantu, 2019). This shifts evaluation away from purely instrumental outcomes towards broader issues of institutional legitimacy and citizen experience.
Institutional reports often connect value opportunities to strategic objectives like better policy targeting, enhanced early warning and forecasting, and improved evidence-informed policymaking. For instance, Engin and Treleaven (2019) highlight that AI increases the capacity of civil servants by automating routine tasks and providing analytical support, potentially freeing up administrative effort for higher-value activities.
Illustrative cases build understanding of what "public value" might look like in practice. In the Italian context, recent analyzes and sectoral reporting address projects such as the use of virtual assistants and automated document handling by INPS to lighten front-office workload and enhance information and service accessibility for citizens, as well as the application of AI-based text analytics by the Emilia-Romagna Region through its SAVIA initiative in support of legislative and regulatory analysis (Ambrosetti, 2024; Osservatorio AI4PA, 2025). The international cases most often mentioned include AuroraAI, an effort to reconfigure service delivery around the needs of citizens through integrated recommendations and pathways across agencies (OECD, 2021b). In these and other cases, the literature stresses that the creation of value depends, with some exceptions, on **organizationa**l and governance condition**s** (data readiness, coordination across units, and clear lines of accountabilit**y)** being met rather than just model performance.

2.2.4 Ethical and Social Challenges

Ethical and social risks are a defining feature of the debate on AI in the public sector. Unlike many private-sector applications, public-sector AI is likely to impact eligibility decisions, enforcement priorities, and access to basic services, making issues around fairness, discrimination, and due process highly salient (Young et al., 2019; Kuziemski & Misuraca, 2020).

Key challenges include privacy and data protection, the risk of algorithmic bias, and the opacity of complex models. Policy frameworks on trustworthy AI stress that public organizations must ensure lawful processing, proportionality, transparency, and human oversight (European Commission, 2019; European Commission, 2020). Explainability and contestability are frequently discussed as requirements for maintaining legitimacy when algorithmic systems support or influence administrative decisions.

Public trust is both a precondition and an outcome of AI adoption. High-profile failures, perceived unfairness, or 'black box' decision-making can undermine trust in institutions, making responsible implementation central to sustained adoption (Margetts & Dorobantu, 2019; NAPA, 2019). The ethical risks in this view are not an add-on from outside but a core dimension of organizational viability and legitimacy.

Other social implications involve the risk of exclusion and unequal access to digital services. If AI-enabled services presuppose digital literacy or depend on biased datasets, they may amplify existing inequalities. Second, there are also workforce implications (ranging from task reallocation to concerns about de-skilling and displacement), which are discussed both in academic and in practitioner-oriented analyzes.

Comparative experiences also illustrate how ethical challenges can become salient even in apparently "low risk" applications, such as automated triage or profiling tools, if the outputs of these tools shape downstream decisions. Multiple authors therefore suggest "ethics and rights by design" approaches, which blend human oversight with procedural safeguards, along with transparent communication to citizens (European Commission 2019; Kuziemski & Misuraca 2020; Armiento 2024).

2.2.5 Governance and Accountability Mechanisms

Governance is an overarching, cross-cutting dimension within the literature: the need to reconcile innovation with legality and democratic accountability. Kuziemski and Misuraca (2020) provided an overview of how governance challenges are posed at the 'frontiers' of automated decision-making: unclear accountability, limited transparency, and the difficulty of auditing complex models. The concept of artificial discretion similarly highlights that the use of AI systems can shift the locus of decision-making-questions about responsibility for outcomes and the appropriate role of human judgment (Young et al., 2019).

Policy instruments have emerged to operationalize responsible AI in the public sector. The core requirements of the European Commission's Ethics Guidelines for Trustworthy AI include transparency, accountability, and human oversight. Later communications from EU policy amplify the dual objectives of excellence and trust. At an operational level, risk-management tools like Canada's Algorithmic Impact Assessment provide structured procedures to assess impacts, determine risk levels, and define mitigation measures prior to deployment.

These institutional reports also stressed data governance (quality, provenance, access control), auditability, and procurement standards allowing models and decision logs to be inspectable and contestable (OECD, 2021a; NAPA, 2019). From this perspective, governance is not limited to ethics principles but includes organizational processes, formal roles, and technical controls enabling oversight along the AI system lifecycle. Different administrations also explored transparency-enhancing instruments, such as public algorithm registers showing where and how automated systems are used, under which safeguards, in support of both public scrutiny and internal accountability. Prominent examples often cited in policy debates are municipal algorithm registers introduced in Amsterdam and Helsinki that aimed at increasing visibility of algorithmic decision support and facilitating contestability in sensitive domains. These initiatives represent a growing trend toward more transparent and controllable algorithmic use, especially in contexts where decisions might have an impact on rights or access to services (Kuziemski & Misuraca, 2020; European Commission, 2019).

2.3 Concluding remarks

Overall, the literature review indicates that scholarship and policy-oriented work on AI in public administration has become both extensive and increasingly organized, offering a broad understanding of how governments approach AI and what tends to shape these initiatives. Across the reviewed sources, contributions repeatedly gravitate around a set of recurring macro-themes, which are consolidated in Table 1.

Macro-themes	**Themes clustered and grouped from the literature**
Adoption Factors	• Technological readiness (Neumann et al., 2022) • Organizational capacity (Neumann et al., 2022) • Favorable policy environment (Neumann et al., 2022) • Shortage of AI skills and expertise (Ambrosetti, 2024; Shrum et al., 2019) • Insufficient funding and resources (Ambrosetti, 2024; Osservatorio AI4PA, 2025) • Public trust in AI systems (Young et al., 2019) • Leadership support and strategic vision (Ambrosetti, 2024; Neumann et al., 2022) • Legacy IT systems and data silos (Shrum et al., 2019; Osservatorio AI4PA, 2025) • Bureaucratic resistance and risk-averse culture (Shrum et al., 2019; Ambrosetti, 2024) • Complex regulatory and legal constraints (Ambrosetti, 2024)
Implementation Strategies	• Pilot testing of AI solutions (Ambrosetti, 2024) • Innovation labs for experimentation (van Veenstra & Kotterink, 2017) • Incremental scaling on small successes (Ambrosetti, 2024) • Agile procurement processes (Ambrosetti, 2024)

	• Cross-agency collaboration initiatives (Osservatorio AI4PA, 2025) • Co-creation with citizens (Kuziemski & Misuraca, 2020) • Training and upskilling public servants (Osservatorio AI4PA, 2025) • Appointing dedicated AI leadership roles or task forces (Osservatorio AI4PA, 2025) • Public-private partnerships for AI innovation (Mikhaylov et al., 2018; Ambrosetti, 2024) • Regulatory sandboxes for experimentation (Ambrosetti, 2024)
Benefits & Opportunities	• Data-driven decision-making and forecasting (Margetts & Dorobantu, 2019) • Reduced administrative burdens (Engin & Treleaven, 2019) • Improved public service quality (Criado & Gil-García, 2019) • Efficiency gains in operations (Wirtz et al., 2019) • 24/7 service access via AI assistants (Osservatorio AI4PA, 2025) • Enhanced citizen engagement at scale (Engin & Treleaven, 2019) • Greater public value creation (Criado & Gil-García, 2019; Mikhaylov et al., 2018)
Ethical & Social Challenges	• Privacy and data protection concerns (European Commission, 2019) • Algorithmic bias and discrimination (Neumann et al., 2022)

	• Threats to fairness and democracy (Margetts & Dorobantu, 2019) • Lack of transparency ("black-box" AI) (Kuziemski & Misuraca, 2020) • Accountability for automated decisions (Kuziemski & Misuraca, 2020) • Erosion of citizen trust (Young et al., 2019) • Digital divide and exclusion risks (Osservatorio AI4PA, 2025) • Workforce displacement concerns (Shrum et al., 2019)
Governance & Accountability	• Public sector AI governance frameworks (Kuziemski & Misuraca, 2020) • Accountable AI procurement standards (Ambrosetti, 2024) • Data governance and quality management (Mikhaylov et al., 2018; European Commission, 2020) • Improving data literacy in government (Osservatorio AI4PA, 2025) • Ensuring algorithmic transparency (Wirtz et al., 2019) • Regulatory oversight and audit mechanisms (Government of Canada, 2024) • Government policy guidance for AI adoption (OECD, 2019)

Table 1: Macro-themes derived from the literature review

Moreover, the table functions as an evidence-based synthesis of the main areas through which the field has framed the debate: it captures the topics that authors most consistently return to, the questions they commonly prioritize, and the dimensions through which AI in government is typically interpreted and evaluated. By structuring the literature in this way, Table 1 also clarifies that the existing knowledge base is not fragmented or scarce; on the contrary, it provides substantial coverage of several relevant dimensions, ranging from the organizational and institutional conditions that enable or hinder AI initiatives, to operational approaches for implementation, to the benefits that AI may generate for public service delivery and decision-making, as well as the ethical, societal, and governance implications that accompany algorithmic systems in public contexts.

At the same time, however, the literature review highlights an important limitation that directly motivates the present study. Despite the breadth of contributions and the apparent consolidation of the field, the implementation challenge remains only partially addressed as an explicit object of explanation. A substantial share of research adopts a descriptive stance, mapping drivers and barriers, proposing conceptual lists, or outlining recommended steps, while providing more limited insight into the mechanisms through which specific organizational and technical conditions become enabling levers or binding constraints in practice. Consequently, the field still offers uneven analytical clarity on how, for example, fragmented data ownership generates iterative redesign and delays, how interoperability debt and legacy infrastructures constrain deployment across organizational units and information systems, or how uneven internal capabilities shape dependence on external vendors and influence implementation trajectories.
This limitation becomes even more pronounced when attention shifts from experimentation to routinization. While pilots are often examined as innovation episodes, comparatively fewer studies investigate what changes when AI initiatives are expected to stabilize within ordinary administrative routines. In this phase, requirements typically escalate in terms of data quality, documentation, traceability and auditability; AI outputs must be embedded into established workflows and legacy IT architectures; coordination becomes necessary across multiple functions (such as IT, legal/compliance, procurement and operational units); contractual arrangements may intensify risks of vendor lock-in; and administrations must absorb the operational burden associated with maintenance, monitoring and model updates. These dynamics

are frequently acknowledged but not consistently analyzed as determinants that shape implementation outcomes and long-term stabilization.

A further limitation concerns governance and accountability. These dimensions are widely discussed through normative principles (transparency, privacy, fairness, and human oversight) and through high-level frameworks, yet their role as practical determinants of implementation remains insufficiently evidenced. In particular, the literature provides limited empirical insight into how compliance and risk-management obligations translate into concrete design and deployment decisions (including explainability-performance trade-offs), how responsibility is allocated across internal units and external suppliers, which monitoring arrangements are feasible under resource constraints, and how accountability demands interact with procurement rules and documentation requirements during scaling. This leaves underexplored the extent to which governance is not merely a boundary condition, but an organizational architecture that can accelerate, slow down, or redirect implementation pathways.

In light of these gaps, the thesis formulates the following Research Question:

"Which organizational, technical and governance-related conditions most strongly influence the successful implementation and stabilization of AI-based projects in public administrations, and through which mechanisms do they enable (or obstruct) the transition from pilot initiatives to routine operational use under public-sector accountability constraints?"

From this perspective, Table 1 has a dual purpose. First, it provides a transparent consolidation of what the literature does cover, making the review more readable and analytically traceable. Second, and more importantly for the argument of this thesis, it makes visible what is missing: by showing how consistently the field clusters around certain macro-themes, the table also evidences that the RQ's focal gap remains comparatively under-discussed in an explicit and systematic way.

Consequently, the contribution of the present research is positioned precisely within this space. Building on the consolidated macro-themes identified through the literature review (Table 1), the study directs attention to the gap articulated in the RQ and approaches it in a more focused and analytically explicit manner, thereby creating the conditions for the subsequent empirical sections to contribute where the literature has so far remained limited, indirect, or inconclusive. The next section (Methodology) therefore outlines the research design, data collection, and analytical procedures adopted to investigate this gap in a rigorous and replicable way.

3. Methodology

This chapter outlines the methodological approach adopted to address the research question. The thesis uses a qualitative design that combines (i) a systematic, concept-centric literature review and (ii) semi-structured interviews with practitioners involved in public-sector digital and AI-related initiatives. The two components are deliberately integrated: the literature review provides the conceptual foundation and identifies the knowledge gap, while interviews generate primary evidence to deepen and contextualize that gap in practice.

After establishing the state of the art and the research gap in the preceding chapter, the study moved from synthesis to empirical inquiry. Specifically, the macro-themes identified in the literature review (Table 1) were used to derive the interview topics and prompts. This ensured that the interview guide systematically targeted the underexplored dimensions highlighted by the gap, while remaining open enough to capture practice-specific nuances and examples.

Following established guidelines for qualitative synthesis and inductive analysis, for example, Webster and Watson 2002; Grant and Booth 2009; Thomas 2006, I explicitly documented every methodological decision taken on search strategy, screening criteria, codebook development, and theme consolidation. This acts as an audit trail and facilitates transparency, interpretability, and methodological rigour.

In what follows, the chapter first describes the literature review methodology (search strategy, screening, and synthesis logic). It then details the interview methodology (sampling, development of the interview guide, data collection, and the coding procedure) showing how the literature-informed framework enabled coherence between the Literature Review and the Findings.

3.1 Systematic Literature Review

The literature review was conducted to consolidate and organize current academic and institutional knowledge on AI adoption in public administration and to build the analytical frame that informs the empirical component. In line with a concept-centric approach (Webster and Watson, 2002), evidence was synthesized around recurring concepts (enablers and barriers, implementation approaches, public value opportunities, ethical and social risks, and governance and accountability mechanisms) rather than summarized article-by-article.

This approach is particularly apt for AI in government, which is a multi-discipline area spanning information systems, public management, and public policy studies and is rapidly changing, hence benefiting from an integrative synthesis underlining convergences, tensions, and gaps across bodies of work.

3.1.1 Search protocol and scope

To begin the search, the scope of this review has been determined based on three boundaries:

(i) the technological domain of AI and closely related techniques, including machine learning and algorithmic decision-making;

(ii) the organizational domain: public administrations and public sector organizations (broadly defined)

The phenomenon of interest is adoption, implementation, diffusion, governance and oversight of AI-enabled systems.

I also stipulated the types of evidence to be considered, including peer-reviewed academic studies and selected high-quality institutional and policy reports, since relevant governance practices and regulatory discussions are frequently documented in grey literature that bears authority in the public sector.

It adopted a time window of 2018–2025 to capture the recent acceleration of experimentation and deployment of AI in the public sector, together with the parallel maturation of governance frameworks and regulatory debate. Earlier works were included selectively when repeatedly referenced as seminal contributions shaping subsequent research streams.

3.1.2 Search strategy and source identification

The literature search used a comprehensive, reproducible strategy that combined structured database queries and targeted retrieval of institutional documents.

Searches were carried out across the major scholarly databases and academic search engines, including "Google Scholar", and, where available, bibliographic databases like "Scopus" and "Web of Science".

To complement this academic coverage, particularly on governance, standards and accountability mechanisms, I retrieved reports and policy documents from reputable organizations, for example, supranational bodies, national governments, and public-sector observatories, prioritising those with clear authorship, methodological transparency and public accessibility.

In addition, search queries were built by combining three concept blocks:
(1) AI-related terms (e.g., *"artificial intelligence"*, *"machine learning"*, *"algorithmic decision-making"*),
(2) public-sector terms (e.g., *"public administration"*, *"public sector"*, *"government"*, *"e-government"*), and
(3) adoption/implementation terms (e.g., *"adoption"*, *"implementation"*, *"digital transformation"*, *"innovation"*, *"governance"*).

To reduce the likelihood of missing relevant studies due to terminological differences across disciplines, I performed both backward and forward snowballing. Specifically, I screened reference lists of key articles and conducted citation searches to identify more recent contributions building on influential works. This step is particularly important for interdisciplinary topics, where relevant evidence may be distributed across heterogeneous outlets.

3.1.3 Eligibility criteria (inclusion and exclusion)

Eligibility criteria were applied to ensure that the final corpus was both relevant to the research questions and suitable for synthesis.

Inclusion criteria. Sources were included if they:
(i) explicitly addressed AI adoption, implementation, or governance in public administration (broadly defined);
(ii) provided conceptual, empirical, or policy-relevant evidence related to at least one focal dimension of the study (enablers/barriers, implementation strategies, benefits/public value, ethical-social risks, governance/accountability).

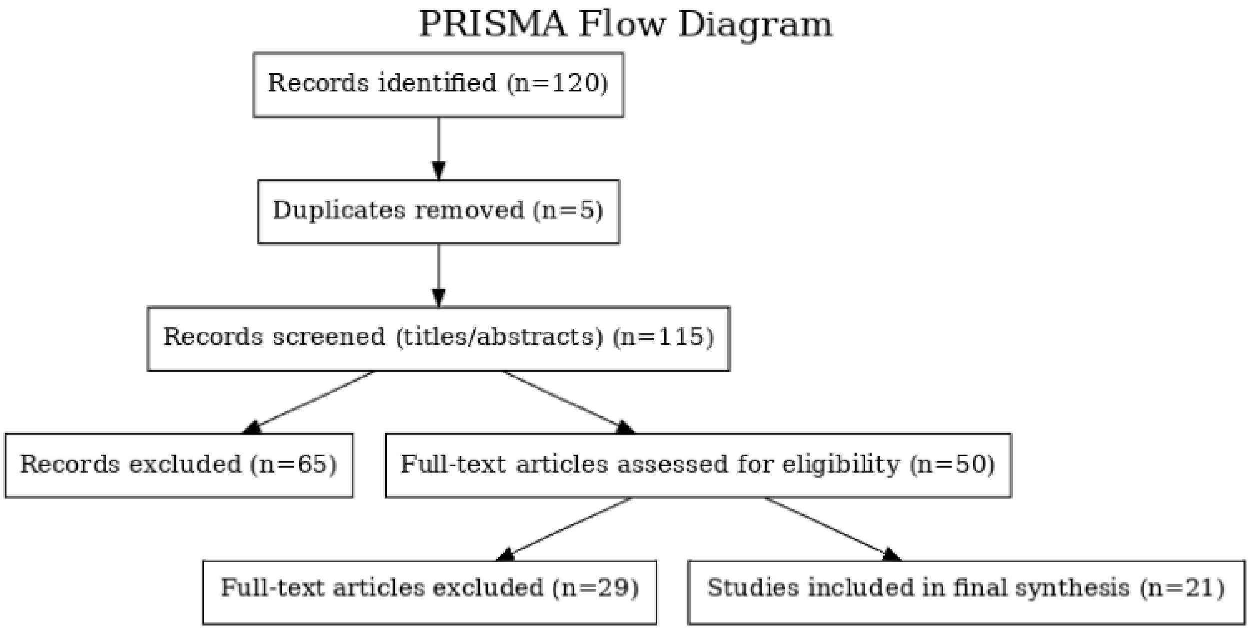
Exclusion criteria. Sources were excluded if they:
(i) were purely technical contributions without organizational, managerial, or governance implications;
(ii) focused on private-sector AI adoption with limited transferability to public administrations;
(iii) lacked sufficient transparency to assess the basis of claims (e.g., unclear methods in empirical studies or weak traceability in reports);
(iv) were not accessible in full text;
(v) were not available in English or Italian, as only sources in these two languages were considered to ensure consistent interpretation and analytical accuracy.

3.1.3 Screening procedure and documentation

Screening followed a staged process consistent with PRISMA logic. First, duplicates were removed. Second, titles and abstracts were screened for topical relevance. Third, potentially eligible records underwent full-text assessment against the inclusion/exclusion criteria. The resulting selection pathway and record counts at each stage are documented in the PRISMA flow diagram included in the thesis, allowing the reader to trace the progression from initial identification to final inclusion.

Where screening decisions required judgement (e.g., borderline relevance), I applied a conservative approach in the early stages, retaining records for full-text assessment, and applied stricter criteria at the full-text stage, where relevance to public-sector AI adoption and governance could be evaluated more precisely.

Figure 1: *PRISMA flow diagram illustrating the literature selection process*



3.2 Semi-Structured Interview Study

Building on the concept-centric synthesis developed in the Literature Review (following Webster and Watson's approach), the empirical component of the study relied on semi-structured interviews to generate actor-level evidence on how AI-related initiatives are discussed, initiated, implemented, and governed in public-sector settings. The interviews were conceived as a direct response to the research gap identified in the preceding chapter: while prior work robustly maps enabling conditions, risks, and governance principles, it provides comparatively less granular evidence on how these dimensions translate into day-to-day decisions, trade-offs, and constraints. The interview data therefore complement the literature by documenting how the literature-derived macro-themes manifest in practice and by enabling an explicit comparison between the state of the art and observed organizational realities.

Importantly, the Literature Review did not only inform interpretation ex post; it also provided the conceptual scaffolding for empirical analysis. The macro-themes identified in Chapter 2 were used as *sensitising concepts* to guide both the development of the interview guide and the subsequent thematic analysis. As detailed in the coding section, transcripts were first coded inductively to preserve proximity to participants' accounts and then organized under the macro-themes established in the Literature Review. This design choice ensures continuity between chapters and provides a transparent analytical pathway from verbatim interview material to the themes reported in the Findings.

3.2.1 Sampling Strategy and Participant Selection

Participants were selected through purposive sampling to include individuals with direct experience of public-sector digital innovation and AI-related initiatives. The objective was not statistical representativeness, but the identification of analytically relevant informants able to shed light on how AI-related initiatives become feasible, implemented, and governed in public administration. In line with the study's focus on AI readiness and enabling conditions (rather than sector-specific technical applications), the sampling strategy prioritised roles positioned to observe cross-cutting organizational and inter-organizational dynamics that typically shape AI feasibility, such as: data governance and quality management, cybersecurity and compliance, procurement and vendor coordination, and accountability arrangements.

Eligibility criteria required participants to provide concrete, experience-based insights into three interrelated areas: (i)organizational conditions shaping readiness for AI (e.g., strategic commitment, data and infrastructure foundations, skills, and change capacity); (ii) implementation pathways and operational choices (e.g., pilot-to-scale trajectories, integration into operational processes, build–buy decisions, and risk mitigation); and (iii) governance and accountability arrangements (e.g., responsibility allocation, transparency expectations, human oversight, and compliance constraints).

Recruitment began with direct outreach to professionals identified as relevant to these areas and was complemented by a limited referral (snowball) approach, whereby initial informants suggested additional contacts with comparable expertise. Importantly, the same eligibility criteria were applied throughout, so that referrals served to broaden access to specialised profiles rather than to expand the sample opportunistically.

CODE	PROFILE	ORGANIZATION / DOMAIN
INT1	ICT Director	Regional Administration – Public service domain
INT2	Regional Officer	Regional Administration – Public service domain
INT3	Management Consultant	Supports regional health directorate
INT4	Project/Service Manager	Consulting firm
INT5	Policy-oriented expert / researcher	AI strategy and projects
INT6	Cybersecurity & compliance consultant	SME / training and compliance
INT7	University professor	Academia
INT8	Journalist	Public sector innovation & AI communication

Table 2: *Interviewees' profile*

The final set of interviewees (Table 2) was designed to ensure breadth of perspectives across roles while remaining tightly aligned with the research question. The sample combines internal public-sector viewpoints (e.g., ICT and digital-transformation responsibilities within a regional administration) with complementary ecosystem perspectives (e.g., management consulting, cybersecurity and compliance support, policy-oriented expertise, and academia). This diversity was intentionally pursued to strengthen the analysis in two ways: first, it reduces the risk that readiness and adoption are interpreted through a single organizational lens, as these processes are often experienced differently by strategic, operational, technical, and governance actors; second, it enables systematic comparison across positions, allowing recurring patterns, tensions, and trade-offs to be assessed across different responsibilities.

This sampling choice is consistent with how the literature conceptualises AI adoption in public administration as a boundary-spanning process, shaped not only by internal capabilities but also by inter-organizational arrangements.

Following an initial familiarisation reading, one interview (INT8) was excluded from the analytical sample because responses remained largely generic and did not provide sufficiently specific, experience-based material aligned with the study objectives. As the interview could not be translated into stable first-level codes, excluding it prior to final coding helped preserve the analytical depth, comparability, and internal consistency of the dataset. On this basis, the empirical analysis and Findings draw on seven interviews (INT1–INT7).

3.2.2 Development of the Interview Guide

The interview guide was developed by operationalizing the literature-derived macro-themes (Table 1) into interview topics, core questions, and role-sensitive follow-up probes. In other words, the literature review did not merely inform interpretation after data collection: it provided the point of departure for designing what to ask and how to ask it. This design served a dual purpose: (i) to ensure systematic coverage of the key dimensions consistently discussed in prior work, and (ii) to elicit practice-based evidence capable of deepening the literature gap by clarifying mechanisms, constraints, and decision rationales observed by actors involved in public-sector innovation. Accordingly, Table 1 functioned as a set of second-level sensitizing concepts guiding the interview prompts. Each macro-theme was translated into open-ended questions phrased in accessible language (to avoid assuming shared academic terminology) while preserving analytical traceability. Follow-up probes were tailored to participants' roles and responsibilities to elicit concrete examples (projects, decisions, constraints) and to clarify causal pathways and trade-offs (e.g., why a pilot scaled or stalled; how accountability was allocated; which data issues emerged in implementation).

The resulting guide comprised six sections and twelve core questions (the full interview guide is reported in Annex). The sections provide a coherent conversational progression (from context to outlook) while collectively covering the five literature macro-themes (Adoption Factors and Organizational Readiness; Implementation Strategies and Operational Pathways; Benefits and Public Value Opportunities; Ethical and Social Challenges; Governance and Accountability Arrangements).

Structurally, the first sections establish respondents' role and their organization's broader innovation and digital-transformation context, which provides the baseline against which AI-specific choices can be interpreted. The subsequent sections then move to AI emergence, enabling conditions, risks and ethical considerations, and governance. This progression is intentional: it mirrors the way the literature-derived macro-themes were transformed into interview questions and, as a consequence, it increases the likelihood that answers naturally populate those same analytical dimensions. The coherence later observed between literature macro-themes and second-level interview codes is therefore a direct outcome of the research design: questions were built from the macro-themes to probe the gap, and responses generated empirical detail that could be organized under the same conceptual scaffold.
Moreover, given the semi-structured format, participants at times anticipated themes that would formally belong to later sections. When this occurred, the conversation was allowed to develop naturally and targeted follow-ups were used to ensure that all core topics were covered.

3.2.3 Data Collection and Management

Interviews were conducted one-to-one in a confidential setting, either in person or via secure videoconferencing depending on participant availability. Prior to each interview, I explained the study objectives, the voluntary nature of participation, and the confidentiality measures adopted. With consent, interviews were audio-recorded to ensure accuracy and to minimize reliance on real-time notetaking.
Recordings were transcribed for analysis. During transcription and reporting, identifying information (names of individuals, offices, or specific projects) was removed or generalized. Participants are referred to through anonymized labels in order to protect confidentiality and encourage candid reporting, particularly on sensitive topics such as organizational resistance, procurement constraints, and governance gaps.

3.2.4 Qualitative Analysis of Interviews (Inductive Coding)

Interview transcripts were analyzed through a thematic coding procedure designed to ensure (i) an explicit audit trail from verbatim material to reported themes and (ii) analytical continuity with the conceptual framing established in the Literature Review. The macro-themes identified in Chapter 2 (Table 1) informed the construction of the interview guide and served as sensitizing dimensions for the initial reading of the material. However, they did not constitute a predetermined coding scheme.

The coding process was conducted iteratively and remained grounded in the interview data: first-level codes were generated inductively from recurring meanings and implementation-related dynamics emerging across transcripts, and were subsequently refined and consolidated through successive rounds of comparison. Only in a later step these empirically derived codes were grouped into higher-order themes and related back to the macro-themes from the Literature Review, in order to preserve empirical openness while ensuring coherence with the overall conceptual framework and the research gap under investigation.

The coding scheme followed two complementary layers:

1. **First-level (inductive) coding:** Transcripts were read iteratively and segmented into meaning units (sentences or short passages). Each unit was labelled with a concise first-level code capturing the concrete content expressed by interviewees (e.g., data fragmentation, interoperability constraints, procurement bottlenecks, capability needs, privacy/security requirements, explainability concerns, accountability ambiguity). First-level labels were refined across interviews through an evolving codebook to improve consistency (merging overlapping labels, clarifying boundaries, and splitting overly broad codes).
2. **Second-level (literature-informed) structuring:** Once first-level coding stabilized, codes were clustered under the literature-derived macro-themes**,** which were retained as second-level codes. This alignment is a direct consequence of the study design: the interview guide was constructed from the macro-themes, interview data were expected to address those same domains. Retaining the macro-themes as second-level codes therefore provides a stable organising frame across chapters, while first-level codes populate each theme with interview-grounded, context-specific content.

Table 3 below synthesizes this cross-walk by systematically linking the literature-derived macro-themes (second-level codes) to the clustered first-level codes emerging from the interview material, and by substantiating each cluster with short verbatim excerpts and the corresponding interview identifier (INT#).

Literature-derived macro-themes (second-level codes)	Interview-derived first-level codes	Illustrative excerpts from interviews (INT#)
Adoption Factors and Organizational Readiness	**Fragmented data ownership and uneven digital maturity** (data silos, dispersion across units)	"We observed a highly heterogeneous situation: some organizations were more advanced, while others lacked even basic capabilities." (INT1)
	Data preparation and traceability needs (cleaning, documentation, sensitive fields)	"The information systems area… cleans traceability codes." (INT2)
	Legacy systems and interoperability debt (integration across domains)	"Improving interoperability across territorial, hospital, and regional information systems…" (INT3)
	Skills and capability gaps (training not optional; uneven literacy)	"The average age is rather high… so training happens mostly on the job." (INT2)
	Leadership sponsorship and change readiness (strategy + governance of change)	"You need people who have a strategy in mind… and who can provide a strong push for change." (INT1)
Implementation Strategies and	**Pilot-first adoption logic** (PoC as safe entry point)	"It is better to start with pilot projects before

Operational Pathways		adopting solutions across the whole organization." (INT7)
	From pilots to scale: structural barriers (moving beyond isolated experiments)	"There is a structural difficulty in moving from isolated experiments to systemic and scalable initiatives." (INT4)
	Procurement and coordination constraints (tendering, alignment, onboarding)	"They launched a regional tender that all organizations then had to plug into." (INT1)
	Change management and process redesign needs (culture, norms, organization)	"Resistance to change… driven by cultural, regulatory, and organizational factors." (INT4)
	Sourcing model: internal–external configuration (capabilities + partners)	"Building a team combining internal staff and external consultants could be an effective strategy." (INT6)
Benefits and Public Value Opportunities	**Administrative efficiency and time compression** (faster cycles)	"What used to take two days now takes four hours." (INT2)
	Service accessibility and user-facing improvement (citizen interaction)	"A chatbot on the portal… to communicate with users… including topics such as waiting lists." (INT1)
	Decision-support and monitoring (dashboards, indicators)	"They generate monitoring indicators for the different processes." (INT1)

	Resource prioritization and planning (waiting lists, forecasting)	"AI can support planning and management of waiting lists." (INT3)
	Knowledge retention and organizational learning (internal KM)	"The problem is when someone retires… we need to find a way to retain and leverage that knowledge…" (INT2)
Ethical and Social Challenges	**Privacy / confidential data constraints** (limits to reuse/training)	"You cannot train systems on documents that are highly confidential." (INT2)
	Cybersecurity and security-by-design pressures (threat environment)	"We are in a digital war… for example, the Lazio Region case and the ransom demand…" (INT6)
	Explainability / reliability concerns (validation needed)	"Often the answer is good, but sometimes it is incorrect… you need tools to understand and verify it." (INT7)
	Bias, discrimination, and inequity risks (distorted data, opaque criteria)	"There is a risk of systemic discrimination… models trained on distorted data." (INT3)
	Low ethical institutionalization (ethics not embedded)	"No one really thinks about ethics." (INT6)
Governance and Accountability Arrangements	**Human-in-the-loop accountability** (decision responsibility remains)	"There must always be a person who ultimately makes the decision." (INT2)

	Leadership and steering as governance infrastructure (direction + oversight)	"There needs to be central governance of the change process…" (INT1)
	Data governance as a prerequisite (control, stewardship)	"You need proper control and stewardship of the data." (INT6)
	Monitoring, auditability, and operational oversight (supervision mechanisms)	"A system where responses are… monitored by us." (INT1)
	Regulatory alignment and pace mismatch (rules vs speed)	"The issue is speed… it must be continuously updated… yet timelines are not compatible." (INT5)

Table 3: *Coding scheme (second-level themes and first-level concepts)*

By consolidating the coding structure and its evidentiary anchors, Table 3 establishes a transparent analytical baseline for the empirical reporting that follows. It defines the stable second-level thematic architecture adopted throughout the thesis and specifies the interview-grounded first-level content that will be synthesized within each theme. On this basis, the next chapter (Findings) uses the same macro-themes as organizing headings to present the dominant patterns across interviews, highlight points of convergence and divergence, and illustrate them with selected quotations. In doing so, the empirical results can be discussed in direct alignment with the Literature Review and the research gap identified earlier, while maintaining a clear audit trail to the underlying data.

4. Findings

Building on the methodological design outlined in Chapter 3, this chapter reports the empirical material derived from the analytical interview sample (INT1–INT7). The interview profiles, inclusion rationale, and coding architecture are documented in the previous chapter; the focus here is the structured presentation of what participants reported, using a reporting format that preserves traceability to the underlying interviews and defers interpretation to the Discussion chapter.

Because the dataset brings together informants with substantially different roles, the same issue is often framed through distinct lenses (e.g., organizational constraints, delivery and scaling conditions, compliance and risk, or ethical oversight). For this reason, Table 4 is introduced as a navigational device. It does not replicate participants' profiles or organizational affiliations; rather, it summarizes the dominant analytical perspective that characterized each interview. This perspective map supports cross-interview comparison throughout the chapter by clarifying how convergences in content may coexist with differences in emphasis.

Perspective	Code
Digital governance; data; infrastructure; citizen services	INT 1
Operational constraints; administrative processes; service management	INT 2
Interoperability; digital health; implementation constraints and enablers	INT 3
AI delivery; scalability; cloud and integration conditions	INT 4
Prudence; skills; public-sector AI trajectory; ethics	INT 5
Security; risk; regulatory requirements; organizational training	INT 6
Ethics; human oversight; responsibility; capability gaps	INT 7

Table 4: *Interviewees' perspective*

On this basis, the section that follows explains the thematic structure used to organize and report the findings. The five macro-themes provide the stable headings of the chapter, while the perspectives summarized in Table 4 serve as a complementary reading key for how the evidence within and across themes is articulated.

4.1 Thematic structure used to report findings

Findings are organized under same themes identified in the Literature Review and, as specified in Chapter 3, they were retained as second-level codes for structuring the interview analysis. In this chapter, the macro-themes therefore function as stable reporting headings that ensure continuity between the conceptual framing and the empirical evidence.

Within each macro-theme, the reporting is articulated through sub-sections that capture recurrent clusters of first-level codes**.** These clusters reflect how participants connected issues in practice: interviewees frequently co-mentioned certain elements, described them in sequence as part of the same process, or presented them as mutually dependent constraints and enablers. Sub-sections are used to represent this empirical granularity without fragmenting the overall structure.

Importantly, these sub-sections are descriptive rather than interpretive. They do not introduce new conceptual categories, nor do they anticipate the explanatory argument developed in the Discussion. Their role is to organise the evidence in a way that makes recurring linkages visible and supports systematic reporting within each macro-theme. Where recurrence is observed, it is documented through participant codes and, where appropriate, illustrated with short excerpts.

Because AI-related initiatives are embedded in broader digital transformation programmes, some issues legitimately span multiple analytical domains. Accordingly, a given phenomenon may reappear in more than one macro-theme (for example, data governance discussed as a readiness prerequisite, as an implementation constraint, and as a governance requirement). When this occurs, repetition is intentional: the issue is reported where it is most relevant to the analytical function of the theme, while consistent terminology and explicit traceability to interview codes preserve coherence across the chapter.

4.1.1 Adoption factors and organizational readiness

4.1.1.1 Strategic orientation and leadership

Participants described AI initiatives as emerging within broader digital transformation agendas. Across interviews, the degree to which AI was approached as a strategic lever was reported to depend on leadership attention, prioritization capacity, and the ability to coordinate across organizational units. In internal accounts, leadership was not described only as top-level sponsorship but also as the practical ability to align multiple stakeholders (IT, service directorates, procurement offices, and data owners) around shared objectives.

Strategic orientation was also discussed in relation to ‘problem framing’. Rather than starting from AI as a technology, internal actors often framed priorities in terms of service problems (e.g., service backlogs, citizen access, system monitoring), with AI positioned as one possible instrument within a broader set of digital tools.

In public-sector AI–related contexts, strategic orientation was frequently articulated through the goal of improving managerial and policy decision-making. INT1 framed digital governance to consolidate information flows and create tools that enable regional planning and resource allocation.

“A central part of my role is to provide decision-makers with support tools that can gather the information we hold and enable health planning across the whole region.” (INT1)

INT3 likewise reported a shift from perceiving digital projects as purely technical compliance to recognizing their strategic value for service quality and sustainability, especially when new leadership teams promoted an objectives-oriented approach to innovation.

External respondents stressed leadership as a condition for ‘informed steering’ of AI initiatives: leaders were described as needing to understand trade-offs (benefits, risks, organizational effort) and to create decision spaces where experimentation can occur within clear boundaries. In this view, leadership is closely tied to the ability to set expectations and to prevent “technology push” dynamics.

4.1.1.2 Data readiness and information governance

Data readiness emerged as the most recurrent enabling (or constraining) factor across interviews. Interviewees referred to data quality, availability, standardization, documentation and ownership as practical determinants of whether AI use cases can be initiated and whether they can be scaled beyond pilots. Respondents also discussed data readiness as uneven across public organizations, with different entities exhibiting different maturity levels.

Participants described the issue in concrete terms: datasets are often distributed across systems and organizational units; records may be incomplete or encoded with heterogeneous standards; and access may be constrained by both organizational rules and privacy requirements. For several respondents, these issues mean that an “AI layer” cannot be effective if data governance and integration work are not addressed first.

In the regional administration context, data readiness was described as inseparable from efforts to integrate administrative and domain-specific information flows. Participants cited initiatives such as core digital record systems, centralized payments and authorization systems, monitoring dashboards and business intelligence as both products of digital transformation and prerequisites for more advanced analytics.

“Strengthening the core digital record systems and deploying business intelligence tools for analysis and monitoring are central to supporting decisions.” (INT3)

Multiple interviewees described interoperability and data integration as necessary to reduce fragmentation between service providers, local service units and regional directorates. INT3 explicitly linked interoperability to the ability to deliver continuous care and to avoid duplication, framing it as a structural condition for data-driven planning.

“Improving interoperability between territorial, service provider and regional information systems is necessary to overcome informational fragmentation and reduce duplication.” (INT3)

From an academic perspective, INT7 underlined that data-intensive systems (including supervised learning approaches) require historical data of adequate quality and governance. This point was raised as a practical constraint affecting feasibility, as models depend on training datasets that represent the relevant population and processes.

"To make these systems work you need data to train them: supervised learning requires an historical dataset that can be used to train the model." (INT7)

Overall, interviewees described data governance not only as a technical exercise but also as an organizational one, requiring clear rules on access, purpose limitation and stewardship, particularly when sensitive datasets are involved.

4.1.1.3 Infrastructure, interoperability and cloud migration

Infrastructure conditions were frequently discussed as both an enabling layer and a constraint shaping the pace of AI initiatives. Participants referred to legacy systems, heterogeneous platforms and limited integration capabilities as obstacles to scaling.

Delivery-oriented participants emphasized that AI is rarely "added" to an organization in isolation: AI components depend on stable data pipelines, interoperable systems and scalable computing environments. In this respect, cloud migration was repeatedly mentioned as a turning point.

INT4 described cloud migration in public administrations as a process often triggered by external policy directions and national strategies, requiring administrations to abandon obsolete on-premises infrastructures and to restructure internal capabilities.

"In many cases, moving to the cloud was driven by national strategies and regulatory directions that effectively made it necessary to abandon outdated on-premises infrastructures." (INT4)

At the same time, cloud adoption was described as enabling subsequent innovation steps: scalable and interoperable environments were reported to be preconditions for data-intensive and AI-enabled services.

"Cloud adoption has been a turning point not only for modernizing IT, but also for creating enabling conditions for other emerging technologies such as AI, which requires scalable and interoperable environments." (INT4)

Interoperability was repeatedly framed as a ‘non-optional’ requirement in complex public service ecosystems. Participants described interoperability needs both horizontally (across organizational units) and vertically (across local-regional-national systems), highlighting that fragmented infrastructures tend to confine AI experiments to isolated silos.

Internal respondents described interoperability initiatives as ongoing programmes rather than discrete projects and stressed that AI use cases are expected to build on these programmes. In this view, AI feasibility is shaped by how far administrations have progressed in modernizing architectures and data exchange standards.

4.1.1.4 Skills, roles and learning mechanisms

Interviewees consistently referred to skills and learning mechanisms as prerequisites for AI-related initiatives. Skills were described at multiple levels: specialized technical competencies (data management, AI engineering, evaluation), managerial competencies (ability to commission, monitor and govern AI solutions), and operational competencies (ability to use tools appropriately in day-to-day work).

Some respondents also emphasized that public administrations need ‘translation’ capabilities: the ability to translate service needs into technical requirements, and to translate technical properties (limitations, confidence, failure modes) into operational rules for use.

Several participants noted that capacity-building should not be limited to “AI specialists”. INT5 argued that competencies are needed ‘at all levels’ and that administrations should be able to discuss projects with experts before taking decisions, rather than adopting tools hastily.

“Competencies are needed at all levels, not only among leaders… and decisions should be taken after discussing with experts, without moving too fast.” (INT5)

From the compliance and security perspective, training was described as a condition for adoption and for risk mitigation. INT6 stressed that introducing tools without training reduces actual uptake and increases the likelihood of misuse.

“The tool should be introduced only once employees are trained; otherwise, it is not used because it is not understood.” (INT6)

Learning was framed as continuous rather than one-off. INT6 noted that both technologies and regulatory requirements evolve rapidly, implying that training programmes need to be recurrent and tailored to organizational needs.

"Training must be continuous because technologies evolve constantly; organizations also need to select the right tools based on their own needs, and a mixed team of internal staff and external consultants can support this evolution." (INT6)

Finally, multiple interviewees highlighted multidisciplinary teamwork. Particularly in public service delivery, effective projects were described as requiring coordination between IT specialists, data experts, legal/compliance profiles and domain professionals who can validate outputs and contextualize results.

4.1.1.5 Organizational culture, change capacity and risk appetite

Beyond skills, interviewees described organizational culture and change capacity as determining whether AI initiatives remain exploratory or become operational. External delivery actors reported that public-sector organizations often display risk aversion and procedural rigidity, which can discourage experimentation and slow down project approvals.

INT4 explicitly connected the limited diffusion of AI projects in public administrations to cultural and organizational constraints, describing initiatives as 'rare and fragmented' despite growing attention to AI topics.

"AI projects in public administration are still rare and fragmented, partly due to persistent resistance to change and organizational constraints." (INT4)

Expectation management was an associated theme. INT5 warned against "enthusiasm without variables", describing a risk of excessive expectations when AI is discussed without adequate consideration of organizational and societal constraints.

"It would be better to be more prudent: many people are enthusiastic without considering the variables, creating excessive expectations." (INT5)

Internal respondents recognized organizational constraints but also reported signs of increasing strategic awareness and willingness to move beyond isolated projects, especially when digital transformation is linked to service sustainability and to measurable objectives.

Interviewees also described organizational fragmentation as an operational culture issue: when multiple entities adopt heterogeneous solutions independently, learning and scaling are hindered. Several participants described centralization and standardization choices as responses to this fragmentation.

4.1.1.6 External pressures and enabling ecosystem

A major cluster of readiness factors related to the external institutional environment. Interviewees repeatedly referred to national programmes, funding streams and regulatory directions as catalysts that shape both priorities and timelines. These drivers were described as particularly influential for infrastructure modernization and for the diffusion of digital health services.

INT3 described a "hybrid" pathway in which external pressures (notably PNRR) intersect with internal strategic intent. PNRR funding was reported as a catalyst due to its strict timelines, measurable objectives and earmarked investments.

"The National Recovery and Resilience Plan (PNRR), with its timelines, measurable objectives and earmarked funding, has acted as a catalyst for digital solutions, setting clear directions on infrastructure modernization and digital service channels." (INT3)

External delivery respondents referred to national cloud and interoperability programmes as enabling layers, while also noting that externally driven modernization can create pressure when internal capabilities are insufficient. In such cases, administrations were reported to rely on external support for delivery and project management.

The broader ecosystem was repeatedly mentioned as a source of knowledge and capacity. Participants referred to collaborations with universities, external consultants, technology providers and specialized SMEs as practical channels through which administrations access expertise, especially under capacity constraints. In this ecosystem view, readiness is partially relational: it depends on the ability to coordinate and govern partnerships over time.

From a security standpoint, INT6 connected the increase in compliance requirements to an evolving threat landscape, emphasizing that digital transformation proceeds in parallel with heightened security and resilience expectations (including critical infrastructure obligations and cybersecurity frameworks).

4.1.2 Implementation and operationalization strategies

4.1.2.1 Use case selection and scoping

When moving from general interest to operational initiatives, participants highlighted the importance of selecting use cases that are feasible given current data and infrastructure conditions and that address salient administrative priorities. Use case selection was described as an exercise in balancing ambition with constraints, and as a practical step where organizational readiness is tested.

In public-sector AI–related accounts, concrete examples included: decision-support tools for waiting list management and service planning; document-intensive process automation (e.g., authorizations and administrative controls); and citizen-facing support services (e.g., chatbots and digital portals). These examples were typically framed as responses to operational bottlenecks and policy priorities.

“Enhancing the use of artificial intelligence and predictive analytics to support planning and the management of service backlogs is among the initiatives currently being designed.” (INT3)

Delivery-oriented participants reported that early stages often focus on bounded tasks where outputs can be validated relatively easily (for instance, extracting information from structured and semi-structured documents, or supporting operators with summarization and classification). This was described as a common approach to reduce perceived risk and to create internal reference cases.

Across interviews, scoping was also linked to the identification of responsible boundaries for automation: multiple respondents noted that AI should be used first to support humans (e.g., accelerating information retrieval) before moving to uses that materially determine service outcomes.

4.1.2.2 Procurement, contracting and vendor coordination

Procurement and contracting practices were repeatedly described as shaping implementation. Interviewees referred to tender timelines, specification burdens and the translation of needs into technical requirements as practical constraints on operationalization. In several accounts, procurement was presented not as an administrative formality but as a design stage that influences what can be built and how it will be governed.

INT1 described the use of centralized tenders to standardize investments across public service delivery entities with different digital maturity levels. Centralization was presented as a mechanism to reduce fragmentation and to ensure consistent architectures across organizations.

"With PNRR funds, the Region made a strong choice: it centralized the investments rather than leaving them to individual organizations, and launched a central tender." (INT1)

External participants noted that AI projects increase procurement complexity because administrations are asked to specify not only functional requirements but also constraints related to data protection, cybersecurity, explainability and auditability. In contexts with limited prior experience, defining such requirements ex ante was described as challenging.

Interviewees also mentioned that tender logic tends to privilege measurable deliverables, while AI projects can require iterative refinement. As a result, some participants described the value of modular procurement or phased contracting approaches that allow administrations to adjust specifications as learning progresses.

Vendor coordination was described as relevant where projects involve multiple suppliers (platform providers, cloud providers, system integrators, specialized AI vendors). Coordination needs were reported to increase when interoperability and data-sharing arrangements are still evolving or when responsibility boundaries are unclear.

4.1.2.3 Delivery models, integration and operational constraints

Interviewees reported that operationalization requires embedding AI components into existing workflows and information systems. Integration was described as a non-trivial effort that involves data pipelines, interfaces with legacy systems, access control configurations and coordination with operational units.

INT3's account of regional public service delivery digitalization illustrates this integration logic: systems such as electronic records, monitoring dashboards and administrative governance platforms were described as interconnected components rather than standalone projects, with AI envisaged as an additional layer only once these components support stable data flows.

Delivery-oriented participants referred to different delivery models (custom development, configuration of vendor platforms, hybrid approaches). Choices were described as shaped by procurement constraints, time pressure (particularly under PNRR), and the level of control administrations wish to retain over data and model behavior.

INT4 highlighted that the shift to cloud environments requires administrations to restructure internal capabilities and processes, suggesting that delivery plans must include organizational support and change management, not only technical build activities.

"This was a forced modernization that also required a restructuring of internal capabilities, both technical skills and operational processes, to fit the new technological model." (INT4)

Operational constraints were also discussed in terms of 'fit' with administrative procedures. Participants noted that even technically sound solutions can remain unused if they do not integrate with how work is organized, how responsibilities are assigned, and how decisions are documented.

4.1.2.4 Experimentation, piloting and scaling pathways

A common operationalization pattern involved staged experimentation. Participants referred to pilots and incremental rollouts as ways to manage uncertainty and to build internal confidence. At the same time, several interviewees noted that pilots can remain isolated if governance and integration issues are not addressed early.

From a delivery perspective, the diffusion of large language models (LLMs) was described as changing the pace and accessibility of experimentation. INT4 explained that pre-trained generative models can reduce initial requirements compared to traditional machine learning, enabling faster proofs of concept.

"Compared to classical machine learning, where data collection and labelling are lengthy, pre-trained generative models enable tangible results in much shorter timeframes, reducing time-to-value." (INT4)

INT4 also noted that LLM-based solutions can lower entry barriers for some use cases, while still requiring careful governance when deployed in organizational contexts, particularly where outputs may influence administrative decisions.

"While traditional machine learning often requires substantial investment in specialized skills and data governance, LLM-based solutions have democratized access to experimentation, yet governance remains essential." (INT4)

Several respondents described scaling as contingent upon three operational ingredients: (a) stable data pipelines and interoperability; (b) clear operational responsibilities (who validates, who monitors, who intervenes); and (c) a delivery model that includes maintenance and updates. Without these ingredients, scaling was described as difficult even when pilots are successful.

4.1.2.5 Performance measurement and feedback loops

Performance measurement was discussed mainly in operational terms: reducing processing times, improving monitoring capacity, increasing service accessibility and, in some contexts, improving planning quality. In accounts where projects are still in early phases, metrics were described as desired capabilities rather than established routines.

Internal respondents referred to dashboards and monitoring systems as practical tools to track processes and outcomes. In public service delivery settings, monitoring tools were also linked to public visibility and accountability pressures, as performance indicators can be scrutinized by oversight bodies and citizens.

External delivery actors noted that defining success metrics is intertwined with procurement and compliance requirements, as administrations are asked to define deliverables and constraints early, sometimes before learning effects occur. Some respondents described this as requiring a balance between measurable milestones and space for iterative refinement.

Participants also mentioned feedback loops: user feedback, monitoring of system performance, and continuous updates were described as important for sustaining benefits and addressing errors or drift, particularly when systems interact with evolving administrative rules.

4.1.3 Benefits and public value opportunities

4.1.3.1 Administrative efficiency and workload reduction

Efficiency gains were among the most consistently mentioned benefits associated with AI and, more broadly, with digital transformation. Respondents reported expectations of time savings, workload reduction and process streamlining in administrative activities characterized by high volumes and repetitive tasks.

In operational accounts (including INT2), AI was described as potentially supporting the reduction of turnaround times for procedures involving extensive documentation, where preliminary automation or assisted processing could free time for higher-value activities. Rather than replacing staff, these benefits were often framed as helping civil servants focus on tasks requiring judgement and interaction.

External delivery participants cited document analysis and information extraction as areas where benefits can be realized early without fully automating discretionary decisions. They described the ability of LLM-based tools to support summarization, classification and search across large repositories as practical applications.

INT3's description of governance platforms (e.g., centralized payments and authorization/accreditation processes) also reflects an efficiency logic: digital systems were reported to improve administrative coordination, with AI envisaged as a potential accelerator once data are structured.

4.1.3.2 Decision support and planning capabilities in complex public services

In the public service delivery domain, participants repeatedly framed AI-related initiatives in terms of decision support. Business intelligence, dashboards and predictive analytics were discussed as tools that can help administrations monitor performance, allocate resources and manage service backlogs.

INT1 described the development of monitoring dashboards that integrate information from multiple information systems used across service providers and local service units, linking these tools to the broader aim of supporting political and managerial decision-making.

"My role has involved developing business intelligence systems and monitoring dashboards that draw from our information systems to support regional decision-making." (INT1)

INT3 mentioned planned initiatives aimed at applying AI and predictive analytics to waiting list management. This illustrates how perceived "public value" was articulated in operational terms: addressing a high-visibility service issue through better planning tools.

In addition, participants described the use of analytical tools to monitor organizational performance and to identify anomalies or bottlenecks. These tools were framed as supporting both internal management and accountability, especially when service indicators are subject to external scrutiny.

4.1.3.3 Citizen-facing services and access

Citizen-facing services were frequently mentioned as an area where AI-enabled solutions may improve access and user experience. Interviewees referred to conversational agents, digital portals, mobile applications and digital service channels services as examples of innovations oriented to the "centrality of the user".

INT1 referred to a chatbot developed on the regional service portal to support citizen communication on salient issues such as emergency services and service backlogs.

"We developed a chatbot on the regional service portal to communicate with users on topics such as high-demand service units and service backlogs, issues that are particularly salient for citizens." (INT1)

INT3 described digital health applications and platforms as mechanisms to simplify access and enable more continuous interaction between citizens and the health system, while also framing digital service channels as a pathway from emergency use to ordinary service provision.

In these accounts, AI was positioned as potentially supporting front-office capacity (handling frequent questions), facilitating navigation of services, and improving the timeliness of information provision. However, respondents also noted that citizen-facing systems amplify the visibility of errors and therefore increase the need for reliability and supervision.

4.1.3.4 Service quality, timeliness and personalization

Beyond efficiency, interviewees described potential benefits in terms of improved service quality and timeliness. In public-sector AI–related accounts, these benefits were articulated through improved continuity of service provision, better coordination across service providers and more timely access to information.

Several participants linked quality improvements to interoperability and to integrated data flows that reduce fragmentation. In this view, AI is part of a broader move towards more integrated services, rather than an isolated technology.

Interviewees also referred to personalization as a potential benefit, particularly where digital platforms can enable a more continuous relationship between citizens and service providers. This was discussed cautiously and typically in connection with strong privacy and governance requirements.

Delivery-oriented respondents associated LLM-based solutions with new interaction modalities, such as natural-language interfaces that can help users access information more easily. They also noted that such benefits depend on reliable underlying sources and robust integration, because language models may otherwise produce plausible but incorrect outputs.

4.1.4 Ethical and social challenges

4.1.4.1 Privacy and data protection in sensitive domains

Ethical challenges were frequently discussed through the lens of privacy and data protection, particularly in public service delivery contexts. Respondents described privacy safeguards as shaping both technical design and governance arrangements. Compliance frameworks (notably GDPR) were often referenced as baseline obligations for data processing and risk management.

From a compliance and cybersecurity perspective, INT6 emphasized that AI-related benefits are accompanied by risks tied to data governance and security, and that organizations must retain control over personal data management.

"Any benefit of AI comes with risks, starting from data governance and the security of personal data." (INT6)

Internal respondents highlighted the sensitivity of sensitive personal data and described privacy and security constraints as shaping choices about architectures, access controls and the feasibility of using external services. In these accounts, privacy is treated as a design constraint, not an afterthought.

4.1.4.2 Bias, fairness and inclusiveness

Concerns about bias and fairness were mentioned primarily in relation to decision-sensitive applications and to the potential social consequences of automated or semi-automated outputs. Participants referred to the need to avoid discriminatory effects and to ensure that data-driven systems do not reproduce existing inequalities.

Although discussions were often general, public service delivery was repeatedly framed as a domain where fairness concerns are heightened due to direct implications for citizens' wellbeing and access to services. Respondents noted that these concerns increase when AI outputs are used to priorities cases or allocate resources.

Some participants also discussed inclusiveness in terms of "digital divide" dynamics: if AI-enabled services become primary channels, administrations need to ensure alternative access routes for citizens with limited digital literacy.

4.1.4.3 Transparency, explainability and contestability

Transparency and explainability were described as central to legitimacy and acceptability of AI-enabled tools in the public sector. Participants noted that public administrations are expected to justify decisions and to enable scrutiny by citizens and oversight bodies; therefore, systems that influence procedures must be understandable and traceable.

External delivery actors connected explainability to procurement and vendor management: administrations need to request documentation, logging and audit capabilities when acquiring systems, especially where complex models are used.

INT5 raised the difficulty of keeping ethical and regulatory frameworks aligned with rapid technological change, referring to the need for a shared 'diffuse ethics' and to the speed of AI development as a governance challenge.

"There is much discussion around this, think of the AI Act. We need a shared diffuse ethics, but the pace of technological evolution makes it hard to keep frameworks updated." (INT5)

Contestability was implicitly discussed through the expectation that humans remain capable of reviewing and overriding system outputs. Participants noted that contestability is not only a legal principle but also an operational capability, requiring interfaces, logging and workflows that support review.

4.1.4.4 Human oversight and professional responsibility

The need for human oversight emerged as one of the most explicit safeguards mentioned across interviews. This was particularly salient in public-sector AI–related discussions, where participants emphasized that professional supervision is needed to validate outputs and to avoid over-reliance on automated recommendations.

INT7 stressed that, in domains affecting citizens' lives, someone with adequate expertise must remain responsible for evaluating AI outputs and intervening when results are implausible or unsupported.

"There must always be supervision by a professional: in high-stakes domains, someone capable must verify whether the AI output reflects reality or is unfounded, because we are dealing with high-stakes public outcomes." (INT7)

Participants also described human oversight as requiring organizational investment: allocating time for review, defining responsibilities, and ensuring that staff can meaningfully contest or correct system outputs. Without such arrangements, oversight risks remaining a formal requirement rather than an operational practice.

4.1.4.5 Reliability, quality assurance and "hallucination" risks

A further set of challenges concerned reliability and quality assurance. While not all participants used technical terminology, several referred to the risk of incorrect outputs, especially in citizen-facing systems and in domains with high stakes. This issue was often discussed in connection with generative AI, where outputs may be fluent but unreliable if not grounded in validated sources.

Delivery-oriented participants described this as reinforcing the importance of controlled experimentation, validation protocols and human-in-the-loop approaches. Internal actors noted that public administrations face reputational and legitimacy risks if tools disseminate incorrect information to citizens or if automated outputs are perceived as arbitrary.

Interviewees therefore described reliability as both a technical issue (testing, monitoring) and an organizational issue (who validates, what happens when errors occur, and how citizens can seek clarification).

4.1.4.6 Workforce implications and capability divides

Social challenges were also discussed in terms of capability divides and workforce implications. Participants noted that rapid technological change can outpace organizational learning and create gaps between those who can effectively use and govern AI tools and those who cannot. These gaps were described as relevant both within administrations (between specialized units and operational staff) and, in some accounts, among citizens.

Training and continuous learning were therefore framed not only as readiness factors but also as safeguards to prevent exclusion and misuse. Some participants described the risk that tools may be informally adopted without governance if staff use external applications without adequate guidance.

In this connection, the introduction of AI tools was described as potentially reshaping tasks rather than eliminating them: participants foregrounded the need to redesign workflows so that staff roles evolve coherently with the introduction of automation and decision-support tools.

4.1.5 Governance and accountability arrangements

4.1.5.1 Data governance roles and access control

Governance arrangements were reported to encompass both data governance and the allocation of responsibilities across actors. Interviewees referred to the need for clear roles concerning data stewardship, access authorization, documentation and retention policies. In internal accounts, these roles were connected to the ability to consolidate information flows for planning and monitoring.

Participants noted that governance becomes more complex when data are distributed across multiple organizations (e.g., different public service delivery entities) or when systems rely on external suppliers. In these cases, governance includes not only internal rules but also contractual and inter-organizational arrangements.

Several respondents described access control and traceability as operational priorities: knowing who accessed which data and for what purpose was presented as essential to both compliance and accountability, particularly for sensitive domains.

4.1.5.2 Risk management, compliance and security-by-design

Risk management was frequently connected to compliance and cybersecurity. Interviewees discussed regulatory requirements as shaping organizational responsibilities and as requiring security-by-design approaches in the development and deployment of AI-enabled services.

INT6 referred to an expanding compliance landscape, highlighting that privacy and security obligations are increasingly central to digital innovation projects and require organizational planning rather than ad-hoc responses.

"European regulatory requirements around privacy and security are becoming more stringent; projects need to be planned with compliance and security built in from the start." (INT6)

From a delivery standpoint, security and compliance were also framed as procurement requirements: interviewees indicated that administrations should specify security controls, logging and monitoring expectations when commissioning AI-enabled systems.

Internal actors pointed out that compliance requirements can also shape architecture choices, for instance when deciding whether to process data in-house, on national cloud infrastructures, or through external providers. These choices were described as connected to both risk tolerance and data sovereignty expectations.

4.1.5.3 Accountability allocation across administrations and suppliers

Interviewees reported that public-sector AI projects are commonly delivered through external suppliers and partners, raising questions about accountability allocation. Participants referred to the need to clarify responsibilities for model behavior, data processing, security controls and system monitoring, especially where solutions involve complex supply chains.

Several respondents described accountability as requiring clear boundaries between “technical responsibility” (e.g., development and maintenance) and “institutional responsibility” (e.g., decisions about use, validation and communication to citizens). In this view, outsourcing does not remove the administration’s responsibility to justify and control system use.

Internal ownership was repeatedly mentioned as important even when development is outsourced. Respondents described ownership in practical terms: the ability to define requirements, validate outputs, monitor performance and decide when to intervene or suspend use.

4.1.5.4 Monitoring, auditing and lifecycle management

Monitoring and lifecycle management were described as components of responsible governance. Although detailed auditing practices were not always specified, participants mentioned the importance of continuous monitoring, performance tracking and the capacity to intervene when systems underperform or generate undesired outcomes.

In sensitive domains, the emphasis on human oversight was complemented by the need to document processes and ensure traceability of outputs. Participants also referred to the challenge of keeping systems aligned with evolving administrative rules and organizational contexts, implying the need for iterative updates.

From the delivery perspective, governance over time was also described in terms of maintenance responsibilities: AI tools require updates (e.g., new data, new rules, model recalibration), and administrations need to ensure that contracts and internal capabilities cover post-deployment activities.

4.1.5.5 Organizational governance mechanisms

Finally, interviewees referred to governance mechanisms such as coordination structures, internal guidelines and cross-functional committees, even when not described in formalized terms. Participants described the need to coordinate ICT, legal/compliance, procurement and service units to decide on acceptable use, risk controls and operational procedures.

In these accounts, governance is operationally expressed through routines: conducting risk assessments, defining access rights, documenting processes, and setting review procedures. The degree of formalization varied across contexts, but the underlying need for coordination was recurrent across interviews.

4.2 Closing remarks

This chapter has presented the empirical material generated through the interview study by reporting participants' accounts within the literature-derived macro-themes retained as the second-level structure of the analysis. The objective was deliberately descriptive: to document the issues raised by interviewees, the linkages they drew between constraints and opportunities, and the main points of convergence and variation across perspectives, while preserving traceability to the underlying interviews.

Across the chapter, AI-related initiatives are consistently portrayed as embedded in wider digital transformation trajectories rather than as stand-alone technological projects. Interviewees repeatedly located feasibility in the presence (or absence) of enabling layers, most notably data readiness and data governance arrangements, infrastructural modernisation (including interoperability and cloud migration), and organizational capabilities such as skills development and cross-functional coordination. These elements are presented as operational prerequisites that shape whether AI use cases can be initiated, translated into functioning solutions, and sustained over time.

The evidence further indicates that the transition from exploration to operationalisation is mediated by concrete implementation pathways and constraints. Procurement and vendor coordination recur not only as access mechanisms but also as determinants of delivery timelines, system configuration choices, and the distribution of responsibilities across actors. Integration into existing information systems and workflows emerges as a central effort, alongside the definition of routines for validation, monitoring, and intervention. While pilot-first approaches are frequently described as pragmatic entry points, the ability to scale is consistently tied to stable data pipelines, internal ownership, and maintenance and governance arrangements that extend beyond initial rollout.

With respect to public value, benefits are primarily articulated through tangible operational and service-related opportunities, while being framed as conditional upon reliability, supervision, and the quality and accessibility of underlying information. Ethical and social concerns are likewise described in practice-oriented terms, including privacy and confidentiality constraints, bias and inequity risks, explainability and verification needs, and the potential consequences of deploying systems whose outputs may appear plausible while being incorrect. In turn, governance and accountability emerge as a cross-cutting dimension that connects readiness and implementation, through requirements for stewardship, traceability, security-by-design, compliance routines, and explicit allocation of responsibility across organizational boundaries.

Taken together, these findings establish the empirical foundation for the thesis' analytical objective. By mapping interview evidence and role-specific emphases onto the literature-derived thematic scaffold, they enable a systematic comparison between the factors that prior research identifies as critical for AI adoption in public administration and the constraints, choices, and priorities reported by actors involved in, or closely observing, implementation. The next chapter advances this comparison by interpreting the reported patterns in relation to the state of the art, specifying where the evidence corroborates, nuances, or challenges existing claims, and deriving implications for how readiness conditions, implementation pathways, and governance arrangements jointly shape AI adoption trajectories in public administrations.

5. Discussion

This chapter constitutes the interpretive part of the thesis, as it engages with the empirical evidence presented in Chapter 4 in light of the state of the art synthesized in the Literature Review (Chapter 2). It is explicitly oriented towards answering the Research Question formulated at the end of the Literature Review: *"Which organizational, technical and governance-related conditions most strongly influence the successful implementation and stabilization of AI-based projects in public administrations, and through which mechanisms do they enable (or obstruct) the transition from pilot initiatives to routine operational use under public-sector accountability constraints?"*

To address this question, the chapter articulates how the interview findings confirm, qualify, or contradict key claims in the existing research on AI adoption in public administration, and it identifies practice-salient dynamics that remain comparatively underdeveloped in the literature. In doing so, the chapter contributes to the gap highlighted in the Introduction: while scholarship has produced detailed mappings of enabling factors, risks, and governance principles, it has more limited explanatory depth on how these factors interact in practice and which of them become decisive when initiatives move from experimentation to stable implementation within ordinary administrative routines.

The discussion will be structured using the same five macro-themes as the rest of the thesis in order to maintain continuity between the conceptual framework and the empirical findings. Each of the following sections will follow the same pattern: it will briefly recall what the literature highlights, and then juxtapose it with what the interviewees have reported, focusing on (i) what is confirmed by the empirical evidence, (ii) what is further developed using additional mechanisms or boundary conditions that have emerged from practice, and (iii) what are the tensions or trade-offs that make the literature-based expectations more complicated. Where appropriate, the chapter will also highlight issues that seem particularly salient in the interviews but are less explicitly formulated in the reviewed literature.

The chapter will finally conclude with a cross-theme synthesis that will integrate all these insights into a direct and structured answer to the Research Question, and will help to clarify the contribution of the thesis to the understanding of AI implementation trajectories in public administrations.

5.1 Adoption factors and organizational readiness

The literature on AI in public administration converges on a relatively stable set of readiness conditions (Mikhaylov et al., 2018a; Wirtz et al., 2019; Madan & Ashok, 2023). Across academic and institutional contributions, AI adoption is consistently framed as contingent on the availability and governability of data, the maturity of digital infrastructures and interoperability, the presence of relevant skills, and leadership capacity to align organizational units and sustain change over time (Mikhaylov et al., 2018a; Wirtz et al., 2019; OECD, 2021a; Neumann et al., 2022; Madan & Ashok, 2023). The interview evidence confirms the centrality of these dimensions, while refining their analytical meaning by illustrating how readiness is produced in practice and why it becomes constraining when administrations attempt to move beyond episodic experimentation.

A recurring feature of the empirical material is that readiness is not described as an abstract indicator of maturity. It is discussed through the organizational arrangements that make AI use manageable, and therefore defensible, within settings characterised by heterogeneity across units and domains (Kuziemski & Misuraca, 2020; Wirtz et al., 2019). This is particularly clear in relation to data. While the literature frequently treats data readiness through quality, accessibility, and governance principles (Mikhaylov et al., 2018a; Pencheva et al., 2020; OECD, 2021a), interviewees describe the binding issue as the work required to render information reusable under accountability constraints. Data exist, yet ownership and standards are fragmented, documentation is uneven, and substantial effort is required to reconcile traceability fields before datasets can be mobilized in a defensible manner (INT2).

This operational account becomes sharper when contrasted with the pilot-to-scale transition, which the literature commonly treats as a critical threshold for public-sector AI initiatives (Wirtz et al., 2019; Neumann et al., 2022; Madan & Ashok, 2023). A proof of concept can often be sustained through locally curated datasets and informal coordination. Long-term deployment requires stable pipelines, consistent stewardship, and traceability practices that can withstand audits and organizational turnover (INT1; INT2). The interviews therefore provide a mechanism-based explanation of a point that remains comparatively high-level in the literature: adoption is not constrained primarily by data scarcity, but by the absence of institutional arrangements that allow data to be mobilized across boundaries in ways that remain controllable and lawful (Madan & Ashok, 2023; Kuziemski & Misuraca, 2020; Pencheva et al., 2020).

From this perspective, the interview data invite a more distributed interpretation of readiness. Readiness is not located in a single unit or function, but depends on how decision rights over data access, classification, and reuse are allocated across organizational components, and on whether these components can coordinate without relying on ad hoc arrangements (Kuziemski & Misuraca, 2020; Mergel et al., 2019). In practical terms, the capacity to document provenance, apply consistent standards, and maintain traceability over time becomes part of the organization's ability to justify AI-enabled practices ex post, particularly when multiple offices contribute inputs to the same process (European Commission, 2019; Government of Canada, 2024).

Interoperability and legacy infrastructures are treated in a similar manner. Although the literature frames integration debt as a general barrier to AI adoption and digital transformation in government (Mikhaylov et al., 2018a; Wirtz et al., 2019; OECD, 2021a), interview accounts emphasize its direct consequences for routinization and stabilization. Where information systems remain fragmented across domains, initiatives tend to remain localized because it is difficult to stabilize end-to-end flows, monitoring routines, and consistent definitions across the service ecosystem (INT3). In such contexts, interoperability functions less as a general "maturity" variable and more as a condition for embedding AI into workflows rather than keeping it adjacent to core processes (Mergel et al., 2019; Wirtz et al., 2019).

Capabilities and skills are also confirmed as important in the literature on public-sector AI adoption (Mikhaylov et al., 2018a; Wirtz et al., 2019; Madan & Ashok, 2023), yet interviewees place particular emphasis on translation and assurance capacity: the ability to articulate implementable requirements, align them with procurement and compliance constraints, and maintain verification routines that preserve human responsibility over outputs (INT4; INT6). Leadership is relevant in this respect not only as sponsorship but as steering capacity that keeps enabling investments (data governance, integration, cloud migration) coherent and protected despite their delayed visibility (INT1; INT5).

This also helps explain why readiness work is repeatedly described as prior and ongoing rather than as a one-off preparatory phase. Interviewees implicitly describe path dependence: once an administration commits to certain data models, integration choices, or access-control solutions, subsequent AI use cases are either enabled or constrained by those earlier decisions. While the literature highlights the role of foundational investments (OECD, 2021a; Madan & Ashok, 2023), the interviews clarify that their practical significance rests on their capacity to stabilize cross-unit coordination and to reduce the transaction costs involved in converting isolated initiatives into shared organizational capabilities (Mergel et al., 2019; Kuziemski & Misuraca, 2020).
Taken together, these comparisons indicate that the readiness dimensions emphasized in the literature are empirically corroborated (Mikhaylov et al., 2018a; Wirtz et al., 2019; Madan & Ashok, 2023), while the interview material specifies how they become decisive: through stewardship, traceability and integration work that renders AI feasible and defensible across organizational boundaries (Kuziemski & Misuraca, 2020; Government of Canada, 2024; European Commission, 2019).

5.2 Implementation strategies and operational pathways

The literature commonly portrays implementation in public administrations as a progression from pilots toward scaling, while emphasising procurement rigidity, coordination complexity, and organizational resistance as persistent constraints (Wirtz et al., 2019; Mikhaylov et al., 2018a; Neumann et al., 2022; Madan & Ashok, 2023). Interview evidence supports the prominence of pilot-based strategies, but it also clarifies why pilot activity frequently fails to translate into sustained use: scaling is where feasibility gives way to the requirement of effective oversight.

Pilots are described as useful because they allow administrations to explore feasibility while limiting immediate exposure to failure (INT7). At the same time, interviewees report structural difficulty in moving from isolated experiments to systemic and scalable initiatives (INT4). What accounts for this discontinuity is not simply the need for additional resources; it is the need for organizational embedding. Making solutions usable in routine settings requires connecting outputs to systems of record, stabilizing data pipelines, and building monitoring and validation routines that can function in day-to-day administrative work (INT1; INT4). When these elements are absent, AI remains adjacent to processes: it may generate outputs, but it is not incorporated into accountable service delivery.

A key point of divergence with some optimistic adoption narratives is that interviewees treat scale as a change in problem definition. At pilot stage, administrations can tolerate ambiguity in roles, datasets, and performance thresholds. At scale, the same ambiguities become liabilities, because they undermine operational responsibility and make it difficult to defend outcomes under scrutiny. This distinction suggests that the pilot-to-scale “gap” is often less technical than institutional: it is the point at which accountability, controllability, and auditability must be made concrete.

Procurement emerges as the point where the literature’s emphasis on constraints can be reinterpreted more constructively (Wirtz et al., 2019; Neumann et al., 2022; Madan & Ashok, 2023). While prior work often highlights procurement as a source of delay and rigidity (Wirtz et al., 2019; Neumann et al., 2022), the interviews show procurement as a design stage in which oversight is effectively specified. Tender specifications and contracting choices shape whether auditability, monitoring features, access controls, and security-by-design requirements are embedded in enforceable terms (INT1; INT6). The relevance of this point is amplified in multi-actor delivery environments. Outsourcing may increase delivery speed, but it does not displace accountability; it raises the importance of responsibility allocation and internal competence to validate outputs, monitor performance, and intervene when necessary (INT2; INT6; INT7).
The interviews also clarify a recurring tension between iterative development logics and public-sector procurement. Where the literature at times frames agility in tension with

formal procedures (Mergel et al., 2019; Wirtz et al., 2019), the empirical material points to a third option: an “iterative but governed” implementation approach, in which experimentation is structured through staged requirements, clear acceptance criteria, and monitoring obligations. In this setting, the capacity to specify what must be controlled, rather than only what must be delivered, becomes a determinant of whether procurement enables learning without eroding accountability.

Change management is present across accounts, yet it appears less as a generic cultural obstacle and more as the integration of procedural safeguards into routines. Verification steps, training practices, documentation expectations, and escalation paths for uncertain or erroneous outputs are repeatedly described as requirements for dependable use (INT4; INT7). The interviews therefore sharpen the implementation narrative by identifying the practical transition that separates pilots from stable use: the organization must be able to operate AI as a controllable, auditable component of service delivery rather than as an isolated technical demonstration.

Importantly, the implementation pathway is shown to be tightly coupled with readiness conditions. Integration and monitoring routines presuppose stable data pipelines, coherent access rules, and interoperable systems; when these foundations are weak, change management efforts face structural limits (OECD, 2021a; Neumann et al., 2022; Madan & Ashok, 2023). This interdependence is consistent with the literature’s socio-technical framing (Mergel et al., 2019; Pencheva et al., 2020), but the interviews make the sequencing effect more visible, highlighting that organizations are rarely able to compensate for missing foundations through project-level adjustments alone.

5.3 Benefits and public value opportunities

The literature associates AI adoption with efficiency gains, improved decision support, monitoring capacity, and enhanced citizen-facing services, while situating these outcomes within public value considerations such as fairness, legality, and trust (Wirtz et al., 2019; Margetts & Dorobantu, 2019; Criado & Gil-García, 2019; Pencheva et al., 2020; Madan & Ashok, 2023). Interview evidence supports these benefit domains, but it repeatedly frames benefits as dependent on organizational maturity and assurance capacity, rather than as direct outputs of deploying AI tools.

In the literature, the notion of "public value" is often invoked to emphasize that administrative efficiency is not sufficient as a success criterion (Criado & Gil-García, 2019; Margetts & Dorobantu, 2019; Pencheva et al., 2020). The interview material reinforces this point by showing that benefit claims are routinely assessed against institutional exposure. Respondents do not deny efficiency potential; they qualify it by asking whether benefits can be realized without creating new verification burdens, new points of failure, or opacity in citizen-facing interactions.

When benefits are discussed, they are described through concrete organizational effects: time compression in administrative processes (INT2), monitoring through dashboards and indicators (INT1), planning and prioritization support in complex service domains (INT3), and citizen-facing interfaces designed to improve accessibility and responsiveness (INT1). These accounts correspond closely to the literature's benefit categories (Wirtz et al., 2019; Pencheva et al., 2020; Criado & Gil-García, 2019). They also highlight the extent to which benefits are closely linked with enabling layers such as cloud migration, interoperability and data integration (INT1; INT4). In this sense, AI is frequently experienced as an accelerator of broader digital capabilities: it improves speed, monitoring and service interaction when the underlying digital substrate can support stable flows and controlled access (Mergel et al., 2019; OECD, 2021a; Pencheva et al., 2020).

A further refinement concerns how benefits are distributed across organizational roles. Internal actors tend to frame value in terms of service priorities and operational continuity, whereas external delivery and compliance perspectives often highlight scalability conditions, risk containment, and the cost of maintaining supervision. These differences do not indicate disagreement on outcomes; they reflect different "cost centres" of adoption, and they help explain why an initiative may be attractive in principle yet contested when organizational responsibilities are specified.

Interview evidence also clarifies how legitimacy risk mediates the benefit narrative. The literature emphasizes that value depends on trust and that citizen-facing use cases are exposed to scrutiny (Margetts & Dorobantu, 2019; European Commission, 2019; Pencheva et al., 2020). The interviews sharpen this point through the practical issue of reliability: systems may generate plausible responses that are occasionally incorrect, creating a requirement for validation and supervision routines (INT7). This suggests that the feasibility of high-visibility benefit realization is shaped by the organization's assurance capacity (monitoring, verification, and escalation) rather than solely by technical performance.

The conditional nature of benefits also implies that measurement and evidence of value become part of the implementation challenge (Criado & Gil-García, 2019; Pencheva et al., 2020). Where benefits are tied to faster cycles or improved monitoring, administrations still need credible baselines and indicators to demonstrate improvement, especially when procurement and oversight require formal justification (OECD, 2021a; Government of Canada, 2024). In this respect, the interviews implicitly align with the literature's emphasis on legitimacy, demonstrating value is itself a governance task, not only a technical evaluation.

A further benefit domain, less prominent in high-level adoption narratives, concerns organizational resilience. Respondents treat knowledge loss through turnover as a concrete administrative problem and frame AI as potentially supporting knowledge retention and internal learning (INT2). The interviews therefore refine the public value discussion by showing that stable benefits depend on the capacity to embed AI into routines and supervise its outputs, and by extending the benefit narrative to include capability preservation.

5.4 Ethical and social challenges

Ethical and social challenges occupy a central position in the literature on public-sector AI, reflecting the distinctive legitimacy constraints under which administrations operate (Margetts & Dorobantu, 2019; Mikhaylov et al., 2018a; Pencheva et al., 2020; Wirtz et al., 2019). Privacy, bias, transparency and explainability, contestability, and human oversight are repeatedly treated as core requirements for trustworthy adoption (European Commission, 2019; Wirtz et al., 2019; Young et al., 2019; OECD, 2021a; Armiento, 2024).

Interview evidence confirms the relevance of these concerns while clarifying that ethical constraints shape adoption trajectories primarily through institutional capacity, specifically, through whether safeguards are embedded as routine practices rather than remaining at the level of principle.

Privacy and confidentiality appear as immediate constraints on data reuse and training (INT2), while bias concerns are linked to distorted datasets and opaque criteria that may generate inequitable outcomes (INT3). Explainability, in turn, is discussed through verification needs: outputs may be generally useful yet occasionally wrong, which makes procedures and tools for checking and override essential in operational contexts (INT7). This operational framing adds specificity to the literature's emphasis on explainability: it is relevant insofar as it is actionable within workflows and supports responsibility allocation.

A relevant point for the literature comparison is that interviewees rarely treat ethical principles as abstract trade-offs. They describe ethics as something that becomes operational through constraints on data use, through verification requirements, and through the design of roles and escalation paths. Accordingly, ethical challenges translate into adoption barriers when organizations lack the routines that make compliance and responsibility workable in practice (European Commission, 2019; Kuziemski & Misuraca, 2020; Government of Canada, 2024).

The interviews further suggest that ethics may be unevenly institutionalized. Training, documentation, monitoring, and escalation practices are not consistently embedded (INT6), which implies that ethical requirements can constrain scaling because the organization cannot demonstrate continuous control. Cybersecurity pressure reinforces this logic by requiring security-by-design and sustained vigilance rather than one-off compliance (INT6). The comparative evidence therefore supports the literature's ethical agenda while clarifying the principal channel through which ethical issues influence implementation: the operationalization of safeguards within organizational routines

(European Commission, 2019; OECD, 2021a; Kuziemski & Misuraca, 2020; Government of Canada, 2024).

This reading also clarifies how privacy and security pressures reshape implementation choices (European Commission, 2019; OECD, 2021a; Kuziemski & Misuraca, 2020). Rather than simply "slowing down" projects, these constraints influence architecture and sourcing decisions, affect what can be tested with real data, and determine which use cases are considered viable (European Commission, 2019; OECD, 2021a; Wirtz et al., 2019). The empirical material therefore supports the literature's ethical agenda, while indicating that the decisive variable is institutional capacity: where safeguards are embedded, ethics supports controlled deployment; where they are not, ethics becomes a reason to remain confined to pilots.

5.5 Governance and accountability arrangements

Governance and accountability are consistently treated in the literature as foundational requirements for AI in public administration, given the obligation to justify decisions and preserve legality under democratic scrutiny (Margetts & Dorobantu, 2019; Kuziemski & Misuraca, 2020; Young et al., 2019; European Commission, 2019; Armiento, 2024). Interview evidence confirms governance centrality and illustrates that governance functions as an operational infrastructure through which AI-enabled processes remain controllable, particularly in multi-actor delivery environments.

Human oversight is repeatedly framed as a baseline expectation (INT2), yet interview accounts imply that oversight is meaningful only when organizational arrangements enable control. Data stewardship is described as a prerequisite for accountable AI use (INT6), and monitoring practices are treated as operational necessities through which administrations retain oversight over outputs and system behaviour (INT1). In this sense, governance is enacted through auditable records, defined roles, and supervision routines rather than through declarative commitments.

The interviews thereby support a view of governance as a set of operating arrangements. Oversight is sustained through concrete instruments (monitoring logs, review routines, and clear escalation mechanisms), rather than through generic statements of responsibility, as stated in the literature (Government of Canada, 2024; European Commission, 2019; Kuziemski & Misuraca, 2020). This is especially relevant for systems that are updated over time: without structured review and traceable records, accountability is difficult to sustain even when initial deployment was acceptable.

Boundary-spanning accountability becomes particularly salient in vendor ecosystems and inter-organizational arrangements (Mikhaylov et al., 2018b; Kuziemski & Misuraca, 2020). The literature warns that responsibility may become diffused across supply chains (Mikhaylov et al., 2018b; Kuziemski & Misuraca, 2020). Interviews make clear that procurement and contracting choices shape where responsibilities for maintenance, monitoring and intervention sit (INT1; INT6). This reinforces procurement as a governance lever, because auditability and supervision requirements need to be specified and contractually enforced at the procurement stage for oversight to remain feasible after deployment.

Interview accounts also suggest that accountability is negotiated across organizational boundaries, not merely assigned. Procurement choices determine whether administrations can access the information needed to supervise systems, and whether they retain practical levers to intervene when performance degrades or when context changes. This reinforces a key implication of the comparative analysis: vendor involvement does not only raise "outsourcing" issues, it raises design questions about who can observe, verify, and contest system behaviour during routine operation (Kuziemski & Misuraca, 2020; Young et al., 2019).

The temporal dimension of governance is also emphasized. Interviewees point to a mismatch between technological evolution and slower institutional adaptation (INT5), highlighting the need for periodic review, updating, and the capacity to suspend or redesign systems when conditions shift. These lifecycle arrangements are central to sustaining accountability over time, particularly when systems are updated or when organizational contexts change.

5.6 Answering the Research Question

The integrated analysis indicates that successful AI implementation in public administration depends primarily on an organization’s capacity to make AI operationally governable under public accountability constraints. The decisive issue is rarely whether an AI system can be developed, acquired, or technically deployed. What becomes determinative is whether AI can be embedded within arrangements of organizational control that remain compatible with legality, traceability, oversight and responsibility allocation, particularly when initiatives evolve from experimentation to routinized operation. This is the point at which implementation trajectories tend to diverge: some initiatives consolidate into stable capabilities, whereas many remain confined to episodic pilots.

A first mechanism concerns data stewardship and traceability, understood as an organizational capability rather than a generic prerequisite. While the literature frequently frames data readiness in terms of quality, accessibility and governance principles, the interview evidence refines this by showing that the binding constraint lies in the work required to render data reusable in a defensible way across organizational boundaries. Fragmented ownership, uneven standards, incomplete documentation and sensitive-data constraints produce a recurring pattern in which administrations possess data without being able to mobilise it reliably and lawfully for AI initiatives. The pilot-to-scale transition makes this particularly visible: while a proof of concept can often be sustained through local datasets and informal coordination, stable deployment requires pipelines and stewardship practices that can withstand audits, organizational turnover and cross-unit reuse.

Interoperability and integration capacity constitute a second mechanism shaping implementation outcomes. Implementation success is closely connected to the ability to embed AI into systems of record and everyday workflows. When AI remains peripheral (operating as a stand-alone layer disconnected from core infrastructures), maintenance, monitoring and organizational adoption become fragile, and oversight is harder to institutionalize. Interview material repeatedly highlights legacy systems and interoperability debt as structural constraints that explain why administrations may generate pilots but struggle to consolidate solutions at scale. In this respect, integration is not an ancillary technical detail; it is the bridge between experimentation and routinized use, and therefore a major determinant of sustainability.

Leadership and strategic orientation also emerge as influential, but their relevance appears primarily institutional rather than rhetorical. The empirical evidence suggests that leadership matters insofar as it enables boundary-spanning coordination across units with heterogeneous maturity, reduces fragmentation in ownership and decision-making, and sustains change management beyond the initial innovation phase. Where this coordinating capacity is weak, projects become dependent on individual champions and remain vulnerable to discontinuity; where it is present, administrations are more likely to allocate responsibilities, legitimise process redesign, and maintain momentum when implementation encounters predictable frictions.

The most consequential cluster of determinants concerns governance and accountability as operational infrastructure. The research confirms the centrality of principles such as transparency, fairness, privacy and accountability in public-sector AI, while showing that their practical effectiveness depends on whether they are translated into routines and instruments. Oversight is sustained through documentation, monitoring logs, review checkpoints, and escalation mechanisms, rather than through generic statements of responsibility. This operationalization is critical because AI systems evolve over time: updates, changes in data and shifting contexts can erode accountability even when initial deployment was acceptable, unless administrations can maintain traceable records and structured review.

These dynamics become even more salient in vendor-mediated ecosystems. The study shows that external provision does not only generate a generic “outsourcing risk”; it creates a governance design problem concerning who can observe, verify and intervene once solutions are deployed. Procurement and contracting therefore emerge as analytically central to implementation success, because they shape whether auditability, supervision requirements and security-by-design obligations are specified in enforceable terms. When these levers are weak or underspecified, responsibility can become diffused across organizational and contractual boundaries, reducing the administration’s capacity to supervise the system during routine operation and to intervene when performance degrades or context changes.

Across macro-themes, the thesis also clarifies that the realisation of public value is conditional on what can be described as assurance capacity. The interview evidence aligns with the literature in recognizing benefits such as efficiency gains, decision support and service improvement, while consistently framing these benefits as dependent on whether outputs can be monitored, validated and corrected within ordinary work practices. Ethical and social issues (privacy, bias, explainability and contestability), therefore, appear not as parallel add-ons but as dimensions that become manageable only when safeguards are institutionalized through training, documentation, monitoring and escalation routines. Where such operational safeguards are underdeveloped, the value proposition becomes more vulnerable and legitimacy exposure increases, especially in citizen-facing settings.

Overall, the thesis answers the Research Question by showing that the factors with the greatest influence on implementation success are those that enable administrations to move from feasibility to operational control. Implementation consolidates when data stewardship, integration capacity, organizational coordination and accountability mechanisms are stabilized in practice; conversely, implementation tends to stall when these mechanisms remain insufficiently institutionalized, because AI cannot be governed in ways that satisfy public-sector requirements of responsibility and legitimacy.

The next chapter builds on this basis by consolidating the thesis' main conclusions, outlining the principal theoretical and practical contributions, and discussing the limitations of the study and avenues for future research.

6. Conclusions

6.1 Reconnecting the research path

This thesis has examined the implementation of Artificial Intelligence (AI) in public administration by adopting an organizational and governance-oriented perspective. The point of departure has been the recognition that, in the public sector, technological feasibility is not sufficient to explain adoption outcomes. Public administrations operate under legal, procedural and public-observation constraints, and they are expected to pursue objectives that exceed efficiency alone, including equity, transparency and legitimacy. In this context, AI initiatives cannot simply be "introduced"; they must be translated into administrative practices that remain compatible with accountability requirements and sustainable within ordinary organizational life.

Building on this positioning, the following Research Question has been formulated: *"Which organizational, technical and governance-related conditions most strongly influence the successful implementation and stabilization of AI-based projects in public administrations, and through which mechanisms do they enable (or obstruct) the transition from pilot initiatives to routine operational use under public-sector accountability constraints?".*

The study intentionally adopted an implementation focus. "Successful implementation" was conceptualized as the ability of an AI project to move from promise to stable operationalization, meaning that it becomes embedded in workflows and managed through arrangements that preserve accountability and legitimacy over time. This definition was introduced to avoid two frequent simplifications: equating success with the existence of experimentation, and equating success with purely technical performance.

To address the Research Question, the thesis combined a concept-centric literature review with a qualitative empirical investigation based on semi-structured interviews. The literature review consolidated academic and institutional contributions into macro-themes that recur across the field, while also identifying a motivating gap:

implementation is often addressed indirectly through high-level principles or descriptive taxonomies of drivers and barriers, leaving less clarity on which factors become most decisive in practice and how they interact when projects attempt to move beyond pilots. The empirical component was designed to deepen this gap through practice-based evidence. The interview guide was built by operationalizing the literature-derived macro-themes into accessible questions and role-sensitive probes, thereby ensuring conceptual traceability between the analytical framework and the primary data. Interview material was analyzed through inductive first-level coding and subsequently structured under the same macro-themes, so that empirical evidence could be compared systematically with the state of the art and discussed within a coherent interpretive scaffold.

On this basis, the comparative analysis offers a clear set of answers to the Research Question. The evidence shows that the successful implementation is mainly driven by the degree to which public administrations can transform feasibility into operational control within the constraints of accountability. Projects mature when the readiness of data is turned into organizational mechanisms of stewardship, documentation, and traceability that make information reusable and defensible within and across organizational units; when interoperability and integration facilitate the embedding of AI results into systems of record and business as usual rather than being relegated to the periphery; and when internal capacities, with leadership support, maintain boundary-spanning coordination processes beyond the life of specific individual champions. Scaling up, in turn, relies on governance being realized as an operational infrastructure through monitoring, review points, and escalation paths, and on procurement and contracting systems that operate as levers to embed auditability, access rights, and supervision obligations in enforceable terms, especially in vendor-managed ecosystems. In the absence of such infrastructure, projects are likely to remain piloted since the expectations of public value become contingent on the lack of assurance capacity and the ethical requirements of privacy, bias, explainability, and contestability cannot be shown to be continuously controlled in the course of ordinary administrative work.

6.2 Contributions and implications

This thesis contributes to the debate on AI in public administration by strengthening the connection between concept-centric consolidation of the literature and implementation-oriented explanation. The literature review showed that the field is not lacking in coverage: academic and institutional contributions already map a broad set of adoption drivers, risks and governance principles. At the same time, the review highlighted that implementation is often addressed through descriptive taxonomies or normative frameworks, offering less clarity on how determinants interact and which ones become binding constraints when initiatives attempt to progress from experimentation to stable operationalization.

The empirical chapters deepen this gap by making visible the organizational mechanisms through which frequently cited determinants become decisive in practice. Rather than treating data readiness, infrastructural maturity and governance as static "preconditions", the study shows how they operate as capacities that determine whether AI can be rendered controllable and defensible under accountability constraints. In this perspective, adoption is not the uptake of a tool but an institutional translation process: AI must be embedded in infrastructures and workflows while remaining compatible with legality, traceability, oversight and responsibility allocation. This mechanism-based account clarifies why pilots are often rational and widespread, yet consolidation is less frequent: routine adoption requires a qualitative shift from experimentation to operational control, sustained through data stewardship, integration, monitoring and review routines, and enforceable governance arrangements.

The implications are not confined to theory. The study suggests that practical success depends less on identifying attractive use cases in the abstract and more on designing implementation conditions that persist after deployment. Procurement and contracting emerge as formative moments in which governability is materially configured, because they determine whether administrations retain access to the information needed for oversight and the levers required for intervention. Similarly, assurance routines (monitoring logs, verification practices, escalation mechanisms and lifecycle review) are shown to be central to sustaining both performance and legitimacy over time. The thesis therefore supports an understanding of responsible public-sector AI in which governance is not treated as an external constraint but as the institutional architecture through which implementation becomes feasible and durable.

6.3 Limitations

The outcome of this thesis must be considered in the context of the research design and the empirical focus of the study. The research design of this thesis to apply a qualitative approach through conducting semi-structured interviews is suitable for examining the organizational mechanisms, rationales of decision-making, and implementation processes that cannot be easily quantified. This research design enhances the explanatory power of the study and enables the researcher to interpret how the enabling factors and barriers are translated into concrete implementation processes. However, it also means that the contribution of this thesis is aimed at facilitating the transferability of analysis rather than generalization: the outcome of the study points out the patterns and mechanisms that are likely to be significant in similar contexts within the public sector, but also recognizes that their presence and relative significance may differ across administrations.

This is a closely related aspect to the composition of the empirical material. The interview sample, although sufficient for a qualitative analysis, is still relatively small and therefore cannot possibly exhaust the diversity of public administrations, policy areas, or implementation frameworks. Furthermore, the sampling approach was designed to favor roles that are positioned to observe cross-cutting constraints (such as data governance, interoperability, compliance, procurement, and accountability), as these aspects are often decisive for whether AI projects can escape the boundaries of episodic experimentation. This improves the explanatory power of the thesis regarding the conditions of governability and organizational control, but it also means that other perspectives are less immediately represented, especially those of front-line workers in public services who are actively engaged in the day-to-day delivery of services and citizens as end-users.
As a result, the thesis is stronger in explaining organizational implementation processes and governance mechanisms than in assessing user-level experiences or perceptions of fairness in specific service encounters. Future research could address this limitation by

expanding the number of interviews and broadening the range of informants across administrative levels and functions, including operational staff and service users, so as to test the robustness of the mechanisms identified here and to capture a wider range of implementation experiences.

Contextual specificity constitutes a further limitation and directly connects to the geographical focus of the study. The empirical investigation is situated in the Italian public administration context, which is shaped by institutional features (procurement practices, administrative cultures, legal constraints, and uneven digital maturity), that may differ in meaningful ways from those of other countries. While the mechanisms discussed in this thesis are consistent with the international literature, the degree to which a given factor becomes binding, and the way in which factors interact during the pilot-to-scale transition, may vary across national and institutional environments. For this reason, the thesis should be read primarily as an interpretive framework for understanding implementation mechanisms and their interactions, rather than as a prediction that identical configurations will emerge in the same way across different public sectors. Comparative research across countries and administrative systems would be particularly valuable to assess how procurement regimes, governance traditions and infrastructural baselines condition implementation trajectories.

Finally, the research has limitations in its ability to detect long-term implications. AI develops over time through updates, training data changes, and context of operation shifts. While the results underscore the significance of lifecycle management and the gap between the pace of technological change and the pace of institutional adaptation, the research design does not enable direct observation of how governance structures perform over time after deployment. Longitudinal and comparative designs, such as tracking initiatives beyond initial implementation and across different organisational settings, would strengthen understanding of whether, and under which conditions, AI-enabled practices remain stable, accountable and effective as contexts change.

6.4 Directions for future research

The limitations identified above point to concrete directions for future research. Longitudinal studies would strengthen the empirical basis of the field by examining implementation beyond initial deployment and by assessing whether monitoring routines, audit trails and responsibility arrangements remain effective as models are updated, data and operational contexts evolve, and organizational turnover occurs. Comparative designs across administrations, policy domains and countries would further clarify the extent to which the mechanisms identified in this thesis are robust across institutional environments, or instead conditioned by differences in procurement regimes, legal constraints, administrative cultures and baseline digital maturity.

Methodologically, multi-method approaches could consolidate cumulative knowledge by combining mechanism-oriented qualitative analysis with quantitative indicators of implementation durability and performance over time (e.g., continuity of use, frequency of revisions, escalation events, or variation in processing times and error patterns). Moreover, extending empirical coverage to front-line public servants and citizens would also allow a more direct assessment of legitimacy, contestability and trust when AI is embedded in routine service delivery or rights-sensitive decisions, and would provide evidence on how organizational safeguards are experienced in practice.

Bibliography

- Ambrosetti. (2024). *Il ruolo e gli impatti dell'intelligenza artificiale nella Pubblica Amministrazione*. The European House – Ambrosetti.
- Armiento, M. B. (2024). *Pubbliche amministrazioni e intelligenza artificiale: strumenti, principi e garanzie*. Editoriale Scientifica.
- Criado, J. I., & Gil-García, J. R. (2019). Creating public value through smart technologies and strategies. *International Journal of Public Sector Management*, 32(5), 438–450. doi: 10.1108/IJPSM-07-2019-0178.
- Engin, Z., & Treleaven, P. (2019). Algorithmic government: Automating public services and supporting civil servants in using data science technologies. *The Computer Journal*, 62(3), 448–460. doi: 10.1093/comjnl/bxy082.
- European Commission. (2019). *Ethics Guidelines for Trustworthy AI*. High-Level Expert Group on Artificial Intelligence.
- European Commission. (2020). *Artificial Intelligence: A European approach to excellence and trust*.
- Formit & Trilateral Research. (2024). *AI and Generative AI Adoption by Local and Regional Administrations*. EU Committee of the Regions – Economic Policy Commission.
- Government of Canada. (2024). *Algorithmic Impact Assessment*. Open Government Portal.
- Grant, M. J., & Booth, A. (2009). *A typology of reviews: An analysis of 14 review types and associated methodologies. Health Information & Libraries Journal, 26(2), 91–108.*
- Kuziemski, M., & Misuraca, G. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, 44(6), 101976. doi: 10.1016/j.telpol.2020.101976.
- Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic Inquiry. SAGE Publications.*
- Madan, R., & Ashok, M. (2023). *AI adoption and diffusion in public administration: A systematic literature review and future research agenda. Government Information Quarterly, 40(1), 101774.*

- Margetts, H., & Dorobantu, C. (2019). Rethinking government with AI. *Nature*, 568(7751), 163–165. doi: 10.1038/d41586-019-01099-5.
- Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, 36(4), 101385. doi: 10.1016/j.giq.2019.06.002.
- Mikhaylov, S. J., Esteve, M., & Pencheva, I. (2018a). Artificial intelligence in public administration: Mapping the state of the art. *Public Administration Review*, 78(6), 998–1007. doi: 10.1111/puar.12990.
- Mikhaylov, S. J., Esteve, M., & Campion, A. (2018b). Artificial intelligence for the public sector: Opportunities and challenges of cross-sector collaboration. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2128), 20170357. doi: 10.1098/rsta.2017.0357.
- National Academy of Public Administration (NAPA). (2019). *Artificial Intelligence and its Impact on Public Administration*.
- Neumann, O., Guirguis, K., & Steiner, R. (2022). Exploring artificial intelligence adoption in public organizations: A comparative case study. *Public Management Review*, 24(7), 1076–1100. doi: 10.1080/14719037.2022.2048685.
- OECD. (2021a). *State of the Art in the Use of Emerging Technologies in the Public Sector*. OECD Observatory of Public Sector Innovation.
- OECD. (2021b). *AuroraAI – Human-centric artificial intelligence in Finland*. OECD Observatory of Public Sector Innovation.
- Osservatorio AI4PA. (2025). *AI adoption trends in the Italian public sector*. AI Observatory Reports.
- Pencheva, I., Esteve, M., & Mikhaylov, S. J. (2020). Big Data and AI – A transformational shift for government: So what now? *Public Administration Review*, 80(6), 952–955. doi: 10.1111/puar.13219.
- Thomas, D. R. (2006). *A general inductive approach for analyzing qualitative evaluation data. American Journal of Evaluation, 27(2), 237–246.*
- Webster, J., & Watson, R. T. (2002**).** *Analyzing the past to prepare for the future: Writing a literature review. MIS Quarterly, 26(2), xiii–xxiii.*

- Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—Applications and challenges. *International Journal of Public Administration*, 42(7), 596–615. doi: 10.1080/01900692.2018.1498103.
- Young, M. M., Bullock, J. B., & Lecy, J. D. (2019). Artificial discretion as a tool of governance: A framework for understanding the impact of artificial intelligence on public administration. *Perspectives on Public Management and Governance*, 2(4), 301–313. doi: 10.1093/ppmgov/gvz014.

Annex

Section 1: Experience and Organizational Context

1. Could you describe your current role and responsibilities, particularly in relation to innovation or digital transformation projects, including those carried out in collaboration with public administration?
2. Based on your direct or indirect experience, how would you describe your organization's (or the ones you work with) approach to innovation in public service delivery?

Section 2: Digital Transformation and Technology Adoption

3. From your perspective, what technological developments are currently having the most significant impact on the evolution of public services or operational models in public administration?
4. In your view, how has the adoption of new technologies in public administration come about? Has it been more a reaction to external pressures, or the result of a genuine strategic willingness to evolve?

Section 3: First Encounters and Approaches to AI

5. When and in what context did Artificial Intelligence first emerge in the projects or discussions you were involved in?
6. How would you describe your organization's (or your public clients') current stance or approach toward the adoption of AI? (e.g., cautious, exploratory, strategic?)

Section 4: Enabling Conditions and Strategic Factors

7. Based on your experience, what conditions or factors do you consider most relevant to effectively introduce AI into public administration?
8. What organizational capabilities or resources do you believe are most critical to support AI-related projects in the public sector? (e.g., skills, leadership, data governance, technical infrastructure)

Section 5: Challenges, Risks, and Ethical Considerations

9. In your opinion, what are the main challenges, resistances, or risks associated with introducing AI into public sector contexts?

10. In your experience, how are ethical issues related to AI (such as transparency, fairness, accountability) being addressed, if at all?

Section 6: Reflections and Future Outlook

11. Looking ahead, what role do you think Artificial Intelligence should play in the future of public administration?

12. Based on your experience, what key steps or priorities would you recommend for a public administration aiming to integrate AI effectively and responsibly?