DOI: 10.17573/cepar.2024.1.05 *1.01 Original scientific article*

Organisational Enablers of Artificial Intelligence Adoption in Public Institutions: A Systematic Literature Review[1]

Nina Tomaževič
University of Ljubljana, Faculty of Public Administration, Slovenia
nina.tomazevic@fu.uni-lj.si
https://orcid.org/0000-0001-8126-1971

Eva Murko
University of Ljubljana, Faculty of Public Administration, Slovenia
University of Rijeka, Faculty of Economics and Business, Croatia
eva.murko@fu.uni-lj.si
https://orcid.org/0000-0002-2868-3726

Aleksander Aristovnik
University of Ljubljana, Faculty of Public Administration, Slovenia
aleksander.aristovnik@fu.uni-lj.si
https://orcid.org/0000-0003-1345-9649

Received: 6. 12. 2023
Revised: 5. 4. 2024
Accepted: 15. 4. 2024
Published: 17. 5. 2024

ABSTRACT

Purpose: The purpose of the presented study was to develop a set of recommendations for decision-makers (policymakers and public managers) and public employees to enhance the effectiveness and efficiency of organisational elements in the adoption of artificial intelligence (AI) in public institutions.

Design/methodology/approach: Utilising a systematic literature review following the PRISMA protocol, the study examines the organisational enablers of AI adoption in public institutions. Comprehensive search queries in the Scopus database identified relevant literature focusing on the

1 This article is a revised and expanded version of the paper entitled '*Artificial intelligence adoption and organisational transformation for smart public institutions*', presented at the NISPAcee conference, Belgrade, Serbia, 25–27 May 2023 and of the chapter entitled '*Uvedba izbranih disruptivnih tehnologij in organizacijske spremembe v institucijah javnega sektorja*' in the monograph 'Digitalna preobrazba javne uprave v teoriji in praksi' (ed. Aristovnik, Kovač & Jukič, 2024). The article is a result of a research program/projects funded by the Slovenian Research and Innovation Agency (ARIS) under grant numbers P5-0093, J5-2560 and J5-50165.

intersection of AI technologies and various organisational elements. The analysis was facilitated by NVivo 12, enabling a structured examination of key organisational facets for people, culture, structure, processes, and technology within public institutions.

Findings: Previous studies on AI adoption in public institutions identified numerous enablers of AI adoption associated with organisational elements like people/employees, structure, culture, technology, and processes. Several surveys and case studies stress the importance of concentrating on the introduction or transformation of these organisational elements prior to or concurrently with the adoption of AI.

Academic contribution to the field: By applying a systematic literature review protocol, the study represents the first holistic and systematic review of specific organisational elements that can serve as enablers of AI adoption in public institutions.

Research limitations/implications: This systematic literature review was subject to several limitations. Firstly, the division of AI literature between natural and social sciences, with the former focusing on technical aspects and the latter on broader organisational themes, may have resulted in an incomplete depiction of the intersection of AI and organisational change. Secondly, despite the broad search queries, inherent limitations of keyword-based searches may have excluded some relevant studies. Thirdly, considering the rapid evolution of AI technology, our review may not fully encapsulate the very latest developments in the field as it covers literature published until May 2023. Finally, the interpretation and coding of literature, despite the use of NVivo 12, involved subjective elements that could affect the study's outcomes.

Practical implications: Drawing from experiences in the private sector, public institutions are increasingly adopting AI technologies across various subsectors such as public finance (taxation), research, healthcare, law enforcement, defence, education. This requires a transformation in both hard (structure, processes etc.) and soft aspects (people, organisational culture etc.). Therefore, the enablers identified in the study can serve as guidelines for decision-makers and implementers of AI at all levels of public institutions.

Social implications: If adopted effectively and efficiently and used professionally and ethically, the use of AI in public institutions can bring many benefits to society, such as transparency, justice, cost and time efficiency, high quality services, and improved collaboration between different stakeholders in society.

Originality/significance/value: Our study makes a distinct contribution by shifting the focus from technological barriers to organisational enablers of AI adoption in public institutions. It bridges a critical gap in the literature by integrating both technical and social science perspectives, providing valuable insights for theory and practice in the fields of organisation and management.

Keywords: *AI adoption, artificial intelligence, organisational changes, organisational enablers, public institution, systematic literature review*

JEL: H83, M12, O33

1 Introduction

The concept of "thinking machines" first emerged in the 1950s when the British mathematician Alan Turing posed the question of whether machines could engage in cognitive processes. In his seminar paper published in collaboration with Haugeland in 1950 (Turing and Haugeland, 1950), he introduced the "Turing test" to define thinking, requiring a machine to converse with humans in a manner indistinguishable from a human. The term "artificial intelligence" that is today widely used was coined by John McCarthy, a maths professor at Dartmouth in 1955. McCarthy employed this phrase as a neutral term to describe the then emerging field (Siebel, 2019). Following the conceptualisation of artificial intelligence (AI), interest, research and the volume of investments in these systems have grown tremendously, especially in the last decade, in both the private and public sectors to improve problem-solving and decision-making as well as implementation processes in high-uncertainty environments (Androutsopoulou et al., 2019; Desouza et al., 2020; Mikhaylov, 2018; Murko et al., 2023a).

Public institutions have already joined the wave of AI adoption (Murko et al., 2023b). First, this referred to systems that use AI to: a) enhance the quality of internal processes and public service delivery through automated decision-making and data analytics (de Sousa et al., 2019; Hodzic et al., 2021); b) improve the quality of public services (Ojo et al., 2019); c) identify the risks more effectively (Ojo et al., 2019); and thereby d) increase the accuracy of human decision-making, which is prone to biases and errors (Compton et al., 2022). Particularly during the COVID-19 lockdowns that also saw public administration buildings being closed, public services were chiefly provided through online platforms (Fischer et al., 2022; Mergel et al., 2023). The pandemic consequently heightened the demand for both proactive service delivery and a significant transformation of public institutions' digital services. Second, public institutions play the role of regulators and enablers of the efficient adoption of AI in private business entities. Still, the enthusiasm for introducing AI into the public sector is inevitably accompanied by some degree of uncertainty and possible challenges. Risks of AI include the widening of divides in society, infringing on citizens' privacy rights, and clouding public decision-makers' accountability (Floridi et al., 2018). AI-related challenges are frequently outlined and debated as lists of significant topics. These include considerations to do with policy, legal aspects, governance and ethics, all of which call for careful attention (Desouza et al., 2020; Dickinson and Yates, 2023; Leslie, 2019; Mikhaylov et al., 2018). AI can create new challenges or intensify existing policy concerns, especially in areas like job displacement, taxation, justice and equality, safety and privacy concerns, and the application of force (Gasser and Almeida, 2017). Avoiding or mitigating such risks requires thoughtful preparation, strategies and regulation (Dwivedi et al., 2019; Androutsopoulou et al., 2019; de Sousa et al., 2019), which are all closely connected with the organisational aspects of public institutions.

To introduce AI as smoothly as possible, policymakers and public managers must recognise and understand the range of possibilities for using this technology and, most importantly, the way that AI interrelates with the organisation's key elements, such as structure (Rudko et al., 2021), processes (Waardenburg et al., 2021), employees (Pan and Froese, 2022) and organisational culture (Farrow, 2020). Not even the best and latest technologies can guarantee effective and efficient operations if changes are not also introduced in areas of the organisation (e.g., horizontal and vertical mobility, agile project management), leadership (e.g., mentorship, change management) and human resources management (e.g., internal training, knowledge management). Public institutions may downplay the risks of adopting AI by misunderstanding the subsequent organisational changes required for their efficient transformation. This means more detailed insight is needed to understand the organisational changes that are required while adopting AI as seamlessly as possible.

The topic of AI in the public sector has become ever more relevant and is attracting greater attention among researchers around the world (Androutsopoulou et al., 2019; Bullock et al., 2020; Campion, 2022; de Sousa et al., 2019; Desouza et al., 2020; Mergel et al., 2023; Mikalef et al., 2022; van Noordt and Misuraca, 2022). Nevertheless, what is missing is a study that exclusively systematically and holistically distils the elements down to facets (sub-elements) within the gamut of the organisation with regard to public institutions. This makes addressing this gap through a focused literature review study essential. In our systematic literature review (SLR), we aimed to assess the increasingly relevant topic of AI in public institutions by compiling existing research covering various organisational elements, facets, and research contexts. The goal of the SLR was to consolidate scientific evidence to support the argument that a holistic and systematic organisational setting is a critical enabler of the effective and efficient adoption of AI in public institutions.

Accordingly, the main objective of the paper is to present analysis of AI adoption and associated organisational changes in public institutions to gain insight into the state-of-the-art and to design proposals for public managers and policymakers regarding the effective and efficient adoption of AI in public institutions together with organisational changes before and/or during AI adoption. The study presents a comprehensive Systematic Literature Review (SLR) of scientific literature retrieved from the Scopus database based on specific inclusion/exclusion criteria and limited to querying the context of AI adoption and changes in the extended (public) organisational setting. A descriptive evaluation of the body of literature is followed by content analysis based on a specific pattern of analytic categories derived from a typical research process. Finally, the findings are rigorously reviewed to identify, classify, interpret and summarise relevant literature in terms of changes in organisational elements while adopting AI and to identify implications for public sector institutions.

2 Literature review

2.1 Artificial Intelligence in General and in Public Institutions

Various definitions of AI can be found in the literature, each stressing the concept of programmed non-human intelligence designed to execute particular tasks (Dwivedi et al., 2019). Some definitions are based on the specific disciplines utilising AI systems, while others reflect different phases of the AI life cycle (Berryhill et al., 2019). Russell and Norvig (2016) characterised AI as systems that replicate human cognitive functions like learning, speech and problem-solving. Kaplan and Haenlein (2019) offered a more comprehensive definition, describing AI as holding the capacity to autonomously process and learn from external data, thereby achieving certain goals through adaptable methods (Dwivedi et al., 2019). Wirtz, Weyerer and Geyer (2019) examined various AI definitions and suggested a unified definition, seeing AI as a computer system's ability to exhibit problem-solving and human-like intelligent behaviour, supported by key competencies like understanding, perception, action and learning.

The European Commission (EC, 2019) defines AI as "systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals". AI technology identifies patterns in large amounts of data to predict outcomes for similar instances (Dwivedi et al., 2019). It can be defined as a technology for advanced prediction (Agrawal et al., 2017; Mergel et al., 2023). Artificial intelligence is a multifaceted field that includes numerous subsets and methodologies, encompassing machine learning, deep learning, artificial neural networks, natural language processing, automated decision-making, robotics, and computer vision, among others. Despite the diversity of these technologies, the papers selected for our study do not delineate a specific type or subset of AI. Instead, they broadly refer to the term "artificial intelligence." This observation aligns with the findings of Krafft et al. (2019) and van Noordt (2022), who noted that a significant portion of the literature (social sciences) does not explicitly define "AI." Consequently, our use of the general term "AI" throughout this paper reflects this ambiguity in the source material. We are, therefore, unable to provide a precise explanation of what subsets or types of AI the authors referred to, mirroring the broader trend of employing the term "AI" without specification. This approach underscores the need for clarity and specificity in scholarly discussions on AI to enhance the precision and applicability of research findings.

Various industries are increasingly adopting AI applications to improve decision-making and reduce costs by analysing vast amounts of data. The most obvious ones are technological giants that use AI on a large scale in areas like advertising placement and product recommendations. Other industries, such as financial services and healthcare, are also finding ways to use AI to reduce fraud, predict customer behaviour, improve patient outcomes, and discover new treatments. The use of AI in transportation, including autonomous vehicles, promises safety, environmental benefits, and improved quality of life. The industrial, manufacturing, energy and military sectors are also incorporating AI applications to improve efficiency and streamline their operations (Siebel, 2019; Dwivedi et al., 2019; Stone et al., 2016; Li et al., 2017).

AI holds the potential to revolutionise numerous industries, including the public sector, which stands out as an area where AI could have a substantial impact. This impact is seen in enhancing public services, internal operations, and decision-making processes. Additionally, AI can positively affect process automation, cognitive insight generation, and cognitive engagement (Mikalef et al., 2023). In some instances, AI is already delivering considerable benefits and adding public value for citizens. This potential has sparked growing interest in employing AI within the public sector to transform internal service delivery and policy formulation (Misuraca and Van Noordt, 2020). AI-supported public services have become a key focus for policymakers, leading to substantial government investments in either procuring or developing AI solutions. These investments aim to explore the potential of AI in substituting or aiding human decision-making processes, either by completely automating decisions or assisting in decision preparation (Mergel et al., 2023). Public sector organisations generate large amounts of data, creating a lot of potential for applications of AI technologies (Dwivedi et al., 2019). When used ethically, AI and big data sources can improve the public sector's operations by freeing up workers' cognitive resources for higher-value tasks (Eggers et al., 2017). AI has the potential to increases the quality of public services, build citizens' trust, boost efficiency, reduce time and costs, handle complex tasks and enhance competitiveness and public value creation (Zuiderwijk et al., 2021; Criado and Gil-Garcia, 2019; Kankanhalli et al., 2019). Mehr (2017) discusses several challenges faced by public institutions for which AI applications are deemed highly suitable. These challenges include the allocation of resources, handling of large datasets, the shortage of experts, dealing with predictable scenarios, executing procedural and repetitive tasks, and aggregating and summarising diverse data.

To date, the typical instances of public sector AI adoption are virtual assistants, e.g., chatbots, providing information about public institutions or responding to queries, pattern detection to improve information modelling during disaster responses, analysis and early warning to combat fraud and increase accountability, facial recognition for surveillance and security purposes etc. (Androutsopoulou et al., 2019; Bassey et al., 2022; Mergel et al., 2023; Tan et al., 2021; OECD, 2022; van Noordt and Misuraca, 2022). Despite being studied by many academic disciplines, AI in the public sector has not yet been subjected to systematic and holistic research by organisational science scholars. A selection of partial studies that have already been conducted is presented in the next subchapter.

2.2 Research on Artificial Intelligence and Organisational Changes

A reasonable amount of prior research is already available with respect to use cases and lessons learnt, benefits, opportunities, challenges, barriers and enablers of AI adoption in public sector institutions (Androutsopoulou et al., 2019; Berryhill et al., 2019; Campion et al., 2022; Chatterjee, 2020; Desouza et al., 2019; Haug, et al., 2023; Mikalef et al., 2019; Mikhaylov et al., 2018; Tinholt et al., 2017). Some research studies looked at a specific public sector subsector, e.g., healthcare (Alhashmi et al., 2019), tax administration (Bassey et al., 2022) or municipalities (Mikalef et al., 2022; Schaefer et al., 2021), others at a particular field within a public sector institution, e.g., human resources management (Abdeldayem and Aldulaimi, 2020; Pan and Froese, 2022), some at a given technological solution within the AI family, e.g., chatbots (Androutsopoulou et al., 2019), and some at related scientific fields, e.g., law, ethics (Djeffal, 2020; Floridi et al., 2018; Ireni-Saban and Sherman, 2021; Leslie, 2019).

According to Berryhill et al. (2019) and van Noordt and Misuraca (2022), public sector institutions can use AI to: a) make better decisions and design better policies; b) improve engagement and communication with citizens; and c) improve the quality and speed of public public services delivery. Adopting AI in the policymaking process can make it more data-driven, enable the quicker detection of social issues and ensure better analysis of potential policy solutions with faster feedback loops following the deployment of new policy (Höchtl et al., 2016). On the other hand, internal processes can become more effective and efficient due to the automatising of common operations, while staff can also be augmented and empowered by the recommendations made by AI systems (Mehr et al., 2017).

Ensuring that the considerable benefits of AI in the public sector are achieved is a challenging endeavour. The public sector is lagging behind the private sector when it comes to AI adoption. The complexity of the field and the steep learning curve entailed further complicate matters. Moreover, the unique purpose and context of the public sector create distinct challenges that must be addressed. To understand the subject of AI adoption in the public sector, several detailed literature reviews have already been performed (e.g., de Sousa et al., 2019; Dwivedi et al., 2019; Haug et al., 2023; Ishengoma et al., 2022; Mergel et al., 2023; Pencheva et al., 2020; van Noordt and Misuraca, 2022; Zuiderwijk et al., 2022) in an effort to understand the dimensions of AI in public institutions and its associated challenges, opportunities, and agenda for research, practice and policy. Mergel et al. (2023) and Haug et al. (2023) strongly highlight the need to address the theoretical research gap with regard to AI adoption in the public sector. They stress that the future integration of AI into this sector will be intricately connected with inevitable changes that occur as natural processes over time, such as the ageing workforce that the job market cannot easily replace. The authors also note that changes will also arise as direct outcomes of AI adoption and advancements in the technology itself. While it is still too early to expect detailed insights into the results of the public sector's AI-based digital transformation, analyses that are as holistic and as systematic as possible are extremely useful for further progress with AI adoption in the public sector.

Different frameworks/models have already been designed for the effective and efficient adoption of AI in the public sector (Holmström, 2022; Pechtor and Basl, 2022; Schaefer et al., 2021; Stenberg and Nilsson, 2020; van Noordt and Misuraca, 2020a; Wilson and van der Velden, 2022; Wirtz and Müller, 2019). The Technology Acceptance Model (TAM, along with its iterations TAM 2 and TAM 3) and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT 2) are among the most commonly used frameworks with respect to the adoption of technology. These models primarily concentrate on individual adopters' beliefs, perceptions and intentions to use technology (Neumann et al., 2022; Rondan-Cataluña, 2015). Yet, these frameworks have been criticised for being overly simplistic and having a narrow focus (Shachak et al., 2019). Shachak et al. (2019) and Chen et al. (2021) therefore proposed implementing multi-dimensional approaches that can better capture the complexity of issues surrounding the implementation and use of new disruptive technologies. Schack et al. (2019) recommended adopting and developing theoretical frameworks and methodologies that account for multiple, interrelated, socio-technical aspects.

A model that moved beyond individuals' point of view is the Technology-Organisation-Environment (TOE) framework designed in 1990 by Tornatzky et al. for organisational-level, decision-making adoption. It explains three types of factors: technological, organisational and environmental. The basic TOE framework has been widely applied to explain the development of innovative capabilities in both the private (Aboelmaged, 2014; Abhay et al., 2007; Kuan and Chau, 2001) and public sector (Al Hadwer et al., 2021; Desouza et al., 2020; Neumann et al., 2022), e.g., in healthcare (Chang et al., 2007; Yang et al., 2021) and in municipalities (Mikalef et al. 2022; Schaefer et al., 2021). According to this framework, institutions that adopt and implement technological innovations are influenced by organisational factors like a public institution's size, organisational structure, management support, culture, financial and human resources (Al Hadwer et al., 2021; Chang et al., 2007; Jöhnk et al., 2021; Kazley and Ozcan, 2007; Liu, 2011; Neumann et al., 2022). Technological factors include internal and external technologies, such as information and data risks, systems security and complexity, electronic records, and source risks (Al Hadwer et al., 2021; Chang et al., 2007; Yang et al., 2013). The environmental factors encompass industry or public sector subsector requirements, government regulation (e.g., GDPR), differences between urban and rural areas, customer readiness and citizen expectations (Kazley and Ozcan, 2007; Neumann et al. 2022; Yang et al., 2013). The TOE framework's popularity might lie in the holistic approach and the explicit emphasis on organisational and environmental factors – alongside the technological ones that tend to dominate in most other frameworks (Neumann et al., 2022). It is also focused on technology adoption on the organisational level, not only the individual one, which is the biggest novelty of the model. On the other hand, while discussing the organisational factors within the TOE, in many studies they were not only purely organisational, but also touched on the financial aspect (e.g., cost savings (Mikalef et al., 2020) or funding (van Noordt and Misuraca, 2020b)), regulation (e.g., regulatory support) (Al Hadwer et al., 2021) and end-user participation (van Noordt and Misuraca, 2020b). This explains why we decided to focus on a model that would delve more deeply into the factors that influence AI adoption from only the organisational point of view.

Further, when studying organisation as a scientific field we can find authors who have already looked at different organisational aspects concerned with the adoption of AI in the public sector. Such aspects were factors inhibiting the adoption of artificial intelligence on the organisational level (Alsheiabni et al., 2019), changes in the organisational structure (Rudko et al., 2021), change management (Jöhnk et al., 2021; Waardenburg et al., 2021), leadership (Effendi and Pribadi, 2021; Jahankhani, 2020), organisational performance (Mikalef et al., 2023), knowledge management (El Asri and Benhlima, 2020) etc. All of the above studies concentrated on a particular aspect of organisation and did not tackle other aspects in a way that would provide a holistic insight into the enablers/barriers (before) and consequences/benefits (after) of AI adoption in public institutions. The above considerations led us to design research that would study the organisation as a complex construct (not in the sense of an institution) in terms of all of its elements and facets in the role of enablers of AI adoption.

2.3 Organisational Elements and Related Facets

With the intention to systematically and holistically focus on the organisational enablers, our study is based on use of the Leavitt model as an initial framework for AI adoption in public institutions. Leavitt's model is an established model that includes all essential organisational elements, and was originally called the Diamond Model (Leavitt, 1964). Leavitt's Diamond is a widely accepted conceptual model in organisational literature that views an organisation as a system of four interconnected elements: people, structure, tasks and technology. The author states that these variables involve many transactions with each other. Thus, changing one of them results in a change in other components. The model therefore provides a holistic view of the complexities of organisation and has been widely used as the basis for understanding and realising organisational changes (Jamali et al., 2011). While planning for a change (e.g., the adoption of a new ICT) in any kind of business, many mistakes are often made and consequent problems/challenges must be tackled. Changes often fail due to a lack of planning and systematic preparation. The initiators of the change often treat the initiatives isolated from other parts of an institutional organisation, which implies that the change will probably be unsuccessful. It is almost impossible to implement any important change without it having an effect on other organisational units, processes, employees or other stakeholders, whether intentional or not. This makes it necessary to be aware of the effects any change can have on the entire institution and its stakeholders, and to plan accordingly for the change to be as effective and efficient as possible.

Although initially designed for private sector organisations, Leavitt's model has proven to be a valuable foundation for understanding the factors that influence the development of public sector organisations as well (Nograšek and Vintar, 2014). Later, other authors extended the model, adding organisational culture as a fifth element and replacing "tasks" with "processes" (Burke and Peppard, 1995; Kovačič et al., 2004). All of these elements are interdependent, and a change in one element will affect the others (Nograšek and Vintar, 2014). Moreover, Nograšek and Vintar (2014) proposed a different perspective that combines two views. First, digital technology is an essential tool and an enabler that drives digital transformation and hence also AI adoption. Second, the potential for digital transformation depends on the 'readiness' of the socio-technical system's other critical components, namely processes, people, structure and culture, representing the basis of our research framework and a starting point for identifying the most relevant, state-of-the-art scientific literature.

The logic of the five organisational elements (structure, processes, people, culture, technology) of Leavitt's model therefore provided the initial framework within which we try to detect the facets that are facilitating and/or accelerating the adoption of AI in public institutions. Since AI is a technology itself, we were looking for facets within the "technology" element that were understood as prerequisites for AI adoption and represent the existing available technological infrastructure (hardware and software) that is needed for effective and efficient AI adoption in public institutions. In the text below, we describe the research methodology and results, and discuss the key findings concerning AI adoption from an organisational point of view.

3 Research methodology

To accomplish the study's research objectives, we conducted a systematic literature review as an adequate, comprehensive, transparent and replicable way of identifying, selecting and analysing scientific literature regarding our subject of interest (Fink, 2007; Okoli and Schabram, 2010; Page et al., 2021). The search was conducted between November 2022 and May 2023 by applying the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Moher et al., 2009).This approach was chosen because of its transparent procedures that allow for the findings to be replicated and verified (de Sousa et al., 2019). The PRISMA procedure entails four phases: (1) identification; (2) screening; (3) eligibility; and (4) inclusion (Knobloch et al., 2011; Liberati et al., 2009). The scope of relevant studies was established during the identification phase in line with our research objectives:

RO1: To study the organisational aspect of AI adoption in public institutions.

RO2: To identify the facets within organisational elements that enable (facilitate and/or accelerate) the adoption of AI.

Considering the set research objectives, the basis for our research framework was grounded on the extended Leavitt diamond model (Leavitt, 1964; Kovačič et al., 2004; Nograšek and Vintar, 2014), as presented in the literature review section (2.3). The mentioned model contains key organisational elements: people, structure, culture, technology and processes.

The scientific literature on artificial intelligence in public institutions' organisation research was extracted from the Scopus database, a world-leading academic literature collection, in January 2023. To capture all of the specifics and subdomains of AI on one side and organisation research associated with public institutions on the other, the search queries used in the advanced document search included a broad range of keywords related to several AI techniques and public sector levels, identified in the extensive literature review of existing studies in this research area. Accordingly, AI or artificial intelligence is considered to be an umbrella term, including several technologies belonging to the AI family (sometimes overlapping with statistical or data science domains), such as machine learning, neural networks, natural language processing etc.). However, despite the historical works on AI, there is still no commonly accepted definition, leading to many studies only searching for AI literature with the limited query "artificial intelligence" or "ai", possibly leaving out relevant literature.

The search queries for this study hence covered the following AI-related keywords: "artificial intelligence", "ai", "machine learning", "deep learning", "reinforcement learning", "supervised learning", "unsupervised learning", "neural networks", "natural language processing", "computer vision", "image recognition", "facial recognition", "speech recognition", "intelligence systems", "virtual assistant", "predictive analytics", "semi-supervised learning", "machine reasoning", "support vector machine", "chatbot" AND the following public institutions-related keywords: "government", "public management", "public governance", "public sector", "public administration", "public institution", "public policy", "public organisation", "society", "municipality", "ministry", "public service", "e-government", "smart government", "electronic government", "DEG", "digital era government", "digital government", "smart governance", "e-governance", "electronic governance", "digital era governance" and "digital governance". The selected keywords are consistent with different digital government transformation concepts and the general evolution of e-government discourse, including the most recent smart government (Criado and Gil Garcia, 2019). The identification of documents was further fixed with the keywords "organisat*" and "organizat*" and set to search within articles, conference papers, book chapters and books. In addition, the search was set to include titles containing the search words, not limited to any subject area. The initial search returned 110 documents. However, after checking and screening titles and abstracts (the second PRISMA stage) 35 papers were removed for not being related to organisational elements of public institutions (the third and fourth PRISMA stages). This led to 75 documents being identified as relevant to the study on AI and organisational transformation.

Figure 1: Flowchart of determining the database in Scopus

General limitations

– Document type: article, conference paper, book chapter, book
– Language: English
– Period: Not limited
– Keyword search: Title
– Search field: All subject areas
– Result: 110 documents found

Manual examination

– Checking and screening the title and abstract
– Deleting 35 documents that did not cover organisational elements

Exclusion criteria: focus on general operations or only on technical aspects – studies restricted to the technical aspects of AI

Final database

75 documents

Source: authors' elaboration.

The complete versions of identified literature were retrieved and stored using the NVivo 12, a software program for qualitative and mixed-methods research. This software allowed us to code the key elements based on the research framework (people, culture, structure, processes, technology) while reading the identified literature. The coding system enabled us to link similar ideas from different articles, identify contradictions in arguments, compare (dis)similarities and build a structured overview of identified organisational facets when it comes to AI adoption, as is presented in the following section.

4 Results

The detailed systematic literature review revealed the main findings of authors concerning public institutions' adoption of AI. Different studies from numerous countries and public sector subsectors were selected according to the abovementioned methodology. In the analysed papers, the authors describe the enablers and the barriers to AI adoption. The following tables include the facets within the five elements of the Leavitt model (people, structure, culture, technology, processes) that were identified as the key enablers of AI adoption in public institutions.

Table 1: Enablers within the People element

Element – People	Authors
– Top managers' positive perceptions, previous experiences with AI and understanding regarding the application and value of AI – Top management support for integrating AI solutions (e.g., providing time and financial resources, overcoming resistances) – Top management support for the development of an AI adoption strategy – IT managers' openness and trust concerning AI – IT managers' understanding of AI's direct value and implications for citizens' lives beyond just the technological aspects – IT managers' plans for AI adoption – Leadership style – Opinion of an informal leader – High salaries for AI experts – Communication and intrinsic motivation of AI project members, other staff and external partners – Supporting employees to overcome fears of losing a job and de-humanisation or human replacement by robots at work, and fears of additional control – In-house staff knowledge of AI – trainings, tutoring and other knowledge transfers regarding AI and its capabilities, and other IT skills on all levels of the organisation – Employment of external AI specialists – The abilities of front-line officials to interpret data in order to explain the decision-making process and to assume responsibility for the outcomes of those decisions	Alshahrani et al., 2022, Campion et al., 2022, Chen et al., 2023, Criado et al., 2022, Effendi and Pribadi, 2021, Ishengoma et al., 2022, Mikalef et al., 2019, Mikalef et al., 2022, Neumann et al., 2022, Noymanee et al., 2022, Ojo et al., 2019, Peretz-Andersson et al., 2021, Plantinga, 2022, Schaefer et al., 2021, van Noordt and Misuraca, 2020a, van Noordt and Misuraca, 2020b, Wirtz and Müller, 2019.

Source: authors' elaboration.

Despite the technology (AI) and its adoption being discussed in the study, people (i.e., employees – public managers, public servants, external AI experts) must be put first while discussing ICT novelties/transformations that are being introduced into public organisations. Several authors (Alshahrani et al., 2022; Campion et al., 2022; Chen et al., 2023; Criado et al., 2022; Effendi and Pribadi, 2021; Ishengoma et al., 2022; Mikalef et al., 2019; Mikalef et al., 2022; Neumann et al., 2022; Noymanee et al., 2022; Ojo et al., 2019; Peretz-

Andersson et al., 2021; Plantinga, 2022; Schaefer et al., 2021; van Noordt and Misuraca, 2020a; van Noordt and Misuraca, 2020b; Wirtz and Müller, 2019) studied the enablers of successful AI adoption related to the human factor. Many of these authors stress that, first, top management's understanding and positive perception of the application and value of AI are the key enablers of AI adoption, followed by top management's support in terms of developing a strategy, providing resources, and change management activities. The second set of facets concerns IT managers who must be open and trust the AI and understand the AI's value and direct implications for citizens. After designing a strategy, IT managers are those who should be in charge and responsible for the preparation of plans for the AI adoption. Third, besides the formal leaders (managers along with their leadership styles), informal leaders can play a significant role in overcoming the challenges of introducing new technologies. Fourth, in the case of AI adoption, leadership should be focused on communication, motivation (extrinsic and intrinsic), remuneration and ensuring the psychological safety of employees and potential external partners. The fifth set of facets that enable AI adoption is related to the building of competencies in AI and other IT skills – either through training, tutorship or knowledge transfers across the organisation. If no internal capacities are available, external AI specialists must be hired. To sum up, the key sets of enablers of AI adoption related to the internal human factor are the attitudes and actions of top and IT managers, notably their leadership approaches (communication, motivation etc.), human resources management (hiring and HR development) and, last but not least, change management.

Table 2: Enablers within the Structure element

Element – Structure	Authors
– Establishing new/alternative organisational structures/ forms (roles) and processes – Engagement and collaboration across organisations, e.g., innovative public–private partnerships and procurement models – Strong exchange with other institutions regarding joint projects and the potential of AI – e.g., a governmental inter-organisational AI agency – Intra-governmental digital service units are increasingly becoming a vital alternative for introducing new technologies due to their capacity to attract talent and expedite the implementation process – The sharing of data and transferring of knowledge between organisations must be encouraged by: (1) understanding the data that are available and required; (2) inter-and cross-organisational alignment between project interests and expectations surrounding the data sharing; and (3) engagement within the organisational hierarchy, leading to the unification of expectations on the top and bottom levels of the organisation – Internal collaboration: data and knowledge from different departments along with a common understanding of the aims, benefits and goals of AI projects – Clarifying roles and responsibilities within the collaboration (e.g., by appointing champions) – Project-oriented measures, agile project management	Alshahrani et al., 2022, Campion et al., 2022, Chen et al., 2019, Chen et al., 2023, Ishengoma et al., 2022, Mikalef et al., 2019, Mikalef et al., 2022, Plantinga, 2022, Schaefer et al., 2021, van Noordt and Misuraca, 2020a, van Noordt and Misuraca, 2020b

Source: authors' elaboration.

While examining the changes in organisational structure that enable AI adoption, researchers (Alshahrani et al., 2022; Campion et al., 2022; Chen et al., 2019; Chen et al., 2023; Ishengoma et al., 2022; Mikalef et al., 2019; Mikalef et al., 2022; Plantinga, 2022; Schaefer et al., 2021; van Noordt and Misuraca, 2020a; van Noordt and Misuraca, 2020b) detected the following sets of enablers: (1) introducing new organisational structures, e.g., projects along with agile management approaches; (2) inter-organisational collaboration, e.g., public–private partnerships, joint projects etc.; (3) intra-governmental digital service units that attract talents and accelerate implementation; (4) knowledge transfer and data sharing between and within organisations (on all hierarchical levels); and (5) intra-organisational collaboration – between the organisational units (departments) – to ensure a common understanding of the goals, purpose and benefits of the AI adoption. Accordingly, the key enablers concerning the organisational structure are the collaboration between and within public institutions and other stakeholders, reorganisations, and the introduction of agile management.

Table 3: Enablers within the Culture element

Element – Culture	Authors
– Focusing on AI's public value rather than on AI as a technology itself – Cultivating awareness of what AI is, not only as a term but also its importance, tools, applications – Promoting awareness of the potential opportunities and risks associated with AI in governmental environments among general managers, political appointees and street-level bureaucrats – Cultivating a culture of cross-institution collaboration, developing collaborative management – Organisational culture as an important element in facilitating the adoption or rejection of new technologies – A culture of innovativeness and the right mix of financial and other incentives along with a push from higher levels – Innovations that all stakeholders perceive as 'value adding' – Innovations regarded as easy to use and to experiment with – Innovations compatible with the organisational values – IT managers guided by public values will implement more ethical AI technologies – IT managers developing an organisation-wide readiness perspective, not merely infrastructure investments and pools of data – Senior management allowing experimenting with new ideas and technologies – Methods of agile project management and a culture that allows a degree of failure – Individual motivation – identification of employees interested in AI and thinking flexibly and innovatively	Alshahrani et al., 2022, Campion et al., 2022, Criado et al., 2022, Ishengoma et al., 2022, Mikalef et al., 2022, Neumann et al., 2022, Ojo et al., 2019, Plantinga, 2022, van Noordt and Misuraca, 2020a, van Noordt and Misuraca, 2020b.

Source: authors' elaboration.

The vast majority of researchers who concentrated on facets within the "People" element, which are mostly related to top and IT management support, leadership style and staff competencies, stress that the "Culture" element is just as important as the formal aspects of management, leadership and human resources management. The key enablers of AI adoption in the findings of Alshahrani et al. (2022), Campion et al. (2022), Criado et al. (2022), Ishengoma et al. (2022), Mikalef et al. (2022), Neumann et al. (2022), Ojo et al. (2019), Plantinga (2022), van Noordt and Misuraca (2020a) and van Noordt and Misuraca (2020b) may be summarised as falling into six groups: (1) focusing on the public value of AI along with its applications and benefits; (2) awareness of the opportunities and risks of AI, and fostering a culture of cross-institution collaboration; (3) building a culture of innovativeness where innovations are perceived as 'value adding' by all stakeholders, as easy to use and to experiment with, and are compatible with the organisation's existing values; (4) values of IT managers (ethics and the value of AI from an organisation-wide readiness perspective, not only relative to investments in technological infrastructure; (5) adaptability, agile project management, and a culture that tolerates failures and learning; and (6) individuals' values (flexibility, innovativeness) and their motivation to be involved in AI adoption projects. It may thus be concluded that the introduction of AI is not only about the changes in the organisational structure and human resources management, which are mainly focused on formal aspects of the organisation. It is important that managers on all levels engage in building a strong culture with values such as openness, innovativeness, agility, collaboration, trust and ethics to ensure that the changes brought by the AI adoption are as smooth as possible.

Table 4: Enablers within the Technology element

Element – Technology	Authors
– Highly developed digital government infrastructure with sufficient bandwidth, processing power of server hardware, memories, networks – Compatibility of existing information systems with new AI technology – A large network of interconnected computers – Devices that immediately process large amounts of data – Technologies for the easier storage and analysis of large data sets – A sufficient amount (big data) of reliable and high-quality data that must be cleaned, integrated, structured and secured for model learning – Privacy protection and mitigation of ethical risks – Governance and management of databases for the acquisition, management and storage of various data – Ability to easily connect different data in distinct systems – Inter-organisational and effective data exchange – Functioning data ecosystem, including Internet of Things (IoT) systems and digital services – Top-down approach – alignment of data infrastructure and data strategy – Possibility of data analytics – Coordinating the AI with potential users' actual needs	Alhashmi et al., 2019, Alshahrani et al., 2022, Campion et al., 2022, Ishengoma et al., 2022, Mikalef et al., 2022, Neumann et al., 2022, Noymanee et al., 2022, Ojo et al., 2019, Plantinga, 2022, Schaefer et al., 2021, van Noordt and Misuraca, 2020a, van Noordt and Misuraca., 2020b, Wirtz and Müller, 2019

Source: authors' elaboration.

While addressing the "technology" element, it is essential to view it broadly; namely, as infrastructure that is crucial when it comes to AI adoption. Several authors (Alhashmi et al., 2019; Alshahrani et al., 2022; Campion et al., 2022; Ishengoma et al., 2022; Mikalef et al., 2022; Neumann et al., 2022; Noymanee et al., 2022; Ojo et al., 2019; Plantinga, 2022; Schaefer et al., 2021; van Noordt and Misuraca, 2020a; van Noordt and Misuraca, 2020b; Wirtz and Müller, 2019) highlight the presence of already mature digital infrastructure as an important enabler of AI adoption. Public institutions already functioning with higher degrees of eGovernment maturity and possess greater experience with ICT in their day-to-day work are better positioned for adopting AI due to their existing infrastructure, mindset and skills. A large network of interconnected computers is fundamental for supporting the complex computations and data processes inherent in AI systems. Moreover, devices capable of immediately processing large data sets are essential for real-time decision-making and service delivery, a vital component of public sector operations. On the other hand, less digitally mature organisations may need to first update their existing IT systems to make them compatible with new AI technologies.

Data is the lifeblood of AI systems. A sufficient amount of reliable, high-quality data is required for AI model learning and development. This data must be cleaned, integrated, structured and secured, underscoring the importance of robust data governance and management. Different datasets have to be integrated, and data sharing between different organisations is highly recommended. Further, a functioning data ecosystem, inclusive of IoT systems and digital services, is pivotal. The alignment of data infrastructure with an overarching data strategy, using a top-down approach, ensures coherence and direction in AI implementation. The ability for comprehensive data analytics further empowers public institutions to derive actionable insights and make informed decisions.

The fact that AI systems handle vast amounts of data, including sensitive information, makes privacy protection and the mitigation of ethical risks paramount. This entails not only technological safeguards but also policy frameworks that govern the use of data and AI applications. Effective governance mechanisms must be established to address these concerns, thereby maintaining public trust and assuring compliance with legal standards. Finally, the successful adoption of AI in public institutions crucially depends on the alignment of AI capabilities with potential users' actual needs. This user-centric approach ensures that AI solutions are tailored to meet specific public needs, in turn enhancing service delivery and public engagement.

The successful adoption of AI in public institutions' technological infrastructure is a multifaceted endeavour. It not only calls for technological advancement but also strategic planning, robust data management, ethical considerations, and user-centric design.

Table 5: Enablers within the Processes element

Element – Processes	Authors
– Development of a public business model for implementing AI solutions – Quantifying the organisation's AI maturity given that maturity is a measure that relates to the institution's readiness and AI capability – Strategy as the key factor in determining the success of AI adoption – Re-engineering of existing processes – Core processes must be as digital as possible to process large amounts of data usable for analysis – The integration of AI into existing processes – Implementing regulations and procedures to ensure that AI technologies function within reasonable and acceptable limits – Developing the capability to design AI initiatives that are goal-oriented and focused on citizens' needs – Establishing AI deployment guidelines that incorporate standards for data collection and sharing	Campion et al., 2022, Chatterjee, 2020, Ishengoma et al., 2022, Mikalef et al., 2022, Neumann et al., 2022, Noymanee et al., 2022, Ojo et al., 2019, Schaefer et al., 2021, van Noordt and Misuraca, 2020a, van Noordt and Misuraca, 2020b, Wirtz and Müller, 2019, Zheng et al., 2018.

Source: authors' elaboration.

While investigating the changes in processes associated with AI adoption, researchers (Campion et al., 2022; Chatterjee, 2020; Ishengoma et al., 2022; Mikalef et al., 2022; Neumann et al., 2022; Noymanee et al., 2022; Ojo et al., 2019; Schaefer et al., 2021; van Noordt and Misuraca, 2020a; van Noordt and Misuraca, 2020b; Wirtz and Müller, 2019; Zheng et al., 2018) detected several enablers. The suggested first step towards AI adoption is to develop a public business model tailored to AI solutions. This model serves as a blueprint, guiding the integration of AI technologies into public sector operations. Understanding an institution's AI maturity is pivotal in this transition. Maturity in this context refers to an institution's readiness to integrate AI into its processes and enhance its existing AI capabilities. Quantifying this maturity permits organisations to gauge their preparedness for AI adoption, identifying areas of strength and opportunities for development. It serves as a diagnostic tool that informs decision-makers about the steps needed to make them more AI-ready.

Strategy emerges as a key determinant in the success of AI adoption. A well-crafted strategy provides direction and clarity, aligning AI initiatives with the organisation's overarching goals. It ensures that AI adoption is not an isolated effort but part of the bigger organisational vision. Re-engineering existing processes is an essential step on this strategic journey. It involves a critical examination and redesign of current operational processes to make them more compatible with AI technologies. This re-engineering assures that core processes are digitalised to handle and analyse large volumes of data, a precondition for effective AI functionality. Further, it facilitates the seamless integration of AI into existing workflows.

Adopting regulations and procedures is vital for ensuring that AI operates within reasonable and acceptable boundaries. The regulatory framework should address ethical considerations, data privacy and security concerns, providing clear guidelines on how AI technologies should be deployed and managed. Building the capacity to design goal-based and citizen-centric AI initiatives is another crucial enabler found in the literature. AI solutions should be developed with the end-user in mind, focusing on enhancing service delivery and citizens' well-being. This approach ensures that AI technologies are not merely advanced but also relevant and beneficial to the citizens.

Finally, establishing AI deployment guidelines is imperative. These guidelines should include criteria for standardising data collection and sharing, ensuring consistency and quality in data management. In conclusion, the successful adoption of AI within organisational processes is a multifaceted undertaking. It requires a strategic approach, process re-engineering, digital transformation, regulatory oversight, and a focus on citizen-centric solutions.

5 Discussion

Even though AI is still a relatively new technology, especially when talking about its implementation in public institutions, politicians, public managers, public servants and researchers are already aware that it will have a significant influence on decision-making processes and the design, delivery, quality and efficiency of public services (Mergel et al., 2023). According to Bartollotta and Gritt (2021) and Mergel et al. (2023), AI might lead to new public service models (externally), along with reorganisations, and changes in both employee skills and decision-making processes. On the other hand, the results of our research also indicate the opposite, which means the above-listed organisational elements must be viewed as important enablers of effective and efficient AI adoption.

Before commencing our research, similarly to Mergel et al. (2023) we had assumed that the adoption of new technology must always be considered in terms of the broader organisational context which public institutions are embedded in and that AI is no exception. Our research shows that the key organisational facets within Leavitt's organisational elements (Nograšek and Vintar, 2014) that influence/enhance AI adoption are: (1) top management support, IT managers' openness to AI, leadership (communication, motivation), the development of employee skills (all related to the People element); (2) reorganisations, inter- and intra-organisational collaboration, agile management approaches (all related to the Structure element); (3) building a culture of innovativeness, collaboration, ethics, flexibility and adaptability (all related to the Culture element); (4) mature digital infrastructure (both hardware and software), robust data management and privacy protection (all related to the Technology element); and (5) developing new business models based on a maturity assessment and the design of strategies for process re-engineering, integrating the AI into existing processes, and developing new regulation and standards (all related to the Processes element).

While discussing the practical implications of our findings, we must bear in mind that public institutions' adoption of AI holds the potential to provide numerous benefits and public value to citizens, residents, businesses and NGOs. To gain insight into the state-of-the-art of AI adoption in public institutions, our study focused on organisational elements and their changes before and during the AI adoption. Each organisational element (people, structure, culture, processes etc.) enables/facilitates the adoption of AI. The findings reveal that to exploit the enablers and avoid numerous barriers while adopting AI, the complexity of AI adoption projects must be considered seriously, and these projects have to be managed carefully. Adopting AI in public institutions amounts to much more than simply implementing new technologies. Not purely technological, but several organisational elements dominate public innovation initiatives, such as AI. Practitioners should thus systematically and holistically plan, organise, lead and control AI adoption in public institutions. The results of the literature review may serve as useful guidelines for decision-makers (policymakers and managers) and employees in different types of public institutions while seeking to introduce new disruptive technologies such as AI, and when formulating policies, regulations, strategies and tactics for public institutions' adoption of AI. Moreover, public and private sector stakeholders will have to act as partners in the responsible use of new technologies, value (co)creation and risk sharing to ensure the greater success of businesses and citizens' well-being. In contrast, the biggest obstacles to effective and efficient digital transformation for private sector entities are non-digitalised public services and slow changes in regulatory frameworks. This means that public institutions must join in the digital transformation and, hand in hand with the private sector, not only follow the trends in private businesses but also support them with digital infrastructure (services) and regulation.

Although comprehensive, the presented systematic literature review may have limitations due to the quickly evolving nature of AI and associated organisational change literature. First, the division between the natural and social sciences in AI research creates a challenge. Technical studies in the natural sciences often overlook organisational change aspects, whereas the social sciences sometimes lack specificity while addressing AI's technicalities. Notwithstanding the use of an extensive range of keywords, the inherent limitation of keyword-based searches may have led to some relevant studies being missed out. Second, the dynamic and interdisciplinary nature of AI and public institutions organisation research means some pertinent literature could fall outside the chosen search terms. The reliance on Scopus, although valuable for its extensive collection, might also introduce a selection bias. Relevant studies, especially those published in less recognised journals or in non-English languages, may have been omitted. Third, the field of AI is rapidly evolving, with new developments occurring frequently. The timeframe of the literature search (until May 2023) means that the latest findings, advancements and discussions might not have been captured. Fourth, while NVivo 12 facilitates systematic coding and analysis, the interpretation of literature is inherently subjective. Different researchers might code and interpret the same text in varying ways, potentially influencing the conclusions drawn. Lastly, the findings are based solely on identified scientific literature, which may not comprehensively cover all practical instances of public institutions' adoption of AI. Accordingly, the generalisability of the results could be limited.

Building on the findings of our study, we propose the following directions for further research. First, the research on AI adoption in the public sector should more intensively focus on numerous drivers of novelties' implementation, not only on the technology itself (e.g., on different parts of holistic organisational and business models). Second, multiple stakeholders' involvement while adopting AI should be studied (i.e., consultation and engagement before the change, and analysis of their satisfaction after the change). This means that the enablers and benefits of efficient AI adoption should be measured (quantified) through survey-based assessments by (at least) public managers, public servants and citizens in specific public sector subsectors. Third, while AI adoption is mostly seen as greatly benefitting the development of humankind in the sense of increasing efficiency, transparency etc., researchers should not forget about studying the negative aspects of the use (or even misuse) of new technologies, e.g., breaking values, ethical standards etc.

6 Conclusion

Artificial Intelligence (AI) is rapidly transforming business and private domains of our world. Its gradual adoption by public institutions is revolutionising their operations, resulting in higher efficiency and effectiveness. Numerous studies show that AI's adoption extends beyond the technological realm; it calls for a comprehensive transformation encompassing both tangible and intangible aspects of an institution's organisation, including the technological infrastructure (e.g., equipment, data management, maintenance, security), employee skills, management and leadership practices, organisational culture etc. Consequently, this underscores the importance of policymakers and other decision-makers on all levels considering these organisational elements while introducing new technologies, such as AI, in public institutions.

The successful adoption of AI in public institutions, as revealed by our systematic literature review, intertwines a spectrum of organisational facets on a seamless continuum. At the forefront are people – the essence of any institution – where the leadership of top management and IT professionals is vital. Their understanding, support, and proactive strategies set the stage for AI integration, fostering a culture of innovation and adaptability. This human-centric approach interlaces with structural transformations, advocating agile management and collaborative efforts within and across organisations. Simultaneously, the organisational culture paradigm is shifting towards embracing AI's potential, cultivating an environment in which risks are understood and opportunities are maximised. This cultural adaptability extends into the technological realm where a robust digital infrastructure and data management become the bedrock for AI systems. The integration of AI demands not simply technical compatibility but also a strategic alignment, ensuring that technology serves genuine public needs while respecting privacy and ethical standards. In harmony with these elements are the processes – the operational backbone of AI adoption. Developing AI-focused business models, enhancing organisational AI maturity, and strategically aligning AI initiatives with organisational goals illustrate a conscious effort to mould processes that complement AI's capabilities. This strategic approach is underpinned by re-engineering efforts and (internal) regulatory frameworks, assuring that the integration of AI is smooth, ethical and citizen-centric. In essence, the journey of AI adoption in public institutions entails a harmonious orchestration of people, structure, culture, technology and processes. While distinct, each element is interconnected and collectively they driving the transition towards more responsive, effective and efficient public institutions.

Inspired by previous research, our study adopted a comprehensive approach to understanding the organisational elements linked to AI adoption in public institutions. It identifies five key organisational factors critical for integrating innovations: people (skills, motivation, change management), organisational culture (leadership, a culture fostering experimentation), structure (hierarchical changes, departmental involvement, agile methods), processes (process re-engineering, strategic planning for AI) and technological infrastructure (IT system maintenance, data management). The study points to the importance of addressing each of these elements because they present distinct opportunities and possible challenges in the context of adopting AI. It is crucial to meticulously study and maximise the use of enablers to optimise the benefits for all stakeholders in public institutions.

References

Abdeldayem, M. M. and Aldulaimi, S. H. (2020). Trends and opportunities of artificial intelligence in human resource management: Aspirations for public sector in Bahrain. International Journal of Scientific and Technology Research, 9(1), pp. 3867–3871.

Abhay, N. M., Prabhudev, K. and Anitesh, B. (2007). Antecedents and Consequences of Internet Use in Procurement: An Empirical Investigation of U.S. Manufacturing Firms. Information Systems Research, 18(1), pp. 103–120.

Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. International Journal of Information Management, 34(5), pp. 639–651.

Agrawal, A., Gans, J. and Goldfarb, A. (2017). What to expect from artificial intelligence. MIT Sloan Management Review, 58(3), pp. 22–27.

Al Hadwer, A. et al. (2021). A Systematic Review of Organizational Factors Impacting Cloud-based Technology Adoption Using Technology-Organization-Environment Framework. Internet of Things. 15. doi: 10.1016/j.iot.2021.100407.

Alhashmi, S. F., Salloum, S. A. and Abdallah, S. (2019, October). Critical success factors for implementing artificial intelligence (AI) projects in Dubai Government United Arab Emirates (UAE) health sector: applying the extended technology acceptance model (TAM). In Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2019 (pp. 393–405). Cham: Springer International Publishing.

Alshahrani, A., Dennehy, D. and Mäntymäki, M. (2022). An attention-based view of AI assimilation in public sector organizations: The case of Saudi Arabia. Government Information Quarterly, 39(4), 101617.

Alsheiabni, S., Cheung, Y. and Messom, C. (2019). Factors inhibiting the adoption of artificial intelligence at organizational level: a preliminary investigation. In M. Santana, and R. Montealegre, ed., AMCIS 2019 Proceedings.

Androutsopoulou, A. et al. (2019). Transforming the communication between citizens and government through AI-guided chatbots. Government information quarterly, 36(2), pp. 358–367.

Bassey, E., Mulligan, E. and Ojo, A. (2022). A Conceptual Framework for Digital Tax Administration – A Systematic Review. Government Information Quarterly, 39(4), pp. 101754.

Berryhill, J. et al. (2019). Hello, World: Artificial intelligence and its use in the public sector. OECD library.

Bullock, J., Young, M. M. and Wang, Y. F. (2020). Artificial intelligence, bureaucratic form, and discretion in public service. Information Polity, 25(4), pp. 491–506.

Burke, G. and Peppard, J. (1995). Examining business process reengineering: Current perspectives and research directions. London: Kogan Page.

Campion, A. et al. (2022). Overcoming the challenges of collaboratively adopting artificial intelligence in the public sector. Social Science Computer Review, 40(2), pp. 462–477.

Chang, I.C. et al. (2007). Factors affecting the adoption of electronic signature: Executives' perspective of hospital information department. Decision Support Systems, 44, pp. 350–359.

Chatterjee, S. (2020). AI strategy of India: policy framework, adoption challenges and actions for government. Transforming Government. People, Process and Policy, 14(5), pp. 757–775.

Chen, T., Gascó-Hernandez, M. and Esteve, M. (2023). The Adoption and Implementation of Artificial Intelligence Chatbots in Public Organizations: Evidence from US State Governments. The American Review of Public Administration, 02750740231200522.

Chen, H., Li. L. and Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. Journal of Management Analytics, 8(1), pp. 1–33.

Chen, T., Ran, L. and Gao, X. (2019, June). AI innovation for advancing public service: The case of China's first Administrative Approval Bureau. In Proceedings of the 20th Annual International Conference on Digital Government Research, pp. 100–108.

Compton, M. E. et al. (2022). Administrative Errors and Race: Can Technology Mitigate Inequitable Administrative Outcomes? Journal of Public Administration Research and Theory, 33(3), pp. 512–528.

Criado, J. I. and de Zarate-Alcarazo, L. O. (2022). Technological frames, CIOs, and Artificial Intelligence in public administration: A socio-cognitive exploratory study in Spanish local governments. Government Information Quarterly, 39(3), p. 101688.

Criado, J. I. and Gil-Garcia, J. R. (2019). Creating public value through smart technologies and strategies: From digital services to artificial intelligence and beyond. International Journal of Public Sector Management.

De Sousa, W. G. et al. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. Government Information Quarterly, 36(4), p. 101392.

Desouza, K. C., Dawson, G. S. and Chenok, D. (2020). Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. Business Horizons, 63(2), pp. 205–213.

Dickinson, H. and Yates, S. (2023). From External Provision to Technological Outsourcing: Lessons for Public Sector Automation Form the Outsourcing Literature. Public Management Review, 25(2), 1972681.

Djeffal, C. (2020). Artificial intelligence and public governance: Normative guidelines for artificial intelligence in government and public administration. In Wischemeyer, T. and Rademacher, T., ed. Regulating Artificial Intelligence. Springer International Publishing.

Dwivedi, Y. K. et al. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, p. 101994.

EC. (2019). A Definition of AI: Main Capabilities and Scientific Disciplines. High-Level Expert Group on Artificial Intelligence. European Commission. At https://digital-strategy.ec.europa.eu/ en/library/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines, accessed 18 October 2023.

Effendi, G. N. and Pribadi, U. (2021, March). The Effect of Leadership Style on the Implementation of Artificial Intelligence in Government Services. In IOP Conference Series: Earth and Environmental Science, 717(1). 012018. IOP Publishing.

Eggers, W. D., Schatsky, D. and Viechnicki, P. (2017). AI-augmented government. Using cognitive technologies to redesign public sector work. Deloitte.

El Asri, H. and Benhlima, L. (2020, December). Artificial Intelligence based Knowledge Management in Public Administration: A Mapping Study. In European Conference on Knowledge Management (pp. 250–XVII). Academic Conferences International Limited.

Farrow, E. (2020). Organisational Artificial Intelligence Future Scenarios: Futurists Insights and Implications for the Organisational Adaptation Approach, Leader and Team. Journal of Futures Studies, 24(3), pp. 1–15.

Fink, A. (2007). Conducting research literature reviews: From the internet to paper (2nd ed.). Sage.

Fischer, C., Siegel, J., Proeller, I. and Drathschmidt, N. (2022). Resilience Through Digitalisation: How Individual and Organisational Resources Affect Public Employees Working from Home During the COVID-19 Pandemic. Public Management Review, 25(4), pp. 1–28.

Floridi, L. et al. (2018). AI4People—an ethical framework for a good AI society: opportunities, risks, principles, and recommendations. Minds and machines, 28, pp. 689–707.

Gasser, U. and Almeida, V. A. (2017). A layered model for AI governance. IEEE Internet Computing, 21(6), pp. 58–62.

Haug, N., Dan, S. and Mergel, I. (2023). Digitally-induced change in the public sector: a systematic review and research agenda. Public Management Review, pp. 1–25.

Höchtl, J., Parycek, P. and Schöllhammer, R. (2016). Big data in the policy cycle: Policy decision making in the digital era. Journal of Organizational Computing and Electronic Commerce, 26(1-2), pp. 147–169.

Hodzic, S., Ravselj, D. and Alibegovic, D. J. (2021). E-Government Effectiveness and Efficiency in EU-28 and COVID-19. Cent. Eur. Pub. Admin. Rev., 19, 159.

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. Business Horizons, 65(3) pp. 329–339.

Ireni-Saban, L. and Sherman, M. (2021). Ethical Governance of Artificial Intelligence in the Public Sector. Routledge.

Ishengoma, F. R. et al. (2022). Integration of artificial intelligence of things (AIoT) in the public sector: Drivers, barriers and future research agenda. Digital Policy, Regulation and Governance, 24(5), pp. 449–462.

Jahankhani, H. et al. (2020). Strategy, leadership, and AI in the cyber ecosystem: the role of digital societies in information governance and decision making. Academic Press.

Jamali, M., Shafiezadeh, E. and Jozani, M. (2011). Information Technology and its Deficiencies in Sharing Organizational Knowledge. International Journal of Business and Social Science, 2(8).

Jöhnk, J., Malte W. and Wyrtki, K. (2021). Ready or not, AI Comes — An Interview Study Of Organizational AI readiness factors. Business and Information Systems Engineering, 63(1), pp. 5–20.

Kankanhalli, A., Charalabidis, Y. and Mellouli, S. (2019). IoT and AI for smart government: A research agenda. Government Information Quarterly, 36(2), pp. 304–309.

Kaplan, A. and Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), pp. 15–25.

Kazley, A. S. and Ozcan, Y. A. (2007). Organizational and environmental determinants of hospital EMR adoption: A national study. Journal of Medical Systems, 31, pp. 375–384.

Knobloch, K., Yoon, U. and Vogt, P. M. (2011). Preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement and publication bias. Journal of Cranio-Maxillofacial Surgery, 39(2), pp. 91–92.

Kovačič, A. et al. (2004). Prenova in informatizacija poslovanja. Ljubljana: Ekonomska fakulteta.

Krafft, P. M. et al. (2020). Defining AI in policy versus practice. In Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, pp. 72–78.

Kuan, K. K. and Chau, P. Y. (2001). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. Information and Management, 38, pp. 507–521.

Leavitt, H. J. (1964). Applied organization change in industry: structural, technical, and human approaches. In S. Cooper, H. J. Leavitt, and K. Shelly, ed. New perspectives in organizational research, pp. 55–71. Chichester: Wiley.

Leslie, D. (2019). Understanding artificial intelligence ethics and safety: A guide for the responsible design and implementation of AI systems in the public sector. Available at SSRN 3403301.

Li, B. H. et al. (2017). Applications of artificial intelligence in intelligent manufacturing: A review. Frontiers of Information Technology and Electronic Engineering, 18(1), pp. 86–96.

Liberati, A. et al. . (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. PLoS Medicine, 6(7), e1000100.

Liu, C. F. (2011). Key factors influencing the intention of telecare adoption: An institutional perspective. Telemedicine and e-Health, 17, pp. 288–293.

Mehr, H., Ash, H. and Fellow, D. (2017). Artificial intelligence for citizen services and government. Ash Cent. Democr. Gov. Innov. Harvard Kennedy Sch., no. August, pp. 1–12.

Mergel, I. et al. (2023). Implementing AI in the public sector. Public Management Review, pp. 1–13.

Mikalef, P., Fjørtoft, S. O. and Torvatn, H. Y. (2019). Artificial Intelligence in the public sector: a study of challenges and opportunities for Norwegian municipalities. In Digital Transformation for a Sustainable Society in the 21st Century: 18th IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society, I3E 2019, Trondheim, Norway, September 18–20, 2019, Proceedings 18, pp. 267–277. Springer International Publishing.

Mikalef, P. et al. (2022). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. Government Information Quarterly, 39(4), p. 101596.

Mikalef, P. et al. (2023). Examining how AI capabilities can foster organizational performance in public organizations. Government Information Quarterly, 40(2), p. 101797.

Mikhaylov, S. J., Esteve, M. and Campion, A. (2018). Artificial intelligence for the public sector: opportunities and challenges of cross-sector collaboration. Philosophical transactions of the royal society a: mathematical, physical and engineering sciences, 376(2128), 20170357.

Misuraca, G. and Van Noordt, C. (2020). AI Watch-Artificial Intelligence in public services: Overview of the use and impact of AI in public services in the EU. JRC Working Papers, (JRC120399).

Moher, D. et al. 2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. PLoS Medicine, 6(7), pp. 1–6.

Murko, E., Umek, L. and Aristovnik, A. (2023a). Artificial intelligence in the public sector: Linking research and practice. In The Future of Public Administration Enabled Through Emerging Technologies: 31th NISPAcee Annual Conference, pp. 1–9. NISPAcee.

Murko, E. et al. (2023b). Artificial intelligence in public administration: Evidence from bibliometric analysis. In IIAS-SEAPP Doha Conference 2023 Developmental States and Professionalization of Public Administration and Public Policy, pp. 1–20, IIAS.

Neumann, O., Guirguis, K. and Steiner, R. (2022). Exploring artificial intelligence adoption in public organizations: a comparative case study. Public Management Review, pp. 1–28.

Nograšek, J. and Vintar, M. (2014). E-government and organisational transformation of government: Black box revisited?. Government Information Quarterly, 31(1), pp. 108–118.

Noymanee, J., Iewwongcharoen, B. and Theeramunkong, T. (2022, March). Artificial Intelligence Maturity Model for Government Administration and Service. In 2022 International Conference on Digital Government Technology and Innovation (DGTi-CON), pp. 66–70. IEEE.

OECD. (2022). Tax Administrations Continue to Accelerate Their Digital Transformation. At https://www.oecd.org/tax/administration/tax-administrations-continue-to-accelerate-their-digital-transformation.ht/, accessed 19 October 2023.

Ojo, A., Mellouli, S. and Ahmadi Zeleti, F. (2019). A realist perspective on AI-era public management. In Proceedings of the 20th Annual International Conference on Digital Government Research, pp. 159–170.

Okoli, C. and Schabram, K. (2010). A guide to conducting a systematic literature review of information systems research. SSRN Electronic Journal, 10(2010), pp. 1–52.

O'Neill, M. M., Booth, S. R. and Lamb, J. T. (2018). Using NVivo™ for literature reviews: The eight-step pedagogy (N7+ 1). Qualitative Report: an online journal dedicated to qualitative research since 1990, pp. 21–39.

Page, M. J. et al. (2021). The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. Systematic Reviews 10(89): 1–11. https://doi.org/10.1186/s13643-021-01626-4

Pan, Y. and Froese, F. J. (2022). An interdisciplinary review of AI and HRM: Challenges and future directions. Human Resource Management Review, 33(1), p. 100924.

Pechtor, V. and Basl, J. (2022). Analysis of suitable frameworks for artificial intelligence adoption in the public sector. IDIMT-2022 Digitalization of society, business and management in a pandemic.

Pencheva, I., Esteve, M. and Mikhaylov, S. J. (2020). Big Data and AI–A Transformational Shift for Government: So, What Next for Research? Public Policy and Administration, 35(1), pp. 24–44.

Peretz-Andersson, E. et al. (2021). AI Transformation in the Public Sector: Ongoing Research. In 2021 Swedish Artificial Intelligence Society Workshop (SAIS) (pp. 1-4). IEEE.

Plantinga, P. (2022). Digital discretion and public administration in Africa: Implications for the use of artificial intelligence. Information Development, pp. 1–12.

Rondan-Cataluña, F. J., Arenas-Gaitán, J. and Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models: A non-linear perspective. Kybernetes, 44(5), pp. 788–805.

Rudko, I., Bashirpour Bonab, A. and Bellini, F. (2021). Organizational structure and artificial intelligence. Modeling the intraorganizational response to the AI contingency. Journal of Theoretical and Applied Electronic Commerce Research, 16(6), pp. 2341–2364.

Russel, S. and Norvig, P. (2009). Artificial Intelligence: A Modern Approach. 3rd edition, Pearson, London.

Saura, J. R., Ribeiro-Soriano, D. and Palacios-Marqués, D. (2022). Assessing behavioral data science privacy issues in government artificial intelligence deployment. Government Information Quarterly, 39(4), 101679.

Schaefer, C. et al. (2021). Truth or dare? How can we influence the adoption of artificial intelligence in municipalities? In Proceedings of the 54th Hawaii International Conference on System Sciences.

Schedler, K., Guenduez, A. A. and Frischknecht, R. (2019). How smart can government be? Exploring barriers to the adoption of smart government. Information Polity, 24(1), pp. 3–20.

Shachak, A., Kuziemsky, C. and Petersen, C. (2019). Beyond TAM and UTAUT: Future directions for HIT implementation research. Journal of biomedical informatics, 100, p. 103315.

Siebel, T. M. (2019). Digital transformation: survive and thrive in an era of mass extinction. Rosetta Books, New York.

Stenberg, L. and Nilsson, S. (2020). Factors influencing readiness of adopting AI: A qualitative study of how the TOE framework applies to AI adoption in governmental authorities (Dissertation). At https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1460888&dswid=-8938, accessed 20 July 2023.

Stone, P. et al. (2016). Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. Stanford University.

Tan, E., Mahula, S. and Crompvoets, J. (2022). Blockchain Governance in the Public Sector: A Conceptual Framework for Public Management. Government Information Quarterly, 39(1), 101625.

Tinholt, D. et al. (2017). Unleashing the potential of Artificial Intelligence in the Public Sector. Capgemini Consulting.

Tornatzky, L. G., Fleischer, M. and Chakrabarti, A. K. (1990). Processes of technological innovation. Lexington, MA: Lexington Books.

Turing, A. M. and Haugeland, J. (1950). Computing machinery and intelligence. The Turing Test: Verbal Behavior as the Hallmark of Intelligence, pp. 29–56.

van Noordt, C. (2022). Conceptual challenges of researching Artificial Intelligence in public administrations. In DG. O 2022: The 23rd Annual International Conference on Digital Government Research, pp. 183–190.

van Noordt, C. and Misuraca, G. (2020a). Evaluating the impact of artificial intelligence technologies in public services: towards an assessment framework. In Proceedings of the 13th International Conference on Theory and Practice of Electronic Governance (ICEGOV '20). Association for Computing Machinery, New York, NY, USA, pp. 8–16.

van Noordt, C. and Misuraca, G. (2020b). Exploratory Insights on Artificial Intelligence for Government in Europe. Social Science Computer Review, 40, pp. 1–19.

van Noordt, C. and Misuraca, G. (2022). Artificial Intelligence for the Public Sector: Results of Landscaping the Use of AI in Government Across the European Union. Government Information Quarterly, 39(3), 101714.

Waardenburg, L., Huysman, M. and Agterberg, M. (2021). Managing AI wisely: From development to organizational change in practice. Edward Elgar Publishing.

Wilson, C. and van der Velden, M. (2022). Sustainable AI: An integrated model to guide public sector decision-making. Technology in Society, 68, 101926.

Wirtz, B. W. and Müller, W. M. (2019). An integrated artificial intelligence framework for public management. Public Management Review, 21(7), pp. 1076–1100.

Wirtz, B. W., Weyerer, J. C. and Geyer, C. (2019). Artificial intelligence and the public sector—applications and challenges. International Journal of Public Administration, 42(7), pp. 596–615.

Yang, J., Luo, B., Zhao, C. and Zhang, H. (2022). Artificial intelligence healthcare service resources adoption by medical institutions based on TOE framework. Digital Health, 8.

Yang, Z. et al. (2013). Analyzing the enabling factors for the organizational decision to adopt healthcare information systems. Decision Support Systems, 55, pp. 764–776.

Zheng, Y. et al. (2018). SmartHS: An AI platform for improving government service provision. In Proceedings of the AAAI Conference on Artificial Intelligence, 32(1).

Zuiderwijk, A., Chen, Y. C. and Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. Government Information Quarterly, p. 101577.