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AI implementation in European public administration: institutional dynamics, cultural traits, and regulatory implications.

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AI implementation in European public administration: institutional dynamics, cultural traits, and regulatory implications. A foreword.

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Introduction

The focus of this doctoral research is the complex and multifaceted process of Artificial Intelligence (AI) implementation within public administration (PA), with a specific emphasis on the European Union (EU) socio-political system and a specific inquiry into the Italian context. The thesis comprises three interconnected papers that collectively analyse the transition from technological adoption to substantive organisational integration of AI. Situated within the thematic area of "data and information for local and regional governance", the project addresses the paradigms of AI implementation. The overarching objective of this introduction is to provide a cohesive background that guides the reader through the research, moving beyond technical issues to explore AI as a trans-disciplinary phenomenon requiring insights from sociology, political science, law, and philosophy.

To appreciate the necessity of a multi-disciplinary approach, one must first address the problem of defining AI. Defining AI presents significant challenges, as no single definition commands universal consensus, and conceptions evolve alongside both the technology and the human interaction with it. Computer scientists generally discard the term, preferring "machine learning" to describe *the process of computers improving their own ability to carry out tasks by analysing new data, without a human needing to give instructions in the form of a program, or the study of creating and using computer systems that can do this* (Cambridge Dictionary, n.d.). Conversely, the EU AI Act defines an "AI system" as *a machine-based system designed to operate with varying levels of autonomy that may exhibit adaptiveness after deployment and which, for explicit or implicit objectives, infers from the input it receives how to generate outputs—such as predictions, content,* *recommendations, or decisions—that can influence physical or virtual environments* (Article 3). This regulatory definition resonates with widely recognised academic characterisations that define AI by its ability to interpret external data, learn from it, and utilise those learnings to achieve specific goals through flexible adaptation (Haenlein & Kaplan, 2019).

Focusing solely on technical definitions fails to account for the inherent complexity of the phenomenon. To broaden our understanding of AI, one must first interrogate the concept of intelligence itself. In their seminal work, Russell and Norvig (2021) define AI as a field ultimately devoted to understanding and constructing intelligent actors capable of taking the "best possible action in a situation", a level of performance analogous to that expected of a human. For these authors, this involves "acting rationally": behaving in a manner designed to achieve the best possible outcome based on the agent's beliefs and information. Russell and Norvig favour this approach of developing "rational agents", noting that it encompasses various other conceptualisations of AI.

The framing of AI as "rational" or "intelligent" is often a device used by providers to attribute to computer systems desired characteristics that they do not actually possess. Despite the marketing, contemporary systems are firmly classified as "Weak" or "Narrow" AI: as Floridi (2025) contends, these systems possess "zero intelligence", demonstrating a great capacity to solve problems only within precisely engineered circumstances. Following Floridi's observation, we have "enveloped" the world, making it friendly for autonomous systems rather than adapting the systems to human complexity. Consequently, these technologies perform exceptionally well in controlled environments, while humans frequently experience frustration when forced to modify their own behaviour to facilitate the requirements of the machine.

The question remains: why are these systems characterised as "intelligent"? Historical context provides a few insights. The term was coined in the 1950s at the foundational Dartmouth Summer Research Project on Artificial Intelligence. At its inception, AI was envisioned as an automated tool rooted in mathematical logic and deductive reasoning, potentially capable of bridging the gap between engineering (the mechanical) and biology (the human) to automate "human intelligence" (McCarthy et al., 1955). However, that vision remains largely aspirational. The AI experienced today is, fundamentally, an inference tool based on large-scale data and statistical methods.

This modern iteration of AI is not a spontaneous technological evolution; rather, it is predicated upon the vast quantities of data currently being produced, collected, and repurposed. As Kate Crawford (2021) argues in *Atlas of AI*, this system relies on opaque practices, such as the often precarious and underpaid labour required for data preparation, advanced machine learning models trained on data scraped through grey processes, and the mineral extraction necessary to build chips and data centres. Furthermore, the development of these systems requires immense capital investment with the expectation of significant financial returns.

Crawford elaborates:

> "AI is neither artificial nor intelligent. Rather, artificial intelligence is both embodied and material, made from natural resources, fuel, human labour, infrastructures, logistics, histories and classifications. AI systems are not autonomous, rational or able to discern

anything without extensive, computationally intensive training with large data sets or predefined rules and rewards. In fact, artificial intelligence as we know it depends entirely on a much wider set of political and social structures. And due to the capital required to build AI at scale and the ways of seeing that it optimises, AI systems are ultimately designed to serve existing dominant interests. In this sense, artificial intelligence is a registry of power" (Crawford, 2021, p. 8).

Only by acknowledging the systemic nature of AI we can interrogate its political and social relevance within the context of public administration. In general, this thesis accepts and embraces Crawford's conceptualisation of AI as a systemic phenomenon, while renouncing on giving a precise, formal definition that would not be able to capture its complexity.

This thesis is grounded in three critical empirical observations.

First, the majority of AI technologies deployed within European public sectors are provided by external, primarily American, entities and are proprietary models. The European Union operates predominantly as a market of users rather than a hub of providers. With the EU landscape dominated by US players, often based in Ireland, the tools available to public administrations are rarely open-source or locally developed. This dependency raises profound questions regarding security, data protection, and strategic independence.

Second, recent advancements in user experience (UX) have significantly lowered the barriers to user accessibility. Unlike previous generations of technology, general-purpose model with text or voice interactions are now easily utilised by non-experts. Consequently, there is growing evidence of both sanctioned and "shadow" AI usage within public administrations (explored in Paper 2), where employees adopt tools independently of formal organisational oversight.

Third, the integration of AI has become "by default" through its ubiquity in everyday productivity suites. Whether through Microsoft Copilot embedded in office software, Google's AI-generated search results, or the accessibility of ChatGPT via common messaging platforms like WhatsApp, users are increasingly exposed to AI. These systems are becoming fundamental to tasks previously reserved for human intelligence, such as text editing and synthesis.

In this environment, the EU AI Act serves not merely as a technical safety regulation but as a strategic instrument of digital sovereignty. However, a central assumption of this thesis is the EU's unique geopolitical position as a primary regulator and user of AI, rather than a primary provider. While this suggests a potential Brussels Effect, wherein EU standards become global norms, the reality is much different. The recently proposed Digital Omnibus (19 November 2025) suggests that the interests of foreign providers may have successfully captured and weakened the implementation of what was intended to be a strict regulatory framework (a tension explored further in Paper 3).

This contextual information explains why the EU AI Act has encountered significant opposition from US political figures and prominent industry leaders. By establishing the rules of the game, the Act wishes to exert authority over providers situated largely outside European borders. For a municipality or a public hospital, AI implementation is rarely a purely local affair; it is a process mediated by global technological dependencies and a complex, evolving ethical and legal framework.

Not all global actors subscribe to the view that technology should be subjected to political oversight and regulation. For instance, the tension between technological advancement and political governance was articulated by Peter Thiel, CEO of Palantir, in his 2009 essay, The Education of a Libertarian. Thiel believes in a fundamental antagonism between the two forces, concluding that:

> "We are in a deadly race between politics and technology. The future will be much better or much worse, but the question of the future remains very open indeed. We do not know exactly how close this race is, but I suspect that it may be very close, even down to the wire. Unlike the world of politics, in the world of technology the choices of individuals may still be paramount. The fate of our world may depend on the effort of a single person who builds or propagates the machinery of freedom that makes the world safe for capitalism" (Thiel, 2009).

This perspective views political intervention not as a safeguard, but as a potential hindrance to the machinery of capital freedom. Technology has such force that it can counterbalance and even overcome politics and regulation. In the context of this thesis, Thiel's deadly race serves as a provocative counterargument (and wakeup call) to the European effort to assert any form of control over technology through the AI Act.

Now, a brief mention of the main definitions of PA is appropriate. The scholarly definition of public administration has evolved in time. While the Anglo-American tradition often emphasises the managerial and decision-making functions of the executive, viewing administrators as agents navigating bounded rationality (Simon, 1947), the Eurocentric perspective offers a more formalistic constraint recognised (and, perhaps, influenced in turn) by Max Weber. Public administration is the term used to *define the formal arrangements under which public organizations serve a government, ostensibly in the public interest* (Johnston, 2015). PA is the executive backbone of the State, where every action must be anchored in legal authority to ensure impartiality in the process of pursuing the general interest.

The current push towards AI-mediated public administration implies a fundamental redefinition of the relationship between the State and its citizens. As public administrations become increasingly reliant on the technology, the future of the public sector will be determined by how these tools are implemented to safeguard public value, transparency, and accountability. Understanding the implementation process is therefore essential for evaluating the evolution of the state and the future of public service delivery in an increasingly data-driven society.

Given the theoretical and empirical tensions explored thus far, a central question emerges: in the encounter between AI and public administration, who adapts to whom, and what are the subsequent implications for governance? While public administrations are historically characterised by a degree of institutional inertia, they are not immune to transformation. The digital government movement of recent decades serves as a primary example of how profoundly technological shifts can reconfigure the public sector. AI now possesses the potential to catalyse a similarly transformative era, challenging traditional bureaucratic structures.

While social and political contexts have been touched upon, the motivations for selecting the theme of AI implementation in PA are rooted in empirical and theoretical issues as well.

Public administration is, fundamentally, a text-based entity: paper trails (logs) are a fundamental tool in the exercise of power and accountability. Primary functions revolve around the implementation of laws and policies, the procedural generation of documentation, and formal communication with citizens and other organisations. Consequently, the transition from a phase of speculative adoption of AI to one of substantive implementation is historically significant given the wide potential impact. Empirically, this research is positioned within the post-GPT 3.5 era, as of late 2022, a period defined by unprecedented global investment in infrastructure, specifically regarding calculus power sustained by semiconductor manufacturing and data-centre expansion. These material investments, coupled with the availability of vast training datasets facilitated by cheap outsourced labour, have fundamentally altered the technological landscape.

Actually, the urgency of this research increased significantly during the doctoral journey due to the release of newer and more powerful models. The sudden ease of use afforded by Large Language Models (LLMs) propelled AI to the forefront of socio-political discourse. However, the non-deductive nature of these models presents a unique risk profile for the public sector, as generated outputs do not guarantee truthfulness and often perpetuate biases. While AI offers great promise, its deployment in public administration has already yielded significant failures. A primary example is the Dutch childcare benefit scandal (Hadwick, 2021), where biased algorithmic fraud detection led to devastating social consequences and the resignation of Rutte's cabinet. Such disasters and the growing and often undisclosed usage of similar tools have made the necessity of robust regulation self-evident, directly influencing the trajectory of the subsequent EU AI Act.

Finally, not certainly for importance, looking at current theoretical trajectories, the e-Government school remains the primary locus of investigation for this topic, as evidenced by the consistent and expanding body of literature in journals such as Government Information Quarterly and Information Polity. Increasingly, AI in public administration is being analysed through the diverse lenses of sociology, political science, law, and philosophy. While traditional frameworks such as the Technology Acceptance Model (TAM) and the Technology-Organisation-Environment (TOE) framework are being adapted for AI (e.g., Uren & Edwards, 2023, Madan & Ashok, 2023), the contemporary literature remains fragmented and predominantly conceptual in nature.

Therefore, this research seeks to contribute to a trans-disciplinary understanding of AI by synthesising disparate theoretical approaches. Drawing from several disciplines, as is characteristic and appropriate of public administration studies, this thesis maintains a particularly keen focus on political science. In doing so, it aligns with the view of public administration as a trans-disciplinary science that thrives on the integration of diverse methodologies and perspectives (McDonald et al., 2022).

Identifying the gap

This investigation proceeds from the identification of a significant gap in the existing literature. While AI offers considerable promise for enhancing PA through more efficient procedures and alternative service delivery mechanisms, its practical application remains scarce. Current research indicates that AI deployment in the public sector remains largely circumscribed and confined to pilot projects, proofs of concept, and experimental stages (de Almeida & dos Santos Júnior, 2025; Mergel et al., 2023; Sousa et al., 2019).

While the literature on AI adoption, namely the phase where an organisation, specifically top management, matures the decision to pursue technological acquiring, has become quite extensive (e.g., Babšek et al., 2025; Madan & Ashok, 2023), the knowledge on AI implementation is comparatively scarce. Following the conceptual framework provided by Damanpour and Schneider (2006), implementation is defined as the sphere of "events and actions that pertain to […] preparing the organisation for its use, trial use, acceptance of the innovation by the users, use of the innovation until it becomes a routine feature of the organisation."

The decision to focus on implementation rather than mere adoption is a response to the current state of administrative evolution outlined in the previous paragraphs. Unlike previous waves of digitalisation that focused on data storage or process automation, the current era of AI challenges the cognitive and discursive foundations of public service.

The scarcity of implementation studies is partly due to the novelty of the technology, which limits the number of empirical cases available for grounded theoretical advancement. This thesis addresses this scarcity by exploring the persistent constraints, organisational, cultural, and institutional, that facilitates or impede AI from becoming a routine, integrated feature of administrative life.

Research questions and methods

The research is guided by a central General Research Question: *How do public administrations navigate the transition from AI adoption to meaningful implementation within the specific institutional and regulatory landscape of the European Union?*

This overarching question is decomposed into specific inquiries at each analytical level, ensuring a convergence of findings. The macro-level research questions (Paper 1) establish the regulatory implications and sectoral obligations of the AI Act, defining the mandatory "playing field". The meso-level questions (Paper 2) identify the institutional pressures and mechanisms emerging from national strategies, explaining what is strategically incentivised. Finally, the micro-level questions (Paper 3) investigate the cultural features and complementary factors that favour or hinder implementation in Italian municipalities, testing whether the macro and meso drivers survive the encounter with ground-level reality. The interrelation of these questions allows the thesis to provide a coherent response to the central problem of the PhD, moving from the rules (Macro) to the pressures (Meso) and finally to the human and cultural realities (Micro).

The research logic is both sequential and parallel. Temporally, it began at the Macro level (Paper 1) with an analysis of the EU AI Act. This was the necessary starting point to understand the foundational "rules of the game" and the sectoral obligations (e.g., in Health or Education) that will define the legal boundaries of implementation for years to come. Once these boundaries were established, the research branched into two parallel inquiries into the organisational side of the phenomenon.

The research employs a qualitative multi-level design to capture the multidimensional nature of AI implementation across three distinct layers:

Level	Analytical focus	Paper
Macro: Regulatory compliance and sectoral trends.	Regulatory: The "Hard Law" (EU AI Act) that sets the overarching legal boundary conditions and sector-specific obligations.	Paper n. 1
Meso: EU National Strategies and institutional mechanisms.	Institutional: the national strategies that exert institutional pressure and shape organisational behaviour.	Paper n. 2
Micro: Organisational culture in Italian municipalities.	Organisational: The internal cultural traits, values, and beliefs that either facilitate or impede the routine use of AI.	Paper n. 3

Co-authored with Prof. Pedro Gomes Rodrigues, my host and guide during the semester in Lisbon, the Macro level paper is titled “How regulatory compliance to the AI Act will shape AI implementation in the European public sector. Implications and sectoral trends”. The EU has recently introduced the AI Act, the world's first comprehensive legislation aimed at providing a legal framework for AI usage across different use cases associated with different risks for human rights and well-being. This paper addresses the critical challenge of translating the complex, recently regulated environment of the EU into clear, actionable implications for policies and organisations. The research is based on the analysis of the general and specific norms target public sector organisations that deploy AI systems, visually synthetised. The identified obligations were translated into implications that can be incorporated into policies and organisational-level strategies. Furthermore, we explored real world use cases of AI in different public sectors to identify if certain sectors are more regulated than others, leading to no definitive conclusion. Our main contribution resides in the analysis of the AI Act, focusing the impact on PA, and translating obligations into implications. We conclude that the successful adoption of AI is contingent upon coordinated policies across different governance levels, a renewed commitment to building robust internal technical and cultural capacities, and, crucially, a shift toward holding external AI providers equally responsible for the public value outcomes of the tools they make available for PA. On the other hand, PA should be more proactive in experimentation and private-public partnership engagements.

On the Meso level (Paper 2), I analysed the institutional discourse within the AI national strategies of EU member states. This choice anchors the research to discursive neo-institutionalism—a promising strain of theory that allows for the uncovering of how political discourse constitute an institutional mechanic capable of fostering change. It explores how organisations change not necessarily because of technical efficiency, but because of the need for legitimacy in a shifting political environment. This paper, titled “Exploring new and old institutional pressures on public administration. AI national strategies in the EU read through the lenses of institutional theory”, starts the analysis from the macro level. Through this work I explored the forms of institutional pressure that arise from the most recent AI national strategies published by EU member states. Using discursive neo-institutionalist principles and Oliver’s (1991) tripartite categorisation of sources of institutional pressure, I performed a thematic analysis to uncover traditional and new institutional dynamics. Through the discussion, I touched upon four elements: efficiency versus legitimacy gains through AI implementation, organisational change, the role of regulation and political discourse. The work is exploratory in nature, given the novelty and evolving nature of the work's subject. To investigate the Meso-level dynamics, the research employs Discursive Neo-Institutionalism. This choice is anchored in the understanding that institutional change is often preceded and facilitated by changes in public discourse. This strain of theory is particularly promising for AI studies as it may focus on how soft law and political visions exert pressure on organisations to adopt technology long before legal or ethical frameworks are fully established. This discursive analysis explains the intended reality of the EU: a modern, efficient, and technologically sovereign space.

However, the intended reality of high-level discourse frequently collapses when it encounters the lived reality of the street-level, local bureaucrat. To capture this divergence, the research anchors its micro-level inquiry in the Italian Case Study. The choice of Italian municipalities is dependent on the location of my research project: Italy. Organisational culture is a context-dependent phenomenon that cannot be captured through superficial metrics alone. It requires going deep into the artefacts of the organisation, interrogating the shared assumptions, beliefs, and values that constitute the local administrative identity (Schein, 1992). Italy, with its long-standing bureaucratic tradition and the current pressure of the PNRR (Recovery Fund), serves as a representative laboratory for European implementation challenges. By using a case-study design, the research prioritises depth over breadth, providing the necessary counter-narrative to the macro-level regulatory and meso-level institutional findings. This creates a methodological triangulation: Paper 1 identifies what is legally required, Paper 2 identifies what is strategically incentivised, and Paper 3 reveals what is culturally enabled.

The third paper, co-authored with the invaluable support of my Tutor, Prof. Stefano Campostrini, is titled "An inquiry on organisational culture: a key driver for a thriving public sector in the age of AI. A case study of Italian cities". Focusing on the micro level, it presents the findings from an inquiry into organisational culture across several Italian cities. Its core purpose is to gain an empirical understanding of the values and beliefs that factor into AI implementation. The most endorsed conceptual models of AI adoption and implementation acknowledge organisational culture as a significant factor. However, its specifics are often not deepened, nor is its relationship with other factors thoroughly explored. We draw upon Schein's (1992) tripartite framework of organisational culture as a theoretical base, considering that it was developed through many years of ethnographic research in an organisation in the ICT sector, allowing for several traits to be transferred to the theme of AI in PA. The study employed a case study methodology alimented by semi-structured interviews, recognising that the more profound, on-site side of the research represents a future endeavour that can be based upon this inquiry. We find that organisational culture is at the centrepiece of several connected challenges in AI implementation, describing an organisational reality that may discourage AI implementation if innovative and collaborative value systems are not strategically developed in organisations. We then discuss the relevance of these findings in relation to the Italian investment strategy for the digital transition of public administration.

The rest of the thesis is composed of the three papers here outlined. Additionally, at the end, I offer a few general conclusions and thoughts on the overall research and limits are disclosed.

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How regulatory compliance to the AI Act will shape AI implementation in the European public sector. Implications and sectoral trends.

Alessandro Grassi, Pedro Gomes Rodrigues

The EU has recently introduced the AI Act, the world's first comprehensive legislation aimed at providing a legal framework for AI usage across different use cases associated with different risks for human rights and well-being. In this paper, we set out to address the critical challenge of translating the complex, recently regulated environment of the EU into clear, actionable implications for policies and organisations. The research is based on the analysis of the general and specific norms target public sector organisations that deploy AI systems, visually synthetised. The identified obligations were translated into implications that can be incorporated into policies and organisational-level strategies. Furthermore, we explored real world use cases of AI in different public sectors to identify if certain sectors are more regulated than others, leading to no definitive conclusion. Our main contribution resides in the analysis of the AI Act, focusing the impact on PA, and translating obligations into implications. We conclude that the successful adoption of AI is contingent upon coordinated policies across different governance levels, a renewed commitment to building robust internal technical and cultural capacities, and more proactivity in experimentation through private-public partnership engagements.

Keywords: Public Administration, Artificial Intelligence, AI Act, Public sectors, AI Use Case.

1. Introduction

The digital transformation of the public sector constitutes a central element of the European Union's (EU) strategic agenda, prominently reflected in the AI Apply overarching strategy, the Next Generation EU funding objectives, the national strategies, and the recovery plans. Within this transformation, artificial intelligence (AI) is hailed as a critical technology with the potential to address major societal challenges and to improve key public services such as healthcare, transportation, and education (Tangi et al., 2023; Wirtz et al., 2019a). AI adoption and implementation are the object of a flourishing area of academia, with a growing corpus of conceptual and empirical publications (Babšek et al., 2025a; Madan & Ashok, 2023b; Sousa et al., 2019).

While AI offers considerable promise for enhancing public administration (PA) through more efficient procedures and alternative service delivery mechanisms, potential adverse impacts on citizens and ethical concerns remain strong (de Fine Licht & Folland, 2025; Floridi et al., 2018; Sattlegger & Bharosa, 2024). The rise of AI Ethics is tightly connected to tragic, negative outcomes of AI implementation that occurred in the past, famously the Dutch scandal that arose from the deployment of a fraud detection in social benefits system (Giest & Klievink, 2024; Sattlegger & Bharosa, 2024).

While AI ethics has come to the forefront of discourse, challenges persist in achieving truly trustworthy AI (Agbabiaka et al., 2025; Berman et al., 2024; Pham & Davies, 2025; Tangi et al., 2023), given that trust-building is a key pursuit of institutions (Parviainen et al., 2025).

In this context, the AI Act (Regulation 2024/1689) entered into force on 1 August 2024, mandating differed compliance deadlines. August 2026, rapidly closing in, is a key deadline for the public sector.

The applicability of the AI Act is pervasive. The comprehensive definition of AI articulated in Article 3: “a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.” The crucial term here is “infer,” as AI is firmly a statistical tool characterised by its ability to produce outputs rooted in statistical data analysis and utilise those learnings to achieve specific goals through flexible (Haenlein & Kaplan, 2019a). AI, while a profoundly useful technology, is not an “intelligent” agent (Floridi, 2025).

Understanding what AI is represents a central focus in the AI Act. Article 4 of the AI Act prescribes the adoption of measures by organisations, including public sector organisations, to ensure a sufficient level of AI literacy of their staff. It is no coincidence that this article is placed into the General Provisions: it is not possible to understand the contemporary world and one's role in it without a basic knowledge of AI.

The AI Act is the result of a long political process. On the 21st of April 2021 the Commission published a first Proposal to regulate AI in the EU. Since then, the political discourse revolving around AI development, implementation and regulation has been growing.

A key issue in the current political discourse is the question whether the AI Act is too pervasive in respect to extra-UE approaches (Wang et al., 2025). A state of over-regulation can be reached when an area or market, in this case the AI industry, becomes excessively legislated or subjected to an onerous regulatory burden. The accusation is particularly pronounced from the perspective of the United States, which, given the market interest of US-based companies, is keenly interested in European regulation to align as closely as possible with the US (un)regulatory approaches, as remarked by US Vice President JD Vance at the 2025 AI Action Summit in Paris:

> *we believe that excessive regulation of the AI sector could kill a transformative industry just as it's taking off, and we'll make every effort to encourage pro-growth AI policies. And I'd like to see that deregulatory flavour making its way into a lot of the conversations of this conference*.

The AI industry participated in the definition of the AI Act, as many lobbying tools are available to interest groups in Brussels. For instance, regulatory capture has been observed in the definition of this legislation (Lancieri et al., 2025; Wei et al., 2024). An example of the results of the capture process is the limited applicability for general-purpose AI systems, such as tools like ChatGPT or Gemini, that are largely unregulated beyond basic transparency obligations, even if they can be (inappropriately) used in high-risk situations, e.g., a citizen asking for a medical opinion.

While in less than one year the AI Act will enter into force in public sector organisations, the understanding of the implications of this regulation in the AI implementation process are still not much explored in the specific context of PA.

All considered, we aim to answer two research questions:

(1) What are the regulatory implications of the AI Act on public sector organisations that implement AI systems?
(2) Are there any identifiable differences in different public sectors (Health, Education, etc.) in terms of obligations?

Given the EU AI Act's recent passage, focusing on the implications of AI implementation in the public sector represents a novel and policy relevant contribution.

The paper is organised as follows. First, we provide an overview of the of the AI Act, focusing on the principles and the specific provisions that can impact on public sector organisations that seek to deploy AI. Second, we'll specify our research design and disclose the limits of the approach. Third, we'll present a few considerations. Finally, we'll discuss our results, finishing with a few concluding remarks.

2. An overview of the EU AI regulatory environment

The objective of the AI Act is highly ambitious: to establish a harmonised and transparent AI governance across the entire territory of the Union, considering ethical, value-based, and European identity aspects. The AI Act stands today out as one of the most comprehensive pieces of legislation, specifically emphasising reliability, transparency, and alignment with fundamental rights and values (Pham & Davies, 2025).

The AI Act does not police citizens behaviours. Its rules are focused on organisations, particularly how they develop, market, use AI systems for various purposes and use cases. The AI Act does not regulate directly the technologies; it focuses on the way they are used and calibrates the intensity of regulation depending on the level of risk.

To achieve this, it defines rules for providers and deployers (respectively, AI suppliers/developers and AI users) that represent the two main roles in AI implementation. Public sector organisations, save exceptional cases, are on the deployer side of the equation, given that the expected lack of internal technical skills will not permit in-house development of AI systems in most cases. Anyhow, for the scope of this paper, we assume that PA is not a provider, as we focus on the implications of AI implementation, not development.

The regulatory approach of the AI Act, similarly to the GDPR (Regulation 2016/679 on data protection), is based on the concept of risk, *the combination of the probability of an occurrence of harm and the severity of that harm*, defined in Art. 3(2). Two complementary phases are normed: a risk-assessment phase (top-down), where it's up to the provider to determine the level of risk based on the norms and associated guidelines (Art. 96), before putting the system on the market or in service, and often as early as during the model training; and a risk-management phase (bottom-up), which tasks both providers and deployers with the implementation of governance systems and post-market monitoring. The chain of risk involves all parties, including public authorities.

Crucially, the AI Act prohibits AI systems associated with unacceptable practices and use cases (Table 1), which are inherently harmful to human rights, equality, non-discrimination, and the rule of law, regardless of the field of use. Nonetheless, a few exclusions are permitted, especially for specific public sectors (law enforcement, healthcare).

	Prohibited practices (Art. 5)	Exceptions – not prohibited
a.	subliminal techniques beyond a person's consciousness or purposefully manipulative or deceptive techniques, if it distorts behaviour or impairs decision capacity leading to significant harm	-
b.	exploits any of the vulnerabilities due to age, disability or a specific social or economic situation, if it distorts behaviour or impairs decision capacity leading to significant harm	-
c.	social scoring, when leading to detrimental or unfavourable treatment in social contexts that are unrelated to the contexts in which the data was originally generated or collected, or that is unjustified or disproportionate to the social behaviour or its gravity;	-
d.	making risk assessments of natural persons in order to assess or predict the risk of committing a criminal offence, based solely on the profiling or on assessing their personality traits and characteristics	to support the human assessment of the involvement of a person in a criminal activity
e.	create or expand facial recognition databases through the untargeted scraping of facial images from the internet or CCTV footage	-
f.	infer emotions of a natural person in the areas of workplace and education institutions	except for medical or safety reasons
g.	biometric categorisation systems that categorise individuals based on their biometric data to deduce or infer their race, political opinions, trade union membership, religious or philosophical beliefs, sex life or sexual orientation	any labelling or filtering of lawfully acquired biometric datasets, such as images, based on biometric data or categorizing of biometric data in the area of law enforcement
h.	real-time remote biometric identification systems in publicly accessible spaces for the purposes of law enforcement	unless authorised by a judge and strictly necessary for searching specific targets or prevent certain crimes

Table 1: Prohibited practices and relative exceptions (Art. 5)

High-risk systems (Table 2) are generally associated with PA, as use cases frequently involve the elaboration of citizens' personal data, decision-making that impact on citizen's lives, and other prominent areas. Examples include applications within critical infrastructure (e.g., transportation), professional education/training (e.g., exam evaluation), healthcare systems (e.g., robotic surgery, smart hospital bed management), law enforcement (e.g., evidence evaluation, case law review), migration, asylum, and border control (e.g., asylum application processing), and judicial administration (e.g., AI for searching past sentences). The AI Act is mostly dedicated to the regulation of high-risk applications. We did not analyse the specific cases of Annex I, as they're not relevant for the scope of this review.

Nonetheless, as evidenced in Table 2, there are several exceptions that are highly relevant for PA. For instance, AI use cases that are aimed at mere procedural efficiency are not high-risk, even if employed in sectors like Health, Education, or Justice.

Crucially, the sole detection of financial fraud in eligibility assessment procedures for public services and benefits it's not considered high-risk if it does not profile individuals, while credit scoring in general is. The European Commission has the power to update the list of high-risk use cases in Annex III, adding or removing (Art. 7). The Commission, especially the nascent AI Office, maintains a strong policy role, crucial in shaping AI implementation by establishing best practices, promoting shared ethical values, and facilitating knowledge transfer.

<table>
<tr><th>Area</th><th>High risk use cases (Art. 6) and practices (Annex III) relevant for PA, except 6(1) and Annex I.</th><th>Specific exceptions (Annex III) – not high risk</th><th>General exceptions – not high risk</th></tr>
<tr><td>Biometrics, except if prohibited under Art.5 or other EU/national laws</td><td>• remote biometric identification systems,
• biometric categorisation according to sensitive or protected attributes or characteristics,
• emotion recognition,
• always high-risk if it performs profiling of natural persons</td><td>• remote biometric verification only to confirm that a specific natural person is the person he or she claims to be</td><td rowspan="8">• if it does not pose a significant risk of harm to the health, safety or fundamental rights of natural persons, including by not materially influencing the outcome of decision making,

• any of the following conditions is fulfilled:

a. the AI system is intended to perform a narrow procedural task,

b. the AI system is intended to improve the result of a previously completed human activity,

c. the AI system is intended to detect (not influence) decision-making patterns or deviations from prior decision-making patterns and is human reviewed,

d. the AI system is intended to perform a preparatory task to an assessment relevant for the purposes of the high-risk use cases</td></tr>
<tr><td>Critical infrastructure</td><td>• safety components in the management and operation of critical digital infrastructure, road traffic, or in the supply of water, gas, heating or electricity,
• always high-risk if it performs profiling of natural persons</td><td></td></tr>
<tr><td>Education</td><td>• determine access or admission,
• evaluate learning outcomes,
• assessing the appropriate level of education that an individual will receive or will be able to access,
• monitoring and detecting prohibited behaviour of students during tests,
• always high-risk if it performs profiling of natural persons</td><td></td></tr>
<tr><td>Employment</td><td>• recruitment or selection of natural persons,
• make decisions affecting terms of work-related relationships,
• promotion or termination,
• tasks allocation based on individual behaviour or personal traits or characteristics
• monitor or evaluate the performance and behaviour,
• always high-risk if it performs profiling of natural persons</td><td></td></tr>
<tr><td>Eligibility assessment</td><td>• evaluate the eligibility of natural persons for essential public assistance benefits and services, including healthcare services, as well as to grant, reduce, revoke, or reclaim such benefits and services,
• evaluate the creditworthiness of natural persons or establish their credit score,
• risk assessment and pricing in relation to natural persons in the case of life and health insurance,
• evaluate and classify emergency calls,
• dispatch emergency first response services,
• always high-risk if it performs profiling of natural persons</td><td>• detecting financial fraud</td></tr>
<tr><td>Law enforcement, except if prohibited under Art.5 or other EU/national laws</td><td>• assess the risk of a natural person becoming the victim of criminal offences,
• as polygraphs or similar tools,
• evaluate the reliability of evidence in the course of the investigation or prosecution of criminal offences,
• assessing the risk of a natural person offending or re-offending not solely on the basis of the profiling,
• assess personality traits and characteristics or past criminal behaviour,
• profiling in detection, investigation or prosecution of criminal offences,
• always high-risk if it performs profiling of natural persons</td><td></td></tr>
<tr><td>Migration and border control, except if prohibited under Art.5 or other EU/national laws</td><td>• as polygraphs or similar tools,
• assess any risk,
• assist in the examination of applications for asylum, visa or residence permits,
• detecting, recognising or identifying natural persons,
• always high-risk if it performs profiling of natural persons</td><td>• verification of travel documents in border control</td></tr>
<tr><td>Justice and democracy</td><td>• assist a judicial authority in researching and interpreting facts and the law and in applying the law to a concrete set of facts,
• used in a similar way in alternative dispute resolution,
• influencing the outcome or the voting behaviour in an election or referendum,
• always high-risk if it performs profiling of natural persons</td><td>• does not include AI systems to the output of which natural persons are not directly exposed, e.g., to organise, optimise or structure campaigns</td></tr>
</table>

Table 2: High risk use cases and practices (Art. 6 and Annex III) relevant for PA and relative exceptions (Art. 6 and Annex III). Use cases of Art. 6(1) and Annex I are not included.

The final two categories are limited risk use cases, where there is an obligation of transparency associated with certain use cases (e.g., Generative AI, chatbots). Minimal risk use cases are not regulated (e.g., spam filters).

General purpose AI systems have their own specific norms, but even for models with systemic risk, the rules are limited to precise prescriptions that fall on the providers (Art. 55). Given the focus on the deployment side, we'll not review these norms as they don't target PA in specific ways.

Clearly, the AI Act is intrinsically linked with, and often reliant upon, other key pieces of EU legislation – here briefly mentioned limited to norms relevant for PA. Most notably, the AI Act operates in conjunction with the GDPR, which provides the overarching legal framework for the processing of personal data. Compliance with GDPR's principles, such as lawfulness, fairness, and data minimisation, is a prerequisite for the development and deployment of AI systems, particularly concerning high-risk applications as outlined in Art. 26(9). Furthermore, the AI Act is complemented by the Data Act, which aims to unlock the value of data by facilitating access to and use of data, especially in protected Regulatory sandboxes (Art. 57, 58, and 59). Beyond data-specific laws, the AI Act is grounded in and seeks to uphold the fundamental rights enshrined in the European Convention on Human Rights and the EU Charter of Fundamental Rights.

Specific to the Health sector, the European Health Data Space (EHDS) represents an important normative innovation. It seeks to build upon and complement the GDPR by addressing specific challenges in the healthcare domain, thereby facilitating secure access to and the reuse of electronic health data for purposes such as research, innovation, and public health. The EHDS clearly defines which data categories are in scope for secondary use and under what conditions regarding quality and governance, establishing a framework of common rules, standards, and infrastructure, including national data access bodies, to streamline data access for authorised users. This framework aims to prevent the use of health data for prohibited purposes, such as assessing insurance risks or purely commercial exploitation by data intermediaries, whilst ensuring equitable access for research and public policy initiatives. Furthermore, it promotes the secondary use of health data through mechanisms enabling the aggregation of data from diverse sources to maximise collective benefits, all while upholding robust safeguards for the protection of individual rights and privacy. The EHDS represents a best practice that can be replicated in other public sectors to answer specific, sectoral challenges.

3. Research design and limitations

The paper combines two different, complementary approaches. On one side, we focused on the legal analysis of the AI Act text, including the Recitals associated with each Article, to understand the general obligations for deployers and the specific provisions and derogations for public sector organisations, presented in as a visual flowchart in Figure 1. Once a final list of obligations was reached, we discussed the potential implications through several iterations until saturation. The analysis presented in Figure 2, therefore, reflects the authors' perspectives and experiences.

The AI Act was accessed through the official web portal *artificialintelligenceact.eu*, consulted multiple times during the year 2025, last in October 2025.

At the moment, some clarifications, e.g., the guidelines named in Art. 96, are yet to be published, becoming available in February 2026. Therefore, the following section is speculative in nature as it tries, in a sense, to anticipate the Commission's guidelines, focusing on the implications for public sector organisations that deploy AI systems of different risk-level. To analyse the impact in real world scenarios, we needed to examine actual cases of AI implementation.

First, we noted that a single, comprehensive, and updated source of European AI applications in the public sector is not currently published. The AI Act prescribes the publication of high-risk use cases data (Art. 71), thus refinement in the future will be possible.

We therefore scraped data from various online sources:

- the AI Watch dataset, which includes 143 documented cases of AI implementation in public sectors in Europe up to 2021 (Molinari et al., 2021);
- the OECD's Observatory of Public Sector Innovation (OPSI) case study library, which includes 35 AI case studies in EU member states up to May 2025;
- a selection of recently published case studies discussing AI applications in specific public sectors (Bennett Moses & Chan, 2018; Giest & Klievink, 2024; Hadlington et al., 2024; Holmes et al., 2019; Jagtiani et al., 2025; Sun & Medaglia, 2019).

The coding approach of the AI Watch dataset is appropriate to respond to our second research question, since use cases are classified according to the OECD COFOG Divisions (public sectors). Consequently, we coded the data of the remaining two sources with the same method, in order to expand and update the first set with more recent use cases.

The findings of the case analysis are presented in Table 3, which connects identified AI use cases across sectors with risk levels identified in the AI Act (Table 2).

Given that AI is a rapidly evolving technology, we expect our results to become obsolete in the case of dramatic development in data sources, algorithms, and environmental conditions.

4. Sectoral trends, implementation process and implications of the regulation on PA as deployer of AI systems

According to our analysis, public sectors have developed varied relationships with AI technologies—some are embracing it, such as Defence (Hadlington et al., 2024) and Health (Nasseef et al., 2021; Sun & Medaglia, 2019), while others are still experimenting with proofs of concept.

Looking at use cases of AI in PA (Table 3), the adoption and maturity of AI applications vary significantly across different public sectors. As highlighted by Sousa et al. (2019), not all COFOG Divisions have been the object of academic interest in the past, e.g., Defence is not as covered due to the strategic implications and military secrets. Matter of fact, Defence is largely kept outside of the AI Act applicability.

Table 3 reveals several overarching patterns. While commonalities exist, the specific manifestations of AI applications differ across COFOG divisions. Health, in particular, seem a relatively mature sector, leveraging AI to accelerate the process of drug testing, drug discovery, analysis of medical records and medical data, and even to open up a new branch of medicine (i.e., genetic medicine).

The political message that the AI Act will have profound impacts on organisations, including PA, is not supported by our analysis, as the current applicability is limited to specific use cases. Several applications of AI in PA are not as regulated as believed. Tools to make tasks more efficient (e.g., forward emails and internal communications), improve the result of a previously completed human activity (e.g., text editing), detect decision-making patterns (e.g., to fight corruption), or perform a preparatory task to an assessment are not considered high-risk even when applied in highly regulated sectors, like Education or Health, unless they infringe other pieces of legislation.

<table>
<thead>
<tr><th>COFOG Division</th><th>Trends of AI use cases in PA</th><th>Expected average risk level</th><th>If exceptions are applicable</th></tr>
</thead>
<tbody>
<tr><td>1. General public services</td><td>Process automation, chatbots, procurement support</td><td>Low risk</td><td></td></tr>
<tr><td>2. Defence</td><td>Autonomous systems (air/sea/land), intelligence, surveillance, logistics</td><td colspan="2">AI Act not applicable if the technology is used only for military reasons</td></tr>
<tr><td>3. Public order and safety</td><td>Predictive policing, facial recognition, video/audio analytics, investigation support, court support</td><td>High risk</td><td rowspan="8">Low or minimal risk</td></tr>
<tr><td>4. Economic affairs</td><td>Financial regulation, economic forecasting, competition analysis</td><td>Low risk</td></tr>
<tr><td>5. Environmental protection</td><td>Environmental monitoring (remote sensing/sensors), climate modelling, biodiversity tracking</td><td>Low risk</td></tr>
<tr><td>6. Housing and community amenities</td><td>Smart city infrastructure (utilities, lighting), urban planning, traffic management, waste management</td><td>High risk</td></tr>
<tr><td>7. Health</td><td>Diagnostics (imaging), drug discovery, personalised treatment, public health surveillance, record analysis</td><td>High risk</td></tr>
<tr><td>8. Recreation, culture and religion</td><td>Heritage preservation/digitisation, archive/library management, visitor experience (VR), recommendations, aerial archaeology.</td><td>Low risk</td></tr>
<tr><td>9. Education</td><td>Personalised learning platforms, automated grading, tutoring systems, learning analytics</td><td>High risk</td></tr>
<tr><td>10. Social protection</td><td>Eligibility assessment, fraud detection, benefits administration, case management</td><td>High risk</td></tr>
</tbody>
</table>

Table 3: Main AI use cases across COFOG Divisions and associated expected average risk level under the AI Act (own elaboration based on our use cases analysis, combined with the level of risk per use case detailed in Table 2, as detailed in the methodological section).

While the defining legal criterion remains the use case, which is often unrelated to a specific sector, sectoral trends are indeed emerging. This is to be expected, considering the effects described in theoretical frameworks like the diffusion of innovation theory (Roger, 1962) and institutional theory (Caplan & Boyd, 2018; Dimaggio & Powell, 1983).

Interestingly, the regulation does not apply to public authorities of third countries and international organisations when acting in the

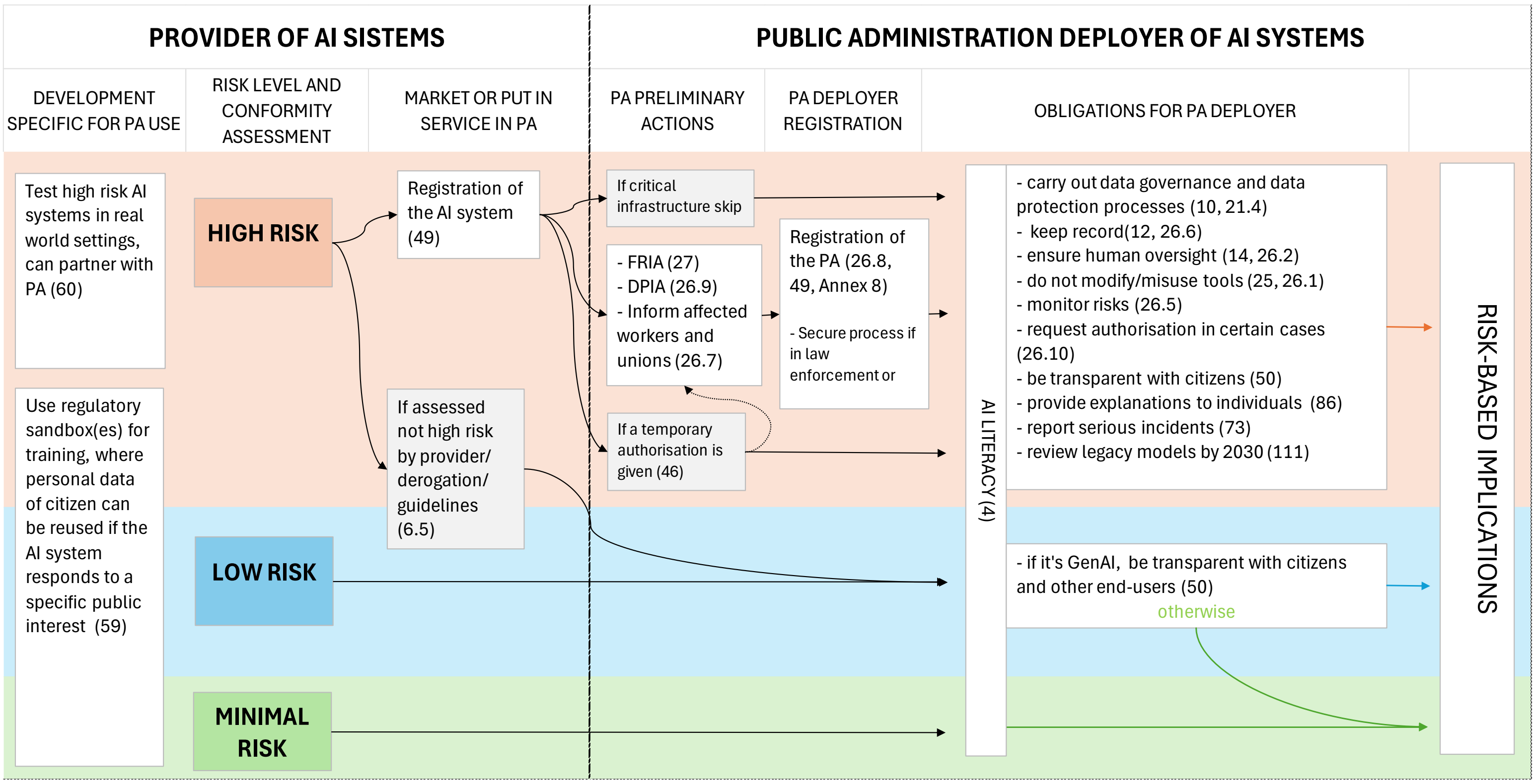

Figure 1: flowchart of PA-related norms and PA as deployer obligations under the AI Act. Pertinent articles are put in parenthesis in each box, e.g., AI literacy (4): Art. 4.

framework of international agreements for law enforcement and judicial cooperation.

4.1 Implementation process in PA according to the AI Act

Figure 1 describes the implementation process of an AI system from the legal perspective of the AI Act provisions, a process that appears immediately simpler for low and minimal risk applications than high-risk ones.

The development of high-risk AI systems can be done in partnership with public bodies (Art. 60), especially during the testing phase under real world conditions. Public sector organisations can collaborate with providers to prototype, fine-tune, and adjust AI systems to specific conditions. The partnership option is crucial, since AI works best under controlled environments and predicable situations, that administrations can contribute to codify by sharing best practices.

When the provider registers a high-risk AI (Art. 49), the process that leads to implementation, as exemplified in Figure 1, starts with two key assessments. The Fundamental Rights Impact Assessment (FRIA) evaluate the potential impact on fundamental rights, such as privacy, non-discrimination, and freedom of expression. This process involves identifying risks and implementing measures to mitigate them before the system is deployed. A Data Protection Impact Assessment (DPIA) is a requirement under the EU's AI Act for high-risk AI systems that process personal data. The AI Act mandates a DPIA to assess risks to fundamental rights, including privacy, and requires a summary to be provided to the national authority. If the high-risk system has an impact on the organisations' employees, both Unions and affected individuals must be informed before proceeding.

The initial assessments are to be uploaded in the mandatory registration process that any public authority or administration must complete before any high-risk deployment, as detailed in Art. 26(8), 49, and Annex VIII. The organisations in two policy areas, Law enforcement and Migration, asylum, and border control, are registered on a separate portal.

Exceptionally, high-risk systems in critical infrastructures are exempt from this process, given the strategic nature of the application and the fact that infrastructures do not, in principle, target specific individuals.

Moreover, if there's an urgent need and public interest, a temporary authorisation can be given to deploy any AI system, skipping all these preliminary phases for a limited period (Art. 46).

While AI literacy (Art. 4) is a cross obligation for any organisation using AI systems, the more consistent obligations are for deployers of high-risk systems. Most obligations are the same regardless of the nature of public or private organisation, except for the need to request authorisation in certain circumstances pertaining to law enforcement per Art. 26(10); and the requirement to update legacy systems, if they are used in the public sector to comply with new legislation (Art. 111), an exceptional provision given that legacy systems are substantially untouched by the AI Act.

RISK LEVEL	OBLIGATIONS	IMPLICATIONS
HIGH RISK	a) AI literacy (4) b) carry out data governance and data protection processes (10, 21.4) c) keep record (12, 26.6) d) ensure human oversight (14, 26.2) e) do not modify/misuse tools (25, 26.1) f) monitor risks (26.5) g) request authorisation in certain cases (26.10) h) be transparent with citizens (50) i) provide explanations to individuals (86) j) report serious incidents (73) k) review legacy models by 2030 (111)	a) general training to understand what AI is b) carry out data governance, data preparation if data is processed internally c) ensure log keeping processes d) who validates possess the necessary competence, training and authority, for remote biometric recognition 2 people are needed e) take organisational measure to use in accordance with instructions ▪ remind algoritmic bias in processes ▪ train to interpret, decide when discard input f) carry out monitoring and impact assessments g) create protocols and templates to handle inter-administration communications h) embed transparency policies and artifacts in specific use cases i) explain decision making to affected citizens who request it j) create an incident management protocol k) keep a record of legacy systems
LOW RISK	a) AI literacy (4) b) if GenAI transparency with citizens and other end-users (50)	a) general training to understand what AI is b) embed transparency policies and artifacts in specific use cases (e.g., chatbots)
MINIMAL RISK	a) AI literacy (4)	a) general training to understand what AI is

Figure 2: PA as deployer obligations and relative implications (own elaboration, Articles in parenthesis)

4.2 Implications for PA

While the specific organisational models and sectoral nature of PA can lead to different approaches in responding to the AI Act obligations, we propose a few implications (Figure 2) that represent actions and policies that public sector organisations have to, or may benefit from, implementing.

As a principle and often a requirement, embedding transparent-by-default policies and relative artifacts (e.g., watermarks) clearly communicate the role of AI in the organisation to the public.

All public sector organisations must provide general training to ensure that the personnel understand the fundamental concepts of what AI is and how it functions (Art. 4).

For high-risk AI systems, the training has specific objectives. Internal processes must ensure that the individual who validates the AI outputs possesses the necessary competence, training, and authority. Not just anyone can be put in charge of the validation process, as both technologic and domain-specific knowledge are needed. In remote biometric recognition at least two distinct authorised people are required for validation. It is critical to remind the staff about the potential for algorithmic bias and overreliance, embedding periodic reminders and providing specific training to mitigate potential consequences. Personnel must be trained on how to interpret AI outputs and decide when to discard input or override the algorithm, which implies at least a general knowledge of data analysis, statistical methods, and informatics. Public employees should be prepared to explain decision-making processes that include AI in any capacity to affected individuals, that have the right to request clarification directly to deployers (Art. 86).

Administrative tools like protocols and procedures, for instance, can ensure that AI systems are used strictly in accordance with their established instructions, delivered by the providers. To favour smooth operations, public sector organisations may benefit from templates to handle compliant communication between different administrative bodies, when required.

Crucially, PA should routinely carry out monitoring and impact assessments of the AI systems to evaluate both the performance and discover early possible negative consequences, to immediately communicate to the provider and the competent authority. Log maintenance is a key feature, especially if the authentication system becomes evidence in case of incidents. A detailed incident management protocol to address and respond to any malfunctions or security breaches involving the AI systems seems crucial to ensure preparedness.

Finally, public sector organizations should keep a comprehensive record of legacy systems that must be replaced, developed, or integrated with new AI technologies by 2030. (Art. 111).

5. Discussion

In this paper, we set out to address the critical challenge of translating the complex, recently regulated environment of the EU into clear, actionable implications for policies and organisations.

By regulating AI systems based on risk levels, the AI Act addresses ethical concerns such as bias, fairness, and privacy. The AI Act potentially bridges algorithmic fairness and non-discrimination law by shifting processes to “ethical by default” practices (Laux et al., 2024). Addressing bias early is crucial, as it can perpetuate discrimination and inequity.

Strategies for mitigation include improving data quality, developing fairness-aware algorithms, and implementing robust auditing processes. The AI Act represents a significant step towards enforcing best ethical practices, but challenges remain in balancing different risks, outcomes, and costs. While the cost of complying with the new regulation is deemed generally high, the overall economic impact of the AI Act has been called into question and may be lower than initially estimated (Haataja & Bryson, 2021). In some public sectors this effect may be close to none, as the barriers to innovation can depend on other factors upon which AI can have a very limited effect.

Our reflections (Figure 1 and 2) are in line with the most endorsed conceptual models of AI adoption and implementation processes (Madan & Ashok, 2023; Maragno et al., 2023; Wirtz et al., 2019). Several predicted challenges, especially in handling data and people as two key pillars, showed up as direct legal implications in the AI Act.

Foundational to the AI Act framework is literacy—a general knowledge of how AI works and what to expect (Pinski & Benlian, 2024). Awareness is crucial as it allows employees to view AI as a versatile tool and recognise the importance of high-quality inputs (e.g., debiased data) as a prerequisite for high-quality outputs.

Drawing on the Technology Acceptance Model (Davis, 1989), the adoption of AI by individuals in public administrations can be explained by how their perceptions of the AI's usefulness and ease of use influence their attitude towards it (Ahn & Chen, 2022; Xu et al., 2024; Yu et al., 2023). There is a high degree of intimacy and personal disposition towards AI, which may be developed, guided, and nurtured through formative actions.

Equipping public employees with domain know-how (Pumplun et al., 2019), is not merely a best practice or future endeavour, as the responsibility for open misuse ultimately rests on deployers. While jurisprudence is not yet clear on the issue, let's imagine two situations. In the first case, the responsibility of a shooting rests on the shooter, not the gun factory or the gun itself; In the second scenario, the responsibility for a dog attacking someone can rest on the owner, depending on the situation. Between these two cases, somewhere, rests AI. Even if, today, AI is closer to a gun than a dog, since it does not possess any form of intelligence (Floridi, 2025).

6. Conclusions

Our main contribution, anticipated in the first research question, resides in the analysis of the AI Act, focusing the impact on PA, and translating obligations into implications that can be incorporated into policies, e.g., checklists, in AI implementation processes in public sector organisations. By integrating the constraints and demands of the AI Act with the analysis of use cases, we illustrated several implications of AI Act, in terms of training, organisation model, and possible toolkits.

While encouraging, we did not find a definitive answer to the second question, even if sectoral trends are to be expected. For instance, Education appears a generally high-risk sector compared to others. Future research may bridge this gap, considering that our conclusions are limited by the rapid technological development and the evolving regulative landscape.

The successful adoption of AI is contingent upon coordinated policies and organisational actions across different governance levels, a renewed commitment to building robust internal technical and cultural capacities, and, crucially, a shift toward holding external AI providers equally responsible for the public value outcomes of the tools they make available for PA. On the other hand, PA should be more proactive in experimentation and private-public partnership engagements. A cultural shift, from traditional bureaucracies to innovative, risk-mindful mindsets, seems appropriate and timing.

Our results have direct positive impacts for PA practice and policy, by empowering public managers and policy makers to adopt the strategic mindset necessary for effective AI implementation, limiting the complexity to key obligations and actionable implications.

A final note on theory, while not the focus of this paper, is important. It appears that present conceptual models of AI implementation in PA may be too complex and wide when confronted with the few, operable rules that apply to deployer public sector organisations. Therefore, adapted conceptual models that differentiate the role of PA, which is mostly as a deployer, would be of great contribution to develop simple, clear guidelines. While general concepts are fundamental and welcome, differentiating between AI implementation in high-risk use cases and AI implementation in low or minimal risk use cases can improve our collective understanding of this complex, crucial phenomenon. Furthermore, directing and specifying the key issues for PA can focus new research towards the most pressing matters.

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Exploring new and old institutional pressures on public administration. AI national strategies in the EU read through the lenses of institutional theory.

Alessandro Grassi

Abstract

Through this work I explore the forms of institutional pressure that arise from the most recent AI national strategies published by EU member states. Using discursive neo-institutionalist principles, I performed a thematic analysis to uncover traditional and new institutional dynamics. Through the discussion, I touch upon three elements: efficiency versus legitimacy gains through AI implementation, organisational change, and the role of regulation and political discourse. The work is exploratory in nature, given the novelty and evolving nature of the work's subject. In the conclusions I depart with a few directions for further institutional analysis.

Keywords: Public Administration, Artificial Intelligence, Institutional Theory, Thematic analysis, Neo-institutionalism.

1. Introduction

Institutional theory has traditionally provided robust frameworks for understanding stability, change, and the diffusion of practices within organisations, including public administration (PA). These theoretical perspectives offer insights through concepts such as myths and ceremonies, conceptualised in foundational works of scholars like Meyer & Rowan (1977) , Zucker (1977, 1987), DiMaggio & Powell (1983) and the earlier work of Selznick (1957).

The disruptive potential and unique characteristics of artificial intelligence (AI) raise critical questions about the continued explanatory power and applicability of established institutional frameworks in a rapidly evolving world (Rudko et al., 2025). This paper seeks to compare AI national strategies across the European Union (EU) to identify which institutional mechanism (old and new) are guiding the process of adoption and implementation of AI in the public sector. This research strongly emphasises the pivotal role of narrative in shaping institutional change (Schmidt, 2008) and employs thematic analysis. This perspective is highly relevant in the current historical phase, given the pervasive public discourse connected to AI (Denia, 2025).

While previous studies have used AI national strategies to infer policy and practice implementation, often deploying content analysis to quantify the prevalence of different topics (Fatima et al., 2020; Hjaltalin & Sigurdarson, 2024a; van Noordt et al., 2025), the aim here is to explore and discuss the reasons why certain themes arise in these documents and what are the implications in terms of the institutionalisation process of AI technology in the public sector.

The integration of AI into PA is widely heralded as presenting significant opportunities (Desouza et al., 2020; Neumann et al., 2024; Wirtz et al., 2019). This shift is driven by a collective understanding that AI has the potential to enhance how governments operate and interact with their constituencies, moving beyond mere automation to a deeper transformation of public sector functions (de Almeida & dos Santos Júnior, 2025; Li et al., 2023). However, this integration process simultaneously introduces fundamental challenges to existing organisational structures, processes, and norms in PA, analysed in a growing corpus of literature specifically addressing these issues (Ahn & Chen, 2022a; Criado & Gil-Garcia, 2019; Giest & Klievink, 2024; Mergel et al., 2023; Wirtz et al., 2021; Wirtz & Müller, 2019).

While AI is not entirely novel – as elements such as machine learning have long circulated within the public sector, albeit not always explicitly identified as such – what differentiates the current landscape is the transformed relationship with technology, especially after the release of Chat-GPT 3.5 in late 2022. AI is now substantially more accessible, particularly because its interfaces are increasingly language-based, reducing the need to possess advanced technical skills. Generative AI, in particular, appears exceptionally promising for PAs in the EU, especially for streamlining text-based procedures (Weerts, 2025).

While critical issues surrounding AI adoption are now increasingly being discussed, my questions pertain to the frontiers of its actual implementation, as empirical observations suggest that widespread applications of advanced AI systems are not yet numerous across PA (Babšek et al., 2025a), often limited to pilot projects or proofs of concept (Sousa et al., 2019).

In the public sector, the absence of norms and rules can inhibit or discourage innovation. Prior to the recent establishment of the AI Act, there was a noticeable lack of a clear and operable legal framework governing its deployment (Pham & Davies, 2025). In some cases, AI tools have been fiercely critiqued, if not declared outright illegal. The AI Act is aimed to bridge this gap, providing a unified legal framework in the overall EU strategy.

While PA, as an institution, is generally considered stable and slow to change, technology can overturn institutional arrangements (Powell et al., 2017), as seen in the last decades with the e-Government movement. However, the pressure to adopt AI might operate differently compared to the diffusion of previous digital technologies. This distinction arises because the impetus for AI adoption could be driven more by socially constructed perceptions and narratives regarding AI's potential than by cost-benefit reasoning (Amrollahi & Abedin, 2024). Moreover, Generative AI "talks back" and participates in social construction processes (Grodal et al., 2024), introducing a potential new actor.

This paper specifically seeks to address two research question, formalised as following:

(1) Which core institutional pressures concerning public administration emerge out of EU members AI national strategies?

(2) Which mechanisms are shaping AI implementation in public administration, according to institutional theory?

The two research questions are tightly connected, as (2) is based on the results of (1). The thematic analysis process and research design follows a refresh on relevant literature to provide theoretical grounding. The results are then discussed, leading to the conclusions.

In addressing these questions, the central hypothesis is that AI adoption patterns within PA largely follow existing institutional contours highlighted by institutional theory. In order to avoid a mere reproduction of results, theoretical orthodoxy, and confirmation bias, the confines of traditional theoretical stances will be relaxed in order to incorporate new, contemporary ideas as suggested by Powell & DiMaggio (2023), as described in the next section. The continued relevance of institutional theory in explaining AI adoption in PA will be discussed throughout the paper.

2. Literature review

Broadly defined, institutional theory can be understood as "a family of theories that analyse organisational behaviours by examining how institutions interact with one another and the society" (Ansell, 2021). Institutional theory focuses on elements such as symbolic systems, cognitive scripts, and moral templates. These fundamentally frame human behaviour.

Earlier iterations, often termed “old” institutional theory, primarily stressed the significance of formal institutions, advocating for principles of good governance, adherence to laws, and the establishment of rigid structures (Selznick, 1996). However, since the late 1970s, neo-institutionalism (NI) emerged, significantly relaxing the definition of an institution. This broader conceptualisation, while offering considerable analytical scope, has also attracted critique, some suggesting that "institutions became everything" (Alvesson & Spicer, 2019), therefore potentially reducing the theory's explanatory power. In line with the underline social constructivism theory, institutions are often understood as symbolic entities or "myths" (Berger & Luckmann, 1966). Nevertheless, a key strength of NI lies in its high flexibility, accepting that organisations can exhibit irrationality, incoherence, and be affected by competing sets of norms (Hwang, 2023). This nuanced understanding is particularly pertinent when examining PA, a sector inherently "subject to strong institutional requirements" and "high levels of scrutiny" (Scott, 2014).

Central to NI are several interconnected concepts that depict organisational behaviour and change within institutional environments. A primary concept is legitimacy, whereby organisations actively seek social legitimisation through their adopted behaviours and structures. Legitimacy can be viewed as the social perception that an organisation’s actions are desirable, proper, and appropriate in relation to the environment’s set of norms, values, and beliefs (Suchman, 1995). The pursuit of legitimacy is perceived fundamental for acceptance within a given field, even though it does not necessarily ensure organisational survival (Hallett & Ventresca, 2006).

Organisations are subjected to various forms of pressure, forces that can significantly lead to the emergence of new norms and practices (C. Oliver, 1991, 1992). These pressures can be categorised into distinct types: functional pressures, which relate to demands for efficiency and productivity; political pressures, stemming from shifts in power dynamics or policy directives (e.g., national strategies); and social pressures, arising from an extended set of beliefs, cultural norms, and accepted practices within society. Oliver’s tripartite model is the base framework to systematise the results of the thematic analysis.

NI has traditionally assumed that technological aspects are largely governed by professional norms based on concepts of efficiency, and are typically kept separate from traditional institutional pressures, which are primarily governed by social expectations (Daft, 2021; Meyer & Scott, 1983; Ritzer, 1996; Rudko et al., 2025). This assumption is not relevant in the case of AI in this historical phase, as political and social expectations have the potential to play a similar or even greater role than functional pressures.

Perhaps, the most widely known concept within NI is isomorphism. This refers to the process by which organisations tend to adopt similar structures, practices, and policies to conform to these various institutional pressures, ultimately aiming to gain or maintain legitimacy (DiMaggio & Powell, 1983). In the context of PA, the historical emphasis has often been on legitimacy-seeking behaviours, aligning with societal expectations and bureaucratic norms. However, contemporary public sector organisations – especially service providers – experience high pressures towards functionality and digitalisation, reflecting shifts in societal expectations, political mandates, expenditure cut, and evolving functional requirements (Neumann et al., 2024a). This dual pressure marks a significant evolution in the institutional landscape confronting public sector organisations.

Defining AI itself presents a significant challenge for NI, precisely because the socially constructed aspects of AI – those elements that shape its narrative, inform social expectations, and frame its implementation – are not yet fully realised (Rudko et al., 2025). While scholars often understand AI through an "umbrella-matrioska" definition, encompassing a wide array of technologies and approaches, a universally accepted definition remains elusive in broader discourse. The AI Act adopts a techno-legal definition, highlighting AI for its capacity to infer an output given specific data and statistical models, and to then use that output to impact reality either directly or by informing human decision-making. For the sake of brevity and to maintain focus on the core institutional questions, this paper accepts the AI Act's definition, while concurrently recognising that the definitional issue is quite complex and warrants more extensive reasoning than can be afforded here.

On one hand, the connotation “artificial” itself has been accused of propelling the idea of a neutral, immaterial technology, hiding the “dark side” of AI behind a curtain of objective amorality. It’s a fact that AI can be unfair. Looking at the defence sector, AI applications are not fair in principle, as AI is intended as an advantage over potential threats (Hadlington et al., 2024). Crime prediction, fraud detection, and CV screening are examples of AI technologies often described as biased.

On the other hand, while the concept of “intelligence” is still an open philosophical debate, statistical-based AI can be described, at best, as an “Agent without Intelligence" (Floridi, 2025). A central theoretical theme in NI, addressed by Rudko et al. (2025), is the pervasive "myth of rationality" often associated with AI. Algorithms do not possess a true understanding of concepts, even when capable of predicting the correct tokens, e.g., generative AI can explain what an ABAB rhyming scheme is, but it does not grasp the underlying concept, failing to use it correctly (Mancoridis et al., 2025). If an AI exhibits true human reasoning capabilities, it’s usually because humans are hidden in the process, similarly to the proverbial historical case of the Mechanical Turk chess machine. The term “Potemkin AI” has been used to describe tools that are labelled “AI” for mere marketing reasons (Sadowski, 2022), referring to the Potemkin village concept: building a façade to make people believe that something’s better than it would otherwise appear. In conclusion, the perception of AI's rationality largely remains part of the broader myth and narrative surrounding the technology, rather than reflecting its actual capabilities (Haenlein & Kaplan, 2019).

This discrepancy between myth and reality presents a fertile ground for NI analysis, particularly concerning how organisations conform to, or diverge from, these powerful yet potentially inaccurate social expectations. Expectations, combined with AI's growing accessibility that shifts it from a technical tool toward a techno-social phenomenon, feed into the automation bias (Goddard et al., 2012), also known as algorithmic bias. This refers to an over-reliance on AI tools, particularly when their fundamental functioning is misunderstood, appearing objective and impartial reasoning machines. In public administrations, this can manifest critically in false legal references within AI-generated official documents, such as judgments or other administrative acts. There are, of course, ongoing projects actively addressing these significant challenges, often outlined in national level policy documents, strategies, and roadmaps.

Several published articles are based on the analysis of national AI strategies, even though they seldom refer to institutionalist approaches. I present here three of the most relevant for this research. Fatima et al. (2020) found that these policy documents are "a rich source of information when it comes to understanding how nations see opportunities to modernize the public sector and transform industries". Their content analysis was built upon several organising themes such as public sectors and industries, data, algorithms, capacity development, and governance, identifying different conceptual areas.

Recently, Hjaltalin & Sigurdarson (2024) mixed discursive positioning and content analysis to achieve three main aggregate dimensions of discourse, focusing on AI applications in the public sector: empowerment through innovation, enhanced administrative practices, and improved service delivery. Their focus on public value theory led to a different framing than this work, but very similar results.

Finally, van Noordt et al. (2025), consistently with previous studies, employed content analysis, finding fourteen policy initiatives that are frequently named in AI strategies. The most occurrent, data management, ethical design principles, public-private partnership, skills, AI awareness, and legislation, once again present a diversified but consistent panorama of themes.

While foundational works, the implications in terms of NI frameworks have yet to be addressed.

3. Methodology and data

To assess the institutional mechanisms shaping the integration of AI into PA, this research analyses how AI in PA is presented within national strategies across the EU. In institutional theory, a discursive analysis approach aims to infer institutional mechanisms by analysing how specific themes are presented, discussed, and framed within public discourse (Kushnir & Yazgan, 2025). As official policy documents, these national strategies are a critical component of the public discourse on the topic.

Given the nascent nature of AI in PA as a research topic and the interest on explaining the rooted social mechanism rather than isolating the dominant topics, I chose thematic analysis. This method allows for an in-depth interpretation of the data, enabling us to identify both established, traditional issues in e-Government and new, AI-specific emergent themes. In contrast, content analysis would have been better suited for a quantitative comparison of document content across countries and/or years, an objective that falls outside the scope of this paper.

The data for this study consists of the most recent national AI strategies from each EU member state, as of a final check in July 2025 (Table 1). In cases where a new strategy was announced but not yet published (e.g., Malta, Germany), the most recently available official document was used. The search yielded at least one document for every country, with the exception of Latvia. In the absence of an available official document for Latvia, a report curated by the European Commission's AI Watch initiative was used as a proxy, as it provided a comprehensive synthesis of the country's public sector AI policy.

While the primary data source were the official national strategy documents, several governments have published additional guidelines and reports created in collaboration with private sector entities, academia, and other stakeholders. However, the scope of this analysis was confined to the main, government-led strategy documents to ensure a consistent and comparable dataset.

The documents vary significantly in both name and length. While most are explicitly titled "strategy," others use alternative labels such as "action plan," "roadmap," or "programme." The length of these documents also differs substantially, ranging from concise documents like Lithuania's 2018 strategy (20 pages) and Denmark's plan (28 pages) to more extensive ones, such as those from Croatia (178 pages), Greece (154 pages), Sweden (136 pages), and Romania (132 pages). This variation in length often reflects different levels of detail and scope, including the targeted timeframe, which ranged from two to ten years.

Despite these formal variations, the strategies share a degree of commonality. However, differences in their maturity are also evident.

Table 1: AI national strategies of EU member states (up to July 2025)

2018	Lithuania	The Lithuanian Artificial Intelligence Strategy: A Vision of the Future
2019	Portugal	AI Portugal 2030
	Czech Republic	National AI Strategy
	Malta	The Ultimate AI Launchpad 2030
	Netherlands	Strategic Action Plan for Artificial Intelligence
	Slovakia	2030 Digital Transformation Strategy for Slovakia
2020	Bulgaria	Concept for the development of Artificial Intelligence in Bulgaria until 2030
	Cyprus	*Εθνική Στρατηγική (National AI Strategy)
	Hungary	Hungarian AI Strategy
	Latvia	Latvia AI Strategy Report (original document unavailable)
	Poland	Policy for the Development of Artificial Intelligence in Poland from 2020
	Austria	Artificial Intelligence Mission Austria 2030
	Belgium	National Convergence Plan for the Development of Artificial Intelligence
2021	Slovenia	National Programme to Promote the Development and Use of Artificial Intelligence by 2025
2022	Finland	Artificial Intelligence 4.0 programme – Finland as a leader in twin transition
	Croatia	Digital Croatia Strategy for the period until 2032
	France	*Stratégie Nationale pour l'IA (2ème phase)
2023	Germany	*KI-Aktionsplan (AI Action Plan)
2024	Denmark	Strategic Approach to Artificial Intelligence
	Estonia	*Tehisintellekti tegevuskava 2024-2026 (Artificial Intelligence Action Plan 2024-2026)
	Greece	Blueprint Greece's AI Transformation
	Ireland	Ireland's National AI Strategy: AI – Here for Good - Refresh 2024
	Italy	Italian Strategy for Artificial Intelligence 2024-2026
	Luxembourg	National AI Strategy
	Romania	*Strategia națională în domeniul inteligenței artificiale 2024-2027
	Spain	AI Strategy 2024
	Sweden	The AI Commission's Roadmap for Sweden

* The document was translated through Google Translate

While some countries have well-established and recently updated strategies, others—such as Greece and Romania—were still in the final stages of development or early implementation as of the data collection period. These variations in maturity and specific application focus are largely reflective of unique national priorities and contexts.

An official English version of the documents was available for the majority of the EU member states. For five cases, indicated with an asterisk in Table 1, the document was translated into English using Google Translate to ensure it could be included in the analysis. The use of machine translation for some documents has the potential for nuances to be lost.

To structure the thematic analysis, I implemented the six-phase protocol to thematic analysis originally developed by Braun and Clarke (2006), as recently reviewed by Ahmed et al. (2025): (1) familiarisation with data, (2) generating initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) writing the report.

I have divided the themes into three organising themes, based on Oliver's tripartite model of the sources of institutional pressure (1991), reviewed in the previous section. Oliver's model was specifically chosen for its capacity to provide theoretical grounding, distinguishig functional pressures, typical in technological implementation, from political and social pressures.

Given the diverse scope and varying lengths of the national strategies, immediate comparability across all documents was not feasible. While these strategies discuss a broad range of topics—including the private sector, education, and funding— this research focuses specifically on the PA domain. To ensure the analysis remained focused and manageable, a sub-corpus was created by extracting only the sections directly addressing AI in the public sector from the original 27 documents. This targeted approach allowed us to move beyond a general overview and focus on more comparable information relevant to the paper's core research question.

I began with a comprehensive, active reading of the documents to gain an initial understanding of their content and to confirm the necessity of a focused approach. Given that the total word count for all documents exceeded two thousand pages, I determined that reducing the corpus was essential to conduct a meaningful thematic analysis (Attride-Stirling, 2001).

To create a manageable and relevant sub-corpus, the qualitative data analysis software Atlas.ti was employed to systematically identify paragraphs containing key terms related to public administration, similarly to Hjaltalin and Sigurdarson (2024). The initial search included the keywords "public administration", "public sector(s)", "public service(s)", and "bureaucracy", including their semantic domains. To ensure that all relevant mentions were capture, I included sector-specific terms such as "healthcare", "defence", and "police". This initial automated coding process yielded a corpus of 1,091 paragraphs, totalling 151,138 words.

This initial selection was then subjected to a manual review to enhance data quality and relevance. Paragraphs that were not directly pertinent to the research focus were systematically excluded, such as those containing indexes, titles, references, or merely passing, out-of-context mentions of the keywords. This manual refinement resulted in a cleaner, more targeted corpus of 724 relevant paragraphs, consisting of 75,209 words, with a mean of 2,786 words per EU member state.

Successive iterations of searching, reviewing, coding (initial coding was supported by counting the frequency of keywords), and defining themes were performed on this final corpus using Microsoft Excel. I acknowledge that thematic analysis is an interpretive method that relies heavily on the researchers' reflexivity. Consequently, the themes identified are, to some extent, influenced by the author's prior knowledge and experience.

4. Results

National AI strategies across the European Union (Table 1) reflect a diverse yet often harmonised approach to leveraging AI for the public sector modernisation. As stated in Bulgaria's strategy, "most national AI strategies in the EU include modernising public administration as a priority". The usage of the term "modern" to describe a PA that makes use of AI is commonly used, recurring 70 times across 15 national plans.

Each country has articulated its own vision, but common threads concerning PA emerged as particularly prominent across the various strategies.

Thematic analysis yielded the results synthesized in Figure 1.

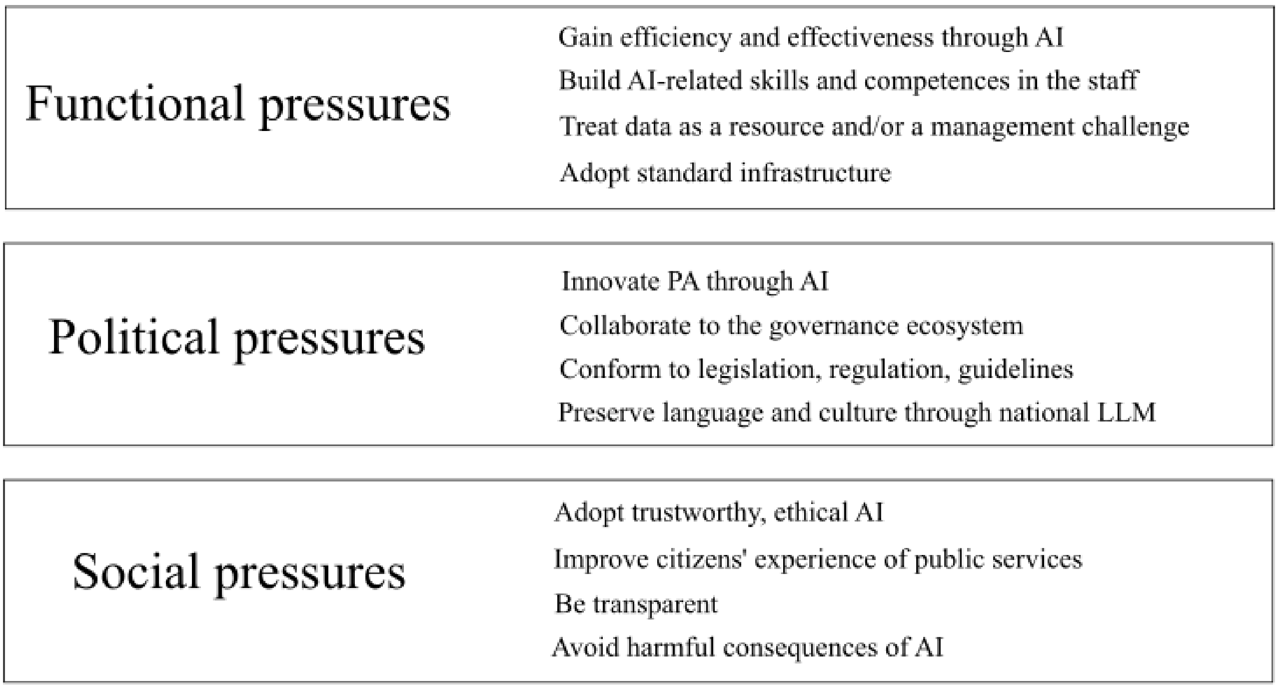

Figure 1: Key institutional pressures regarding AI in PA emerging from the analysis of AI national strategies of EU member states (own elaboration based on Oliver's 1990 conceptual model).

Some documents do not contain all the themes, nor they are ubiquitously discussed in the exact same way. For example, France's 2022 strategy elaborate on the second phase of an overarching strategy, while Germany's most recent one is focused on the healthcare sector, which has its own additional issues in respect to PA in general. Furthermore, some countries like Estonia are recognised as more advanced on e-Government development and thus might stress over different challenges than other countries, like Romania, which stated that it "ranks last among the Member States. Only 16% of Romanian online users actively interact with e-government services, compared to the EU average of 64%", quoting the DESI 2022 index.

4.1 Functional pressures

The main outcomes of AI in PA are consistent with the reviewed literature, where efficiency and effectiveness gains represent a common goal. PA is commonly depicted as having ample margins of improvement, as not being as efficient as possible in terms of management. AI is described as a tool that can scale up operations by freeing up public personnel of repetitive tasks. The win-win situation that is commonly depicted is that public workers can be liberated of repetitive, low-risk tasks and focus on high-value tasks and AI validation and control.

A universal recognition of the need to invest in AI education, skills development, and lifelong learning is apparent across all member states, and now enshrined in Article 4 of the AI Act. This extends to targeted programs for civil servants, highlighting that human capital is perceived as a primary bottleneck for successful AI integration, regarding data management skills in particular. The emphasis on fostering AI literacy across the general workforce and public administration aims to ensure effective adoption and responsible use of AI.

The importance of data spaces is a recurring theme, with data correctly described as the essential fuel for AI. In several strategies this involves developing comprehensive data management schemes, promoting open data and data sharing through national portals, and establishing centralised data hubs and repositories. PA is generally seen lacking in this department.

Infrastructure is considered a cornerstone to AI in most strategies. Aside from the InvestAI EU overarching plan, multiple EU countries stated that they are committing significant resources to this area. Key investments are being made in High-Performance Computing (HPC) and supercomputing, with several nations either installing new systems or leveraging international partnerships to enhance their computational capacity. Similarly, the development and utilisation of cloud infrastructure is a priority, with some countries focusing on legislative frameworks to facilitate its use within the public sector. Connectivity, including broadband, 5G, and IPv6, is also recognised as a basic prerequisite for both organisations and citizens' access to AI tools.

Despite the strategic efforts in these areas, a number of challenges persist. The fragmentation and lack of interoperability of existing infrastructure and data systems in PA – which are often siloed, as well as legal and regulatory barriers that impede data sharing, especially considering that PA mostly treat sensible, personal data of citizens. Several national strategies quote both the AI Act and the GDPR as legal cornerstones.

4.2 Political pressures

AI national strategies prescribe a change in mindsets and approaches to administration, calling for innovation and experimentation. A common strategy involves the deployment of pilot projects across different areas of public service, including health, education, and traffic management. These projects are regarded as critical reference implementations, providing valuable experience and knowledge that can be leveraged for wider-scale adoption. Public datasets of use-cases in PA are the AI Watch dataset (last updated in 2021) and OCSE's OPSI dataset (last updated in 2024), representing sources for in-depth, grounded analyses.

Parallel to these pilots, governments are creating dedicated spaces for experimentation and innovation, including regulatory sandboxes. Innovation laboratories are being established in specific departments to cultivate a more agile "start-up culture". This is complemented by the creation of AI competence centres and innovation hubs, such as those in Estonia and Luxembourg, which aim to lower the barriers to entry for AI development and foster interdisciplinary collaboration. Events like hackathons and innovation competitions are being used to stimulate creative problem-solving and engage a diverse range of stakeholders in addressing public sector challenges.

Different players come across different roles in the analysed strategies. The collaborative, multi-stakeholder authorship of these national strategies suggests that the institutionalisation of AI is a socially negotiated process, with each actor carving out a specific role for themselves, evident in the composition of authors of AI strategies (public, private, academic).

The national strategies reveal a complex social process of AI governance and co-creation, with distinct actors playing different, yet interconnected, roles. The discourse identifies a collaborative network where each group contributes to the implementation and ethical oversight of AI in PA. Software developers and tech companies are primarily conceptualised as the drivers of technological progress. Their role is multifaceted, encompassing solutions development, providing foundational infrastructure, and shaping marketisation and financial models. Their deep involvement in R&D places them at the forefront of innovation. Similarly, several strategies identify experts and consultants as crucial facilitators, with their primary functions revolving around knowledge transfer and helping public sector organisations integrate complex AI systems.

In this collaborative landscape, academia's role is defined by its expertise in foundational knowledge and long-term development. It is responsible for education and training future specialists, contributing to knowledge transfer through research. Crucially, academia is identified as a key partner in formulating ethical frameworks, providing the necessary theoretical grounding for responsible AI. Meanwhile, governments are positioned as the central authority, with a wide-ranging role. They are responsible for strategic formulation and overall policy making, establishing regulation and legal frameworks, and acting as essential public infrastructure providers.

The public sector is viewed as both a recipient and a co-creator of AI. Its unique position as a data collector and provider makes it a vital partner, while its role as the primary agent for process digitalisation and transformation is key to changing how services are delivered. Public organisations also act as a direct co-creator of solutions and is the ultimate deployer and user of these technologies in the public sector.

Linguistic and cultural preservation in LLM tied to Generative AI represents an emerging theme. Since most language models deployed in the EU area are trained by US tech companies, several governments considered strategic to maintain government-sponsored language model training. Language reflects cultural tweaks and nuances that can be lost in translation, causing sociolinguistic biases that can lead to severe consequences (Gupta et al., 2025). For instance, US LLMs might reflect regulative and cultural stances on the possession and carry of firearms, in a completely different fashion from what European norms would imply.

4.3 Social pressures

Society and the private sector at large are framed as the ultimate beneficiaries and a critical feedback loop for AI implementation. As the end-user of AI solutions, they also act as a source of accountability, and their collective choices are often seen as vital to technology acceptance and trust building across society. In this process, stakeholders require transparent decision making, not limited to disclosure of AI usage. Appropriate procurement processes, respect of privacy and human rights, are imperatives put on PA.

A second goal is to incorporate AI in citizens-PA relationships, while building trust. European societies nowadays are used to interact with chatbots, a technology that public sector organisations have widely incorporated, even though several strategies point out that older and/or poorer populations should not be excluded from public services as they have a lower capacity to access AI. The relationship between citizens and administrations is built on a social contract, that AI must reinforce, not erode, in the strategic approach to technological implementation.

The underlying idea expressed in the strategies is that if adoption checks all the input and process requirements, then trust building or maintenance is an expected outcome. Otherwise, public sector organisations and government at large risk facing dire social and political consequences, as often happened in the past when things went downhill, e.g., the previously cited SyRi case.

5. Discussion

PA is expected to comply with the vision outlined in these documents usually written by a mix of influential authors/stakeholders (big techs, consultants, politicians, policy makers, academics). The results are in line with previous literature, as the identified themes, while interpreted through a different framework, suggest continuity with Fatima et al. (2020), Hjaltalin and Sigurdarson (2024), and van Noordt et al. (2025). Similarly, Rudko et al. (2025) find that AI research in organisational studies is closely aligned with critical topics such as ethics, privacy, transparency, and law.

According to NI principles, national strategies pressure organisations, particularly in the public sector, by defining what’s expected and, on the opposite, should be avoided. Nations consistently articulate goals of streamlining processes, reducing costs, and enhancing citizen experience through AI.

The shared idea that a modern PA uses AI – paying attention to its several challenges – emerges as a clear and loud message and desiderata. Adopting AI as a strategy to gain legitimacy bears the risks of fostering change not because each and any organisation need it, but as a mere social performance.

5.1 Legitimacy versus efficiency

The question of whether PA genuinely gains or loses legitimacy by incorporating AI into its processes is a critical one. As previously highlighted, Rudko et al. (2025) note that NI traditionally assumes technological aspects to be external pressure elements, primarily governed by norms rooted in concepts of efficiency (Daft, 2021; Ritzer, 1996), and thus kept distinct from institutional pressures that are instead founded on the social expectations placed upon organisations and the rule of law. This has changed in recent years. The "imperative to digitalise" (Bennich, 2024) and the pressure to implement AI, directly drives legitimacy-seeking behaviours within PA. Consequently, a possible trade-off between legitimacy and efficiency may arise (Richardson & Joshi, 1997). Given that many market solutions for AI are not highly customisable, as AI solutions are often highly standardised and therefore produce similarities in specific institutional fields (Caplan & Boyd, 2018), PA's existing processes must adapt to the available technology, or risk appearing old, antiquated, and inefficient in the public eye. For organisations, particularly in the public sector, relying on tools that provide answers centred around a statistical mean (or so-called "stochastic parrots") signifies a potentially lower capacity to act on the fringes, the "exceptional cases" as independent agents. Anyhow, even if the adoption policy described in the strategies is successful in terms of efficiency, it can still fail in terms of legitimacy (Wallner, 2008).

The possible dichotomy between legitimacy and efficiency has been widely discussed in literature since the early modern sociological studies. For instance, in Max Weber's legal-rational ideal-type, where authority is legitimised by adherence to rules and norms while ensuring administrative efficiency, can be seen as an early attempt to inquire on the intercurrent relationship. The balance of the two can be quite difficult to maintain, as most modern nations find out in times of political or economic crises. As well argued by Offe in his Contradictions of the Welfare State (1984),

> *there is no functional need for explicit legitimation as long as 'everything goes well' and role acceptance is forced upon citizens either by their own utilitarian/instrumental motives and/or, at least, by the absence of feasible alternative roles and social mechanisms. To put it in slightly different terms, as long as every citizen takes part in market relationships that allow him or her to do so continuously, there is no apparent reason to challenge the legitimating rules of political power or even to think about them in cognitive terms. As everyday experience teaches, and as I have argued in the preceding sections, this happy condition of normality can hardly be assumed to be the normal case.*

Perhaps unsurprisingly, this contradiction is not directly addressed in the reviewed strategies. Indirectly, posing that PA should work towards maintaining or developing citizens' trust in the technology and the institutions can be interpreted as a call to balance legitimacy and efficiency. Furthermore, shared governance may be interpreted as a tool that help maintain legitimacy through a system of accountability checks among stakeholders.

It should be noted that in niche cases stressing this dichotomy is not appropriate, at least when data shows a perfect correlation of the two variables (the question on how to measure them is open) or they're independent (Richarson & Joshi, 1997).

5.2 Organisational change

NI generally aims to explain change rather than conformity. By observing how public organisations are implementing AI in reality, more than analysing the technology itself, institutional research can provide new ventures for theory and perhaps meaningfully support public managers in this historical phase.

PA practices and working methods are already changing, for instance, by shifting towards smart working, teleworking, and communications, impacting on jobs (Adamczyk et al., 2021; Arntz et al., 2016). The impact may differ considering different organisations and even different roles and jobs, even in PA (Bonomi Savignon et al., 2024). For instance, large and small administrations may present differences – in terms of skills, but also the capacity to navigate regulations concerning advanced technologies.

Cloud computing, cybersecurity, data management, and protection, and now AI adoption and implementation often require roles, like a Digital Transition Officer or a Data Protection Officer, that are simply unsustainable for local governments below a certain population (and therefore budgetary) threshold.

As a results, several organisations lack AI technical capabilities and become over reliant on external skills and competences. There's a growing recognition of the need to reintegrate specialised functions that were previously outsourced, evident in digital era governance frameworks (Dunleavy & Margetts, 2010, 2023). Reintegration is often “not efficient” and thus in open contrast with business-type public management logics, strongly defended through systems of institutional hooks that inhibit change unless wider policy initiatives are undertaken (Öberg & Sundström, 2025).

5.3 Regulation

AI currently dominates public discourse and is often strategically protected within certain political ecosystems from external influences. In the United States, for instance, a prevailing narrative suggests that robust regulation of AI could lead to the nation losing the “AI race” with China (Wang et al., 2025). This perspective often frames AI development as primarily a private sector endeavour. Conversely, China's model features significant state ownership or direct participation in the foundational infrastructure of AI, including servers, software, and code, as expected within China's value system (Chen et al., 2025).

Between these two players, the EU advanced a regulatory strategy based on the European value system, aimed to fostering economic growth while ensuring that core tenets are respected, especially on the ethical side (what’s appropriate or not in AI usage) rather than the technological side (what’s technically possible or not). The repeated articulation of values suggests a proactive stance to mitigate risks like algorithmic bias and privacy infringements, which is particularly crucial for public sector applications where citizen trust is considered paramount and a strategic target (Agbabiaka et al., 2025; Berman et al., 2024; Kattnig et al., 2024; Parviainen et al., 2025). In this area, developing national language LLMs, something which would be hardly invested in by extra-EU businesses, is considered a way to protect small enterprises and ensure that cultural stances are reflected in citizens’ interactions with chatbots.

Furthermore, since public sector organisations act accordingly to rule of law (risking legitimacy otherwise), without a complementary and timely revision of the normative corpus they cannot, in several instances, adopt AI. For instance, GDPR’s regulations on personal data storage may make highly difficult for European PA to access cutting-edge AI tools developed and located externally. As mentioned, the EU overall strategy is aimed at bridging these issues, but the time needed for such policies to produce any effect is usually long, while "ready or not, AI comes" (Jöhnk et al., 2021).

Anyhow, the AI Act provides a unified legal framework across the EU. Its designation as a regulation, instead of a directive, grants it a higher degree of direct applicability and uniform enforceability across all member states. As a directly applicable regulation across all EU member states, it constitutes a binding governmental mandate that leaves little room for discretionary compliance at the national or organisational level. This direct legal compulsion forces public sector organisations to align their AI governance and implementation practices with a common, centrally determined template. Unlike mimetic strategies, which might involve voluntary imitation of perceived successful peers (e.g., in the adoption of a digital twin like other successful city projects), or normative pressures deriving from professional and technical standards defined by "AI experts", the AI Act directly imposes homogeneity through legislative force, thereby standardising the institutionalisation of AI practices across diverse administrations. For instance, the required governance processes in high-risk environments directly shapes organisational structures by defining roles and procedures as per Section 2 of the AI Act.

Nonetheless, several EU member states, like Italy, are developing further legislation, as stated in many of the AI Strategies reviewed, to reduce uncertainty. The rule of law in PA demands predictability, legal certainty, and clear, pre-defined procedures where outcomes are determined by adherence to established legal norms rather than by risk assessments, that involve a degree of discretion: the public sector's need for clear, unequivocal legal bases for action are core to the institutional identity. PA is usually risk-adverse environment: not providing a specific legal contour for AI implementation may lead to avoidant behaviours (C. Oliver, 1991).

6. Limits

Several limitations stem directly from the research design. While the themes identified are in line with previous research, the interpretative nature of thematic analysis introduced personal perspectives in the analysis, something that more quantitative approaches, like content analysis, try to minimise. As described, I chose Oliver's framework (1991) as it is a good fit to categorise the sources of institutional pressure in technologically challenged environment, while other approaches exist.

Key challenges in conducting this study include the rapid evolution of both AI technology and related regulatory landscapes, potentially outpacing the analysis.

Finally, this paper tried to condense decade's worth of NI research, clearly leading to an overview focused on painting a picture, on one side, and integrate new elements and suggestions into the well-established knowledge. NI has several strains or schools, and while I focused on social and discursive stances, looking at AI implementation through historical or rational-economic lenses may have yielded additional insights.

7. Conclusions

This article introduced a new layer of complexity into the academic discourse over the implementation process of AI in EU public sector organisations by analysing how national strategies pressure PA. Exploring the implications of recurrent and relevant topics, several institutional mechanisms that highlight the need for organisational change were identified.

First, the focus on efficiency and efficacy gains through AI might pressure administrations towards indiscriminate adoption, in order to be perceived modern, functional, ultimately legitimate. Second, the multi-actor panorama that emerges from the analysis and review puts public sector organisations in a position of general weakness, as they do not develop the technology, nor possess technical skills: organisational change may happen as a consequence of adoption and/or overreliance to the tools and the external influence of stakeholders. Third, the absence of clear and operable rules, specific to the public sector, may hinder adoption. In sum, avoidant behaviours may become the only safe and clear option, sacrificing both legitimacy and efficiency in order to maintain institutional arrangements. Specifically, there are two main possible responses according to NI that future research may look for: immunisation (rejecting AI, which squanders its significant potential) and imitation (adopting AI simply because others do, without clear purpose or a strategy).

While the EU is now heavily investing in AI development and the supporting infrastructure, competing with large corporations remains a significant challenge. Decades of experience, substantial financial resources, and the ability to offer highly competitive salaries to managers, workers, and AI experts (a level of compensation PAs simply cannot match) arise questions on the active/passive role of PA in the AI age. Furthermore, data centres, architecture, and software environments that allow AI to function are often privately owned.

The question on the adequacy of institutional theory in explaining AI adoption and implementation processes is new but not unprecedented. Recent scholarship, notably that by Rudko et al. (2025), has begun to address several theoretical issues. While their work analyses published research on AI within the field of business organisation, one of the traditional venues for NI, I focused on PA. It's easy to concur with their assessment: even though NI is considered a relatively late-stage research program, the inherent novelty of AI – particularly its distinct socially constructed aspects – significantly reduces the risk of producing low-utility research by "reinventing the wheel," becoming tautological, or offering mere pseudo-progress (Alvesson & Spicer, 2019). NI provides a robust framework for understanding the adoption and implementation patterns of AI, particularly as they largely follow existing institutional contours shaped by regulative, normative, and cultural-cognitive elements. The pervasive narratives and social expectations surrounding AI, categorised in themes, exert significant influence on PA. In conclusion, traditional institutional mechanisms look largely unchallenged by AI.

Nonetheless, the charging of AI with increasingly salient socially constructed elements and cultural stances raises significant questions regarding the revisiting of NI, given the possible role of this technology in its own institutionalisation process.

Future research will focus on how public sector organisations are changing the organisational model to leverage AI. In particular, the question on whether PA implements AI to gain efficiency and/or legitimacy opens new directions. Finally, a framework to assess the impact of AI implementation both on the organisation and on public values seems urgent.

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An inquiry on organisational culture: a key driver for a thriving public sector in the age of AI. A case study of Italian cities.

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Abstract

This paper presents the findings from an inquiry into organisational culture across several Italian cities. Its core purpose is to gain an empirical understanding of the values and beliefs that factor into AI implementation. Conceptual models of AI adoption and implementation acknowledge organisational culture as a significant factor. However, its specifics are often not deepened, nor is its relationship with other factors thoroughly explored. Drawing on Schein's (1992) tripartite framework of organisational culture as a theoretical base, the study employed a case study methodology alimented by semi-structured interviews. We find that organisational culture is at the centrepiece of several connected challenges in AI implementation, describing an organisational reality that may discourage AI implementation if innovative and collaborative value systems are not strategically developed in organisations. We discuss the relevance of these findings in relation to the Italian investment strategy for the digital transition of public administration.

Keywords: Public Administration, Artificial Intelligence, Organisational culture, Case study, Municipalities.

1. Introduction

Artificial intelligence (AI) presents a significant opportunity for public administration (PA). AI isn't entirely new to PA; for decades, there have been various experimentations showcasing its usefulness and inherent risks, in areas like urban planning and fraud risk assessment (Desouza et al., 2020; Neumann et al., 2024; Wirtz et al., 2019a). However, the practical application of AI within PA remains circumscribed, largely confined to pilot projects and experimental stages (Sousa et al., 2019).

To uncover the reasons behind technological underemployment, we ran an inquiry on organisational culture in eight Italian cities, using Edgar Schein's framework (1992), to understand how culture shapes and informs decision-making in the field of digital transition, in general, and AI implementation, specifically.

While organisational change and culture is one of the principal challenges in AI implementation (Maragno et al., 2023; Tangi et al., 2023), and a recurrent feature in conceptual models (Babšek et al., 2025; Madan & Ashok, 2023), it has not been widely studied in recent years in European public sector organisations.

The technological landscape has evolved with the emergence of new AI forms, particularly generative AI, text-based AI, and AI agents (Haenlein & Kaplan, 2019). While past applications within PA were somewhat narrow, new technology seems to have wider potential applications, especially on bureaucratic processes (Weerts, 2025). Nowadays, AI is more readily available and accessible. Nevertheless, appropriately using AI tools isn't straightforward or immediate, and needs structured governance mechanisms and organisational adaptation through a, often substantial, change management process

(Butcher & Beridze, 2019; Zuiderwijk et al., 2021). Using these tools, that are based on inferential methods, requires an awareness of their functioning in order to understand their outputs and make informed decisions. This concept is also enshrined in the AI Act, the European Union's on AI, which states in Article 4 that all staff shall receive adequate basic training on AI before using it. The AI Act is only a piece of the EU strategy, focused on both the possible opportunities and the threats of AI to European core values (Pham & Davies, 2025). Training does not mean that everyone should become able to program AI. What's required of users is keeping a critical, sceptic mindset to counterbalance risks such as automation bias (Goddard et al., 2012). However, the use of AI isn't solely determined by individual behaviour or perception (Ahn & Chen, 2022a); it's also shaped by the organisations these individuals belong to and the acceptance of the wider society (Horvath et al., 2023).

Our hypothesis is that organisational culture, among the several factors identified in the literature (Madan & Ashok, 2023), is one of the most crucial aspects of digital transition and AI implementation in Italian local governments. Values and beliefs embedded in the culture can favour, or hinder, the willingness to experiment and adopt new technologies.

Specifically, we are interested in exploring the traits of information culture, an Information System studies specification, where "*the value and utility of information in achieving operational and strategic goals is recognized"* (Curry & Moore, 2003), in contrast with traditional cultural stances in PA. Without an appropriate information culture, nurtured in public sector organisations, the uncritical use of AI can lead to significant risks (Floridi et al., 2018; Wirtz et al., 2019b).

The study focuses on Italian PA, particularly large municipalities. Italian cities represent an interesting case study due to several factors.

Municipalities have authority upon the same functions of government: social care, local enforcement, youth policies, urban planning, and so on, meaning they share the same core missions, objectives, means and legal frameworks. Despite having similar aims and tasks at hand, Italy has few large municipalities, just 136 exceeding 50.000 population in 2025 and collectively hosting 1/3 of the total population, while the vast majority (5.521 in 2025) are very small, under 5.000 population. This distribution is not uncommon nor the most skewed, e.g., in France currently just 124 municipalities exceed 50.000 population, over about 35.000 total municipalities.

Moreover, the workforce is very old, the oldest in the European Union according to the European Commission (Stimpson et al., 2023). In fact, over half of Italian municipal employees are over 55 years old (Campostrini & Grassi, 2021, 2024). Therefore, a very high number of retirements are expected within the Italian PA in the coming years, a phenomenon that is already quite evident.

Finally, Italy exhibits significant territorial disparities, with some territories boasting high GDP levels while some remote areas are among the most underdeveloped in the European Union according to Eurostat official data. While organisational culture research is largely case-based and contextual, environmental conditions typically studied in institutional theory can clearly affect several organisations (Strandgaard Pedersen & Dobbin, 2006). In Italy, a correlation between development and administrative capacity, especially in structural funds implementation, has been noted (Milio, 2007). Therefore, *ceteris paribus*, cities located in disadvantaged areas might have a lower capacity to advance in digital transition, as since 2022, the Italian National Resilience Recovery Plan (NRRP), adopted thanks to the Next Generation EU-funds, empowered digital transition strategies across municipalities through structural funds.

These issues look even grimmer as PA will need to respond to challenges of unprecedented scale, particularly ageing populations, which raises concerns about the sustainability of public finances and local social care systems. Nonetheless, AI has the potential to foster innovation in PA (Wirtz et al., 2022). Since 2020, the landscape of digital administration has evolved significantly, driven by external pressures like the pandemic's demands for organisational and cultural adaptation (e.g., remote work and evolving PA-citizen relationships) (Moser-Plautz & Schmidthuber, 2023). Again, since 2022, NRRP included unprecedented investments in digital technologies. In this complex landscape, AI implementation has become a central strategy in PA (Hjaltalin & Sigurdarson, 2024).

While culture is recognised by almost all scholars as a factor of AI adoption and implementation, several questions remain largely unanswered, particularly what is driving change and how PA is responding in terms of culture and organisation.

The research question is formalised as follows:

(1) Which features and characteristics of organisational culture favour of hinder AI implementation in Italian municipalities?
(2) Which complimentary factors favour of hinder AI implementation in Italian municipalities?

In order to explore such pressing matters, our research centred on interviews with digital transition managers in some of the Italian municipalities.

After a review, aimed to provide the theoretical lenses of our analysis, the paper is structured as such: methodology and results of the interviews, a discussion over the findings, and conclusions.

2. Literature review

Organisational culture is central to our research. Edgar Schein's (1992) defines culture as "*a pattern of shared basic assumptions learned by a group as it solved its problems of external adaptation and internal integration, which has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems*". Culture doesn't emerge from a vacuum, but rather from the social context within a certain organisation. Furthermore, it's not a static concept; it's dynamic, shaped by the internal response to external challenges and vice versa. Culture is a way to reduce the "*cognitive burden of inventing new solutions for every contingency, of having to make choices for every fork in our existential pathways, of having to decide anew the fundamental values that should inform our choices, and of having to make up the norms for organized living* […]" (Patterson, 2014).

This paper is largely based on the theoretical framework proposed by Edgar Schein, partially because it was elaborated through years-long observation in Digital Equipment Corporation (DEC), belonging to an industry with high affinity with the current AI industry. Culture has concrete, visible manifestations, which Schein, in line with previous research (Gagliardi, 1990), calls artifacts. In the context of PA those can include policies, strategies, and planning documents. They also extend to established processes, rituals, organisational charts, and datasets. Budget choices are also reflections of an underlying culture. These artifacts were observed in a 2020 DIGISER survey, addressed at European cities, that provide a secondary source of data to root our study(Bianchi et al., 2022) – more in the methodology section. Adapting Schein's model to PA, Van Wart (1998) further distinguish two levels of artifacts: on one side, material aspects (e.g., workspace, dress code, technologies of the organization), while on the other behavioural features like activities, routines, and processes.

According to Schein, culture is like a pyramid, or perhaps an iceberg, where the visible part, the artifacts, represent only a fraction of the whole. At a deeper level, espoused beliefs and values. Objectives, ideals, aspirations, values, ideologies and rationalizations are examples of such deeper features. This second level can be explored through ethnographic research, case studies, and interviews, core methods in organisational culture research (Strandgaard Pedersen & Dobbin, 2006). In PA, cultural analysis involves understanding how a bureaucratic-legal culture reconciles with an information-digital culture, considering the different belief systems that characterise these substructures. We investigated these aspects through several interviews we conducted in June 2025.

Finally, basic underline assumptions permeate organisations. For example, the conception of time in PA may be composed of two main subcultures: working office hours (time flows at the rhythm of office hours), versus smart working (time flows at the rhythm of task-objective completion). Assumptions have clear reflections on behaviour: a colleague may be uncomfortable working at a dissonant rhythm in respect to their taken-for-granted assumption of how time flows in their specific subcultural environment. We did not focus on assumptions in this study, as a long-term on-site ethnographic analysis is necessary in order to uncover them.

Schein's work has been impactful for theory and practice, especially in the field of organisational culture research. Culture has been empirically tested for its capacity to foster innovation (Hogan & Coote, 2014). Nevertheless, in PA principles of tradition, hierarchy, and bureaucracy often prevail (Boufounou et al., 2024), potentially hindering initiatives.

While prominent, Shein's framework is not the sole theoretical basis of this paper. The Organizational Culture Assessment Instrument is a widely employed model developed by Cameron and Quinn (1999) and grounded in their Competing Values framework. The framework conceptualises four fundamental types of organisational culture: Clan, Adhocracy, Market, and Hierarchy. The four types are described by two key dimensions: flexibility versus stability, and internal versus external orientation. While Clan and Adhocracy cultures stress organisational flexibility and adaptability, Market and Hierarchy cultures favour control, order, and stability. Italian PA, legalistic in spirit, is mainly Hierarchical. A cultural environment focused on procedural consistency, repeatability, low risk, and compliance with rules, seem quite distant from the Adhocracy domain, ideal for experimentation and innovation.

Organisational culture research, much like neo institutionalism, arise during the 70's on the wave of social constructionism (Berger & Luckman, 1966). As noted by Strandgaard Pedersen & Dobbin (2006), these two branches of research, while both stressing the role of culture (e.g., Dimaggio & Powell, 1983; Scott, 2014), were traditionally kept separate, since they focus on different levels of analysis (intra-organisation vs. inter-organisations), explanandum (continuity & differences vs. change & similarities), and explanans (search for identity vs. search for legitimacy). In their final remarks, they conclude that cultural analysts may benefit from a wider view of what's happening at field-level, while neo-institutionalists should implement more contextual elements. T-O-E frameworks (Tornatzky & Fleischer, 1990), for instance, widely include elements from both research programmes. Since then, a wider view of culture has become the norm, recognising that cultural shifts shape institutions and vice versa (Thornton et al., 2012). Agreeing, we strived to balance specific, highly contextual findings with general, wider views on the relationship between AI and PA. Therefore, while rooted in organisational culture research, our work implemented several ideas stemming from neo-institutionalism, e.g., in inquiring how administrations are interacting with one another.

The prominence of values and beliefs in qualifying culture is not uniform in literature. In particular, the idea that values are shared uniformly in an organisation seems too strong an assumption – not shared by all scholars. Giorgi et al. (2015) describe further and integrated ways of conceptualising culture. Narratives, for example, are powerful ways of conveying sense; frames can limit and shape behaviours; categories characterise differences and similarities; and finally, toolkits can mix different concepts. In any case, values have a prominent role in organisational culture.

Looking at PA, values were traditionally considered less important than rationality and norms. Max Weber, and many others after him, espoused the idea of a depersonalised PA, where bureaucrats strive to devoid action of personal elements, in order to, for instance, guarantee equal treatment and prevent corruption. New Public Management, fostering the application of rational principles to decision making, is close in spirit, while recognising the role of individual leadership. After decades of cultural studies, scholars looked more closely to the role that values play in PA, shaping actual behaviour and decision making (Molina, 2009). PA is not only made up of rules, norms, and coded, expected behaviours, but of actual people, each with their own dispositions, identities, and beliefs that can be influenced by outside forces upon which organisation may have no control.

Culture is a feature of several conceptual models of AI in PA. For instance, Jöhnk et al. (2021) identify five categories of AI readiness factors and their indicators, derived from expert interviews and literature review to guide (private and public) organisations in AI adoption decisions: strategic alignment, resources, knowledge, culture, and data. Culture and knowledge stand out particularly, in respect to Article 13 of the AI Act, which requires users to understand how to interpret AI outputs, how the systems target specific demographics, which are the necessary human oversight measures. For (Tangi et al., 2023), organisational change and culture represent a key dominion of AI implementation.

Due to the rising prominence of advanced technologies, like AI, in the public discourse, information culture is gaining traction in PA. Information culture reflects the diverse values and attitudes attributed to information by individuals within an organisational context. Notably, information culture exists in organisations regardless of whether it facilitates management and is deeply intertwined with the broader organizational culture, often reflecting its underlying values, assumptions, and artifacts (Curry & Moore, 2003; Oliver, 2008). The governance of information is a determining factor for its effectiveness. Models of information governance range widely, from centralised to local control, each with different pros and cons (Oliver, 2008).

In the context of PA, professional bureaucracy is a specific type of organisational structure tightly connected to information culture, particularly relevant in knowledge-intensive environments such as university administration, or in key decision-makers (Deja, 2024). Professional bureaucracy is connected to Adhocracies (Cameron & Quinn, 1999), fundamentally different from personnel bureaucracy, which is typically observed in Hierarchical public sector organisations. In personnel bureaucracy, individuals only interact with a small part of the whole organisation and usually do not know how their work contribute to wider objectives, nor they are called to make informed decisions that are reserved for higher management levels (Deja, 2024).

In PA, Hierarchical bureaucratic cultures can often hinder innovation and adaptability (Cameron & Quinn, 1999; Van Duivenboden & Thaens, 2008; Xanthopoulou et al., 2022). However, organisational culture can be a powerful lever capable of enabling technology acceptance, reinforce usage guidelines, and reduce associated risks. While empowering information culture can be complex and costly (Curry & Moore, 2003), it's a necessary step to avoid unforeseen, negative consequences of digital transition and, moreover, AI implementation.

3. Methodology

Our research is based Yin's (2014) six steps protocol for case studies. This approach, in line with the seminal recommended approaches, allows us to directly engage with key players responsible for digital transition within public sector organisations. We aim to mine insights into the practical challenges and successes of digital transformation and explore the underlying espoused values and beliefs driving the respective strategies.

3.1 Case selection

Case selection was based on a preliminary search and analysis of available data on the status of technological advancement of Italian municipalities. We leveraged existing data from the 2020 ESPON-DIGISER survey (Bianchi et al., 2022). DIGISER was aimed at measuring the digital maturity of a sample of European cities through a multidimensional Digital maturity model (DMM) expressed as a score between 0 and 1.

Digital maturity can be defined as an organization's level of digital transition and its ability to create value through digital technologies, including AI. There is no consensus on a single DMM nor a definition of digital maturity (Thordsen & Bick, 2023). While the specific items can change across different studies, the idea that culture is a very relevant factor is ubiquitously shared (Butt et al., 2024; Thordsen & Bick, 2023).

DIGISER DMM included several dimensions, with a crucial attention on the level of AI adoption and implementation in certain service domains. One grouping dimension, called "institutional capacity", measured the degree of presence of innovation strategy key roles and proneness to experiment, expressed through cultural artifacts adopted in the organisation. Case selection started with the 17 municipalities across Italy (Table 1) that were in the DIGISER sample.

Year 2020 data showed diverse degrees of digital maturity, organisational sizes, and contexts within a single national administrative system, allowing us to carefully consider which cases to pursue. In practice, we wanted to ensure looking at cases with different levels of maturity, size, and geographical collocation, for the several reasons already described in the introduction.

Population was a crucial factor to consider, as it's a proxy for organisational scale and bureaucratic complexity, which can significantly impact technology adoption, since smaller organisations tend to have less resources on average (OECD, 2021).

Table 1: digital maturity score, population and geographical area of the 17 municipalities, 2020 (source: Bianchi et al., 2022)

	Digital maturity score	*Population in 2020 (thousands)*	*Geographical area*
Milan	0.415	1.379	North-West
Gallarate	0.261	53	North-West
Bologna	0.432	391	North-East
Venice	0.443	261	North-East
Ferrara	0.257	132	North-East
Ravenna	0.460	158	North-East
Rimini	0.248	155	North-East
Pordenone	0.257	51	North-East
Florence	0.455	379	Centre
Prato	0.456	195	Centre
Perugia	0.465	166	Centre
Palermo	0.462	663	South
Catania	0.327	312	South
Messina	0.429	233	South
Taranto	0.411	197	South
Pescara	0.380	119	South
L'Aquila	0.303	69	South

More population means more data to collect and process, which justifies the deployment of AI and other large scale, expensive technologies. A population size under 100.000 seems to be associated in terms of simple correlation with lower digital maturity scores in Table 1, according to our calculations.

3.2 Interview protocol and analysis

Data collection was mainly performed with in-depth, semi-structured interviews (Kvale, 1996) conducted in Italian in June 2025.

Before the interviews, we performed a preliminary documental analysis, looking at the observable cultural artifacts that were available online (i.e., official reports, policy documents, strategic plans), and public records pertaining to the digital initiatives of the 17 municipalities. So, field analysis is complemented with wide-ranging documental data, providing context and meaning.

Participants were specifically identified as digital transition officers or chief digital officers within these administrations. Participants were recruited via email invitations, and the interviews were conducted online to facilitate participation.

Out of the 17 organisations, 8 municipalities agreed to participate in the study. Even though small in number, the variety of the participants covers different combinations of digital maturity score, population and geographical area.

It's not easy to get organisations to open up to external observers, especially when inquiring on values and beliefs that may be different in respect to the dominant cultural features. On the other hand, an "*observational and clinical*" approach is necessary (Schein, 1992). To achieve cooperation and ensure trust building, we chose to not record nor transcribe the interviews word-by-word, maintaining confidentiality. This choice is reflected in the way the results are presented, putting the focus on the trends rather than the people.

The reported quotes in the next sections are paraphrased from notes taken during the interviews by one of the authors, performing as rapporteur.

Table 2: interviewees' profiles and context information

	Role	*Population in 2020 (thousands)*	*Geographical area*
Milan	Chief digital officer	1.379	North-West
Ferrara	Chief digital officer	132	North-East
Pordenone	Digital transition officer	51	North-East
Florence	Digital transition officer	379	Centre
Prato	Digital transition officer	195	Centre
Messina	Chief digital officer	233	South
Taranto	Chief digital officer	197	South
Pescara	ICT staff member	119	South

The interviews followed a pre-designed protocol with a list of questions corresponding to a list of research items. The items were pre-determined, based on the reviewed literature. Each interview opened with the request to describe a use case and assess the organisation's trends in digital transition and AI implementation, leaving to the officers to build the narrative. Then, if not yet mentioned, we guided the conversation towards organisational cultural themes, e.g., the stance on innovation versus legalistic/bureaucratic mindsets, collaboration and conflict, and technological acceptance.

After each interview, the notes were digitalised and coded in order to permit information retrieval and iterative analyses. The quotes in the next paragraph are copy-pasted from such notes.

4. Organisational culture in Italian cities in 2025

The interviews reveal a central tension between two competing subcultures in the digital transition domain. On one side is the traditional, deeply embedded value system of the bureaucratic-juridical culture. This system espouses a profound belief in the importance of norms, legal certainty, and established procedure (Hierarchical culture). These features are not looked at as an obstacle but a core value, as interviewees indicated that norms provide legitimacy and a secure pathway for action. Artifacts expressing this value in digital initiatives include the careful development of codes of conduct for AI usage, therefore norming in order to reduce uncertainty.

In direct competition, an emergent Adhocratic value system is driven by a shared belief that the traditional bureaucratic model is no longer adaptive. This belief champions values of innovation, efficiency, and experimentation. It is actioned through strategic endeavours: attract new talents, foster cross-office collaboration, and engage with citizens in novel ways, as evidenced by artifacts like chatbots or hired personnel dedicated to digital facilitation. The proactive search for new solutions and comparison with other European cities are further expressions of the commitment to progress and modernisation.

The challenge of AI adoption is thus framed by the clash between these two value systems: the push for agile experimentation confronts the demand for normative clarity and risk aversion. The cultural clash is often present and recognised, but most interviewee did confirm that both sides are important to foster advancement. In some cases, effective coordination and cross-office collaboration allows to reach results within established procedures; in others, a sense of frustration reflects the inability to foster a cultural change.

4.1. The role of AI: potential and prudence

Many municipalities achieved significant levels of process digitalisation, with several examples clearly demonstrating benefits in terms of efficiency and citizen service. AI is a topic of great interest, yet its adoption is marked by caution and a clear awareness of its limitations, especially in contexts requiring accountability. Looking at AI implementation, digital twins, deployed in several municipalities, make extensive use of machine learning solutions for object recognition in the territory. In two cases, cities are experimenting with Registry Offices, using AI to classify and forward communications. An experiment with a synthetic voice telephone responder has been reported as well.

Except these few examples, the interviews pose the cases in a pre-adoption phase. It was emphasised that the output quality of generative AI is still variable, and critical spirit and mastery of the subject are needed (and often not present) to distinguish adequate outputs from hallucinations. AI is planned to assist in the back-office, particularly on repetitive and ritualistic procedural tasks. The importance of a local data centre was stressed in some municipalities, in order to comply with legal requirements and maintain data ownership. On AI, the approach is more cautious from a legal standpoint, given its potential pervasiveness and also its capacity to infringe on people's privacy, people's rights, and the transparency of administrative action. Uncertainty is perceived like a huge problem.

4.2. Bureaucracy and law in the digital age

Legal culture is confronting technological innovation, often with a cautious approach. The “*Italian tendency to regulate everything*” can impede innovation. In some cases, the legal culture responds well, but in novel areas like AI, "*the first to pull the handbrake*" is precisely the legal figure, due to the need for a clear framework before application. AI, as much as data protection, has rules outlined in terms of "*acceptability*" and “*risk*” and since what’s acceptable depends on the context, it creates an uncertainty that is hard to address in PA. Coercive normative tools are sometimes deployed to prohibit or enforce the use of software in resistant offices.

4.3. Resistance to change

Resistance to change among staff is one of the most significant challenges according to next-to-all the interviews. Despite the generally accepted idea that digitalisation can be an advantage, adherence to paper-based procedures and a lack of "digital awareness" hinder the full adoption of new tools. An interviewee found that "*the first hurdle was to show colleagues that, in fact, in many procedures, digitalisation has reduced their work on the one hand and simplified it on the other.*" While technology has seen exponential growth, the "*organisational and cultural part still has a linear, perhaps even quasi-constant, growth.*" Others noted, "*there is no perception among staff that the work you do is not just for your own service or procedure, but if well-organised, it can serve to simplify the work of others*." Offices often insist on "*implementing even procedural distortions*" and refuse to adapt established processes to new software packages.

4.4. Organisational models and change management

Organisational models may differ significantly. Often, what's perceived as an ideal configuration is simply not possible due to lack of staff, meaning that the same person is often invested in many different areas, further concentrating responsibility on few people. "*If my colleague and I resign, experimentation will stop*". "*For any 4 people that retire, we may be able to recruit one.*" The causes of understaffing are complex, but one is clearly recognised: the standard wage in PA is simply incomparable to the private sector particularly for IT personal. Nonetheless, sometimes recruitment is very successful: in several cases the influx of young ICT experts allowed for the creation of small but very effective offices, functioning similarly to start-ups. In other cases, even just the arrival of a new manager, with experience in more digitally innovative areas of PA like healthcare, was enough to change, albeit slowly, the cultural trajectory of the organisation. Finally, some municipalities opted for the creation of an in-house company to handle all matters related to ICT, with a *de facto* externalisation of all related matters.

4.5. The role of external suppliers

The relationship with external suppliers is central but presents critical issues related to a loss of control, very limited customisation of software packages, and economic sustainability. The traditional model "*I pay, and others work*" functions thanks to funding, but "*you risk losing control and governance.*" Someone noted that many smaller municipalities "*have to trust what the various software houses propose*" leading to the purchase of software that "*does not fully do what they have in mind or, in any case, does not integrate with the processes they have*."

According to almost all the interviewees, the relationship with software houses has changed: in the past, they were willing to make customisations, whereas now "*the solutions tend to be all the same, meaning you either take it as it is, or you don't take it; customisations no longer exist*." In any case, the relationship with third parties is fundamental, as PA does not develop any software internally, but requires technical knowledge to evaluate and assert control. In some cases, there's a belief that PA is still a bit behind in internalising strategic skills, entrusting too much to external consultants.

4.6. The impact of the NRRP on long term financial sustainability

The Italian NRRP has provided a recognised decisive impetus for the digitalisation of municipalities. NRRP has injected substantial financial resources, facilitating the adoption of common digital infrastructures and platforms. "*The NRRP gave us a strong push in this direction because it provided us with standards, templates, and a common way of operating.*" However, everyone observed that the availability of so much sudden funding has distorted the market, leading to an increase in prices and a scarcity of specialised personnel, further pushing homologation of software.

Despite the infusion of NRRP investments, the long-term sustainability of digital projects presents a serious concern. Management and maintenance costs, particularly for cloud services which are subscription-based, will fall on the running expenditures budget of municipalities from the end of 2026. "*When the NRRP will end, the running costs of these investment projects will be the responsibility of PA, and it will be difficult to reverse certain management decisions*." In particular, the migration to the cloud has shifted expenditure "*from the investment side of budgets to the current expenditure side,*" which is "*the one that always suffers the most*" in terms of budget elasticity and capacity to find additional resources. Many innovation projects were "*implemented through funding that intrinsically lacked a business model to guarantee their sustainability. Thus, the model is excellent as long as the funding is there, but as soon as the funding ends, the whole structure collapses.*" As a rule of thumb, "*for every 100 euros invested, you carry forward 20-25 euros of running costs in following years, typically not available.*" According to several interviewees, several municipalities were not strategic in their investments, spending on services with high costs in order to maximise resource allocation, rather than on foundational interventions such as the digitisation of archives.

4.7. Skills and staff training

The shortage of internal digital skills and the need for continuous training are recurring themes. The emphasis is not only on technical skills but also on awareness (a principle enshrined in Article 4 of the AI Act) and the ability to rethink processes. Accessibility to the tools, in order to experiment with solutions and actually use them, is a strategy to foster change. While some buy access credentials for all employees, others adopted a multi-stage strategy starting with smaller groups. "*Training skills does not mean turning an administrative figure into an engineer but making them understand that the repetitiveness of certain tasks, without a knowledge of what precedes and follows them and how they contribute to the overall functioning of PA,*" is not acceptable anymore, shifting narrow specialization towards administrative holism. The tendency to outsource even formative activities to the market was sometimes criticised, as internal transfer of knowledge would be a preferred option.

4.8. Collaboration and multi-level governance

Collaboration between municipalities and the role of regional or metropolitan entities is varied. Most cities are on the lookout for role models, curious about how others responded to similar challenges. Several groups and institutions allow for the exchange of experiences. The National Association of Italian Municipalities (ANCI) ICT roundtable, Major Cities of Europe and the European ENGAGE network were often cited, working on pressing matters like the reuse of know-how and the analysis of the impactful NIS2 directive.

Where present, the metropolitan city (a mid-level institution covering the area surrounding major Italian cities) is effective in supporting smaller municipalities of the area; in any case, a bigger city often has a role of informal leadership in the surrounding territory. Sometimes, differing political affiliations make it difficult to collaborate even among pure technical staff with other municipalities.

There is no homogeneous regional role in digital matters. In some cases, the region has no role at all, except for the occasional regulation. In other cases, a regional strategy and funding may be available. For example, by looking at the official website, Emilia-Romagna focused on coordination, pushing for Local Digital Strategies that continue the tradition of inter-municipal collaboration in the region. Tuscany even dabbled in open-source software development to make available to all municipalities, even if smaller municipalities often outsource their entire digital operations as they lack the minimal human resources and therefore would not be able to access said software.

On AI, it was highlighted that "*production requires formal steps, including the establishment of an ethics committee*". Such a recognition shows a clear signal of advanced cultural maturity, even if implementation degrees vary.

5. Discussion

The digital transformation of Italian PA is at a critical juncture, propelled by substantial investments. While this initiative has accelerated the adoption of new technologies, a closer analysis reveals a series of complex underlying dynamics and structural challenges mostly in line with previous research (Madan & Ashok, 2023). Several local authorities are focusing on AI applications that can actually impact on back-office efficiency (e.g., mail and document sorting, predictive analysis, support for drafting acts), adhering to established best practices rather than out-of-the-box experimentation. It is recognised that the effectiveness of AI is critically dependent on the quality and organisation of the underlying data, further reinforcing the notion that data governance and function reintegration is a fundamental prerequisite (Dunleavy & Margetts, 2023) that in smaller municipalities can be difficult to employ, opening to collaboration strategies.

The speed gap between the exponential growth of technological development (the availability of tools on the market) and the linear growth of information culture (the awareness and capacity to rethink processes and use said tools to generate value) is one issue at hand. Targeted training can have an impact (Terblanche, 2024): public organisations that actively train internal decision-making capabilities and spread AI knowledge, showed a more advanced stage of AI governance (de Almeida & dos Santos Júnior, 2025).

A trend emerged from the interviews: nowadays, organisational culture can be one of the most relevant challenges in digital transformation and AI implementation, as most challenges are rooted in the underlying set of values and beliefs about the meaning and role of PA in the digital state.

The results can be synthesized around two underlying clashes that emerged from our observation and interpretation:

1. "CONFLICT" – "COOPERATION" defines two opposite ways in which people interact, culturally, when considering or working at digital innovation processes.

2. "TRADITION" – "INNOVATION", reflecting two separate stances on how PA operates best in the digital era: keeping to established practices, versus trying out new possibilities.

Based on our observation, the combined dynamics can lead to different outcomes in AI implementation, as we conceptualised in Figure 1.

	INNOVATION	TRADITION
CONFLICT	Experiment	Enforce
COOPERATION	Embed	Escape

Figure 1: dynamics of cultural clashes (own elaboration)

In detail:

A. *Experiment* with new technologies as the result of innovation combined with cultural conflict in the organisation, limiting the stabilisation of the new solutions.
B. *Embed* new technologies in the organisation, when the innovative mindset is espoused, effectively working together to implement new technologies albeit the difficulties residing in change. This situation is the true, long-term AI implementation that is ideally seek out.
C. *Escape* new technologies when both sub-cultures stick to traditional values and actively collaborate in avoiding or postponing implementation.
D. *Enforce* traditional procedures and organisational models when the conflict impedes meaningful advancement, or the new technology is not accepted by the organisation, and its use must be forced upon the staff.

The representation (Figure 1) is not aimed at proposing a theoretical framework at this stage: it is a visual way to illustrate our interpretation of the interviews in our specific case studies.

The theoretical bases are there, though. For instance, the Technology Acceptance Model (Davis, 1989) champions the idea that positive personal attitudes affect the adoption of new technology. In particular, the adoption of AI by staff in PA can be explained by how their perceptions of the AI's usefulness and ease of use influence their attitude towards it (Ahn & Chen, 2022b; Xu et al., 2024). As for citizens, nurturing and building trust goes beyond the specific technology, e.g., AI (Schmager et al., 2023). Trust is built through long term action (a trustworthy government can "spend" that trust on new initiatives, a concept known as trust transfer) and organisational insurance mechanisms, like having a human in the loop or deploying strong transparency practices. Several principles are now enshrined in the AI Act, contributing to the goal of Trustworthy AI (Berman et al., 2024; Tangi et al., 2023).

While fundamental, organisational culture is not the sole crucial factor, thus confirming our hypothesis on one side, while painting a more complex situation on the other. Some variables are even out of the managers' control: e.g., the exogenous pandemic shock put PA on a new trail, accelerating cultural change (Moser-Plautz & Schmidthuber, 2023).

Historically, many local administrations have outsourced a significant portion of their technological and strategic capabilities. With the impetus of the NRRP and the shift to standardised cloud models, this relationship is becoming more critical. On one hand, suppliers are indispensable partners for implementation. On the other, a trend towards a loss of strategic control and customisation is emerging. The "take-it-or-leave-it" solutions of the cloud ecosystems reduce an authority's ability to adapt tools to its specific needs, creating the risk that it must adapt its own processes (even virtuous ones) to the software. Our findings suggest that a process of isomorphism (technological and therefore operational) is currently sustained by the suppliers' business strategies, as observed in past technologies (Caplan & Boyd, 2018).

Reintegration of capabilities to govern and control technology (Dunleavy & Margetts, 2010, 2023) seems quite urgent, considering the closing deadline of the AI Act enforcement, mid-2026. In order to achieve reintegration, organisational restructuring, sustained by change management, is fundamental. According to our results, and in line with common knowledge about the Italian PA, this passage is inhibited by the rigidity of organisations, dictated by the necessity to avoid increasing public expenditure. Recent governmental initiatives seem promising: a recent law (L. 69/2025) proposes a new policy direction characterised on one side by recruitment practices partially dedicated to younger people; on the other side, a greater focus on soft skills and cultural aspects carried on in centralised recruitment by the RIPAM Commission. While the potential impact of this law on local governments is limited, any signal is more than welcome. Sadly, the velocity of change appears to be not adequate.

6. Limits

Our work has several limitations directly stemming from the research design. By focusing on Italian PA, we expect a low immediate transferability of results in other countries. Nevertheless, PA bodies with a similar structure and normative ecosystem may be good candidates.

Furthermore, organisational culture is by definition highly contextual. Even if we accept, in line with recent ideas (Weber & Dacin, 2011), that culture has systemic traits, such traits probably differ in other countries, albeit less so in the EU ecosystem. National cultural dimensions, such as power distance, uncertainty avoidance, and collectivism/individualism, significantly influence organisational culture, affecting how information is managed and shared (Oliver, 2008).

Looking at path-dependency, the Italian history of change towards digital maturity is largely unique, with a once-only large influx of NRRP funding. Therefore, considerations about the digital market are strongly limited to the specific external conditions observed.

While we discussed the situation of smaller organisations by proxy of the interviewees' experiences, we left out regional governments, central agencies, ministries and important public sectors like healthcare and education. Therefore, while some results may be plausibly extended (e.g., the role of culture, size, externalisations), while most remain case specific.

Lastly, the technological and regulative landscape regarding AI is quickly developing, making our results potentially obsolete in the near future.

7. Conclusions

Our approach evidenced the need for continuous, quasi-ethnographic observation of organisational culture in PA. At this point, no one can predict when, to what extent, or how AI will impact. However, every moment of observation must offer useful pointers to understand the potential and limitations for effective impact and to guide any relevant policies. In light of the theoretical basis, our inquiry offers a few of such pointers.

The digital transition in Italian cities is in a phase of rapid evolution. However, profound challenges persist related to post-NRRP financial sustainability, internal cultural resistance, a shortage of specialised internal skills, and the complex interaction with a constantly evolving regulatory and legal framework. In this context, AI is often seen as a tool of great potential for streamlining internal processes, but its adoption is conditioned by a prudent approach, the need for clean and adequate data, and a clear definition of responsibilities. Digitalisation is not merely a technological issue but, above all, an organisational and cultural one, requiring a profound rethinking of processes and mindsets within administrations, where dominant values and beliefs may not favour change.

The interviews, collected through a semi-structured approach, map out a cultural landscape defined not by a single set of beliefs, but by the active and ongoing competition between the legacy values of the administration and the new values it espouses in its drive to adapt to the digital era.

The core strategic axes we found in the analysed cases are propensity to innovation in opposition to tradition, and the capacity of different sub-cultures to collaborate instead of clashing.

NRRP has an ambivalent role. On one hand, these funds act as a powerful catalyst, overcoming the financial and operational inertia that has historically hindered technological modernisation in local administrations. On the other hand, this massive injection of capital generates a long-term sustainability challenge (e.g., cloud subscription fees, maintenance) on often structurally weak budgets once the funding period concludes; secondly, it can distort the market, causing an inflation of project costs and exacerbating competition for scarce specialised skills, while shifting the focus on acquiring immediate solutions without cultural change.

We wish for our inquiry to build onto the argument for better, data-driven policymaking. The avenues for further research are ample and, in our mind, should focus on estimating the long-term impact of economic and budget choices reflected into a continuous loss of public workers associated with timid recruitment. Finally, theoretical research on organisational culture in PA would benefit from further methodological and empirical advancements, as literature is scarce even if culture is recognised as a crucial aspect in AI implementation.

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Conclusions

These brief conclusions draw from each paper's conclusion, circling back to the General Research Question: *How do public administrations navigate the transition from AI adoption to meaningful implementation within the specific institutional and regulatory landscape of the European Union?*

The study set out to explore how AI implementation in PA looks like at Macro (regulatory), Meso (institutional) and Micro (organisational) level. The collective findings of the three papers, while bounded by their respective limits, revealed a significant tension between intended expectations and observed results.

Regarding the efficacy of current theories and policies, it was initially expected that technical efficiency and efficacy would be the primary drivers of AI implementation. However, the results demonstrate that while technical merit may justify adoption, it is not the main driver of implementation. Instead, the transition to routine usage is fundamentally governed by the interplay between various contextual, external, and internal drivers.

One issue, not explicitly addressed but evident throughout the papers, is the problem of adaptation. AI, more than previous software, requires a fundamental change in the virtual and physical environments of public sector organisations. The observed rigidity toward change mirrors the rigidity of the laws and regulations that give form, structure, and permanence to public administration. Consequently, recurrent findings across this thesis suggest that the primary hurdles to AI implementation are non-technical, residing instead in the misalignment between institutional pressures and organisational culture. Consequently, the primary hurdles to AI implementation in PA are non-technical, residing also in the misalignment between institutional pressures and organisational culture.

In this thesis, I proposed a reflection on the social and political dynamics behind AI implementation, both manifest and hidden, and a discussion on the role of public managers as both change catalysts and public champions who must navigate the gap between expectations, pressures, and useful advancement. Without support, avoidant behaviours may become the only safe and clear option, sacrificing both legitimacy and efficiency in order to maintain control.

Ultimately, I conclude that successful implementation is contingent upon a shift toward holding providers responsible for public value outcomes. This may manifest in different ways. On one side, resisting the regulatory capture of the AI Act, at least for public sector organisations, seems ideal. Not having the necessary legal basis will keep on hold European public sector organisations, possibly making the EU less competitive as a collateral effect. On the other hand, a more direct approach, outlined in the AI Act, is the co-creation of AI solutions with providers. PA should be more proactive in experimentation and private-public partnership engagements, seeking out mutual-benefit opportunities with EU based companies. Consumer choice in procurement may be the strongest tool available to public managers.

NRRP has an ambivalent role in the implementation phase. On one hand, these funds act as a powerful catalyst, overcoming the financial and operational inertia that has historically hindered technological modernisation. On the other hand, this massive injection of capital generates a long-term sustainability challenge (e.g., cloud subscription fees, maintenance) on often structurally weak budgets once the funding period concludes; secondly, it can (did) distort the market, causing an inflation of project costs to match available funds and exacerbating competition for scarce specialised skills, while shifting the focus on acquiring immediate solutions without cultural change.

For theoretical advancement, this work contributes by integrating neo-institutionalism and cultural frameworks into the AI discourse, offering an analytical alternative to mainstream e-Government frameworks. Practically, it provides a roadmap for public managers to navigate compliance while identifying hidden cultural barriers that can impede the transition to a routine AI-supported environment. More importantly, it questions whether those barriers should be left standing, especially against predatory actions of foreign interests. In my conclusions, they often should be, especially when AI implementation cannot be clearly supported by evidence of how it will change the institutional and organisational arrangements.

Future research on AI implementation will reside at the intersection of different levels of analysis. It appears that present conceptual models of AI implementation in PA, reviewed across the papers, may be too complex and wide when confronted with the key mechanics I propose in this thesis. I believe that we need models that reflect the actual role of PA as a buyer of services (with rare exceptions).

The approach evidenced the need for continuous, quasi-ethnographic observation of PA. At this point, no one can predict when, to what extent, or how AI will impact. However, every moment of observation must offer useful pointers to understand the potential and limitations for effective impact and to guide any relevant policies. One relevant policy, at least in Italy, is recruitment, motivated by a continuous loss of retiring public workers.

Limitations

A critical reflection on the implementation of AI within PA must necessarily conclude with an acknowledgement of the research boundaries. A single study seldom captures all the complexities of technological change; instead, this thesis focused on the major issues and critiques in the academic and public discourse today.

The limitations can be categorised into three primary domains: the nature of subjectivity and generalisability, the temporal velocity of the object, and the methodological issues.

The first limitation concerns the specific point of view that is reflected in the work and its geographical focus. The methods deployed (content analysis, interviews), while appropriate for the specific research questions, inherit, in a sense, the mental configurations and worldview of the author(s), more than other methods. In plain words, researchers with different backgrounds and knowledge would have probably reached dissimilar results and interpretations. More importantly, the research is situated within the European Union, and the findings draw heavily from a micro-level inquiry into Italian municipalities. Typically, case-study research contends that results from a specific geographic and cultural context cannot be extrapolated to a wider population. However, the principle of analytical generalisation rather than statistical generalisation may still apply: while the cultural artefacts of a municipality in Lombardy may differ from one in Bavaria, the underlying mechanisms of resistance to AI identified in this work provide a test set for new analyses.

Secondly, the research faces a temporal boundary dictated by the unprecedented velocity of technological innovation. To get the idea, I started my PhD voyage in November 2022, just a couple weeks before the release of Chat-GPT 3.5. As of January 2026, when I'm finishing up the last bit and pieces of this thesis, Chat-GPT 5.2 was released (with 19 different released models in between). GPT is just an example: chatbots like Claude, Copilot, DeepSeek, Google Gemini, Grok, have flooded our everyday lives. In this thesis, I focused on chatbots because of the importance of text in PA, but the industry includes speech-to-text tools, OCR recognition, several AI tools that can fundamentally change how PA operates.

There is an inherent risk that by the time implementation reaches a routine phase, the technologies themselves may be completely different. For this reason, the research focused on the structural pillars of administration, which are historically more stable than the technological tools.

Finally, there is a practical limitation regarding data access and administrative transparency. Public administration produces a vast volume of documentation, much of which is shielded by confidentiality or layers of contract clauses with cloud tools providers that, at least in the experiences of some managers I interviewed, often refuse to share the databases even upon request for security or proprietary reasons. Impact assessments independent of providers seems a faraway objective. Research, as of today, has a space in the analysis of the administrative response to those tools.

In acknowledging these boundaries, the research does not claim to offer a definitive word on AI in the public sector. Rather, it offers a foundational map of the implementation frontier, identifying the regulatory fences, the institutional winds, and the cultural terrain that public managers must navigate in the years to come.

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