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Research article

Exploring the factors, affordances and constraints outlining the implementation of Artificial Intelligence in public sector organizations

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ABSTRACT

Artificial Intelligence (AI) is viewed as having great potential for the public sector to improve the management of internal activities and the delivery of public services. However, realizing its potential depends on the proper implementation of the technology, which is characterized by unique factors, that afford or constrain its use. What these factors are and how they affect AI implementation is still poorly understood, and scholars call for studies to add empirical evidence to the existing knowledge. This study relies on a case study methodology and, by adopting an abductive approach, applies a double theoretical perspective: the Technology-Organization-Environment (TOE) framework and the Technology Affordances and Constraints Theory (TACT). Drawing on these combined lenses, we develop a conceptual framework that extends previous studies by showing how AI implementation is the result of a combination of contextual factors that are deeply interrelated and, specifically, how AI-related factors bring new affordances and constraints to the application domain.

1. Introduction

Artificial Intelligence (AI) systems "are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data, and deciding the best action(s) to take to achieve the given goal" (European Commission, 2019).

AI therefore differs from other technologies historically deployed within organizational boundaries (Bailey et al., 2022) and requires the adoption of novel approaches from both academics and practitioners. Indeed, AI systems have the capacity to "make determinations by themselves, as well as evolve their determinations over time once they are deployed in an organization" (Murray et al., 2021, p. 553). To distinguish AI systems from other technological artifacts, in this study we refer to the types of technologies that follow the *if-then* logic – those for which a given set of input instructions produces the same set of outputs (Medaglia et al., 2023) – as "standard technologies".

Similar to the private sector, Public Sector Organizations (PSOs) are beginning to use AI for a better management and delivery of their services (for an overview, see Maragno et al., 2021; Tangi et al., 2022). However, research acknowledged that AI has not yet achieved the disruptive effect expected in the public domain (Dwivedi et al., 2021). Moreover, due to the unique features of AI (Wirtz et al., 2019), previous research on digital government and ICT implementation does not fully apply to this specific technology (Veale & Brass, 2019).

More specifically, the current debate does not offer a comprehensive view of the factors that influence AI implementation, and how they are related to each other and to the surrounding environment (Neumann et al., 2022), nor does it provide a clear view of AI's affordances.

Accordingly, this paper aims exploring how AI has been implemented within public boundaries, to extract the elements that characterize its deployment and to expand the existing knowledge of the actions that AI systems afford, or constrain, PSOs to take. Keeping the focus on this objective, and considering AI systems not as stand-alone artifacts, but as deeply entangled with the organizational aspects, the study intends answering the following research questions: *Which are the factors that characterize AI implementation in public settings? How do these factors afford, or constrain, specific actions in the focal context?*

We rely on a broad definition of implementation in line with Gil-Garcia and Flores-Zúñiga (2020, p. 1), who define it as "how

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organizational-level variables related to government agencies contribute to the success of digital government". This definition considers implementation as a holistic concept, in which technicalities are only one of the factors to be considered. Elaborating on this perspective and leveraging on Nelson and Winter (1982, p.104) assumption that "skills, organizations, and technologies are intimately intertwined", we posit that, to understand the uses and consequences of a specific technology like AI, it is necessary to consider the relationships between people, organizations, and the technology itself (Majchrzak & Markus, 2013). In fact, technologies have "material properties" (Leonardi, 2011, p. 153) that afford different actions according to the context in which they are implemented (Bailey & Barley, 2020).

For investigating the topic, case studies were conducted in 8 European PSOs that are implementing AI. Europe has been selected to ensure generalizability, as all cases act upon a common regulatory framework and system of values. To analyze the data gathered, we rely on a double theoretical lens. First, we use the Technology-Organization-Environment (TOE) framework (DePietro et al., 1990) as an overarching model to understand the factors related to AI implementation within public boundaries. Second, following the Technology Affordances and Constraints Theory (TACT; Majchrzak and Markus (2013)), we complement the previous findings by linking the AI-factors observed in each of the three contexts and casting light on how AI systems, with their features, afford or constrain novel actions (Treem & Leonardi, 2012) with which the existing organizational agency has to deal.

Therefore, by adopting this dual perspective, we develop a conceptual framework that provides novel insights to both academics and practitioners. Specifically, our findings extend previous studies by showing how AI implementation should be considered as a cyclical process, where each context has a set of complex and multifaceted factors that are deeply interrelated to each other and, by connecting the social organizing to the specificities of the focal technology, explains the action possibilities and constraints behind AI implementation. Finally, we also argue that factors, affordances, and constraints vary due to the type of AI system, the characteristic of the service, and the relative organization.

2. Theoretical background

2.1. Artificial Intelligence and organizing

The term AI was first coined in the mid-1950s by McCarthy, but it made its appearance decades ago (Sousa et al., 2019). Several disciplines (such as philosophy, mathematics, economics, neuroscience, and computer engineering) contributed to the development of the relative research field, making it universal (Russell & Norvig, 2010). This multifaceted aspect is mirrored also in the lack of a univocal definition (Collins et al., 2021), leaving still open the debate around 'what is AI' – not addressed in the current study.

Notwithstanding the hype around AI, since the 1950s its development has been characterized by several waves (Wirtz & Müller, 2018), where periods of enthusiasm and disillusion took turns cyclically. Indeed, although the initial premises and the early years of success, the technology missed reaching the expected goals, also influencing the research development and the related funds. In the last two decades, the topic has flourished, due to advances in computational power (Benbya et al., 2021), the exponential increase in data (Samuel et al., 2022), and new machine-learning techniques (McAfee & Brynjolfsson, 2017). Both scholars and practitioners are aware that the usage of AI has the potential to disrupt almost all industries (Raisch & Krakowski, 2021), and some researchers consider it the most important and promising general-purpose technology (Jovanovic & Rousseau, 2005) of our era. Nowadays AI is in use in several applications and, together with other emerging technologies (*e.g.*, blockchain), it is shaping "human action and interaction [...] carrying new opportunities and constraints for organizing" (Bailey et al., 2022, p. 1). Due to these features, AI systems could be labelled as "agenting" (Murray et al., 2021), requiring shifting the locus of agency at the ensemble among human and non-human interactions (Choudhary et al., 2021). Compared to other artifacts, AI is increasingly taking a central role in organizing (Glaser et al., 2021), entailing profound changes and leading developers and organizational agents to transfer and translate their knowledge in a form that machines could use.

These issues only recently started gaining momentum in managerial (Haefner et al., 2021) and organizational (Shrestha et al., 2019) literature, demanding the adoption of novel perspectives (Borges et al., 2021) and posing questions related to the consequences of AI implementation within and outside the relative organization.

2.2. AI and its pervasiveness in the public domain

The public sector is not exempt from AI implementation, its organizational consequences, and the related challenges. This is not surprising since the applications of AI algorithms are continuously spread across different domains (Cockburn et al., 2019).

However, although PSOs have started to invest in AI (Merhi, 2022; Sousa et al., 2019), many of them are struggling with the achievement of the benefits that AI technologies are expected to yield (Medaglia & Tangi, 2022; Mikalef et al., 2023).

In this scenario, scholars have started investigating the topic, with an increasing number of studies published in the last couple of years (Madan & Ashok, 2023), but very scant literature deeply investigates AI implementation in PSOs by adopting an organizational lens, presenting a still rather fragmented picture, and rarely providing a clear and comprehensive view of the phenomenon.

First, scholars started with the identification of the manifold challenges that AI can bring in the given domain. Wirtz et al. (2019) pointed out four classes of challenges related to AI: technological, societal, legal, and ethical. Sun and Medaglia (2019) added the organizational, economical and data management ones. Additionally, Campion et al. (2022) moved a step further by casting light on the challenges of inter-organizational collaborations in the development of AI.

Second, some studies started highlighting the need to go beyond data, infrastructures, and algorithms, to embrace a more rounded view of the organizational issues and capabilities (Mikalef et al., 2021). Related research has highlighted the importance of a clear and positive relationship between AI and organizational agents (Ahn & Chen, 2020; Vogl et al., 2020). In particular, Vogl et al. (2020), following Leonardi (2011), used the word "imbricated" to describe the relationship between public managers and AI, Maragno et al. (2022) highlighted the importance to consider AI as an organizational agent to nurture and Medaglia and Tangi (2022) highlighted how PSOs must increase the digital literacy of public employees. Similarly, Giest and Klievink (2022) demonstrated how AI is fundamentally reshaping governments, changing their tasks and duties, while de Bruijn et al. (2021) pointed out the need for a good balance between AI and human decision-making. For doing that, Grimmelikhuijsen and Meijer (2022) invite PSOs to clarify responsibilities in the complex relations that arose using AI.

In addition, recent studies pointed out the urgency to adopt an empirical perspective to investigate the phenomenon (Wang et al., 2021), as current literature is mainly based on theoretical reflections (*e.g.*, Wirtz et al. (2019)), experiments (*e.g.,* Selten et al. (2023)) or examples (*e.g.,* Giest and Klievink (2022)). Moreover, the growing implementation of AI systems in the empirical realm has not been always consistent (Neumann et al., 2022), requiring a better understanding of the factors, within and around PSOs, that might influence it.

Finally, literature has also explored how AI is changing the way in which PSOs relate to the actors involved in the public sphere. On the one hand, the implementation of AI requires the search for the knowledge relevant to its development outside the organization, thus calling for new forms of collaboration (Bailey et al., 2022) with technological suppliers. However, this perspective has seldom been adopted (*e.g.,* Hickok, 2022). On the other hand, PSOs are starting using AI for the delivery of public services. These applications are a double-edged sword. If they could enhance the value for both citizens and organizations (Scutella et al., 2022), at the same time, since AI algorithms ingest large amounts of data, ethical issues should be properly addressed (Willems er al., 2022).

Thus, a new perspective is needed to distinguish the concerns and challenges specific to AI implementation from those common to standard technologies, and to avoid rediscovering factors that have already been identified in the digital government literature (Madan & Ashok, 2023). Our paper addresses this specific issue by proposing an intersection between the emerging academic debate on the socio-technical challenges of AI and the discussion on digital technologies within the public sphere (Veale & Brass, 2019).

2.3. Technology-Organization-Environment (TOE) framework

To disentangle the factors that characterize AI implementation, we apply the Technology-Organization-Environment (TOE) framework (DePietro et al., 1990), which supports and structures the investigation of the factors that affect the implementation of technologies at the organizational level. Over the years, literature has provided several models for studying the diffusion and implementation of technologies: Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Technology Acceptance Model (TAM) (Davis, 1989), Theory of Planned Behavior (TPB) (Ajzen, 1991), Diffusion of Innovation (DOI) (Rogers, 1995), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003).

Contrary to these models that focus on the individual level to explain the implementation of a technology, the TOE framework (DePietro et al., 1990) relies on the assumption that the factors affecting the implementation of technologies can be divided into three contexts. The *technology* context refers to factors related to the technological sphere: PSOs should evaluate which technology is the most compatible with their internal structure and values (Gil-García & Pardo, 2005), as well as the cost (Savoldelli et al., 2014) and the relative advantage in introducing it (Hiran & Henten, 2020). The *organization* context includes factors related to an organization's internal environment that influence technology's implementation, such as the size of an organization (Tangi & Soncin, 2021) or the attitudes of managers and organizational complexity (Tangi, Janssen, et al., 2020). The *environment* context comprises factors related to the external arena in which an organization is embedded: in public settings, external pressure (Mergel et al., 2019), citizen attitudes (Tangi, Benedetti, et al., 2020), and stakeholder support (Janssen & Klievink, 2009) play a pivotal role.

To the best of our knowledge, few studies rely on this framework to unpack AI features within public boundaries (see for instance Chen et al. (2021); Mikalef et al. (2021); Neumann et al. (2022)). To date, these studies have mainly focused on the factors that are relevant to AI implementation in different public contexts and circumstances and have neglected the in-depth exploration of how AI systems are becoming constitutive agents for PSOs.

2.4. Technology Affordances and Constraints Theory (TACT)

The concept of "affordances" was first adopted in ecological psychology by Gibson (1986, p. 134), who argues that "what the object affords us is what we normally pay attention". People interact with a specific object only after having perceived its utilities. The focus is, thus, on two issues. First, the properties of a specific object are considered as a necessary, but not sufficient, condition (Markus & Silver, 2008). Second, and accordingly, these properties acquire meaning only thanks to the relationship between humans and the above-mentioned object. This concept was translated in the information system scenario by Majchrzak and Markus (2013) with their TACT: to detect the uses and consequences of technologies, it is necessary to understand the interactions between people, organizations, and the technology itself. According to the authors, "*technology affordance*" refers to a potential action that individuals or organizations could do with a specific technology; "*technology constraint*", concerns instead the way(s) in which the given actor is hindered from reaching a specific goal when using the selected technology. It is important not to mistake the former with "*technological features*" (*i.e.,* technology's functionalities) and the latter with "*human and organizational attributes*", as tasks and needs. This distinction is relevant because individuals and organizations do not always realize the potential of a technology or even may use the artifact in a different way from what the designer originally intended. Finally, affordances (and constraints) should not be considered as stand-alone, but they emerge from the human-technology interactions: neither humans nor technologies are empirically important, but they acquire relevance thanks to their relation, which could "produce, sustain, or change either routines or technologies" (Leonardi, 2011, p. 149).

TACT has been increasingly adopted, but it is worth noticing the relevance of adopting this perspective: as previous studies pointed out (*e.g.*, Effah et al., 2021), the continuous evolution of the technology influences the nature of human-technology interactions, conditioning also the related affordances and constraints.

3. Methodology

This study is phenomenon-driven (Eisenhardt & Graebner, 2007), aiming at deepening the theoretical and managerial implications brought out by the adoption of AI within the specific context of PSOs. Thus, it is worth considering "people's intentions, intuitions and interactions as observed at the level of the individual, group, organization, industry or society and as related to the shape, functioning and processes of organizations" (von Krogh et al., 2012, p. 280). Therefore, to cast light on the focal phenomenon, we adopt the case study as research strategy to elaborate theory by combining conceptual and empirical planes (Fisher & Aguinis, 2017). Throughout this process, a certain degree of flexibility in balancing the conceptual and empirical planes was required, to enhance the logic of discovery rather than validation (Van Maanen et al., 2007).

3.1. Case selection

To frame the boundaries of the empirical realm, we selected multiple cases by adopting a theoretical sampling (Eisenhardt, 1989) and following the subsequent criteria. First, the research is grounded in the European public domain since the enhancement of digital technologies within PSOs is one of the priorities of the European Union (European Commission, 2022). Moreover, European countries act upon common regulatory frameworks, strategies, and values. Hence, due to the European extent of this study, we relied on the desk research conducted by the AI Watch initiative of the European Commission's Joint Research Centre (Tangi et al., 2022). This analysis maps AI systems developed by Member States between 2019 and 2021. Overall, 686 projects have been collected through multiple data sources (*e.g.*, news articles, scientific and grey literature, and a survey). We decided to rely on this empirical evidence as: (i) it is published in open data[2]; (ii) the projects have been classified following a taxonomy that provides a structured approach for categorizing AI cases.

Then, the following casing step involved the sampling of specific AI projects. We selected cases "where the focal phenomenon is likely to occur" (Eisenhardt, 2021, p. 149) thus, projects at least in a pilot phase, to be sure that each case has a certain degree of maturity. Moreover, we aimed at including different types of AI systems to develop more generalizable insights. No exclusion criteria have been applied

[2] The database is available at the following link: https://data.jrc.ec.europa.eu/dataset/7342ea15-fd4f-4184-9603-98bd87d8239a

regarding the administrative level, the type of public organization, and the geographical location, to guarantee a higher degree of heterogeneity and to disentangle AI affordances and constraints within different contexts. We scanned the entire database and select the cases where the description was clear and exhaustive, hence we could ensure the fitting with the purpose of the study. We excluded several cases for which it was impossible to find contact information for the interviews. Our final sample consisted of 11 cases. However, some of them were excluded after the first interview, as it emerged that the AI system implemented was not in line with the definition we adopted. Thus, we deepened the 8 initiatives reported in Table 1.

3.2. Data collection

To reduce potential biases (Eisenhardt & Graebner, 2007) and enhance the validity of the findings, we relied on multiple sources of evidence, as summarized in Table 2.

The primary data consisted of two waves of semi-structured interviews, conducted by the first and the second authors, for a total amount of 17 interviews with 12 different informants. The first round of data was gathered between September 2020 and May 2021 while a second round of interviews was held from September to November 2021. In addition, between February and March 2023, we performed follow-up interviews, to get a deeper and updated perspective of each case but also to be sure that we did not miss any relevant information (Orwin, 1994).

The interviews were carried out by the first and second authors with the aim of investigating the technological (*e.g.*, components and features of the technology), organizational (*e.g.*, the relations and the roles of organizational agents who deploy AI systems), and environmental (*e.g.*, the rules that might govern AI usage) factors that are peculiar of the focal technology. The choice to conduct the interviews in pair was made to enhance the quality of the dialogue between the research team and the respondents (Malterud et al., 2016). During this first round of interviews, leveraging on the empirical data, we increasingly focused on the factors that emerged to be tied to AI and the others that, instead, were common to standard technologies. Delving on these findings, later interviews focused on AI-related factors, deepening the actions that are possible through the focal technology and the potential stumbling blocks that limit their achievement (Fayard & Weeks, 2014). Fig. 1 presents the process of data gathering.

Each interview, recorded and transcribed verbatim, lasted at least one hour and was conducted using online tools (Microsoft Teams, Skype, Zoom). At the end of each interview, the first and the second authors shared their initial ideas (Eisenhardt, 1989) and their notes, to disentangle the open points and discuss the understanding of the data. Then, to ensure the reliability of the process, they independently analyzed the data (Mays & Pope, 1995), manually coding the interviews and then cross-checking the unfolding empirical evidence. The involvement of both the first and the second authors is a form of data triangulation (Goffin et al., 2019) and, by combining different perspectives, we enhanced data richness. After this step, the main concepts and extracts were reported in a spreadsheet by the first author and the third and the fourth authors were involved to discuss and review the observations. This phase was crucial in identifying further themes to explore, matching the empirical evidence with the theoretical domain, and to reach a level of agreement between the research team. This cycle of confrontation was repeated, using an abductive approach, until the entire research team was satisfied that the coding was consistent.

Table 2
Data source.

Case	Primary data	Secondary data
1	1 with the Chief Information Officer 1 with the Project Manager	• Authority website • Online news-article
2	2 with the Project Manager	• Authority website • Online news-article • Direct observation: testing of the bot
3	2 with the Chief radiologist 1 with the Head of IT department 1 with the IT official	• Online news-article
4	2 with the Head of the IT Deparment	• Authority website • Online news-article • European Commission documents
5	1 with the Head of transportation department	• Online news-article • Authority website • European Commission documents
6	2 with the Project Manager	• Online news-article • European Commission documents
7	1 with the Head of Digital Transformation 1 with the IT official	• Online news-article • Project website
8	2 with the Project Manager	• Online news-article • Project website

3.3. Data analysis

As the research aims to advance the current academic knowledge on an under-debated issue – *i.e.*, how AI systems are twisted with public organizational actions and agents –, we act on two levels. First, not viewing "the world with a blank slate" (van de Ven et al., 2015, p. 2), we adopted as a mode of inquiry abductive reasoning (Timmermans &

Table 1
Summary of cases.

Case	*Area*	*Population addressed*	*Administrative level*	*Project status*	*AI System*
1	Northern Europe	Around 10 million	Central government	Pilot	Chatbot
2	Central Europe	Around 2 million	Municipality	Pilot	Chatbot
3	Southern Europe	Around 5 million	Public Hospital	Pilot	Computer Vision
4	Central Europe	Around half a million	Central government	Implemented	Computer Vision
5	Northeast Europe	Around half a million	Consortium of municipalities	Pilot	Autonomous vehicle
6	Northeast Europe	Around half a million	Consortium of municipalities	Pilot	Autonomous vehicle
7	Southern Europe	Around 13 million	Central government	Implemented	Machine Learning
8	Northern Europe	Around 1 million	Central government	Implemented	Machine Learning

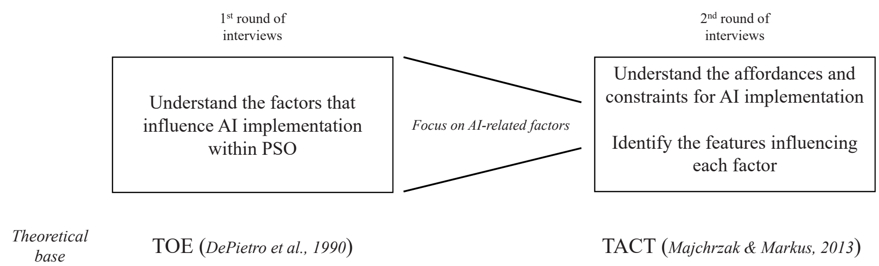

Fig. 1. Data gathering process.

Tavory, 2012), as this logic appears to be particularly suitable to shed light on the uncertain, dynamic, and interconnected phenomena (Sætre & Van De Ven, 2021).

Thus, we built on the TOE framework (DePietro et al., 1990) to revise the empirical phenomenon (Timmermans & Tavory, 2012), highlighting the factors associated with the implementation of AI. This framework allows us to cast light on the complex system of actors, actions, and interactions in which the technological artifact is entwined (Barley, 2020; Majchrzak et al., 2016), shedding lights on previously undistinguishable features. Fig. 2 illustrates the coding structure for the first round of interviews.

Then, once these factors were discovered, we moved to the second stage of abductive reasoning, defamiliarization (Timmermans & Tavory, 2012). In this stage, questioning "the taken for granted and to see data differently" (Vila-Henninger et al., 2022, p. 9), we followed the idea that "the most important aspect of the introduction of a new technology may have nothing at all to do with its perceived primary function […] but with its secondary function made possible by a relation that spreads far and wide" (Bailey et al., 2022, p. 9). The empirical data were analyzed by adopting a structuring approach, following the recursive relations tactic "to capture and analyze an unfolding relation between two constructs" (Fisher & Aguinis, 2017, p. 12).

Moreover, going through the last step described by Timmermans and Tavory (2012) – alternative casing – the TACT (Majchrzak & Markus, 2013) has been adopted as additional theoretical lens to complement the previous findings and deeply understand how AI is entwined with organizational agents, enabling, or obstructing, novel actions (Treem & Leonardi, 2012). Finally, we observed the presence of recurrent patterns in affordances and constraints, based on the features of the cases analyzed. In other words, we observed if and which features of the cases (type of AI, status of the project, geographical extent, *etc.*) may influence the presence or absence of certain affordances and constraints. The initial relationships were then refined *via* replication logic – frequently revising each case to compare and verify the occurrence of specific constructs, relationships, and logics. Fig. 3 depicts the coding scheme of the second round of data gathered.

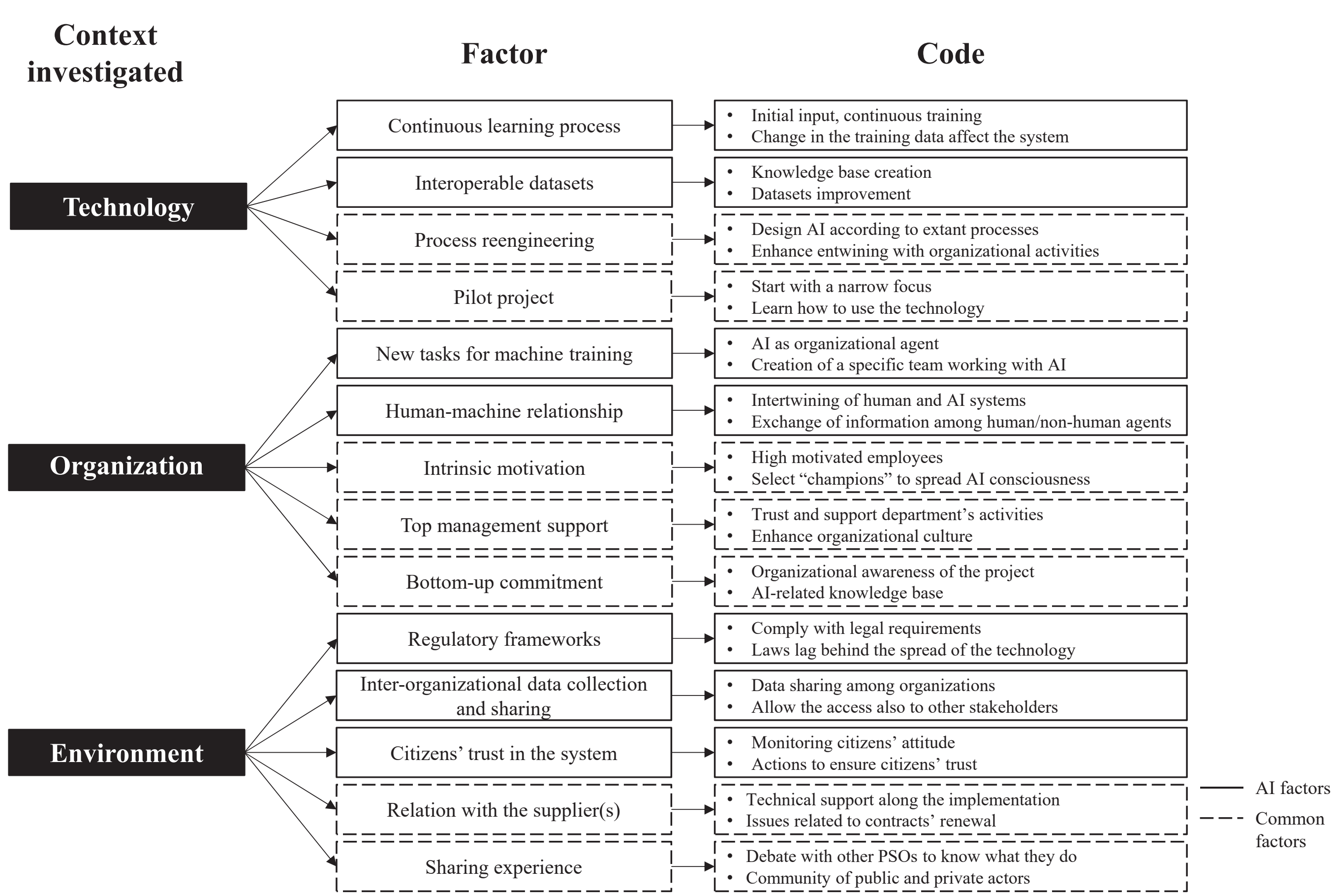

Fig. 2. Data structure, first round of interviews.

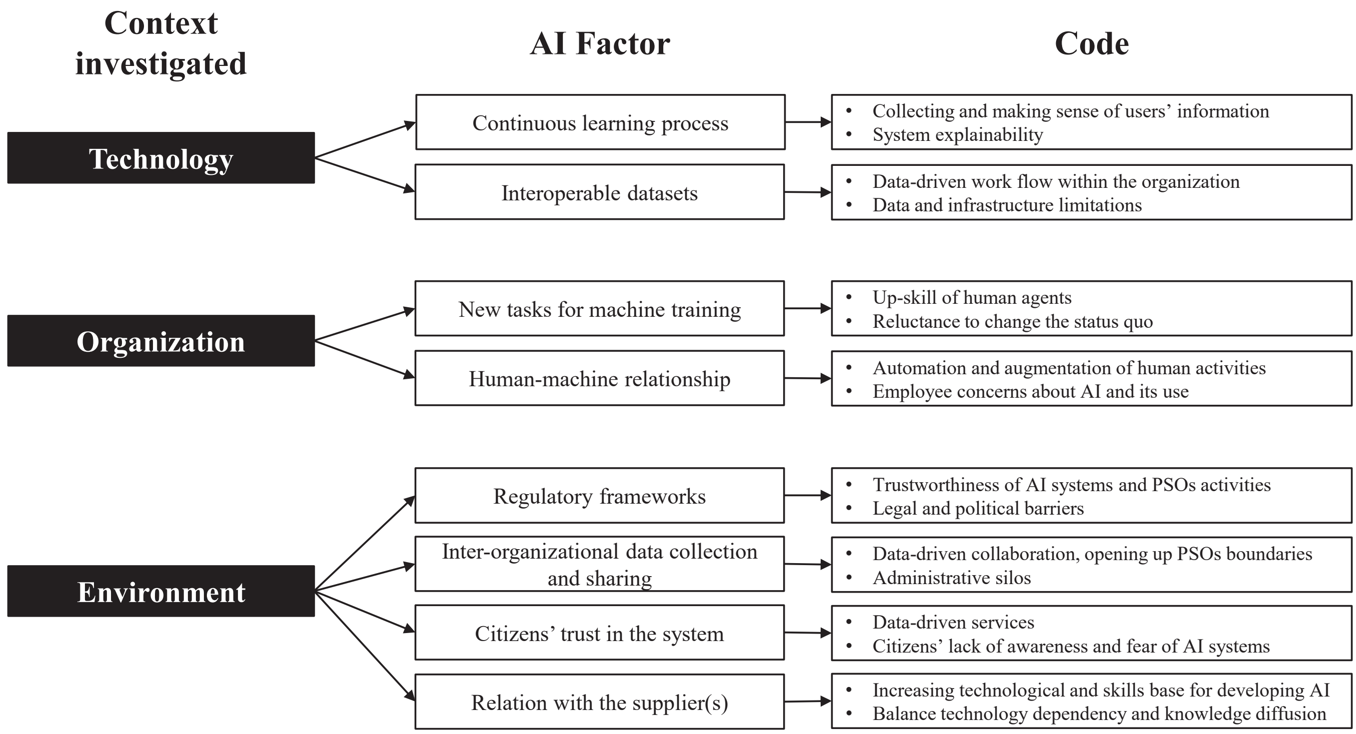

Fig. 3. Data structure, second round of interviews.

In both stages of data analysis, we had clearly in mind that the empirical data gathered have the primacy, but in service of theorizing (Van Maanen et al., 2007). Thus, we have been informed by theoretical ideas, and moving back and forth in a cyclical dialogue between theoretical bases and empirical observations (Dubois & Gadde, 2002), we identified recurrent patterns across cases.

4. Results

This section presents the main insights arising from the comprehensive analysis of the interviews and secondary sources. The results are reported in three main paragraphs, following the technological, organizational, and environmental contexts proposed by DePietro et al. (1990).

As reported in the methodology, when comparing the implementation factors with previous literature on AI and digital government, these factors stand out, requiring a deeper investigation. Therefore, a second dimension was added, dividing 'AI-related factors' with 'common implementation factors'. The list of factors is reported in Table 3.

Moreover, thanks to the process of defamiliarization, the affordances and constraints for each AI-related implementation factor have been identified and reported in Table 4.

Finally, the analysis provides some insights into the elements – such as the type of AI system, project maturity – that can explain the presence, absence or magnitude of constraints and affordances. These elements are discussed based on the results provided in Appendixes A and B, where we reported a list of the recurrence of each affordance and constraint along the cases.

Table 3
Synthesis of AI-related factors and the factors related to digital technology implementation within public boundaries.

	AI-related factors	'Common' implementation factors
Technological	• Ensuring a continuous learning process (Raisch & Krakowski, 2021) • Ensuring interoperable datasets continuously updated (Venkatesh, 2021;von Krogh, 2018)	• Reengineering of existing processes (Mergel et al., 2019) • Starting with a pilot project and a limited scope (OECD, 2019)
Organizational	• Designing new tasks for machine training (Puranam, 2021) • Setting up a novel human-machine relationship (Puranam, 2021;Bailey et al., 2022)	• Ensuring top management support (Curtis, 2019; Gil-Garcia & Flores-Zúñiga, 2020) • Fostering bottom-up commitment (Pitchay Muthu Chelliah et al., 2016) • Leveraging on intrinsic motivation to innovate (Mergel et al., 2019)
Environmental	• Ensuring citizens' trust in the system (Grimmelikhuijsen, 2023) • Ensuring steady suppliers' support for continuous training (Dwivedi et al., 2021) • Being compliant with the Regulatory framework (Mikalef et al., 2021) • Collecting and sharing data from and with outside (Sun & Medaglia, 2019)	• Having access to external competencies (Juell-Skielse et al., 2017) • Ensuring suppliers' support (Nograšek & Vintar, 2014) • Sharing experiences (Curtis, 2019;Picazo-Vela et al., 2018)

Table 4
Formalization of AI affordances and constraints within the given empirical realm.

	Constraints	AI-related factor	Affordances
Technological	• Difficulties in implementing an explainable AI system	*Ensuring a continuous learning process*	• Accurate and faster data analysis
	• Scarce availability of infrastructure • Difficulties in having high quality interoperable data • Difficulties in collecting new data	*Ensuring interoperable datasets continuously updated*	• Creation of a data-driven organization
Organizational	• Reluctance to change • Lack of human resources • Lack of awareness • Employees' mistrust of AI	*Designing new tasks for machine training* *Setting up a novel human-machine relationship*	• Re-qualification of employees • Learn how to work with AI • Automation of simple cognitive tasks • Augmenting the decision-making process
Environmental	• Citizens' mistrust of AI	*Ensuring citizens' trust in the system*	• Enhancing the provision of data driven services
	• Difficulties in estabilishing cooperation with suppliers	*Ensuring steady suppliers' support for continuous training*	• Ensuring adequate skills and technology advanced systems
	• Complexity and dynamism of the regulatory framework	*Being compliant with the Regulatory framework*	• Ensuring trustworthiness and compliance with human rights guaranteed by norms
	• Structural administrative silos	*Collecting and sharing data from and with outside*	• Enhancing collaboration among PSOs

4.1. Technological context

4.1.1. Common technological implementation factors

One of the major decisions when implementing AI, is the evaluation of its proper integration into the current organizational processes and dynamics, starting from its technical aspects. Indeed, as the project manager of Case 8 stated:

> "*The algorithm changes and we needed to find the proper balance around it. All decisions are taken together with the organization, […] because public employees will use the system daily, it is necessary to understand how to integrate it with our routines, and any small change has implications for their [=employees] work.*"

In line with this, Case 1 declared that integration with existing processes is crucial, as AI could improve existing services and support employees' activities. In addition, the interviewees pointed out the importance of starting with a project that has a narrow scope, to constantly monitor the AI system, especially by checking ethical and regulatory issues, but also to learn how to manage the usage of the technology. In fact, as the project manager of Case 8 affirmed, "*the technology is not always used for the intended purposes and also its functionalities have to be progressively discovered and used.*"

4.1.2. AI-related technological factors, affordances, and constraints

A feature of AI that influences its development is its ability to interact, learn, and evolve through continuous relationships with both the environment and humans. Differently from other technologies, AI requires not only technical maintenance but also human resources that engage with it, to nourish the machine with specific knowledge. Therefore, AI needs to be continuously trained to properly support its evolutionary process. According to the project manager of Case 2:

> *"AI learns for itself and, differently and faster than other technologies, it changes over time, even if you don't train it for a while. This technology is more like a living system, acting within the organization."*

And the project manager of Case 3 echoed this view:

> *"Training must start from the very beginning, and then, thanks to deep learning systems, AI becomes 'autonomous'. In the beginning, however, there is no robust data. Thus, humans have to feed the algorithms. Otherwise, the risk of errors is quite big."*

Training and working with the system require the development of an explainable system, as highlighted in previous literature (Grimmelikhuijsen, 2023; Janssen et al., 2022). It was one of the main blocking factors in Case 8, where the explainability of the scores was essential for the use of the system and for enabling the consultants to make the decision. On the opposite, Case 4 was not interested in this at all: the goal was to make the best effort to scan the documents, creating multiple layers of AI without the need to understand how the technology works. For a different reason, it was not an issue even for the municipalities in Cases 5 and 6, as the project was designed to be a pilot, the technical part was only of interest to the technology supplier.

Moreover, data is at the heart of AI implementation. The introduction of AI implies that PSOs build and make available a large amount of data. Controlling, feeding, and managing data is essential for the proper functioning and training of algorithms. We have observed that the greatest progress in AI implementation has been made by those PSOs that have already overcome data management issues, as lagging behind in this step can hinder the entire AI implementation process. For example, Case 5 has introduced a large knowledge base, as reported by the project manager:

> "*We have created a knowledge base, which lays on an infrastructure that starts from the website and then goes much deeper. Leveraging on data we get used to work on data, not feelings.*"

While data creation and curation were generally a common issue across cases, interestingly not all of them shared the same constraints in this direction. This was mainly due to the type of AI system, its purpose, and the relation with the external supplier(s). In some cases, one of the main constraints was the creation of the annotated dataset for training the system: for instance, Case 6 had to merge several databases to allow the machine to learn the addressee of the received communication. Others needed to collect and annotate new data – for example for autonomous vehicles. In other cases, this was not a blocking factor, either because the system was already bought pre-trained and plugged in (Case 2) or because data were already matching the quality needed (Case 3).

Technological affordances are often associated with more effective and efficient systems, that can automate human work and move towards more data-driven decisions and services. This balance between automation and augmentation depends on the type of AI systems implemented: while chatbots serve more towards effective communication, machine learning and computer vision systems work for increasing efficiency.

4.2. Organizational context

4.2.1. Common organizational implementation factors

The degree of human innovativeness, which is the determinant of an organization's propensity to innovate (Wolfe, 1994), is one of the key factors for the implementation of AI.

On the one hand, the awareness of innovation seems to be closely linked to top management involvement, as described by the project manager of Case 6:

> "*The mayor and the deputy mayor are really interested: they know this project, and how it is evolving, and, even if they are very busy, they support and trust our work. This is crucial for the implementation of the AI system.*"

On the other hand, the interviewees revealed the importance of a set of informal linkages among civil servants and the commitment of the whole organization. As the Head of the IT department of Case 4 explained:

> "*One thing that is important is that we have very strong organizational support: everyone in the IT department is following what we are doing, even if they are not personally involved in the project. Everyone is very motivated: they see that there are results, but they also perceive that this is a very interesting technology.*"

4.2.2. AI-related organizational factors, affordances, and constraints

AI implementation requires both technical and non-technical knowledge and skills. In the long-term, in-house technical competencies are essential, and it would be necessary to hire people trained in the use and management of AI, as the CIO of Case 1 suggested. Moreover, various informants pointed out that the relevance of on-field expertise related to the specific domain of application plays a pivotal role. As the head of the IT department of Case 3 affirmed:

> "*The real and fundamental competence is the clinical part, provided by those who know the contents. The information systems are only involved in a second phase, when it is necessary to process images in the cloud and feed the algorithms.*"

The characteristics of AI have a profound impact on organizational processes and practices. AI introduction requires the creation of an *ad-hoc* and permanent team to cooperate with the machine and the design of a different approach for working with a non-deterministic system like AI. The AI trainer of Case 1 is part of a group of people "*who are working as AI trainers*", devoting an increasing amount of their working time to interact with the machine. This requires organizational knowledge of such technology, a general awareness of AI and trust in it. The lack of these elements represents a major constraint. This evidence applies mainly to systems used by employees, like in Cases 3, 7, and 8. In the other cases, the impact is limited to the awareness of what the system can do, to properly offer the complementary services. If the system interacts directly with the citizens, it is necessary to ensure trust and awareness in their relationship with the system, with important environmental constraints.

Additionally, AI is not a fixed entity within a fixed organizational reality. Indeed, AI systems evolve within organizational boundaries, shaping various aspects of organizing, as the Head of the Digital Transformation of Case 7 affirmed:

> "*With the usage of AI, things change further. It is wrong to assume that once the project is completed, nothing will change. If there is a reorganization of the offices, you have to rework the model: otherwise, the system will degrade. Organizational processes and AI systems must be maintained and monitored concurrently: AI is closely linked to the organization.*"

This AI-related feature has several blocking elements that can hinder its implementation. There is the need to free up the time of domain experts and the need to identify employees that are willing to accept a partial, or even complete, change of tasks. The extent of these constraints depends strongly on the domain of analysis, the characteristic of the organization, and the digital literacy of the employees. From our cases, this is one of the most interesting and compelling elements, as it cuts across all cases, regardless of their features.

All the cases are just experimenting with a first AI-related project, so one of the main affordances for the entire organization is to learn how to deal with AI, to work with it, and to understand how these human and non-human agents are connected within the organizational context. This relational phenomenon affects IT people, domain specialists as well as management. Related to this, the interviewees observed satisfaction among the employees involved in the projects, as they perceive a re-qualification in what they consider the future of the technology evolution. Depending on the features of the AI system, some cases highlighted an augmentation of the decision-making process and the automation of simple cognitive tasks.

4.3. Environmental context

4.3.1. Common environmental implementation factors

To enhance the implementation of AI, our cases needed to have access to and leverage on the competencies of external suppliers, thus making organizational boundaries more blurred. External suppliers play a twofold role. On the one hand, PSOs usually delegate the technical development of AI to them who, in some cases, are also the promoters of this innovation, as noted by the project manager of Case 6:

> "*The algorithm training is a business for the supplier. Indeed, in the City's departments we identify the services to be implemented. Normally, the introduction of these AI systems is led by providers who come to us offering their project ideas. We usually agree and test the solution proposed.*"

On the other hand, PSOs also exploit the competencies of external stakeholders to learn how to handle and train AI. This path is followed by different entities and, today, in the early stage of AI implementation, it seems that PSOs could not proceed without the support and consultancy from external actors. However, this pivotal role could be a double-edged sword, as explained by the Head of the Digital Transformation of Case 7:

> "*My role is also to know how to select suppliers, although I hope that, in the future, public organizations can use their internal expertise. Indeed, I am very concerned if they [=the suppliers] leave us: if the contract will not be renewed and there will not be an adequate internal knowledge, the new supplier will have to start again. The learning curve will be very difficult.*"

This statement underlines the importance of strengthening technical expertise within the focal organization over the long term. Moreover, the interviewees pointed out a final remark: the public sector is not a competitive industry, and this feature appears to be extremely relevant for the deployment of AI. Indeed, some interviewees focused on the importance of sharing best practices and experiences with other public bodies.

4.3.2. AI-related environmental factors, affordances, and constraints

Informants highlight how AI is increasingly blurring organizational boundaries. The implementation of AI is not only related to its technological components or its relationship with organizational agents, but also to phenomena and issues that exist outside organizational boundaries.

First, the cases pointed out that the implementation of the systems cannot be aside from policies, national strategies, and frameworks that regulate data management and data sharing. The presence (or lack), of laws and policy frameworks regulating AI implementation could have a positive (or negative) effect. As acknowledged by several interviewees, the development of regulations is key to exploiting AI features, especially in public settings. As the project manager of Case 5 stated:

"*We are more concerned about legal and policy barriers, because here technology develops quicker than legislation. Laws and frameworks should be implemented even more than AI. Nowadays formal guidelines are missing, and our regulatory framework is immature, thus obstructing the full implementation of the technology itself.*"

In addition, especially for the AI systems that interact with the citizens, it is necessary to ensure citizens' trust in the system. For example, in the autonomous vehicle cases (5 and 6), the system was tested with the citizens, to explore their behavior, as stated by the project manager of Case 5:

"*We needed to test people's confidence in using our autonomous vehicle. To do this, we conducted a series of tests with ordinary citizens, observing their behavior and the extent to which they felt safe. It was a big effort for us, but necessary, especially if one day we are going to make these vehicles fully operational.*"

Despite the partial commonality with standard technologies, we observed a difference in the relationship with the suppliers. In particular, the need for continuous training of the system requires a more stable and continuous relationship to avoid a degradation of the system. For example, the project manager of Case 8 stated:

"*Although we are a university and the system is now in use by the organization, we are still working on the project. That is a bit unusual, because it's a live service. However, there is a need for a continuous updating and continuous training activities to avoid the downgrading of system's accuracy. On top of the direct scoring model, there are always these smaller, interesting analytical questions, and I have a couple of labor economists on the team who are interested in these questions and support the retraining of the model.*"

Finally, beyond the sharing of best practices and experiences, AI opens the sharing of components, models, and training data. This sharing process, even if still in its infancy, is likely to lead to the elimination of unnecessary activities (such as collecting data that has already been stored or designing systems that have already been tested). As the Head of the IT department of Case 4 pointed out:

"*As for the data, we published all the data we could, and we announced it on different platforms, where other public or private organizations, as well as citizens, could have accessed to it. Finally, also our software is open source: we also want to share the methods we have adopted.*"

5. Discussion

5.1. Reflection on theoretical gap and theory extension

In this study, we shed light on the complexity of implementing AI in the public sector, highlighting that this process brings together a set of implementation factors that are common to those of standard digital technologies, while adding novel factors that are required when implementing AI and are peculiar to this technology – to do that we employ the TOE framework. Then, thanks to the TACT and as suggested by previous authors (Flyverbom et al., 2016; Leonardi, 2011), we also propose to read these factors by looking at the set of material features that afford, or constrain, different actions (Treem & Leonardi, 2012), extending previous studies on AI implementation in the focal sector.

This dual perspective allows us to shape a conceptual framework (Fig. 4) that links social organizing to the specificities of AI (Faraj & Azad, 2012). The framework offers a novel perspective and enriches the current debate on the implementation of AI, shedding light on the relationships between the contexts observed and explaining the complex and multifaceted factors and features behind AI implementation. As reported in the framework, our data show that AI implementation requires several factors to be present in a PSO. These factors can be divided into common implementation factors, which AI shares with any type of technological implementation, and AI-related factors, which are instead

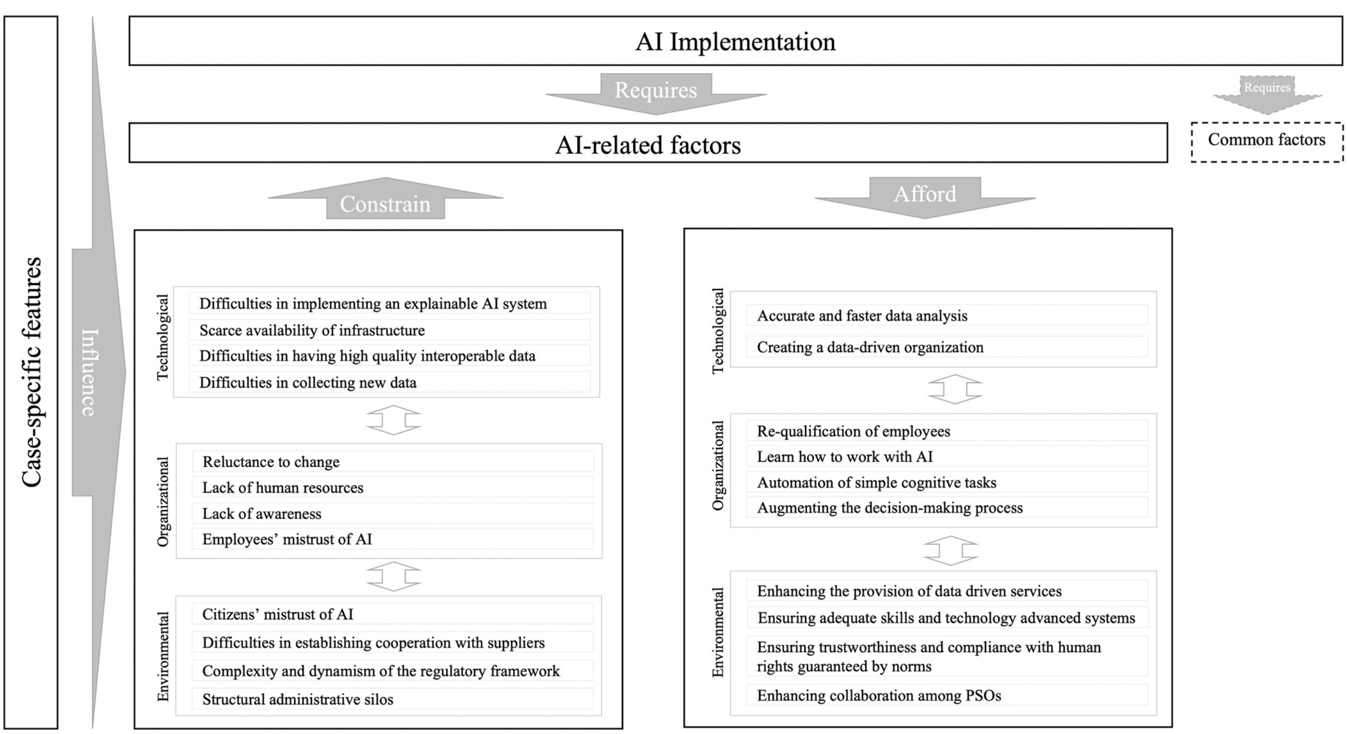

Fig. 4. Conceptual framework.

specific to AI. These latter factors afford or constrain new actions for PSOs. Finally, these relationships are mutated by a set of case-specific features affecting the entire implementation process, such as the type of AI technology and the user of the AI system.

A few studies have tackled AI implementation with this comprehensive approach (see, for instance, van Noordt and Misuraca, 2022) and, to our knowledge, this is the first attempt to create such a comprehensive framework that not only identifies the factors affecting AI implementation but also the elements that afford and constraint its implementation.

Consistent with previous studies, we confirm the relevance of technological factors, mainly data collection and curation (Venkatesh, 2021; von Krogh, 2018), and the need of a continuous improvement for avoiding the degradation of the system (Choudhary et al., 2021). By harnessing the affordances of AI, and the vast amount of data they generate, PSOs could become data-driven organizations, leading to better polices and improved public values (Charles et al., 2022).

However, our data show how the focal technology "favors, [...] and at the same time constrains, a set of specific uses" (Zammuto et al., 2007, p. 752). Indeed, PSOs often struggle to develop the right infrastructure and to create an explainable system (Grimmelikhuijsen, 2023; Janssen et al., 2022). This is even more crucial in the public sector, where PSOs should be able to properly ensure the accessibility and explainability of the AI systems used to achieve a certain goal, otherwise there may be negative consequences for society (Zuiderwijk et al., 2021; Willems et al., 2022). As a result, we can conclude that:

Proposition 1. Implementing AI in Public Sector Organizations requires an understanding of technology's functionalities. AI is likely to afford data-driven activities but, at the same time, it requires that explainability issues are properly addressed, along with investments in data governance and infrastructure.

In addition, we argue that technological features alone are not enough to shed light on the constellation of opportunities and constraints that AI presents. Indeed, AI systems are increasingly gaining centrality for organizing, by automating simple and repetitive tasks and, thus, freeing up human resources to perform more valuable activities (Brynjolfsson & Mcafee, 2017). This organizational aspect cut across all the cases we analyzed and the data show that, to reap the affordances offered by the balance between automation and augmentation, humans have to learn how to interact with the AI systems, thus developing new skills to monitor the machine and make decisions when it offers a suggestion (Giest & Klievink, 2022).

This is often a mined field, full of possible risky biases (Alon-Barkat & Busuioc, 2023), and AI intrinsic features may also hinder the development of systems based on its algorithms. Indeed, AI requires a general organizational awareness of the technology and trust in it, which are both essential, but still far to be reached.

This evidence brings thus us to formulate the following proposition:

Proposition 2. Implementing AI in Public Sector Organizations requires a constant exchange between human and technological agents. AI is likely to afford the augmentation of existing activities and the development of new jobs, but its features, together with a lack of awareness, may increase organizational mistrust, hindering its implementation.

Finally, findings show how AI is a technology that creates a "socio-technical relationship between those who collect the data, the machines that store and process it, the information system designers, and the people who retrieve and use the relevant information" (Vogl et al., 2020, p. 952). Indeed, this technology enhances the possibilities of opening up organizational boundaries to the environment, namely citizens, other PSOs, and suppliers.

Nevertheless, to avoid constraints in AI usage, it is essential to ensure citizens' trust in the system (Gesk & Leyer, 2022; Wang et al., 2021). This relational perspective is in line with previous research (*e.g.*, Scutella et al., 2022) and it is crucial because it highlights how the exchanges should be not only between the machine and the PSO's organizational context, but also with a broader community.

The findings demonstrate that AI is also changing the way PSOs interact with suppliers, opening new forms of public-private partnerships where suppliers are actively involved in developing an AI system, while teaching and learning how to nourish it. However, some downsides to these relationships emerged. In particular, data suggests how this deep engagement demands a revision of public procurement policies to avoid a continuous iteration of the learning curve due to changes in suppliers.

Regarding the linkages between the three TOE contexts, our evidence shows that the technological and the environmental ones are closely related, as the development of a data-driven organization can create new opportunities for collaboration not only with technological suppliers, but also with other PSOs. The other side of the coin is that this process of nurturing AI systems with shared data should be supported by a joint effort of PSOs, which need to avoid operating and handling data in silos.

Finally, our results draw the attention to the role of AI regulation. Interviewees recognize the need to act within clear normative boundaries. Indeed, due to the evolving nature of the technology, there could be a mismatch between AI spread and its normative, thus obstructing proper implementation. Taken together, these considerations lead us to the development of the last proposition:

Proposition 3. Implementing AI in Public Sector Organizations requires engaging with the constellation of actors involved in the public arena. AI is likely to enable novel collaborations with citizens and suppliers. However, this requires a complex management of this ecosystem of actors as well as a clear regulatory framework.

5.2. Theoretical implications

The paper makes several contributions to the existing academic debate in an area where the literature is still scarce. To the best of our knowledge, no study to date has examined the implementation of AI in the public sector with such a large and varied set of empirical evidence (Collins et al., 2021). We offer a comprehensive view of the phenomenon, as well as a better understanding of the factors, within and around PSOs, that might influence AI implementation. This perspective is still missing in the existing literature on the public sector (Neumann et al., 2022), while it is more advanced in studies looking at private companies (see for example Merhi, 2022).

With our comprehensive perspective, we confirm and enlarge the existing literature on the topic, which has so far been mainly based on theoretical studies (Wirtz et al., 2019), or focused on specific AI technologies (*e.g.*, chatbots, Maragno et al. (2022)) or AI features (*e.g.*, explainability, Grimmelikhuijsen (2023); Janssen et al. (2022)).

First, we distinguish between AI-related factors and other implementation factors that are relevant but not unique to AI. The need for this distinction has been highlighted in a recent literature review (Madan & Ashok, 2023). We believe that this intellectual effort is not a mere stylistic exercise, but rather a necessary step to help scholars focus on those factors that differentiate the uptake of AI from what has already been debated in the standard digital government literature.

We confirmed with empirical evidence several aspects related to AI implementation, starting from the need to consider it as an organizational agent entangled (Maragno et al., 2022) in a complex network of relationships with technological, organizational, and environmental elements. Previous studies highlighted how different factors vary depending on the stage of the adoption process (Neumann et al., 2022) and that environmental factors are less relevant. We argue that the case-specific features are much more varied and include – but are not limited to – the type of AI technology, the characteristic of the service, and the organization. We moved away from the prescriptive approach of identifying which are the factors that characterize AI implementation to a more open, complex, and varied approach, identifying which could be the factors depending on case-specific features, such as the context and the type of system.

Finally, the study also contributes to organizational research. Indeed, the research sheds light on the "adaptation of an organization to the situation in which it must operate" (Parsons, 1956, p. 80). The situation in which PSOs have to position themselves is the one brought about by the implementation of AI systems that affect organizational processes and tasks. Thanks to the use of the TOE framework (DePietro et al., 1990), this study creates a bridge between the first and second mandates of organizational theory (Stern & Barley, 1996). Regarding the former, the research identifies the actions afforded and/or hindered by AI features (*first mandate*). Then, the study extends the focus also considering the environmental factors, which are instrumental and affect AI implementation (*second mandate*). From a methodological perspective, we confirm that TOE is a useful framework to deepen AI implementation (Neumann et al., 2022), and we propose a novel approach that combines it with the TACT theory. This choice appears to be suitable to disentangle not only the technical and material features of AI, but also the social elements (organizational and environmental) connected to its implementation.

5.3. Practical implications

The results achieved have important implications for public managers and offer some guidelines that PSOs should follow when implementing AI. The practical implications are discussed according to the three contexts that characterized the narrative of the study: technology, organization, and environment. Moreover, the affordances and constraints perspective can inform public managers with a new lens through which approaching the possibilities offered by AI in relation to the organizational dynamics.

At the technological level, we have highlighted the complexity of AI, which challenges existing organizational practices and requires several precautions to be taken by PSOs. Due to their technological features, AI systems can help public managers and policy makers to increase the reliability of their data-driven decisions and policies. Addressing data issues also requires that public managers need to ensure the explainability of the AI systems (Grimmelikhuijsen, 2023; Janssen et al. 2022), so that both employees can rely on them to perform their jobs and citizens can trust in accessing the services they provide. Furthermore, public managers should constantly monitor the development of the technology, to ensure and exploit its intelligent nature and to avoid system degradation (Choudhary et al., 2021). Concerning the latter, a proper infrastructure is needed, and another important finding regards the need to look for technological knowledge outside PSOs' boundaries. Public managers should be aware of this when designing processes and selecting suppliers for AI implementation.

These aspects also have deep practical implications at an organizational level. More specifically, there is the need for a cultural change that is even more profound than that required by the introduction of other technologies. AI requires a new way of interacting with the machine. Understanding that it also has some human characteristics, and it becomes "increasingly intelligent" (Bailey et al., 2019, p. 642), is a new approach that needs to be introduced and addressed into the organizational culture for its proper implementation. Designing AI systems that are interwoven with current organizational processes and routines, and relying on the creation of small, dedicated groups of people who deal with the machine, seems to be a winning strategy.

More broadly, public managers should be aware that the introduction of AI must be accompanied by profound changes in organizational structure. There will be new types of jobs, or at least new tasks, and there will be: (i) people working for the machine (*i.e.*, training it); (ii) people working with the machine according to a clear division of tasks; (iii) machines replacing people in some tasks, to the extent that people will work thanks to and following machine advice and solutions.

Finally, this has implications for the relationship with the environmental context in which PSOs operate. First, managers should be aware that cooperation is key (Tangi et al., 2022). The implementation of AI makes organizational boundaries more porous (Bailey et al., 2022), calling for the progressive creation of a developmental community that includes both private and public organizations.

The relationship with suppliers needs to change because of the nature of the technology. On the one hand, it needs to be more stable over time, to ensure continuity and avoid system degradation. On the other hand, clear and precise requirements are needed to avoid buying a black box. This must start with the procurement process and continue throughout the implementation phase. In addition, public managers should also monitor citizens' behavior towards services delivered or managed using AI. They need to gather their insights to understand their level of trust in the system and address their fears (Gesk & Leyer, 2022; Wang et al., 2021). In fact, identifying and considering the full constellation of stakeholders to gather and share data, experience, and competencies is probably one of the most important steps public managers need to take, and how this step is taken will be critical to properly implement AI systems and, consequently, to reap the new possibilities offered by the technology.

5.4. Limitations and future research

The study has several limitations and offers avenues for future research. Mainly the helicopter view offered by the study prevents an in-depth exploration of the factors, affordances and constraints identified. Further research can delve deeper into these elements, for instance by focusing on the stakeholders that revolve around the implementation of AI, such as politicians, suppliers, and external partners. Moreover, it might be interesting to complement the perspective of this paper with similar research using different models (*e.g.*, the UTAUT one).

Another limitation and room for further study is related to the fact that AI implementation is a moving target. This study made a static overview of a specific period. PSOs are now at the beginning of AI implementation, with only a few organizations that are already developing AI, although their number is growing. Moreover, the availability of AI to users, both citizens and employees, may change over time as they experience the actualization process (Meske et al., 2023). These elements will lead to the rise of new opportunities and challenges. Future research can start from the factors that we have collected to verify their validity over time and to enrich the list with novel factors that may emerge thanks to the increasing spread of AI systems within public boundaries. Indeed, we aim to start a comparative exercise exploring the implementation factors tied to AI, and how they differ from those of standard technologies. Considering the latter, there is a large body of literature that examines implementation factors from different angles and in different contexts (see for example Gil-Garcia & Flores-Zúñiga, 2020). Our aim is not to re-observe all these factors in our limited set of cases, but rather to classify the sub-set of factors that emerged from our cases to explore the specificities related to AI and the novelties that it brings to PSOs.

We also found that the affordances and constraints identified do not apply to all cases (see Appendix A and Appendix B). This is due to a number of case-specific features (*e.g.*, the user of the AI system, the type of technology) that influence both the presence of a particular affordance or constraint and its magnitude. Our research is limited to acknowledging the existence, complexity, and variety of these features and identifying some of them. We also suggest that this constellation of features plays a key role in AI implementation, and further studies could narrow the scope and delve deeper into a subset of AI systems filtered by some of the identified case-specific features.

Moreover, even though we identify and propose a list of factors that affect AI implementation, future studies could unpack the topic by investigating the relationships between these factors through surveys and quantitative methods. Finally, it would be interesting to compare the factors identified in the public sector with those in the private sector, to see commonalities and differences.

6. Conclusions

The research aims to contribute to the existing literature on AI implementation by shedding light on how its features shape various aspects of organizing within public boundaries.

Therefore, by combining the TOE framework with the TACT, we provide a conceptual framework that sheds light on how AI implementation involves the combination of the factors that emerge in the three organizational contexts and, for each of them, we pointed out what are the affordances and constraints brought forward by AI in the specific empirical domain. The study provides a novel understanding of AI implementation, highlighting how the focal technology relates to “people, organizations, societies, and institutions to create new possibilities” (Lanzolla et al., 2020, p. 347) and constraints in the public sector.

CRediT authorship contribution statement

Giulia Maragno: Conceptualization, Methodology, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Visualization, Project Administration. **Luca Tangi**: Conceptualization, Methodology, Investigation, Writing – Original Draft, Writing – Review & Editing, Visualization. **Luca Gastaldi**: Conceptualization, Validation, Writing – Review & Editing, Supervision. **Michele Benedetti**: Validation, Writing – Review & Editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table 5
AI specific constraints within the given empirical realm.

	AI-related factor	Constraints	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Technological	*Ensuring a continuous learning process*	• Difficulties in implementing an explainable AI system			•	•	•	•	•	•
	Ensuring interoperable datasets continuously updated	• Scarce availability of infrastructure			•				•	
		• Difficulties in having high quality interoperable data		•	•	•	•	•	•	•
		• Difficulties in collecting new data				•	•			
Organizational	*Designing new tasks for machine training*	• Reluctance to change			•				•	•
		• Lack of human resources	•	•	•			•		•
	Setting up a novel human-machine relationship	• Lack of awareness	•	•	•	•	•	•	•	•
		• Employees’ mistrust of AI			•			•	•	•
Environmental	*Ensuring citizens’ trust in the system*	• Citizens’ mistrust of AI	•	•		•	•			
	Ensuring steady suppliers’ support for continuous training	• Difficulties in estabilishing cooperation with suppliers				•	•	•		•
	Being compliant with the Regulatory framework	• Complexity and dynamism of the regulatory framework			•		•	•	•	
	Collecting and sharing data from and with outside	• Structural administrative silos		•		•	•	•		

Appendix B

Table 6
AI specific affordances within the given empirical realm.

	AI-related factor	**Affordances**	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Technological	*Ensuring a continuous learning process*	• Accurate and faster data analysis			•	•			•	•
	Ensuring interoperable datasets continuously updated	• Creation of a data-driven organisation	•		•	•			•	•
Organizational	*Designing new tasks for machine training*	• Re-qualification of employees	•	•	•	•	•	•	•	•
		• Learn how to work with AI	•	•	•	•	•	•	•	•
	Setting up a novel human-machine relationship	• Automation of simple cognitive tasks	•	•	•				•	•
		• Augmenting the decision-making process			•				•	•
Environmental	*Ensuring citizens’ trust in the system*	• Enhancing the provision of data driven services	•	•		•				
	Ensuring suppliers’ support for continuous training	• Ensuring adequate skills and technology advanced systems			•	•			•	•
	Being compliant with the Regulatory framework	• Ensure trustworthiness and compliance with human rights guaranteed by norms			•		•	•		•
	Collecting and sharing data from and with outside	• Enhancing collaboration among PAs	•		•	•	•	•	•	

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