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AI-augmented government transformation: Organisational transformation and the sociotechnical implications of artificial intelligence in public administrations

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ABSTRACT

Implementing artificial intelligence (AI) in public settings requires a fundamental transformation of various social and technical aspects within public administration. However, the transformative efforts required for AI integration and use in government remain underexplored. This study introduces the concept of 'AI-augmented government transformation,' building on sociomateriality and sociotechnical theory, and develops a theoretical framework to explore this phenomenon. By applying this framework and drawing insights from expert interviews, we identify the strategic shifts and socio-technical adaptations essential for integrating AI into public administrations. Our analysis highlights the importance of opening the 'black box' of AI to gain a deep understanding of its underlying technologies and their materialities.

The findings reveal complex interdependencies between AI materiality and the social and technical systems that public administrations must navigate. Specifically, AI, as a novel materiality, introduces new organizational dynamics, enhances employee capabilities, and alters operational routines and practices. These changes complement technical ones, such as upgrades and advancements in data collection and processing. By investigating the complexities of AI-augmented government transformation, this research offers novel and practical insights for policymakers and practitioners navigating the challenges and opportunities of AI integration.

1. Introduction

The era in which artificial intelligence (AI) and its application in the public sector were solely confined to research and exploration is fading. Today, AI encompasses a range of readily available technologies that can be integrated into and utilised in the day-to-day operations of public (and private) organisations, thus transforming these operations. AI is increasingly permeating the public sector as a technology promising to transform government, enhancing the overall efficiency and effectiveness of public services. Government transformation refers to the fundamental changes needed for operating the government, participation, and providing services (e.g., Mergel, Edelmann, and Haug, 2019; Tangi, Janssen, Benedetti, and Noci, 2021). This shift is underscored by a recent report from the European Commission's Public Sector Tech Watch,[1] which identified 1295 cases of AI adoption across Europe, with the technology already operational in 40 % of these cases (European Commission, 2024).

The distinctive attributes of AI mean that particular elements of transformation are required when integrating it into an organisation's work. There are strong interdependencies between the new technology and the other systems in place, with considerable implications for organisational structures, processes, data collection and processing and human–machine interactions. AI has the potential to improve the management and delivery of public services, as well as participation, transparency and openness in public administration (Sun and Medaglia, 2019; Tangi et al., 2022). However, a lack of transformational effort risks incorrect decisions in integrating AI, which may result in unintended, biased and even harmful consequences (Maragno, Tangi, Gastaldi, and Benedetti, 2023; Nouws, Janssen, and Dobbe, 2022) and also in failure to take advantage of the full potential of the technology.

Therefore, there is a need to understand the transformative endeavours that are essential for the effective integration of AI in the

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[1] https://interoperable-europe.ec.europa.eu/collection/public-sector-tech-watch.

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government. This research aims to bridge that gap by analysing the literature on digital government transformation in combination with the literature on AI, an area of research that is still underexplored. Situated at the crossroads of AI integration and transformation in public administration, this research seeks to address the following question: *'What transformational measures and actions are public administrations pursuing in the integration of AI technologies?'*

In the context of this study, AI integration encompasses the complete process from initial design to adoption, implementation and use.

In seeking to answer the research question, rather than engaging in a definitional discussion of what AI is, this paper starts from the assumption that, despite technical differences among AI approaches and systems, an in-depth definition and classification are not always essential to understanding AI-related experiences (Gesk and Leyer, 2022). Any definition applied in this context would have to be very broad, as AI encompasses such a broad range of technologies, and might not even be useful, as it could distract from the focus on transformation.

Instead, the paper draws on sociomateriality (Bostrom and Heinen, 1977) and sociotechnical theory (Leonardi, 2012) to provide a comprehensive perspective on transformation encompassing organisations' social and technical aspects. The study adopts a qualitative approach, using expert interviews to gather insights into the AI integration process in public administration. Data analysis was conducted through a combination of inductive and deductive coding, integrating thematic analyses into the approach.

The research offers a unique perspective that can enrich the understanding of researchers, policymakers and practitioners in the field of government information. It also seeks to contribute to a deeper understanding of AI dynamics in public administration and offer a fresh perspective on an important yet underexplored domain.

The remainder of the study is structured as follows. Section 2 explains the theoretical framework that underpins our analysis. Section 3 delineates the methodology employed and details the data collection process. Section 4 presents the findings of our research. Section 5 discusses these findings in relation to the literature in the field and addresses our study's theoretical and practical implications. Section 6 elucidates the study's limitations and proposes avenues for future research. Section 7 offers conclusions.

2. Theoretical background

2.1. Artificial intelligence and digital government transformation

Technological advancements often necessitate profound transformations within public organisations to ensure the effective utilisation of the new technology (Tangi et al., 2021). This topic is not new and has been a subject of scholarly debate for decades. In the early 2010s, the concept of transformational government, or t-gov, emerged in academic discussions (Weerakkody, Janssen, and Dwivedi, 2011). More recently, scholars have begun exploring this topic under the term 'digital government transformation' (see, for example, Mergel et al., 2019; Tangi et al., 2021). Researchers have offered various definitions of digital government transformation, with a common thread among these studies being the definition of digital transformation as the transformative effect of digital technologies on organisations, extending beyond mere digitisation to encompass the profound effects of digital technologies on organisational structures, processes and practices.

One of the first studies discussing the concept of digital government transformation was published in 2019 (Mergel et al., 2019), and since then the amount of research in this area has grown rapidly. In 2021, Tangi et al. conducted a search on Scopus by combining the keywords 'digital transformation' with 'government' and 'public sector', identifying 142 papers, of which 38 explicitly referred to 'digital government transformation'. The same search was carried out as part of this research in 2025, which yielded 1861 articles (145 from 2021, 240 from 2022, 372 from 2023, and 661 from 2024), with the most recent having been published on 19 May 2025. These numbers provide a rough indication of the substantial expansion of the field in recent years. Adding 'artificial intelligence' as a mandatory keyword to the Scopus search resulted in the identification of only 167 articles, with the most recent update also having been published on 19 May 2025 (Fig. 1). This quick collection of papers cannot encompass the full spectrum of studies on this topic, but it offers a snapshot of the scant literature. Despite the limitations, analysing existing studies on AI and organisational changes in the public sector reveals some insights, challenges and risks. While not providing a comprehensive perspective, the findings of these studies support the notion that the integration of AI into public administration fundamentally alters socio-technical elements, including the bureaucratic structures in which the technology is implemented. This phenomenon is the focus of our study.

As interest in digital transformation has grown, scholars have begun to explore connections between digital government transformation and other related areas, focusing on the role of specific elements in the context of digital government transformation. For instance, Moser-Plautz and Schmidthuber (2023) considered digital government transformation as a response to the COVID-19 pandemic, Yuan et al. (2023) examined the role of social media and Irani, Abril, Weerakkody, Omar, and Sivarajah (2023) explored the impact of legacy systems.

Despite the increasing number and varied nature of these studies, the influence of AI on digital government transformation has received limited attention. AI-augmented transformation represents a distinct departure from previous digital transformation processes. The literature emphasises AI's pivotal role in reshaping organisational structures (Glaser, Pollock, and D'Adderio, 2021; Vatamanu and Tofan, 2025) and the requirement for a distinctive transformation pathway. For example, literature highlights how AI developers and those introducing AI into organisations have to consider the need to transfer knowledge into formats that machines can interpret and for machines to generate information that humans can understand and use (Brynjolfsson and McAfee, 2017). Moreover, advanced AI systems that act with greater autonomy - that can be labelled 'agenting' systems (Janssen and Kuk, 2016; Murray, Rhymer, and Sirmon, 2021) – require a shift in the locus of agency to encompass an 'ensemble' approach involving both human and non-human decision-making (Choudhary, Marchetti, Shrestha, and Puranam, 2023).

In order to capture the distinct transformative efforts associated with the integration of AI into government functions, and to differentiate this shift from digital transformation more generally, we propose the concept of AI-augmented government transformation (AI-GT). This concept deliberately emphasises the 'AI-augmented' aspect of the transformation, superseding the more generic 'digital' label, to underscore the unique characteristics of this transformation that augment human capabilities thereby influencing many socio-technical aspects. By introducing this novel term and using it in our research, we intend to highlight the distinctiveness and significance of the phenomenon.

The AI-GT concept is grounded in the distinction between AI-augmented transformation and other forms of digital transformation, with a particular focus on tracing the transformation back to the materiality of AI. This refers to the ensemble of material artefacts that characterise and distinguish AI, in accordance with sociomateriality and sociotechnical theory (Bostrom and Heinen, 1977; Leonardi, 2012). Furthermore, our notion of AI-GT draws on and expands on existing definitions of digital government transformation (Mergel et al., 2019; Nograšek and Vintar, 2014; Tangi et al., 2021) and conceptualisations of AI as an agent (Maragno, Tangi, Gastaldi, and Benedetti, 2022; Murray et al., 2021). We define AI-GT as follows:

> The organisational changes facilitated by the AI agent and its novel materiality that transform organisational entities and how they operate with others, leading to a new state for both the social and the technical systems within the organisation.

Public administrations risk undermining their ultimate goal of

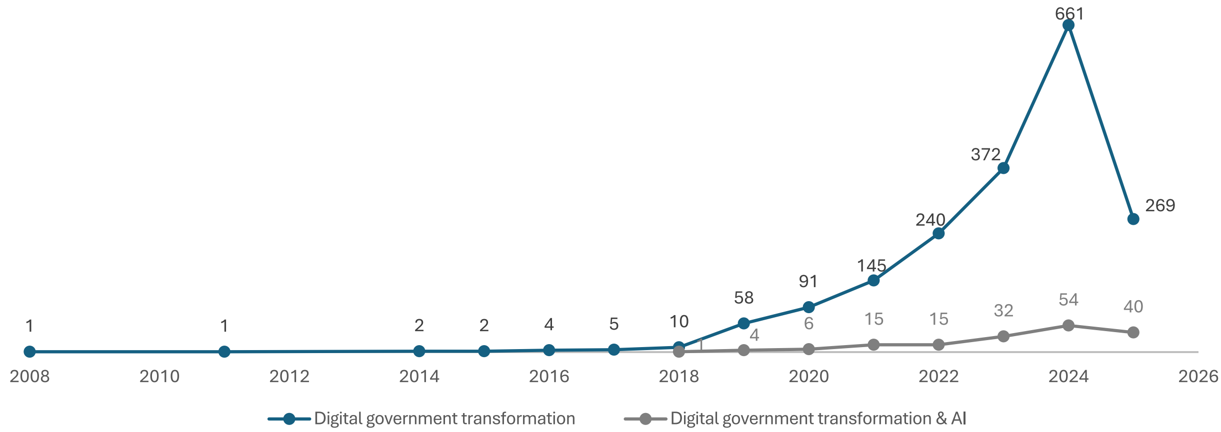

Fig. 1. Number of papers published on digital government transformation and AI over time[2].

- *Source:* Authors, based on Scopus.

[2] The queries used were: (i) digital government transformation: TITLE-ABS-KEY((“digital transformation” AND (“government” OR “public sector”)) OR (“digital government transformation”)) AND (LIMIT-TO (DOCTYPE,“ar”)); (ii) digital government transformation and AI: TITLE-ABS-KEY(((“digital transformation” and (“government” OR “public sector”)) or (“digital government transformation”)) AND (“artificial intelligence” OR “AI”)) AND (LIMIT-TO (DOCTYPE,“ar”)).

enhancing public value if this transformation is not adequately addressed and managed. Among others, a notable example is the child benefit scandal in the Netherlands, where many citizens were falsely accused of fraud (see, for example, Rouwhorst, 2022). Examinations of such cases often focus on improving the algorithm rather than on changing organisational practices to ensure that AI is used effectively. Such a process of change goes beyond the mere adoption of technology; it requires that all aspects of public administration be transformed to take into account the nature of AI. This need should be considered at an early stage when introducing AI and using technology. That is why this research looks at the whole process' intended, from design and implementation to adoption and use.

Nouws et al. (2022) initiated a discourse on algorithmic digital cages. This concept refers to the fact that algorithms can exert control over civil servants and interconnected technical and social systems. In essence, algorithms have the potential to govern or even dictate other systems, such as legal frameworks or decision-making processes. This can result in adverse effects or unintended harmful behaviours when algorithms fail to accurately reflect reality and instead diverge from it. In response to this risk, Nouws et al. (2022) explored the redesign of the algorithm design process.

However, there has been relatively little discussion from the perspective of redesigning and adapting organisations (Chandra and Feng, 2025), despite the urgency of minimising the risk of governing within a digital (AI) cage. Along these lines, recent studies advocate a comprehensive perspective that addresses broader organisational issues and capabilities beyond mere reflections on data, infrastructure and algorithms (Chandra and Feng, 2025; Mikalef et al., 2021, 2023; van Noordt and Tangi, 2023).

Much of the research in this area looks at transformation at the individual level, emphasising the need for a clear and structured way of working between AI and public employees (Ahn and Chen, 2022; Haesevoets, Verschuere, and Roets, 2025; Vogl, Seidelin, Ganesh, and Bright, 2020). In particular, Vogl et al. (2020), drawing on Leonardi (2011), use the term ‘algorithmic bureaucracy’ to highlight the change in the relationship between workers and their tools. Ahn and Chen (2022) point out the importance of training employees to foster the culture of innovation that is essential for successful AI integration. Haesevoets et al. (2025) highlight that individuals prefer AI to assume an advisory or supportive role, rather than a more autonomous one. Janssen and Kuk (2016) and Maragno et al. (2022) underscore the importance of employees recognising AI as an organisational agent and taking a socio-material approach. Additionally, Giest and Klievink (2022) demonstrate that AI fundamentally reshapes government roles, tasks and duties, and Medaglia and Tangi (2022) emphasise the need for public administrations to enhance the digital literacy of employees. Other studies have focused on the decision-making process at the individual level. For instance, de Bruijn, Warnier, and Janssen (2021) note the need for a good balance between AI and human decision-making. Grimmelikhuijsen and Meijer (2022) urge public administrations to clarify responsibilities in the complex relationships that arise when using AI. Furthermore, Selten, Robeer, and Grimmelikhuijsen (2023) provide insights into how public servants respond when AI suggests an action, demonstrating that they follow such guidance only when it aligns with what they already consider the best available option.

Despite valuable individual-level insights, to the best of our knowledge no existing studies have comprehensively explored this type of transformation in the context of the rapid advent of AI and the risks associated with its integration. Only recently have Tangi, van Noordt, and Rodriguez Müller (2023) initiated exploration in this area, using a handful of case studies to examine how public administrations are transforming organisationally in response to AI integration. Their work underscores the pressing need for further research into the organisational challenges posed by AI. Furthermore, researchers often neglect to consider the distinctive characteristics of AI technologies, which can result in findings that are insufficiently specific to AI, failing to identify the transformational elements that are unique to AI implementation (Chandra and Feng, 2025).

This study aims to address this gap by exploring the nature of AI-GT in the public sector. It will contribute to a broader understanding of the interplay between technology and organisational practices in the evolving landscape of government transformation.

2.2. Sociotechnical theory and sociomateriality

This research builds on the principles of sociomateriality and sociotechnical theory to explore AI-GT. Sociomateriality emphasises the importance of technology's physical (material) components in analysing its effects (Leonardi, 2012), whereas sociotechnical theory provides an actionable structure for conducting empirical analysis in this area

(Bostrom and Heinen, 1977). The synthesis of these approaches yields a deep understanding of how technologies drive organisational transformation.

The rise and growth of these theories and concepts stem from a fundamental assumption in the information systems field, namely the recognition that debate centred solely on the concept of 'technology' can be overly simplistic. Such a narrow focus may unintentionally imply that technology consists merely of separate devices or artefacts that operate independently, when, rather, it must be taken into account that these devices gain significance and impact only when integrated into social practices. In simpler terms, by fixating on the term 'technology', this perspective risks overemphasising specific hardware or software components, potentially misleading researchers into perceiving technology integration as a distinct and isolated event, rather than understanding that technologies are deeply embedded in all aspects of organisational life. This realization has spurred discussions around sociomateriality as '*a bold reminder that when we talk either about technologies or organisations, we do well to remember that social practices shape the materiality of a technology and its effects*' (Leonardi, 2012, p. 33). To highlight how social and material agencies are entangled, Leonardi (2011) introduces the metaphor of 'imbrication', derived from the names of roof tiles used in ancient Roman and Greek architecture, where the *tegula* and *imbrex* were interlocking tiles used to waterproof a roof.

Sociotechnical theory elevates the analysis, focusing on how sociomaterial practices integrate into the macro-organisation of work. It posits that organisations are complex sociotechnical systems that can be understood as ensembles of two independent but interactive macro-systems, defined as follows (Bostrom and Heinen, 1977).

- Collective human and material agencies – that is, sociomaterial practices – constitute what sociotechnical theory refers to as the **technical system**. It includes the interaction between materiality (i.e. technological artefacts and data) and human tasks and intentions that make the materials meaningful by incorporating them into social practices.
- The **social system** comprises the human factors that constitute an organisation. These are classified into cultural elements, related to organisational culture and behaviour, and structural elements, including governance, hierarchies, power dynamics and roles.

The mutual shaping of social and technical systems defines a sociotechnical system (Bostrom and Heinen, 1977). Thus, any organisational transformation entails mutual changes in these two subsystems. Revisiting and applying the foundational principles of sociotechnical theory can help in creating a good environment for successful organisational change, particularly when implementing new technology (Appelbaum, 1997; Lyytinen and Newman, 2008).

The application of these theories to explore government transformation is well established. Prior research has demonstrated their relevance and validity in this context, confirming their suitability for our study. Several authors have applied them within the digital government domain (Janssen and Kuk, 2016; Moser-Plautz and Schmidthuber, 2023; Nograšek and Vintar, 2014; Tangi et al., 2021). This study constitutes a pioneering effort to apply these theoretical frameworks to the specific context of AI integration in the public sector, shedding light on the intricate relationships between AI and social and technical systems in this domain. In doing so, this research addresses a significant gap in the existing literature, which has been characterised by a lack of theoretically grounded investigations into AI adoption in public settings (Chandra and Feng, 2025).

2.3. Theoretical framework

Based on the literature on AI and the organisational theories of sociotechnical systems and sociomateriality, Fig. 2 illustrates the theoretical framework for this study.

The foundational premise of the proposed theoretical framework posits that AI represents an emergent and distinct class of artefacts characterised by unique material attributes. Given this, the framework positions AI materiality at its centre. The concept of AI materiality can be examined by considering the inherent characteristics that define AI and distinguish it from other technological artefacts. Therefore, we define AI materiality through AI's key artefactual characteristics, such as its dependence on high-quality, structured data (Dwivedi et al., 2021), lack of transparency or explainability in decision logic (de Bruijn et al., 2021) and continuous learning and retraining needs (Maragno et al., 2022; Selten et al., 2023).

These features act as dynamic constraints and affordances that shape, and are shaped by, organisational contexts. Building on the principles of sociomateriality, our framework incorporates as its cornerstones the four key components that shape the sociotechnical system. Within the discourse on sociomateriality, the materiality of AI, like any other material artefact, becomes functionally integrated in the government only when interwoven – or imbricated, using the terminology of Leonardi (2011) – with the social and technical systems established in an organisation. Our analysis examines the interplay between both systems: the technical system, where AI integration in the government transforms tasks, workflows, IT infrastructures, and data-related processes, and the social system, where it impacts governance, organisational roles, structures, cultures, and human-machine interactions. The relationships between these elements are visualised in Fig. 2 by the connecting lines, that illustrate the complex interplay between them and their entanglement with AI materiality.

3. Methodology

3.1. Data collection

This study adopts a phenomenon-driven approach (Eisenhardt and Graebner, 2007), which involves conducting a detailed examination of an existing phenomenon as the primary driver of the research. In this case, our focus is on the phenomenon of AI's novel materiality and how it is intertwined with the social and technical systems of public organisations – that is, how public administration is transforming to integrate AI. We adopt a qualitative approach, employing expert interviews as our primary research strategy. This approach was chosen because it enables theoretical elaboration by combining conceptual and empirical perspectives (Fisher and Aguinis, 2017). Given the exploratory nature of the study, we maintained a degree of flexibility throughout the interview process to prioritise discovery over mere validation (Van Maanen, Sørensen, and Mitchell, 2007).

We applied several inclusion criteria to identify relevant experts. First, the study is rooted in the public sphere of the EU, where the integration of digital technologies, specifically AI in the public sector, is a strategic objective (European Commission, 2021). Furthermore, EU Member States operate under shared regulatory frameworks, strategies and principles. Therefore, we drew on the desk research conducted by the Public Sector Tech Watch initiative within the European Commission (European Commission, 2024; Tangi et al., 2022), which provides an overview of AI systems implemented by Member States between 2019 and 2021. At the time of writing. The dataset includes 1295 projects identified through various sources, such as news articles, academic literature, grey literature, and surveys. We selected the dataset as our source for two reasons: (i) its availability in open data sources and (ii) the systematic categorisation of projects according to a structured taxonomy, which enabled the systematic identification and classification of relevant cases of AI application.

The first step in this research was to employ a theoretical sampling approach, to establish the parameters of the empirical domain (Eisenhart, 1989). This involved identifying individuals with direct, hands-on involvement in the implementation of AI in public administrations, capable of providing informed perspectives. Our selection was

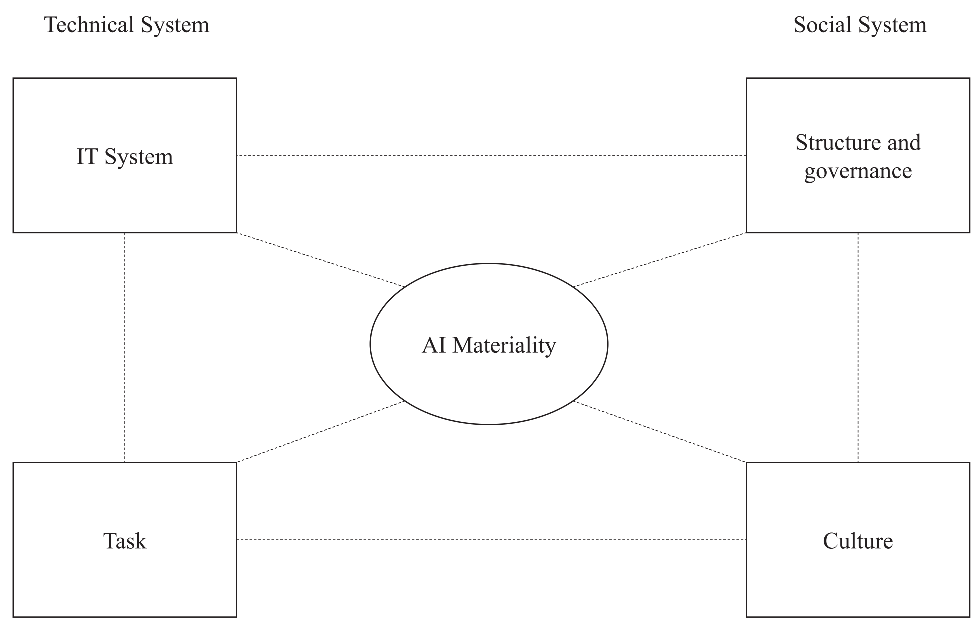

Fig. 2. Theoretical framework.
Source: Authors, adapted from Bostrom and Heinen (1977), Janssen and Kuk (2016), Leonardi (2012) and Tangi et al. (2021).

based on three criteria. First, informants had to be experts or practitioners in the field who were directly involved managing, designing or operationalising AI systems in a public sector context, ensuring that they had first-hand knowledge of organisational transformation. We began with the AI Watch dataset to identify the experts and focused on cases in which the central phenomenon under investigation (AI-GT) was likely to occur (Eisenhardt, 2021). This led us to select projects that were at least in the pilot phase, ensuring a certain level of developmental maturity.

Second, we selected experts involved in projects that, from the description available, appeared to have a certain degree of complexity, to avoid the selection of simple 'plug-and-play' AI applications (e.g., simple chatbots or translation services), thus ensuring that the project manager was an expert in the field of AI. We only considered projects for which contact information for experts was available.

Third, we prioritised experts with substantial expertise in the field. An expert, as defined by Bogner, Littig, and Menz (2009), possesses technical, procedural, and interpretative knowledge that pertains to their specific area of expertise. This knowledge extends beyond a mere structured understanding and includes insights derived from their experiences, responsibilities and duties within their organisational roles. We verified this through both project documentation and introductory exchanges prior to the interviews.

Given this, the selection criteria were based on experts' practical expertise in AI integration. Each selected expert demonstrated direct involvement in AI integration processes and an in-depth understanding of the subject matter. This allowed us to prioritise depth and relevance over breadth, in line with our phenomenon-driven, exploratory approach. In addition, the interviews began with questions about the experts' roles and expertise.

Based on our central research question, we designed a semi-structured interview protocol with open-ended questions focusing on three areas: (i) organisational changes linked to AI use (e.g. new roles, workflows or structures), (ii) the role of specific characteristics of AI systems (e.g. data needs, opacity or retraining, type of AI) and (iii) enabling or constraining organisational conditions and governance. This structure ensured consistency across interviews while allowing flexibility to explore context-specific experiences. The protocol is available in Appendix A.

Our analysis relied on the insights obtained from 14 expert interviews conducted with 14 informants actively involved in the integration of AI solutions in the public sector, primarily IT managers, with some informants from universities or private companies as external project partners. Table 1 provides a list of the informants. The informants all belonged to different organisations and were involved in separate processes.

Table 1
List of informants.

ID No	Role	Country	Level
1	Director – IT directorate	Finland	National
2	Director – IT directorate	Belgium	National
3	Professor – technical university	Greece	National
4	Director – IT directorate	Estonia	National
5	Manager – IT and AI unit	France	National
6	Manager – IT and AI unit	Belgium	Regional
7	Director – IT directorate	Luxembourg	National
8	Manager – IT and AI unit	Sweden	Local
9	Manager – IT and AI unit	Netherlands	Local
10	Professor – technical university	Estonia	National
11	Manager – IT and AI unit	Belgium	Local
12	Manager – IT and AI unit	Portugal	National
13	Director – IT directorate	Latvia	National
14	Manager – IT and AI unit	Estonia	National

Source: Authors.
NB: The 'Country' and 'Level' columns report information about the public administrations in which AI is used.

All interviews were conducted online using Microsoft Teams, Skype or Zoom and lasted at least one hour. They were recorded and transcribed verbatim. The first author carried out all interviews and stored the recordings and transcripts securely in a corporate repository. The second and third authors independently analysed both the recordings and the transcriptions. Following this preliminary phase, the authors exchanged their initial thoughts (see Eisenhart, 1989) and shared their notes to resolve any ambiguities and discuss their interpretations of the data.

3.2. Data analysis

The data analysis was performed through a two-stage coding process, combining first-level (deductive) and second-level (inductive) coding. The first stage involved open coding; primary categories were identified based on the dimensions of the sociotechnical system (Glaser and Strauss, 1967; Saldaña, 2015). This deductive approach allowed us to structure the analysis according to the established theoretical constructs, ensuring its consistency and alignment with the overarching research framework. In the second stage, we applied axial coding, to refine and expand the preliminary list of categories based on insights drawn from the interviews, enabling the identification of more nuanced themes and patterns that emerged across cases. This approach facilitated a deeper exploration and understanding of the informants' specific contexts and experiences.

A cross-validation process was followed to enhance the reliability and robustness of the coding process. The authors were engaged in the coding process, and their interpretations were iteratively compared to address discrepancies, refine the category definitions and ensure consistency in how the codes were applied and interpreted.

Throughout both stages of our data analysis, there was an emphasis on the significance of the empirical data collected, always in the context of contributing to theory development (Van Maanen et al., 2007). Consequently, our approach was characterised by an iterative interplay between theoretical concepts and empirical observations as we continuously moved back and forth in a cyclical dialogue (Dubois and Gadde, 2002). This iterative process was key to identifying recurring patterns across cases, enhancing the depth and breadth of our analysis while ensuring it remained sensitive to contextual variation. Fig. 3 presents the coding structure, with first-level codes derived from the theoretical framework and second-level codes emerging inductively from the interview data.

4. Results

The analysis identified transformational elements related to AI integration in public administrations. As outlined in the methodology section, our analysis is based on AI's material characteristics, to highlight its impact on both technical and social systems. The results are synthetised in Table 2.

4.1. *Artificial intelligence materiality and technical system interdependencies*

The effective integration of AI into public administrations centres on the interconnection between AI materiality and the technical system's tasks and infrastructure. This interdependency underscores the need for public administrations not only to adapt existing processes and systems but also to innovate and create new ones, ensuring that the transformative potential of AI is fully realised in enhancing public service delivery.

4.1.1. *IT system*

Data and infrastructure have been identified as crucial aspects of AI materiality. Providing the infrastructure necessary to support AI extends

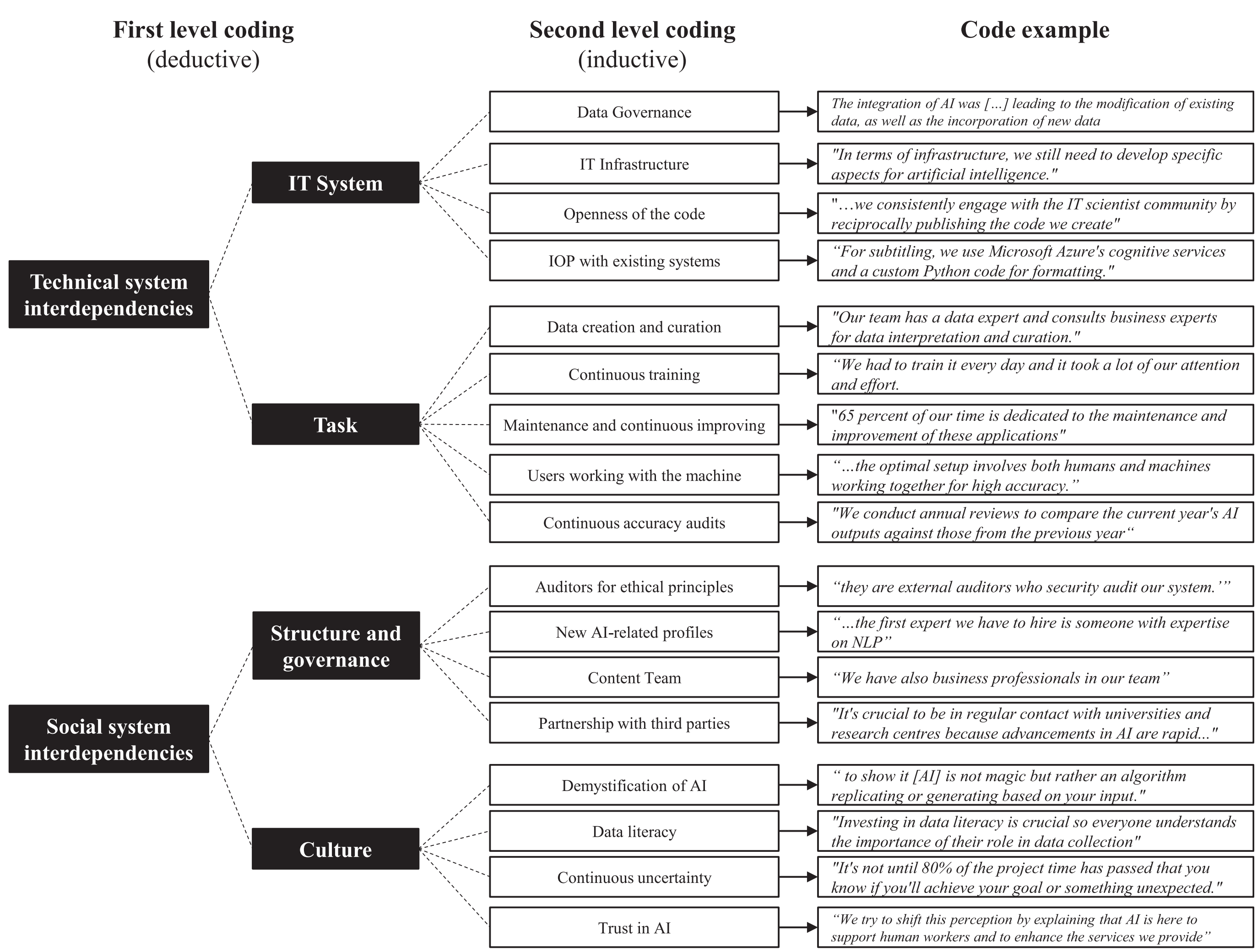

Fig. 3. Coding scheme and examples.
Source: Authors.

Table 2
Synthesis of the results.

AI materiality	Technical system interdependences		Social system interdependences	
	IT system	Task	Structure and governance	Culture
Training *AI requires being trained with large volumes of high-quality, structured data, to learn and perform specific tasks.*	• Reassessment of data collection, processes and curation practices and tools • New data and data governance programmes and strategies • Provision of adequate data infrastructure	• Data labelling • Data generation and curation	• Creation of data governance roles • Cross-functional and multidisciplinary teams supporting training and data management	• Promotion of data literacy and data culture • Awareness of data's value
Autonomous learning *AI can identify patterns and make probabilistic predictions or classifications, with a degree of autonomy.*	• Rethinking of the openness approach and protocols • Reconfiguring systems for oversight and auditing	• Continuous audit of AI outputs • Ethical vigilance • New human-machine interaction mechanisms	• Oversight structure • Specialised AI-related roles • New domain-specific experts • Organisational arrangements to support human-machine collaboration	• Realistic understanding and demystification of AI • Building trust on AI across roles
Regular maintenance *AI requires continuous training, validation, and maintenance to prevent performance degradation over time.*	• Continuous data collection • Infrastructure for iterative updates	• Continuous training • Continuous refinement and improvement of the system	• Dedicated AI maintenance teams • Cross-team coordination and workflows	• Cultural shift towards continues improvement and learning • Acceptance of learning curves and adaptation effort
Rapid technological advancement *AI is characterised by extremely fast advancements in its capabilities, tools, and methods.*	• Modular and scalable infrastructure • Adaptable systems to integrate evolving AI tools	• Innovation scanning • Partnership coordination	• New forms of collaboration with third parties • Flexible procurement and organisational set-up	• Flexible and adaptable approach • Cultural readiness for change and innovation

Source: Authors.

beyond mere changes to physical hardware, encompassing the comprehensive adaptation of existing infrastructures and data management systems to ensure that they can effectively meet the demands of AI applications.

Our interview findings highlight this alignment between data and infrastructure – as aspects of AI materiality – and the technical system in regard to the crucial role of data curation, governance and management. Experts indicated that AI necessitates a reassessment of data collection, processing and curation practices. For instance, one expert noted, 'The integration of AI was changing the rules, leading to the modification of existing data, as well as the incorporation of new data' (No 14).

Beyond the operational need to refine data collection and curation processes, experts underscore how essential it is to establish strategies and programmes to oversee data-related procedures, which they deem a foundational requirement for AI advancement. One expert observed, 'We have a data programme and a data governance programme, which is really important, but we still have to put a lot of effort into these things' (No 6). Similarly, Expert No 4 conveyed their perspective on data privacy and governance, recognising their competence in these domains while also drawing attention to practical difficulties in harmonising related strategies with other organisational components: 'We are [at] a good level in aspects like data strategy and data privacy … when it comes to people and processes, there are bottlenecks that need to be addressed.'

Furthermore, ensuring seamless interoperability between existing infrastructure and new AI technologies has become as a pivotal concern. Given the rapid technological changes, the successful integration of AI requires an adaptable IT architecture that can evolve without disrupting existing operations. Expert No 7 shared their perspective on the challenges in achieving interoperability and the strategic responses required: 'Integrating AI requires a re-evaluation of our entire system architecture … we're looking at how to make our operations more agile to accommodate these new technologies.' This reflection emphasises the need for agility and flexibility in IT architectures to enable the effective integration of AI technologies.

Beyond data and infrastructure, AI materiality is also characterised by specific and unique codes and a dedicated coding approach. The interviews showed how this required the rethinking of the openness procedure, raising the importance but also the challenges both of making codes open and reusing open-source solutions, for transparency, and of fostering a community-driven approach to AI development. An expert praised the benefits of open-source AI solutions: 'The quality of many new AI techniques is even superior when downloaded from GitHub. It [the platform] is free and of higher quality than what is available on the market. Furthermore, we consistently engage with the IT scientist community by reciprocally publishing the code we create' (No 9). This approach fosters innovation and encourages collaboration and knowledge sharing within the broader community, pushing forward the advancement of AI technologies.

4.1.2. Task

The basis of AI materiality lies in its learning capability, which is in turn based on its interaction with data. The requirement for accurately curated and labelled data means that there is a need to integrate new tasks within public administrations, as Expert No 5 noted: 'Because if you need to annotate the data, then you need to train public officers to do it manually. While it is a big issue, it is also sometimes an opportunity to help the public officers to understand how the algorithm would work and how we can train it.' This perspective emphasises the need to integrate AI-related tasks into existing workflows, transforming potential challenges into opportunities for organisational learning and adaptation, and redesigning these workflows to take better advantage of AI.

An innovative approach was adopted in one organisation during the COVID-19 pandemic whereby staff from various departments were mobilised to annotate data, demonstrating a flexible and adaptive strategy on AI integration. This versatility in task management showcases public administrations' ability to reorganise resources to meet AI demands creatively, further embedding AI learning capabilities in daily operations (as identified by Expert No 3).

The continuous learning capabilities of AI, coupled with the potential for performance degradation if the systems are not properly maintained, necessitate an environment in which the ongoing refinement of training and systems is integrated as a routine task. Expert No 12 highlighted the significant commitment this entails: 'We had to train it [a chatbot] every day, and it took a lot of our attention and effort. Teams' resources were allocated daily for a period of 18–24 months before the chatbot's proficiency reached a satisfactory level.' This dedication to continuous engagement ensures that AI systems evolve in alignment with organisational needs, integrating AI learning capabilities with the daily routines and tasks of public administration.

Regular maintenance and continuous enhancement are essential to keep AI systems operational and up to date. Expert No 1 discussed the iterative process of learning and adaptation necessary for AI integration: 'To actually manually fix anything after the translation and the subtitles are done, that is something that we will learn after we really start to run this in a production.' This ongoing process of adjustment and learning underlines the importance of continuous improvement in AI applications. As one expert noted, the operational overhead is significant: 'We manage 14 AI applications with a team of 30 people. 65 % of our time is dedicated to the maintenance and improvement of these applications' (No 12). This statement underscores the resource-intensive nature of AI maintenance, highlighting the need for robust and scalable infrastructural support.

Furthermore, the need for continuous interaction between users and AI systems underscores the importance of designing processes that leverage AI to support human tasks and complement people's expertise. Expert No 10 highlighted the synergy between human judgement and AI capabilities: 'the best combination is with a machine and the human working together because it is actually highly accurate, … especially in atypical cases that the random forest model, designed for typical scenarios, might misjudge.'

Ultimately, ensuring the ongoing accuracy of AI systems necessitates regular audits of their output, owing to AI's non-deterministic nature, which renders it impossible to obtain a complete understanding of the processes that generate specific outputs. This task is critical for maintaining ethical standards and consistent performance. One expert explained the process clearly: 'We conduct annual reviews to compare the current year's AI outputs against those from the previous year, observing any changes, for better or worse. During these reviews, we assess ethical and legal risks associated with AI's performance and strategies on mitigating these risks effectively' (No 1). This commitment to continuous auditing and ethical vigilance ensures that AI applications gain public trust and remain aligned with organisational standards.

4.2. Artificial intelligence, materiality and social system interdependencies

The integration of AI into public administrations is deeply intertwined with the technical domain and the social system; the organisational structure and culture have to be reshaped to accommodate AI's unique materiality. This adaptation underscores public administrations' need to evolve, embracing new roles and ethical frameworks and a culture reflective of AI's transformative potential.

4.2.1. Structure and governance

AI materiality is characterised by autonomy in detecting patterns, selecting variables and making judgments. This highlights the critical role of auditors in ensuring that these systems operate within established ethical, moral and legal frameworks. Expert No 2 discussed the importance of this role, indicating an organisational shift towards ethical oversight that takes into account AI's complexity. This development highlights the changing structural needs within public administrations as AI is increasingly integrated into their operations.

The development of specialised in-house AI-related roles, such as agile developers, natural language processing experts, data scientists, AI specialists and auditors, marks a strategic shift from relying on external expertise to enhancing internal capabilities. This shift aims to integrate AI more closely with operational and strategic objectives. Expert No 5 stressed the importance of internal understanding and management of AI tasks: 'What's crucial is having the necessary skills and insights within our team to comprehend the actions of the consistency team.'

Our interview findings indicate that AI experts are necessary but not sufficient. Expert No 3 highlighted the need for a larger ecosystem, including AI experts and a 'content team' of domain-specific experts, who evaluate and refine the system's output. The expert noted that '[p]eople underestimate how difficult building that ecosystem is', emphasising the challenges of establishing such a multidisciplinary team.

Finally, rapid advancements in AI technology, a key characteristic of its materiality, require public administrations to form partnerships with external organisations, such as universities and tech companies, to access specialised knowledge and foster innovation (Experts Nos 1, 2, 4, 6 and 11). Expert No 2 pointed out the strategic value of these collaborations: 'It's crucial to be in regular contact with universities and research centres.' This approach is instrumental in expanding structural capacities, ensuring that public administrations remain at the forefront of developments in the field of AI. Such partnerships may also be instrumental in overcoming the scarcity of in-house expertise in certain regions and finding the right balance between outsourcing and internal development, as noted by Expert No 5: 'We need to find a good mix between outsourcing and developing by ourselves … with AI, you can't do it alone.'

4.2.2. Culture

The integration of AI technologies demands high data literacy across an organisation. This requirement to understand data, and its analysis and interpretation, is fundamental, marking a shift towards a data-driven decision-making culture. One expert explained: 'One important aspect is to install a data culture among top executives … They should receive training on what data is and how it can be useful for public policy' (No 5). Enhancing data literacy is not only about developing technical skills but also about cultivating collective responsibility for data management, ensuring that everyone recognises the importance of their role in data collection and handling. AI stands or falls on the quality of data, and the result of data processing is new data.

Significant efforts are directed towards demystifying AI and giving stakeholders a realistic understanding of its capabilities and limitations. Expert No 4 emphasised the importance of clear expectations, particularly at the management level: 'We need to educate people, especially in top management, to understand what AI can actually do for the organisation. It is about setting realistic expectations because sometimes there is a belief that one model will solve all problems, which is not the case.' This approach extends beyond management to all levels of the organisation, as Expert No 5 noted: 'It is also an opportunity to do some pedagogy on AI, to show it is not magic but rather an algorithm replicating or generating based on your input. This helps public officers understand how it works'. By demystifying AI, organisations aim to correct misconceptions and build a realistic understanding of AI's role, fostering a culture in which AI is seen as a tool for enhancement rather than a magical or threatening force.

Furthermore, the continuous evolution of AI systems introduces a layer of uncertainty, demanding flexibility and adaptability of public administrations. Public administrations must remain flexible, adaptable and ready to adjust to the dynamic requirements of AI systems. Expert No 2 captured this challenge: 'One of the key challenges was motivating the team to correct and adapt the content of robots.' This sentiment was echoed by Expert No 10, who observed, 'You can have many surprises along the way … It's not until 80 % of the project time has passed that you know if you'll achieve your goal or something unexpected.' This uncertainty necessitates a cultural readiness to embrace change and navigate the unpredictable journey of AI integration.

Finally, building and maintaining trust in AI systems is essential for their integration. This trust is cultivated through transparency about AI's capabilities, continuous education on AI's role within the organisation and an emphasis on how AI can support, not replace, human workers. Expert No 6 discussed a common fear associated with AI: "When people hear 'AI', they think of robots taking over jobs. We try to shift this perception by explaining that AI is here to support, not replace, human workers and to enhance the services we provide." Establishing trust in AI involves demonstrating its value in augmenting human capabilities and alleviating fears and scepticism. This requires that sound governance and control mechanisms be put in place.

5. Discussion

The findings illustrate the complex and deep interdependencies between the new AI materiality domain and the organisational domain, which require the transformation of an organisation's technical and social systems when AI is integrated into its work. Fig. 4 provides an overview of the theoretical propositions derived from the research, along with clarifying examples.

This study started from the premise that AI is characterised by novel socio-material aspects (Dwivedi et al., 2021; Maragno et al., 2023), such as the need to be trained, or the autonomous learning, that serve as dynamic artefacts shaping organisational transformation. It sheds light on how these material characteristics can be transformative for public administrations. The novelty of our study lies mainly in the theoretical perspective adopted to explore and discuss this phenomenon, leading to comprehensive findings that highlight the transformative efforts required for AI integration and the interdependencies among the various variables. This perspective moves beyond the instrumental view often taken in the literature (Maragno et al., 2023; Nouws et al., 2022; van Noordt and Tangi, 2023) and draws attention to the need to transform all organisational elements to fully leverage AI's potential and mitigate its drawbacks. Our findings indicate that AI integration influences multiple interconnected aspects of public administration, including governance, structures, routines, tasks and roles, data and AI technology. This suggests that its effects extend well beyond isolated applications.

This approach places the innovation introduced by AI in the public sector at the centre of our study, with significant implications for engaging with the existing body of literature. We argue that understanding the intrinsic materiality of AI must precede efforts to address the challenges, dynamics, and impacts of AI integration in the public sector. In other words, to effectively analyse the impact of AI, it is essential to open the black box of AI and examine it in greater detail, to gain a thorough understanding of the underlying technologies and their materialities as a starting point. The design choices made at a technical level within this black box shape the outcomes and can only be managed with a detailed understanding of technology.

As AI evolves, other aspects of the sociotechnical system may also need to change to ensure that its benefits are fully realised, and that risks are mitigated. Relying on a socioconstructivist perspective, as is often done in literature on public administration, means overlooking the changing nature of the underlying technology, and associated uncertainties and risks of AI (von Bertalanffy and Sutherland, 1974). A deterministic view of the technology may be equally inadequate, as technology is deeply influenced by social factors – the social relations that serves as the foundation of our work.

Studies on transformations within organisations' sociotechnical systems must trace the origins of those transformations back to the materiality of AI. Scholars often overlook the importance of tracing transformative efforts back to technological materiality. This gap poses the risk of rehashing what has already been learned in two decades of research around digital government transformation, without distinguishing between the unique consequences of AI and those shared with other technologies.

Consequently, there is a risk of lacking a deeper understanding of the novel consequences of utilising these new tools. This risk of overlooking new insights was recently addressed by Maragno et al. (2023). However, much of the literature adopts a more holistic approach, discussing

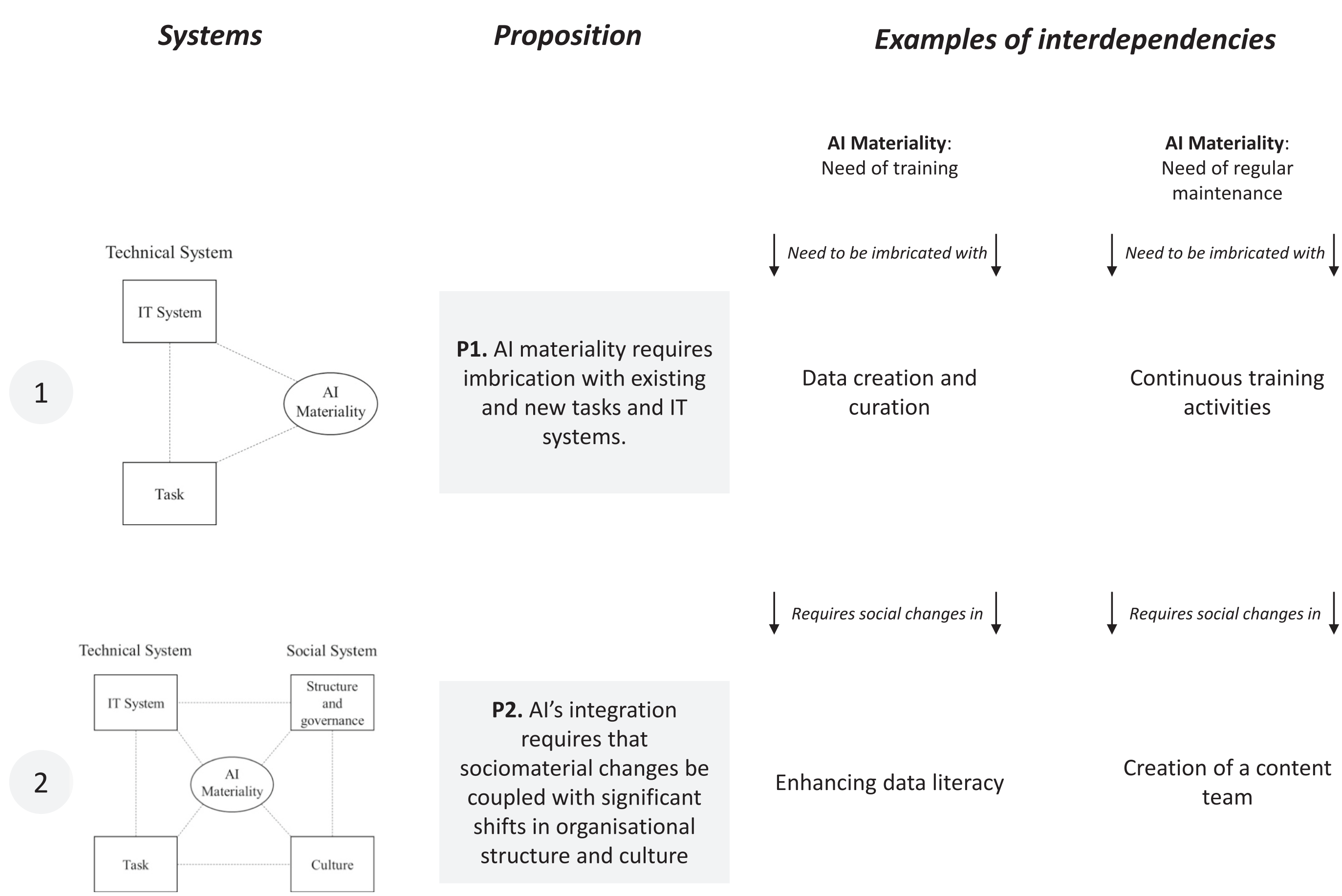

Fig. 4. Theoretical insights and propositions.
Sources: Based on Bostrom and Heinen (1977), Leonardi (2011), and Nograšek and Vintar (2014).

pertinent topics in the context of AI integration, such as leadership or funding constraints (see, for example, Mikalef et al., 2021; Wirtz and Müller, 2019), without directly tying the results back to AI's specific materiality, leaving aside the question of how and why AI differs from past technologies; this concern was also highlighted in a recent review by Madan and Ashok (2023).

According to the assumptions inherent in the concept of sociomateriality, AI materiality achieves its effective application only when integrated in ('imbricated' with) processes and tasks. Our findings demonstrate that this concept of AI materiality necessitates a complex combined transformation of both the technical and the social systems within public administrations. While our findings on the elements of this transformation align with existing literature on the topic (see, for example, Dwivedi et al., 2021; Harrison and Luna-Reyes, 2022; Maragno et al., 2023), our study makes a distinctive contribution by providing a comprehensive overview of these elements. Furthermore, it uniquely situates them within the organisational framework proposed by Leonardi (2011), providing a novel and integrated perspective.

From a technical perspective, we highlight how AI integration demands a shift in the technical framework by compelling public administrations to delineate new tasks to fully leverage these technologies, expanding the literature on the topic (Giest and Klievink, 2022; Maragno et al., 2022). The need for data is intertwined with the development of new tasks for data generation and curation. Moreover, the need to continuously improve the system is interrelated with the need to empower civil servants with responsibilities related to machine training, output monitoring and audits. This transformative aspect of the technical system is imperative to effectively integrate AI, notwithstanding the scant attention it has received in the literature. This observation supports and enriches prior literature (Maragno et al., 2022; Tangi et al., 2023; Wirtz and Müller, 2019), underscoring the transformative effect of the system within public administrations. Therefore, we propose the following.

P1. AI materiality requires imbrication with existing and new tasks and IT systems. This process requires public administrations to invest in transforming current systems, routines and practices into new ones that facilitate the appropriate utilisation of AI.

The final level of analysis pertains to the interrelations between AI implementation and the sociotechnical system. Our research showcases the profound transformational impact of AI on the sociotechnical system, necessitating an in-depth overhaul. Implementing AI requires a pervasive transformation that extends an administration's cultural and structural facets. While the literature predominantly emphasises changes within the technical system (Giest and Klievink, 2022; Maragno, Tangi, Gastaldi, and Benedetti, 2021) (albeit in a fragmented manner), to our knowledge, the discussion on AI's influence on a public administration's social system remains nascent. From a cultural perspective, our findings suggest that the successful integration of AI is significantly contingent upon cultural adaptations, including the demystification of AI, which is often subject to mystification or demonisation due to the cultural environment tending to favour simplistic narratives over nuanced and critical inquiry (Sundberg, Gidlund, Larsson, and Olofsson, 2025). This adjustment calls for the adoption of strategies to manage the ongoing uncertainty associated with AI inputs, processing, and outputs. This involves recognising and accepting the possibility of machine errors: organisations must effectively manage this uncertainty to prevent adverse consequences, ensuring that AI does not diminish the public value generated through incorrect decisions or harmful behaviours, but rather enhances it (van Noordt and Tangi, 2023). These cultural challenges associated with AI integration, as noted in the literature (Ahn and Chen, 2022; Tangi et al., 2023), entail a deeper and broader view of technology that transcends an objectivistic perspective (Nouws et al., 2022), advancing the discussion by enumerating elements of cultural transformation identified in our data.

From a structural standpoint, the transformation induced by AI integration is intertwined with the establishment of new administrative elements. This includes the creation of new teams dedicated to training, auditing, and maintaining these systems – a novel insight gleaned from our cases. This insight also highlights the need to engage with third parties, which demands a paradigm shift: requirements, communication protocols, and supplier oversight must evolve, necessitating a fresh approach to AI procurement, as also highlighted by previous research (McBride, van Noordt, Misuraca, and Hammerschmid, 2024).

Social transformation is closely intertwined with technical transformation, stemming from the emergence of new materialities. We argue that the transformative effects of AI encompass the social system in a novel manner, leading to the formulation of the following proposition.

P2. AI's integration requires that sociomaterial changes be coupled with significant shifts in organisational structure, governance and culture. This involves fostering the widespread cultural understanding of AI, acknowledging the material existence and consequences of the technology, and creating new structures that seamlessly integrate technical changes into systemic organisational transformations.

5.1. Theoretical implications

This study represents a pioneering effort to integrate the discourse on AI into the broader discussion on government transformation. By collecting data on the transformation of public administrations to ensure the ethical and trustworthy use of AI, we contribute novel theoretical implications to the ongoing debate. We posit that implementing AI prompts governments to undergo a distinctive transformation, which we define as AI-GT. Building on this concept, we develop and apply a theoretical framework through our data collection. The introduction of the new concept and framework is the first significant theoretical contribution of this study, enriching the current debate by addressing underexplored areas of research.

To the best of our knowledge, this study is the first to apply sociomateriality and sociotechnical theories (Leonardi, 2011, 2012), commonly employed in the literature on government transformation (see, for instance, Janssen and Kuk, 2016; Tangi et al., 2021), to the domain of AI integration. By applying these theories, we emphasise the relevance of examining AI's unique material properties. We then propose two concepts that theorise AI-GT as a complex interplay among three components: the technical system, the sociotechnical system and the material nature of AI. Using our theoretical framework and analytical perspective, we identify an extensive array of AI-driven transformative elements that influence the social and technical systems within public administrations.

5.2. Practical implications

This study offers valuable insights for policymakers and public administrators, underscoring the urgent need to plan and orchestrate the transformation required to integrate AI technologies effectively. This transformation begins with acknowledging that technologies, including AI, are not neutral entities but rather acquire significance when incorporated into (imbricated with) social practices. As a consequence, they shape and are shaped by organisational culture, structures, and processes. These findings highlight how the transformation can affect all facets of an organisation, including structural and cultural aspects. Furthermore, they emphasise the inevitability of this transformation, given the rapid development and maturity of AI technologies, and the impact on all aspects of public administration. Hence, public administrations must take proactive measures to embrace this change rather than passively endure it, especially nowadays, when AI solutions are more mature and can be easily bought from external suppliers.

Beyond acknowledging the need for transformation, this study provides a preliminary set of transformational changes required by AI that public administrations should adopt. This set can guide public sector managers in considering all relevant aspects of AI-GT and initiating the transformation process. Hence, managers of public administrations need to understand the basics of AI technologies as part of their transformational efforts.

6. Limitations and future research

While this study addresses an urgent and unexplored topic, paving the way for new research avenues, it is not without its limitations. First, despite the growing use of AI in public administrations, its impact on sociotechnical systems is still emerging. We initially introduce the novel concept of AI-GT along with a theoretical framework, which we explored and validated using expert interviews. While the results illustrate the value of this framework, they are drawn from a rather limited number of interviews and should be complemented with additional empirical work. Future research could test and refine this framework in diverse administrative settings, including through large-scale surveys or multiple in-depth case studies, to capture variation across institutional, organisational and national contexts.

Second, to observe and analyse the transformational effort, we made two simplifying assumptions: we treated AI materiality as a singular entity, without differentiating between types of AI systems that may exhibit diverse material characteristics. Moreover, we assumed a one-directional transformation from materiality to socio-technical systems, overlooking the reverse scenario where an organisation's socio-technical system influences the selection, training, and integration of AI systems. Future research could explore these assumptions further to adopt a broader perspective on AI-GT.

Third, the data were collected through expert interviews with managers overseeing AI projects in the public sector. Although the results provide valuable insights into the transformation process, they are insufficient for assessing or measuring the overall magnitude of the transformation. Many of the AI projects discussed are still in the early stages of development, leaving the long-term effects and organisational changes uncertain. Future studies could therefore adopt longitudinal approaches or conduct follow-up evaluations to investigate how AI implementation and associated transformations evolve over time, and under which conditions they produce lasting change.

Forth, the rapidly evolving nature of AI adds complexity to the transformation process. This raises new questions that cannot be fully addressed in the present study, such as: 'What will be the next step?', 'Does a final stage of transformation exist?' and 'When can public administration be considered to have effectively implemented a socio-technical system adapted to AI?' Future research could explore these questions using longitudinal designs and comparative analyses of maturity levels across AI use cases.

Finally, this study does not aim to investigate the outcome of AI integration or assess its impact on public values such as efficiency and quality of service, nor did we explore the conditions under which such a transformation produces positive outcomes. Future research could address this gap by examining the relationship between AI-augmented organisational change and performance outcomes. This would help determine when and how transformation efforts lead to desirable public value. By addressing these limitations directly, future research could provide a more comprehensive and outcome-oriented understanding of AI-GT.

Future research should continue to explore these phenomena through longitudinal studies or in-depth case studies to enrich the empirical foundation for the comprehensive understanding of the topic. Such studies will be vital for validating, consolidating and expanding upon this study's findings, paving the way for a robust understanding of AI-GT.

7. Conclusions

AI has a much bigger impact on governments addressing social and technical elements. Employing sociotechnical theory and sociomateriality, this study defines AI-GT as:

> The organisational changes facilitated by the AI agent and its novel materiality that transform organisational entities and how they operate with others, leading to a new state for both the social and the technical systems within the organisation.

This definition provides a fresh perspective that positions AI integration as a multifaceted sociotechnical phenomenon, emphasising the need to focus on the transformative aspects of AI integration within public organisations having a greater impact. Building on this definition, this study developed a theoretical framework that not only guided the exploration of the subject but also is adaptable for future research.

Our findings shows that AI affects all aspects of public administration. The infrastructure necessary to support data and AI, their operations, use and governance, including education and learning needs to be addressed. First, we argue and demonstrate the importance of opening the black box of AI, to gain a profound comprehension of the underlying data and AI technologies and their materialities. Managers in the field of public administration must understand some of the basics of AI to be able to lead transformation efforts. Learning must go beyond a socio-constructivist view, to deal with the non-deterministic nature of AI systems. The evolving and dynamic nature of AI materiality, along with its associated uncertainties and risks, must be carefully considered. People should be able to learn to deal with AI implementation and use.

Moreover, the study's qualitative analysis and interviews with experts demonstrate that the integration of AI in organisations is deeply intertwined with their organisational practices. The research underscores the need for AI materiality to be interwoven into both established and new tasks. For public administrations, this demands dedication to innovatively transforming existing routines and practices to accommodate AI and adapting their governance to be able to deal with the transformations.

Nevertheless, these steps alone are not enough to unlock the full potential of AI. AI materiality requires these changes to be paired with significant organisational structure, governance, strategic and culture changes. To achieve this, there is a need to develop a widespread understanding of AI within the culture of organisations, recognising the concrete reality of the technology and its potential impact. Moreover, it is crucial to create new infrastructures that facilitate the smooth integration of technological changes, promoting overarching transformation within organisations.

In conclusion, a thorough transformation encompassing technical and social systems is needed when integrating AI into public administrations. This transformation is distinct from the type of change prompted by the integration of traditional technologies, as it originates from the new kind of materiality that AI possesses. As such, it exhibits distinctive traits and poses unique challenges. These results lay the groundwork for further exploration in this domain.

CRediT authorship contribution statement

Luca Tangi: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **A. Paula Rodriguez Müller:** Writing – review & editing, Writing – original draft, Validation, Investigation, Formal analysis, Data curation. **Marijn Janssen:** Writing – review & editing, Writing – original draft, Validation, Investigation, Conceptualization.

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.

The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for *Government Information Quarterly* and was not involved in the editorial review or the decision to publish this article.

Appendix A. Interview protocol

This semi-structured interview protocol was used to guide expert interviews conducted for this study. The questions are grouped thematically to align with the theoretical framework (sociomateriality and socio-technical systems) and the coding structure presented in the data analysis section. Nevertheless, the protocol was applied flexibly, allowing for follow-up questions and adaptation based on the interviewee's profile and the specific AI project discussed.

Introduction

- Can you tell us your name, position, and the department or unit you work in?
- Could you briefly describe the AI system(s) your organisation is using or piloting and how it/they function?
- How long have you been involved in AI projects or with AI-related initiatives in your organisation? And which is your role?

Technical and data infrastructure

- What kind of data was needed to develop and operate the AI system? How was this data acquired and prepared?
- What IT infrastructure or tools were needed to support the AI system?

Skills, expertise, and external collaboration

- Have new types of expertise or capacities become necessary?
- How did you ensure that the necessary skills and expertise were available for AI development and integration?
- To what extent were these capabilities in-house versus outsourced?

Organisational change and capacity

- What organisational changes (e.g. roles, workflows, decision processes) were needed to support the development or implementation of this AI system?
- Were any new teams, committees, or units created as part of this process?

Organisational culture and leadership support

- How would you describe management's attitude towards AI? Was leadership supportive?
- How did other staff or departments respond to the AI project?
- Were there any initiatives to build awareness or internal buy-in?

Closing

- Is there anything we haven't covered that you think is important for understanding your experience?

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