Artificial intelligence adoption and organisational transformation for smart public institutions

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Abstract
Driven by experiences from the private sector, public institutions have also started adopting various artificial intelligence (AI) technologies in numerous subsectors, e.g. healthcare, law enforcement, defence, public finance (taxation), education, social services, transport, and infrastructure engineering. Adopting new technologies requires the transformation of the organisation in both hard (structure, processes, etc.) and soft aspects (people, organisational culture etc.). Namely, the barriers to the new technologies' adoption are usually not the technologies themselves but the enablers influencing AI adoption, such as the organisational, technological infrastructure, individual aspects etc. To exploit the full potential of AI in the public sector, the main objective of the ongoing study, presented in a paper, is to systematically analyse state-of-the-art in the field of AI adoption in public institutions and related organisational changes, in this case with a specific focus on barriers to AI adoption. The purpose of the ongoing study is to design a set of recommendations for decision-makers (policymakers and public managers) as well as for public employees when implementing the processes of AI adoption - to be as effective and efficient as possible. The study was designed as a systematic literature review using the PRISMA protocol. The preliminary results show that previous studies on AI adoption in public institutions detected many barriers to AI adoption related to the organisational elements, such as people/employees, structure, culture, technology, and processes. It is crucial for decision-makers and implementers of AI to understand the possible barriers listed in the paper, which can be used as guidelines for successful preparation for AI adoption at all public institutions' levels.

Keywords: artificial intelligence, organisational changes, organisational transformation, barriers, public institution, systematic literature review

1 Introduction

Since the conceptualisation of artificial intelligence (AI) in the 1950s, the interest, research, and volume of investments in these systems have increased tremendously, especially in the last decade, both in the private and public sectors to support and enhance the quality of decision-making and problem-solving in high-uncertainty environments (Androutsopoulou et al., 2019; Desouza et al., 2020; Mikhaylov, 2018). The literature has offered various definitions of AI, each capturing the key concepts of non-human intelligence programmed to perform specific tasks (Dwivedi et al., 2019). Wirtz et al. (2019) studied different definitions of AI and proposed an integrative definition as "the ability of a computer system to perform human-like intelligent behaviour and

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problem-solving with the help of certain core competencies, including perception, understanding, action and learning". Artificial intelligence encompasses various technologies and approaches, such as machine learning, deep learning, artificial neural networks, natural language processing, computer vision and more, and can be defined as a technology for advanced prediction (Agrawal et al., 2017). AI technology identifies patterns in large amounts of data to predict outcomes for similar instances (Dwivedi et al., 2019).

AI has much potential to disrupt almost all industries, and the public sector is not excluded. On the contrary, it has been identified as one of the sectors where AI can significantly impact public services, internal operations, decision-making, etc. It has the potential to provide, and in some cases is already providing, considerable benefits and public value to citizens. Consequently, there is a growing interest in using AI in the public sector to re-design internal service delivery processes and policymaking (Misuraca & Van Noordt, 2020). Public sector and government organisations generate large amounts of data, creating a lot of potential for AI technologies applications (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 enhance public service quality, build citizens' trust, increase efficiency, reduce time and costs, handle complex tasks and impact competitiveness and public value creation (Zuiderwijk et al., 2021; Criado & Gil-Garcia, 2019; Kankanhalli et al., 2019).

Public institutions have already jumped on the journey of AI adoption as both, first, the systems that use AI and are becoming smart. Smartness, as a technology-centric view, indicates that public institutions can become more resilient by adopting AI and the above-mentioned advantages (Gil Garcia et al., 2014). However, the enthusiasm for introducing AI in the public sector is accompanied by some degree of uncertainty and several possible challenges and barriers. Risks of AI include, for example, widening societal divides, infringing on citizens' privacy rights, and clouding public decision-makers' accountability (Floridi et al., 2018). To introduce AI, public managers must recognise and understand the range of possibilities for using this technology and, most importantly, the possible barriers within the interrelation of AI with the key elements of the organisation, such as structure (Rudko et al., 2021), processes (Waardenburg et al., 2021), employees (Pan & Froese, 2022) and organisational culture (Farrow, 2020). Not even the best and newest technologies can ensure effective and efficient operations if, along with them, barriers are not addressed and changes introduced in the 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 and overcome the barriers to adopting AI by understanding the subsequent organisational changes required for overcoming the barriers and efficient transformation. Hence, more detailed insight is needed to understand the required organisational changes when adopting AI as fluently as possible.

The topic of AI in the public sector has been increasingly relevant and attracting growing attention among the world's researchers. There is a fair amount of prior research already available on the use cases and lessons learnt, benefits, opportunities, challenges, barriers and drivers of AI adoption in public institutions (Berryhill et al., 2019; Tinholt et al., 2017, 2017; Chatterjee, 2020; Desouza et al., 2019; Mikhaylov et al. 2018) as well as on different segments of the organisation related to the adoption of AI, or analysed through TOE framework (technology-organisation-environment) (Alsheiabni et al., 2019; Holmström, 2022; Neumann et al., 2022; Pechtor & Basl, 2022; van Noordt & Misuraca, 2020a; van Noordt & Misuraca, 2020b; Wirtz et al., 2019). There has not yet been a study that systematically distils all of the elements to barriers within the gamut of an organisation in the case of public institutions.

Therefore, the main objective of the paper is to present the preliminary results on the barriers to AI adoption and required organisational changes in public institutions to get insight into the state-of-the-art and design the proposal for public managers and policymakers regarding overcoming the barriers during AI adoption. The following section presents data and research methodology, followed by the preliminary results and discussion of a systematic literature review and conclusion.

2 Data and Research Methodology

To achieve the study's research objectives, it was imperative to identify, categorise, and combine the scientific literature generated regarding our subject of interest (Fink, 2007; Okoli & Schabram, 2010). The search was conducted between November 2022 and May 2023, utilising a systematic literature review by applying the PRISMA protocol (Moher et al., 2009) (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). It encompasses four phases: (1) identification, (2) screening, (3) eligibility, and (4) inclusion (Knobloch et al., 2011; Liberati et al., 2009). The scope of the relevant studies was established during the identification phase according to our research objectives:

RO1: To study the organisational aspect of AI adoption in public institutions.
RO2: To identify and discuss barriers within the organisational elements present upon AI adoption.

Accordingly, the ground for our research framework was based on the established organisational elements initially defined by Leavitt's definition of the organisation to include all of the essential organisational elements illustrated by Leavitt's well-known Diamond Model (Leavitt, 1964): people, structure, culture, technology and processes (Nograšek & Vintar, 2014). The scientific literature on artificial intelligence in public institutions' organisation research was extracted from the Scopus database in January 2023 with the search query, covering 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", "digital governance".

The identification of documents was additionally fixed with keywords “organisat*” and “organizat*” and set to search within articles, conference papers, book chapters and books. In addition, the search was set to include the titles with the selected search query, not limited to any subject area. The initial search returned 110 documents. However, after checking and screening titles and abstracts (second PRISMA stage), 35 papers were removed due to not being related to organisational elements of public institutions (third and fourth PRISMA stages). As a result, 75 documents were identified as relevant to the study on AI and organisational transformation and stored and are being analysed using the Nvivo 12 software program. Twenty-five documents have been analysed so far, and the preliminary results are presented in the next chapter.

3 Results and Discussion

A preliminary systematic literature review revealed the interesting findings of the authors on AI adoption in public institutions. Different studies from numerous countries and public sector subsectors were selected according to the abovementioned methodology. The authors described several aspects of AI adoption in the analysed papers, including the barriers. The following tables list the barriers within the five elements of the Leavitt model (people, structure, culture, technology, and processes).

Table 1: Barriers within the element People

Element - People	**Authors**
- Lack of a strategy for adopting AI - Lack of management support and vision for integrating AI solutions - Lack of know-how on AI both in-house and in the job market - Lack of expertise in other IT skills - Inexperienced organisations depend on motivated staff and external partners - Lack of time - High salaries expected by AI experts - Fear of losing a job and de-humanization or human replacement by robots at work - Fear of additional control	Alshahrani et al., 2022 Campion et al., 2022 Criado et al., 2022 Mikalef et al., 2019 Neumann et al., 2022 Schaefer et al., 2021 van Noordt & Misuraca, 2020a van Noordt & Misuraca, 2020b Wirtz & Müller, 2019

Although speaking about technologies, people/employees must be put first when discussing novelties/transformations being introduced into public organisations within the information-communication technologies domain. Several authors (Alshahrani et al., 2022; Campion et al., 2022; Criado et al., 2022; Mikalef et al., 2019; Neumann et al., 2022; Schaefer et al., 2021; van Noordt & Misuraca, 2020a; van Noordt & Misuraca, 2020b; Wirtz & Müller, 2019) studied the barriers to AI adoption. First, there is a lack of management support and vision for integrating AI solutions into existing practices and a lack of a strategy for adopting AI. A second set of barriers is related to a lack of know-how on AI and other IT skills both in-house and in the job market and subsequent dependence on external partners. A third barrier is financial – AI experts expect higher salaries than those available within the existing payment systems in public institutions. Fourth, a significant barrier is the lack of time when managers and employees are busy with daily routines. As a fifth set of barriers, there are specific fears, such as fear of losing a job, dehumanisation or human replacement by robots at work, and fear of additional control. Finally, some unexpected changes in employees' behaviour can occur when AI is introduced, influencing workflows and input data, which in turn impact AI technologies.

Table 2: Barriers within the element Structure

Element - Structure	**Authors**
- Lack of engagement within the organisational hierarchy - Resistance to sharing data and transferring knowledge between organisations	Campion et al., 2022 van Noordt & Misuraca, 2020a

The main barriers to AI adoption were studied by Campion et al. (2022) and van Noordt & Misuraca (2020a). They identified a lack of engagement within the organisational hierarchy as a key barrier related to the organisational structure. The second issue was the resistance to sharing data and transferring knowledge between organisations due to (1) Privacy and security concerns, (2) Lack of understanding of the available and required data, and (3) Lack of inter-organisational alignment between project interests and expectations around data sharing.

Table 3: Barriers within the element Culture

Element – Culture	**Authors**
- Employees used to the traditional systems do not like AI interventions - Rigid institutional contexts and a strong administrative culture - Lack of awareness about potential opportunities and risks of AI that need to be widely (and wisely) fostered in governmental settings - Lack of culture of innovativeness - innovations not perceived as "value adding" by all stakeholders - IT managers lacking public values - IT managers lacking an organisation-wide readiness perspective, not only infrastructure investments and pools of data	Alshahrani et al., 2022 Campion et al., 2022 Criado et al., 2022 Mikalef et al., 2022 Neumann et al., 2022 van Noordt & Misuraca, 2020a van Noordt & Misuraca, 2020b

When mentioning the barriers to AI adoption, Alshahrani et al. (2022) and Criado et al. (2022) stress that employees used to the traditional systems do not like AI interventions. Moreover, rigid institutional contexts and a strong administrative culture can be additional barriers to smooth AI adoption. Important barriers to AI adoption can be detected as findings of Alshahrani et al. (2022), Campion et al. (2022), Criado et al. (2022), Mikalef et al. (2022), Neumann et al. (2022), van Noordt & Misuraca (2020b), and van Noordt & Misuraca (2020a), summarised in the following groups: (1) Lack of awareness about opportunities and risks of AI, and lack of a culture of cross-institution collaboration; (2) Lack of a culture of innovativeness - innovations need to be perceived as "value adding" by all stakeholders; (3) Lack of appropriate values of IT managers (ethics, the value of AI from an organisation-wide readiness perspective, not only infrastructure investments and pools of data); (4) Lack of individuals' values (flexibility, innovativeness) and motivation.

Table 4: Barriers within the element Technology

Element - Technology	Authors
- The inability to integrate systems and data - Absence of data standards to control what and how data are collected and what format they are stored in - Lack of understanding of the available and required data - Privacy and security concerns - Resistance to sharing data and transferring knowledge between organisations	Campion et al., 2022 Mikalef et al., 2019

The main barriers to AI adoption were studied by Mikalef et al. (2019) and Campion et al. (2022), and the majority of them are data-related, such as the inability to integrate systems and data or the absence of data standards to control what data are collected, how they are collected, and what format they are stored in. Campion et al. (2022) state that the key challenge with AI adoption is resistance to sharing data and transferring knowledge between organisations. Their study showed that the resistance to sharing data was simultaneously caused by (1) Privacy and security concerns (reflecting institutional laws and regulations, the ways in which specific organisational cultures cope with privacy and security, and real threats to security and privacy, given the type of data AI is used for), (2) Lack of understanding of the available and required data, (3) Lack of inter-organisational alignment between project interests and expectations around data sharing, and (4) Lack of engagement within the organisational hierarchy, leading to diverging expectations at the top and bottom levels of the organisation. This preliminary findings show how technology and data are interrelated with people (employees) and cultural aspects.

Table 5: Barriers within the element Processes

Element - Processes	Authors
- Not developing public business model for implementing AI solutions - Lack of appropriate digital transformation and reengineering of existing processes - Core processes not being as digital as possible to process large amounts of data usable for analysis - Poor integration of AI into existing processes - Organisational inertia - Lack of AI deployment guidelines that include criteria for standardising data collection and sharing	Campion et al., 2022 Chatterjee, 2020 Mikalef et al., 2019 Neumann et al., 2022 Schaefer et al., 2021 van Noordt & Misuraca, 2020a van Noordt & Misuraca, 2020b Wirtz & Müller, 2019

When studying the changes in processes related to AI adoption, the researchers (Chatterjee, 2020; Neumann et al., 2022; Schaefer et al., 2021; van Noordt & Misuraca, 2020a; van Noordt & Misuraca, 2020b; Wirtz & Müller, 2019) detected the following barriers: (1) Not developing a public business model for implementing AI solutions, (2) Lack of reengineering of existing processes, since (3) Core processes have to be as digital as possible to process large amounts of data usable for analysis and (4) Poor integration of AI into existing processes. Barriers to AI adoption, related to the process elements, while also having a wider impact, are organisational inertia and lack of AI deployment guidelines that include criteria for standardising data collection and sharing.

4 Conclusion

Artificial intelligence (AI) is entering our business and private spheres at a speed that was not expected a few years ago. Its adoption in the public sector is changing the internal and external processes of public institutions, thus enabling them to embrace the concept of 'smartness' and become more effective and efficient. As revealed in many studies, AI adoption is not only about the technology itself but, on the one hand, requires specific prerequisites, such as infrastructure (e.g. equipment, data management, maintenance, security) and changes in soft aspects of an institution's organisation (e.g. skills, management, culture etc.). Therefore, it is essential for policy- and decision-makers at all levels to understand possible barriers in several organisational elements when planning, implementing and regulating new technologies' adoption in public institutions.

Many authors have already stressed the importance of organisational factors that must be carefully managed when adopting new technologies. In their studies, Mikalef et al. (2019) discovered that the inertial forces and challenges are likely to delay implementation or reduce potential business value if appropriate measures are not taken at the early stages of projects and that the low levels of maturity are primarily a result of organisational or technical hindrances. Van Noordt & Misuraca (2020b) and Schedler et al. (2019) claim that barriers to adopting innovations in government remain the same, no matter what kind of innovation is introduced. They consider the following antecedents influencing the adoption of AI in the public sector: environmental, organisational, innovation-related, and individual.

The ongoing study highlights that five core organisational elements must be considered when introducing innovations into the existing institutions, such as people (e.g., employees – their skills, intrinsic and extrinsic motivation, change management) and organisational culture (e.g., innovativeness encouraging leadership, the experimentation allowing culture), both as soft elements, as well as structure (e.g., transitions at all levels of hierarchy, involvement of all departments, agile methods, collaboration with other stakeholders – private and public organisations), processes (e.g., reengineering of existing processes, preparing strategic plans for AI adoption) and technological infrastructure (e.g., ensuring and maintaining IT systems, data management) as hard elements of the organisational aspect of any public institution. The preliminary results imply that, when adopting AI, the focus is to be given to each organisational element since different possible barriers to AI adoption characterise each. Barriers must be carefully studied and eliminated on time to bring maximum benefits for all stakeholders of public institutions.

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