Expanding AI adoption in public sector organizations: perspectives on management practices

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Abstract

Purpose – The purpose of this study is to enhance the understanding of management practices that expand artificial intelligence (AI) adoption in public organizations.

Design/methodology/approach – The research approach is an exploratory study. Research data were collected from informants representing various organizations working for public or government services in Finland.

Findings – The findings of this study indicate that large-scale AI adoption is a complex process in the public sector. This study identified three main practices of AI adoption: technological design practices, AI project design and management practices and networking practices. Additionally, this study shows that several value drivers and barriers to AI adoption are related to technological, organizational and environmental dimensions. This study emphasizes the importance of developing cross-functional AI capabilities and resources, which are crucial for expanding AI initiatives across organizations and networks.

Practical implications – Expanding and scaling AI adoption across organizational boundaries requires new management practices and multidisciplinary teamwork, from technological skills to AI governance practices and change management.

Originality/value – This study contributes to the emerging research on management practices involved in AI adoption in the public sector.

Keywords Artificial intelligence, AI adoption, AI governance, Public sector

Paper type Research paper

1. Introduction

Artificial intelligence (AI) adoption in public governance remains in its early stages of implementation (Selten and Klievink, 2024; Straub *et al.*, 2023). Public organizations face a range of challenges when adopting AI (Neumann, Guirguis and Steiner, 2024; Misra *et al.*, 2023). Despite these challenges, AI offers several significant technological enablers that can enhance the effectiveness of public sector processes (Madan and Ashok, 2023; Wang *et al.*, 2020; Wirtz *et al.*, 2021).

AI reshapes the traditional decision-making processes of the public sector (Harrison and Luna-Reyes, 2022). As AI adoption also creates new tasks and roles within organizations (Maragno *et al.*, 2023b), it is essential to develop new management practices that support AI

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adoption. Therefore, studying AI adoption from the perspective of management practices is crucial, as AI technologies alone do not create value. Value creation requires changes in practices and processes, including close interaction among users, data, AI technologies, organizational factors and the environment (Desouza *et al.*, 2020).

In this study, AI adoption refers to the development, application and integration of AI into the administrative and service processes of a public organization. Madan and Ashok (2023) advocate for more studies on AI implementation in public administration. Recent AI research has highlighted the essential role of AI adoption in enabling the co-creation of value in public services (Madan and Ashok, 2023; Wirtz, *et al.*, 2021). However, prior research has rarely investigated this orientation from the lens of management practices during AI adoption. Maragno *et al.* (2023a) argue that the factors influencing AI adoption in the public sector are still not well understood, indicating a clear need for further empirical investigation. Thus, more research is needed on technological change and its management in the public sector, as new technologies present increasingly complex challenges (Andrews, 2019).

Selten and Klievink (2024) concluded that AI-enhanced transformation and disruption in public governance have not been realized, despite many articles emphasizing the potential of AI. While organizations have engaged in pilot projects involving AI, organization-wide scaling of AI is still in the early phases in most organizations. Organizations across different sectors have challenges in implementing and scaling AI in organizations (Sjödin *et al.*, 2021; Haefner *et al.*, 2023; Selten and Klievink, 2024). Prior research on the determinants of successful AI adoption remains limited (Maragno *et al.*, 2023; Neumann, Guirguis and Steiner, 2024). Understanding the potential barriers to AI adoption is crucial for public organizations to strategically plan and allocate resources for AI adoption, define relevant policies and co-create strategies (Rjab, Mellouli and Corbett, 2023). Thus, the purpose of this study is to enhance understanding of management practices to expand and scale AI adoption in public organizations. The Technology–Organization–Environment (TOE) framework (DePietro *et al.*, 1990) provided a special lens to analyze the drivers, barriers and management practices in this study.

The research question was as follows:

RQ1. How is artificial intelligence adoption managed in the organizations, and what value drivers, barriers and management practices do artificial intelligence adopters encounter during their artificial intelligence initiatives?

The remainder of this paper is organized as follows. In the following section, a review of the relevant literature is provided. Subsequently, the methodology and data used in the study are described. Then, findings from the interviews are examined. In the final section, the contributions, theoretical and managerial implications and limitations of the study are discussed.

2. Related work

2.1 The adoption of artificial intelligence in the public sector

AI offers ample opportunities to advance the digitization of service processes within the public sector (Madan and Ashok, 2023; Wang *et al.*, 2020; Wirtz *et al.*, 2021). Service processes in numerous public organizations involve large user volumes, numerous transactions and extensive manual paperwork. Hence, there is still a lot of room for improvements regarding data and AI practices and solutions (da Encarnacao, Anastasiadou and Santos, 2024; Lega *et al.*, 2024). AI holds significant and broad potential for enhancing human decision-making (Noorbakhsh-Sabet *et al.*, 2019), especially increasing effectiveness in administration (Ishengoma *et al.*, 2022). Berryhill *et al.* (2019) describe in an OECD working paper that AI will free up nearly 30% of public servants' working time, allowing them to focus on higher-value work duties. The AI adoption process is unlikely to be straightforward, as it introduces new challenges for public sector management (Andrews, 2019; Berryhill *et al.*, 2019). Hjaltalin and Sigurdarson (2024) identified three main approaches to AI adoption in the public sector: empowerment through information, enhanced administrative practices and improved service delivery. Additionally, public organizations must develop new ethical frameworks and governance practices to guide effective AI adoption (Bosco *et al.*, 2024).

2.2 Drivers and barriers of artificial intelligence adoption

Successful AI adoption depends on various factors, including drivers and barriers (Maragno *et al.*, 2023a, 2023b). Both drivers and barriers often exist simultaneously while adopting AI. AI adoption is a change process where current tasks, practices or processes are digitized and renewed. The socio-technical system theory suggests that social and technical factors should be considered in redesigning work and technologies (Sony and Naik, 2020). Digitization, such as AI adoption, is both a technological and social phenomenon (Haefner *et al.*, 2023; Lnenicka *et al.*, 2024). Thus, drivers, barriers and management practices do not occur in a social vacuum. Understanding the nature of drivers and barriers from a large perspective assists managers in public organizations to plan more effective management practices for AI adoption.

Molin (2024) found that cross-domain learning, legal priming and ecosystem growth are crucial pillars for successful AI adoption in a public organization. Maragno *et al.* (2023a) found that AI adoption affords, for example, more accurate and faster data analysis, the development of data-driven organizations, the automation of cognitive tasks, the augmentation of decision-making processes and the enhancement of data-driven services and advanced systems. Misra *et al.* (2023) found several challenges, such as trust and sustainability of AI systems, regulatory and legal uncertainty and lack of capacity and skill. Alshahrani, Dennehy and Mäntymäki (2022) also emphasize misalignment between AI and management decision-making, data sharing, ethics and governance concerns. Recent studies (Madan and Ashok, 2023; Rjab, Mellouli and Corbett, 2023) highlight barriers ranging from IT skills to organizational and cultural factors. Selten and Klievink (2024) found compliance with ethical and legal frameworks, separated data teams, lack of robustness and lack of technical expertise, the most common barriers in public sector organizations. Sun and Medaglia (2019) list similar challenges, but they also emphasize political and policy challenges. Maragno *et al.* (2023a) identified several key constraints, including difficulties in data collection, shortages of human resources, complex regulations, administrative silos and challenges in cooperating with suppliers.

The prior literature points out that there are various drivers and barriers to AI adoption in the public sector. The drivers of AI adoption in the public sector are starting points for AI adoption projects, which often vary between organizations. Similarly, the barriers of AI adoption are factors that resist organizations from starting AI adoption. Drivers and barriers are often two sides of the same coin; barriers for some can be drivers for other organizations. For example, capabilities can be both a barrier and a driver. Thus, organizations should strengthen drivers and minimize the effect of barriers for AI adoption.

2.3 Technology, organization and environment framework

The discussion above showed us that drivers and barriers of AI adoption have technology-, organization- or environment-related features. Successful AI adoption is a complex process, and it requires renewing of organizational structures, routines and processes and bringing together several expertise from different fields (Selten and Klievink, 2024). The TOE framework, introduced by DePietro *et al.* (1990), serves as a conceptual model widely used in studies to explain ICT implementation (Defitri, *et al.*, 2020; Madaki *et al.*, 2023) and AI adoption (Madan and Ashok, 2023; Maragno *et al.*, 2023a; Rjab, Mellouli and Corbett, 2023; Mwogosi, 2024) within public sector organizations. User preferences, organizations and institutional arrangements and the specific features of AI applications affect the organizations' readiness to adopt AI (Madan and Ashok, 2023). Thus, successful AI adoption is the result of a combination of technological, organizational and environmental factors that are deeply interrelated (Maragno *et al.*, 2023a).

Pumplun *et al.* (2019) extended the TOE framework to the requirements of AI. They included availability, data quality and protection and regulatory issues arising from the GDPR as new factors to the TOE framework. They explain the extended TOE framework as follows: Technological factors comprise two main aspects; the first one is the relative advantage, which states that with the help of AI, organizations can learn from data over time; the second aspect of technological factors is compatibility, which subcategories are AI-enhanced business processes and business cases. Organizational factors include culture, including top management support, change management and innovative culture, organizational size and structure and resources, including budget, employees and data. Environmental factors encompass competitive pressure, government regulations, industry requirements and consumer readiness.

Rjab, Mellouli and Corbett (2023) conducted a literature review about AI adoption barriers in smart cities by applying the TOE framework. They found 18 barriers, which they grouped into three main categories: technology, environment and organization. Similarly, Madan and Ashok (2023) conducted a literature review where they identified factors influencing AI adoption from the viewpoint of the TOE framework. They found IT assets, IT capabilities and perceived benefits to be the main factors in the technology context, whereas organizational culture, leadership and inertia belong to the organizational context, and vertical and horizontal pressures represent the environmental context.

2.4 Management practices in artificial intelligence adoption

The specifics of management practices vary across organizations (Delmas and Toffel, 2004; Bloom *et al.*, 2012; Bloom *et al.*, 2019). These practices play a significant role in organizational performance (Bloom *et al.*, 2019). Systematic and well-defined practices offer process-oriented and actionable guidance for AI developers and managers (Papagiannidis *et al.*, 2023). In this paper, we define management practices as systematic, process-oriented managerial behaviors aimed at setting goals, organizing resources and managing and monitoring actions to achieve desired outcomes that align with organizational targets and strategies in AI adoption. Chen and Lee (2007) list several managerial practices, including planning, problem-solving, consulting, delegating, motivating, networking, supporting, developing and monitoring. Accordingly, management practices vary depending on the development goals and the phase of AI adoption – whether in the design, development, implementation or use of AI solutions.

Campion *et al.* (2022) studied the organizational routines that managers use to overcome challenges. These routines are closely linked to organizational practices. In their study, public sector organizations used routines to manage challenges such as demonstrating the benefits of data sharing, working on-site, reframing problems, designating joint appointments and boundary spanners and connecting participants at all levels of the collaboration around the project. AI adoption also affects the organizational design of public sector organizations by altering task division, task allocation, information provision and reward systems (Maragno *et al.*, 2023b). Therefore, organizations must plan, organize and manage these changes in working practices when implementing AI initiatives.

Successful AI adoption requires the combination of technology, organization and environment contexts (Maragno *et al.*, 2023a, 2023b; Mwogosi, 2024). The balance combination of TOE perspectives is also important in scaling AI initiatives across organizational sectors and barriers. Hjaltalin and Sigurdarson (2024) found that efficiency and service delivery dominate AI development strategies in the public sector, whereas citizen engagement, for instance, appears to be underemphasized. Thus, AI investments have primarily focused on technological and organizational domains, whereas environmental opportunities – such as benefits for citizens – have remained underused. Therefore, Hjaltalin and Sigurdarson (2024) call for a stronger focus on broader societal outcomes.

3. Methodology

3.1 Research design

The research design is an exploratory study about the less-researched phenomena. This research design is valid for situations where new insight and understanding are needed on less-researched topics. The adoption of AI in the public sector is still in its infancy (Straub *et al.*, 2023), and there is still limited understanding and experience from its adoption in real-life settings. This study applied a qualitative interview research design to thoroughly explore under-researched phenomena and experiences (Gummesson, 2000). The perspective of this study is more organizational than an individual viewpoint in AI adoption. The participants represent their organization. The qualitative approach using an exploratory study was chosen (Carvalho, *et al.*, 2005), as research questions necessitate in-depth qualitative descriptions and new insight into managing AI adoption.

3.2 Participants

This study consisted of 22 participants (Table 1) selected through purposive sampling from individuals working on digital and AI adoption in the public sector. They represented a rich sample appropriate for in-depth qualitative analysis and ensured thematic completeness in forming new theoretical understanding of less researched phenomena. To address the research questions, research data were collected from informants representing various organizations working for public or government services in Finland. The data includes informants from seven city organizations, two ministries, four government organizations, five educational organizations and four private organizations solving public needs. The participants of this study represent top and middle management and experts who have experience with AI or digital service adoption. Thus, the interviewees consist of AI adopters, as well as specialists and managers dealing with large masses of data or digital development projects. In selecting the target group, the selection criterion was to obtain diverse perspectives from organizations of various sizes and types. Therefore, small and large municipalities, ministries and institutions, educational institutions and semi-public organizations were selected. Participants were required to understand the basics of AI to ensure the research data represented relevant information about the subject of study. Some organizations and participants were highly experienced; others were beginner adopters with large data sets. This ensured that the research data represents relevant information on the adoption and management of AI as part of public services, contributing to the validity of this study.

The selection of participants for AI adoption interviews was guided by criteria aimed at ensuring diverse and representative samples of real-life phenomena (Eisenhardt and Graebner, 2007). Furthermore, these participants were either recognized by the researcher as

Table 1. Participants

No.	Title of participant	Organization	Size and functions of the organization
1	Top management	City organization A	Small; Function: Manages and develops municipal processes and services
2	Middle management	City organization B	Large; Function: Manages and develops municipal processes and services
3	Top management	City organization C	Large; Function: Manages and develops municipal processes and services
4	Middle management	City organization D	Small; Function: Manages and develops municipal processes and services
5	Middle management	City organization (a service sector) E	Large; Function: Manages and develops municipal processes and services; a service sector perspective in this case
6	Middle management	City organization (a service sector) F	Large; Function: Manages and develops municipal processes and services; a service sector perspective in this case
7	Middle management	City organization G	Small; Function: Manages and develops municipal processes and services
8	Middle management	Government organization a	Middle size; Function: Manages documents, processes and reports and develops its systems
9	Middle management	Government organization B	Large; Function: Manages documents, processes and reports and develops its systems
10	Middle management	Government organization C	Middle size; Function: Manages and develops educational processes and services
11	Middle management	Government organization D	Large; Function: Manages documents, processes and reports and develops its systems
12	Middle management	Ministry a	Large; Function: Manages and develops functions, processes and responsibilities in its administrative branch
13	Top management	Ministry B	Middle size; Function: Manages and develops functions, processes and responsibilities in its administrative branch
14	Expert	Educational organization a	Middle size; Function: vocational education services
15	Top management	Educational organization B	Middle size; Function: vocational education services
16	Middle management	Educational organization C	Large; Function: higher education services
17A	Top management	Educational organization D	Small; Function: higher education services
17B	Top management	Educational organization D	Small; Function: higher education services
18	Top management	Private organization solving public needs a	Large; Function: Develops and implements ICT services for public sector

(*continued*)

Table 1. Continued

No.	Title of participant	Organization	Size and functions of the organization
19	Middle management	Private organization solving public needs B	Small; Function: Provides services for entrepreneurs and companies in its region
20	Expert	Private organization solving public needs C	Small; Function: Develops and provides services in its region
21	Expert	Private organization solving public needs C	Small; Function: Develops and provides services in its region

Source(s): Created by the author

advanced AI or digital service adopters or recommended based on their experience with large volumes of data, where the value potential for AI is significant. The researcher selected participants based on their role in the organization. If the organization had a person responsible for AI adoption and development, then they were primarily asked for interviews. Second, a person knowledgeable about AI initiatives in the organization was selected. To avoid selection bias, the researcher did not recruit interviewees through social media. Instead, he selected individuals who are knowledgeable about digitalization and AI implementation initiatives within their organization. However, the study sample did not solely consist of AI enthusiasts, as the interviewees raised critical viewpoints during the interview.

3.3 Data collection

The researcher reached out to potential interviewees by sending them an email in which he outlined the study's objectives and inquired about their willingness to participate as informants. After the interviewees replied with their acceptance to participate in the study, thus providing informed consent, the researcher scheduled the interviews. This research followed the ethical research guidelines of the Finnish National Board on Research Integrity (Tekn, 2019). The interviews were conducted as Microsoft Teams meetings, with each session lasting an average of 45 min. All interviews were video-recorded and transcribed by Microsoft Teams to enable qualitative content analysis. Only one interview was conducted in a face-to-face meeting, and it was audiotaped and transcribed.

The methodological approach consisted of semi-structured interviews. The semi-structured interview approach is a versatile and flexible data collection practice (Kallio, *et al.*, 2016). It suits research topics that are still evolving and involve interviewees at different stages of development with varying experiences in the field. The interview focused on the following main questions: What is the current state of AI applications? What opportunities do you see? Which processes could benefit from it? What obstacles are there to AI adoption? What would be the minimum level of expertise required in the organization at different levels when implementing AI solutions? What collaboration should take place between different departments when implementing AI? AI can enhance task and resource allocation and management. What kind of task volumes do you have, and how are they managed? Where are they located, who is responsible and could they be optimized with AI? What ethical or reliability issues related to AI have you observed, or should they be considered?

3.4 Data analysis

The data analysis of this study is a qualitative content analysis (Schreier, 2012) that included an inductive approach. More specifically, the Gioia methodology (Gioia *et al.*, 2013) was applied in data analysis and in forming new theoretical understanding. The same researcher who planned the research conducted interviews and data analysis. Thus, the inter-coder reliability method was not applicable. However, the researcher reviewed several iterations of the quotes and their codes to minimize misunderstandings of themes and coding categories. The analysis consists of four phases, which are described below.

In the first round of coding, the preliminary themes included “the current state of AI adoption in the organization,” “opportunities,” “obstacles,” “competence needs” and “collaboration”. These initial themes were derived from the interview categories and aligned with existing literature on AI adoption. Shortly after the coding process began, new overarching themes – such as “drivers,” “change management” and “development” – emerged from the data. Consequently, the analysis proceeded by marking all relevant excerpts from the transcribed interviews according to these refined main themes. During this conceptual coding process, quotations mentioning or explaining these main themes were highlighted with different colors in the interview transcripts. All other material was excluded from the research data of this study. In this first phase, the quotes of transcribed data were kept authentic by using direct quotes from the data. During this phase, the researcher’s interpretation was minimal as he collected authentic citations from quotations that belonged to the same main themes. This first round assisted the researcher in focusing on the more detailed analysis of the interview data in the second coding round.

In the subsequent and more detailed analysis, following the Gioia methodology, the grouped direct quotations were organized into a separate Word document according to their conceptual categories. In the second phase, the researcher conducted a reanalysis of the main thematic content. For instance, the quotations categorized under the themes “current state,” “change management” and “development” reflected the interviewees’ descriptions of management practices. Consequently, the researcher concentrated on the themes of “drivers,” “barriers” and “management practices” during the second round of coding. All relevant quotations were reassigned to these new main codes, while unrelated data was excluded. During this second round of coding, all pertinent quotations from the first phase were selected for further analysis. Similar direct quotations were then categorized into new descriptive themes using data-driven open coding, rather than conceptual coding. Thus, they formed new and more detailed thematic content-based categories, such as “More user-friendly AI solutions speed up AI adoption” or “Various rule-based work duties and decisions.” These sub-themes formed the first-order concepts (Tables 2–4). In line with the principles of qualitative analysis, quotations were selected for this analysis if they were relevant to the research questions and provided meaningful insights. As the aim was not to generalize the findings, even single but innovative and insightful quotes from a few participants were accepted, as they enhanced the depth and originality of the conceptualization. This second round of analysis followed the principles of data-driven open coding, a data analysis method without predefined coding categories (Gioia *et al.*, 2013; Strauss and Corbin, 1998). After this action in this second coding round, the recoded sub-themes were grouped according to the technology, organization and environment categories following the TOE approach (DePietro *et al.*, 1990), such as “Technology-related drivers” or “Organization-related drivers.”

In the third coding round, the second-order themes were formed by analyzing and reviewing similarities and connections between the first-order concepts to identify new abstract themes that describe similar concepts (Gioia *et al.*, 2013). As a result of this phase,

Table 2. Drivers for artificial intelligence adoption in the public sector

The TOE category	First-order concepts	Second-order themes	Aggregate dimensions
Technology-related drivers	• AI technologies become easier to develop that lowers technological barriers • More user-friendly AI solutions speed up AI adoption • Many employees are using AI tools autonomously in their work	Ease of use Easier, ready-made AI tools	Improving usability
Organization-related drivers	• Public organizations process a lot of reports, plans and memos, which could be automated • Many public organizations need to manage, control and maintain large masses of physical assets, which could be automated • Some government organizations have exceptionally large and focused data volumes • AI can easily perform certain work tasks or support them • Various rule-based work duties and decisions • Many decisions are basically transparent or public • A complex decision-making environment with various stakeholders calls for new technological solutions • The preparation of laws, plans, etc., requires extensive background research • Cities are multi-sector or ecosystem actors • AI could assist with understanding the background variables of various numbers and phenomena • Old practices do not work anymore • Quality program drivers change	Large data masses Many easy, rule-based tasks Open decision-making Complexity of planning processes Decision-making support needs Internal pressure to renew	Data-driven decision-making opportunities

(*continued*)

Table 2. Continued

The TOE category	First-order concepts	Second-order themes	Aggregate dimensions
Environment-related drivers	• Labor shortage forces to automate processes • The city is growing faster than its staff • Changing financial models, economic situations or production programs forces us to seek new means to improve efficiency • Small organizations need to seek new productivity means • EU regulation provides the framework within which one can safely operate • Political decisions encourage to develop new digital solutions such as AI	Labor shortage Financial pressure for renewing Political pressure for renewing	Strong external pressure to renew

Source(s): Created by the author; main TOE categories adapted from DePietro *et al.* (1990)

Table 3. Barriers to artificial intelligence adoption in the public sector

The TOE category	First-order concepts	Second-order themes	Aggregate dimensions
Technology-related barriers	• Lack of basic understanding regarding the potential AI applications • Old thinking models or skills	Technological competences	Technological competence gap
Organization-related barriers	• Lack of basic understanding regarding the opportunities of AI value propositions and their use cases • Service design skills for AI development • Competence and continuous learning • Lack of time • Lack of funding • Lack of key resources • Seeing the AI project difficult, slow down starting new AI adoption initiatives • Different perspectives • Negative attitude toward AI adoption • Negative thinking models • Poor prior experiences slow down starting new AI adoption initiatives • The prudence of officials and issues of responsibility • Silo-like thinking • Crossing the organizational boundaries • Managers' understanding of how to apply AI • Change of operating culture	Design competences Lack of resources Conflicting expectations Attitude Working culture Leadership	Insufficient AI capabilities Management challenges for AI adoption

(*continued*)

Table 3. Continued

The TOE category	First-order concepts	Second-order themes	Aggregate dimensions
Environment-related barriers	• Challenges regarding understanding different stakeholders hinder cross-functional cooperation • The interest of different actors in the ecosystem	Cross-functional cooperation	Networked collaboration
	• Transparency rules, trustworthiness of AI, and data protection slow AI adoption • Legal obstacles to trying • Security issues • Humans need to make final decisions according to the law	Putting regulations and security into practice	Application of regulation

Source(s): Created by the author; main TOE categories adapted from DePietro *et al.* (1990)

Table 4. The identified management practices of artificial intelligence adoption

The TOE category	First-order concepts	Second-order themes	Aggregate dimensions
Technology-related practices	• AI design capability • Integrate AI systems into the existing software systems • Ethical AI design and development • Transparent and explainable solutions	Identify different requirements for planning	Technological design practices
Organization-related practices	• Linking AI initiatives to the strategy and culture of the organization • Identifying use cases where AI is easy to integrate • Change management for integrating AI into renewing processes and operations • Emphasizing benefits and added value • Change agents who promote new practices • Reducing fear related to AI • Communication, tutoring and training at all levels of the organization • AI-related experiments create new understanding • AI is a moving target that requires continuous adaption • Sufficient personnel resourcing • A multidisciplinary expert group that can support AI initiatives • Ethical evaluation of AI initiatives	Define productive use cases Planning of effective change management Competence development initiatives at all levels Multidisciplinary approach in planning AI adoption	AI project design and management practices
Environment-related practices	• Involving stakeholders in the AI initiatives • Cooperation of different organizations to increase data volumes	Collaboration outside of the organization	Networking practices

Source(s): Created by the author; main TOE categories adapted from DePietro *et al.* (1990)

the researcher developed second-order themes, which were then grouped and summarized into aggregated dimensions that are the new theoretical constructs. Thus, in the fourth phase of analysis, the aggregated categories were formed. They emerged from the material without predefined conceptual coding categories. The results revealed that the interviewed participants reported several similar issues, allowing for the construction of a common understanding. Despite some interviewees being advanced AI adopters, while others were experienced users or beginners, they often emphasized similar thoughts.

Regarding data saturation (Saunders *et al.*, 2018), the researcher soon began to observe recurring instances in coding, particularly in identifying drivers and barriers. Consequently, data saturation was achieved well before all interviews were coded, although some interviews provided more new insight than others. This observation is consistent with the study by Guest, Bunce and Johnson (2006), which revealed that the fundamental elements of meta themes can be identified in as few as six interviews, with data saturation occurring after 12 interviews. However, thematic saturation regarding basic management practices was reached during the analysis of interviews with more advanced AI adopter organizations. In all, 22 interviews enabled both data and thematic saturation. The researcher was able to answer the research questions and form theoretical categories and models by linking the findings and the TOE model, thereby achieving sufficient theoretical saturation (Saunders *et al.*, 2018).

Several methods were used to enhance the trustworthiness of the analysis, as qualitative analysis may have inherent weaknesses in interpreting interview transcripts (Eisenhardt and Graebner, 2007). The empirical data and findings were contextualized within the existing literature and the framework of AI adoption in organizations at a general level. The Gioia methodology (Gioia *et al.*, 2013) provided a grounded theory approach to inductively structure data from single sentences or thoughts into theoretical constructs. Additionally, the aggregated dimensions – representing a new theoretical interpretation of the empirical findings – were reviewed and aligned with relevant literature. This process allowed the researcher to develop a deeper theoretical understanding and create a conceptual model related to the findings and their interrelationships. Regarding methodological limitations, the qualitative approach used in this study does not permit direct generalization of the findings to all public sector organizations. Furthermore, as the data sample reflects this phenomenon specifically within the Finnish context, the generalizability of the results to other countries is inherently limited.

4. Findings

4.1 Drivers for the adoption of artificial intelligence

Several drivers were mentioned regarding the adoption of AI (Table 2). Enhanced productivity and effectiveness through better decision-making are naturally significant drivers because organizations are implementing AI to their processes. The processes of the public sector produce a lot of paper such as various reports, plans and memos, which create a large source of information and a mass of data for natural language processing. As digitization of the public sector increased productivity, AI is expected to be a driver for better transparency, productivity and effectiveness. An informant of an advanced AI adopter from the government organization put it that way:

- The productivity aspect is really important and specifically in the context of tightening public economics, so we have great expectations and investments for these issues that we will find those productivity gains. (Number 11)

- The reason we're developing this is that we want to stay at the forefront. We see it as a competitive advantage, but it requires a lot of work hours, and it requires Euros. (Number 15)

The decision-making environment is often complex in the public sector, and there are several stakeholders. The public sector also has large masses of assets such as buildings, roads, streets, bridges, powerlines and other infrastructure. Additionally, planning, developing, using and maintenance of those buildings and other infrastructure generate numerous interactions and communication needs. This creates new value and productivity potential for the use of AI, as AI can analyze large data masses by combining different data sources:

- Artificial intelligence could play a significant role in planning something like this, that urban planning is a good example of how complicated it is when you have to think about traffic flows, and you have to think about housing and jobs and education, and everything, and then there will be a lot of hassle. (Number 3)
- Very little pre-processing of data is needed for neural networks. (Number 16)

The findings show several drivers for adoption of AI, such as labor shortage in municipalities, old practices are no longer enough in a changed situation, a change in the financing model forces an organizational change, quality management, seeking a competitive advantage or the goals of productivity programs:

- When it's a growing city, your own team is getting smaller and the number of residents and the number of businesses are growing at such a terrible speed, there's no other solution in the equation than to automate. (Number 4)
- And fragmentation and all, and like those expectations that are associated with this activity, are quite high. But there are so few people working on this, so we can't manage this manually in any way. (Number 3)

AI models continually develop and require less training data, which finally speeds up development processes. Personal use of consumer-type AI applications at work lowers the barriers to adopting other AI solutions. The decisions of top management, policymakers or high-level decision-makers may also drive AI adoption. The findings show that AI is seen as a key technology in developing the digitization of public administration and public services:

- The state administration's productivity program is being launched, and now the aim is to improve efficiency and save, so maybe that is one path through which this utilization of artificial intelligence can be done. (Number 12)

4.2 Barriers to artificial intelligence adoption

The barriers are presented in Table 3. Most interviewees mention the lack of basic understanding regarding the opportunities of AI as the biggest barrier for AI adoption. The informants expect more knowledge on how to identify value propositions, potential applications and use cases and how to proceed in AI adoption:

- Just how can you really use it properly and just the reliability of the information and all such things in a way as if there was a general understanding of it. (Number 14)

Lack of time and funding were mentioned as obstacles, as they are evidently barriers in many other development projects as well. Additionally, attitude was mentioned as a barrier:

- First of all, there's a really bad lack of time, you see. (Number 7)

- Well, like with anything new, you know, the biggest obstacles are probably between our own ears. (Number 12)

Interestingly, undeveloped technology was not mentioned as a barrier. However, poor prior experiences in trying AI have slowed implementation. The lack of use cases was seen as an obstacle. Poor experiences are related to not only AI adoption but also unclear use cases and their benefits:

- At that time, like IBM Watson and others got a lot of attention, and it [our AI initiative] was done as a big project. However, for various reasons, it never reached completion. (Number 11)

The prudence of officials and issues of responsibility were also mentioned as barriers. This is evidently a public sector specific feature, as officials have responsibility for taxpayers. AI projects are seen as difficult ones, and transparency rules, trustworthiness and data protection were also seen as obstacles. The different perspectives and understanding problems of different stakeholders were also seen as a barrier.

4.3 Practices for boosting artificial intelligence adoption

It was found that AI projects especially require change management, because operational processes and operating methods should change at the same time. The interviewees stated that transforming organizations to adopt AI is a slow process. It also requires training, examples, change agents and communication about AI's positive outcomes and good management:

- It was really hard to get people to learn about what information they expect to need to make a decision. It's definitely a generic digitization challenge, namely, implementing the changing practices of an organization. (Number 8)
- This is a management issue, and we should reassure people that AI will not take or do their jobs but rather help them perform their work more effectively and better. (Number 16)

It was also pointed out that during the change process, the need for resources and the amount of work can be temporarily greater than before. AI adoption should be connected to the organization's strategy, processes and culture; otherwise, the AI pilots will remain a detached exercise of a few enthusiastic pioneers:

- It is managed that it is so that it is a part of that strategy and the management culture and operating culture. (Number 12)

Experiments and pilot projects help organizations to collect evidence about the benefits of AI solution proposition. However, the staff of the organization should also adapt their thinking to incorporate the use of AI in their work:

- Technology itself is quite mature in most parts, but we as humans need to change our thinking patterns, we need to change our actions, thoughts about action models, even in our context, just a moment, that we can think about things from a completely different perspective. (Number 11)
- The group affected by the change tends to form its own kind of change leadership around the [AI] case. People often assume that there is a designated manager somewhere who is responsible for leading the change. (Number 5)

In the interviews, it was noted that the AI-enhanced change must be implemented across the entire network, especially as the network is often extensive and many end-users might work outside of the organization. If AI applications are integrated into existing systems, then AI adoption becomes easier. Identifying easy and "low-hanging fruits" is important, as it lowers barriers. It is also important to recognize practices and processes where AI does not yet provide value.

Networks, cooperation, tutoring and training were raised as means of competence development regarding AI adoption. A government organization (Number 9) has an AI expert group that has provided value in advising, defining the ethics of AI, implementing and making new ideas regarding AI adoption. The interviews also brought up the fact that advising and development groups should be multidisciplinary teams. Additionally, the teams should have representatives from different levels of the organization ensuring the input of all stakeholders. Successful AI adoption requires the development of basic understanding in all levels of organizations although AI will be bought as a service:

- […] to kind of understand the basic principles and limitations of artificial intelligence. You can try out your own AI solutions or train AI models, which can nowadays be done without coding. (Number 16)
- We do not develop any solutions in-house; instead, we purchase them commercially. In practice, the key issue is having the competence to clearly communicate our needs. (Number 13)

AI adoption requires continuous learning from all staff to keep up with its development pace alongside your current work duties. It was mentioned that AI experiments teach themselves when users learn from using AI.

5. Discussion

5.1 Theoretical implications

The findings of this study provide new empirical evidence about the management practices required for designing, developing and implementing AI projects within organizations. Prior research on the management practices of AI adoption in the public sector is scarce. Thus, this study took a holistic and in-depth approach to this challenge by reviewing management practices in technological, organizational and environmental contexts for expanding AI adoption across organizational silos. Several prior studies have focused on drivers and barriers of AI adoption (Misra *et al.*, 2023; Molin, 2024; Neumann, Guirguis and Steiner, 2024), but there are also some attempts to conceptualize broader organizational perspectives on AI adoption in the public sector (Maragno *et al.*, 2023b; Hjaltalin and Sigurdarson, 2024; Selten and Klievink, 2024). In addition to public sector studies, this paper contributes to management literature and organizational theories (Carlile, 2002, 2004) by highlighting the need for cross-organizational and multidisciplinary working practices in managing new knowledge across organizational boundaries.

This study also provides a scientific contribution to the management of AI by demonstrating the tense relationship between value drivers and barriers. Value drivers motivate investment in AI initiatives, whereas barriers hinder the initiation of AI adoption. Therefore, proven management practices are needed for providing new means to tackle those opportunities and challenges. Thus, this study enriches the emerging literature on AI adoption management (Selten and Klievink, 2024). Aligned with prior research (Maragno *et al.*, 2023b; Selten and Klievink, 2024), this study reveals that AI adoption changes organizations. This study empirically demonstrates that expanding AI adoption requires new multidisciplinary management practices in several areas of organizations, for example, from requirement specification to use case selection, competence development and external networking.

A general challenge in AI adoption is that organizations should be able to implement and expand AI effectively (Sjödin *et al.*, 2021; Haefner *et al.*, 2023; Selten and Klievink, 2024). Although single AI pilot projects provide hands-on experiences with using AI, they do not expand organization-wide management practices unless they are operationalized as technological, organizational and environmental-oriented practices. The systematic managerial approach is necessary to organize, resource, develop and manage new AI-enhanced development projects across organizations and administrative sectors. This study particularly enhances our understanding of management practices by demonstrating that successful management practices of AI adoption are a key issue in developing AI adoption. Aligned with prior research (Sjödin *et al.*, 2021; Haefner *et al.*, 2023; Selten and Klievink, 2024), this study deepens our understanding that public organizations particularly face difficulties in scaling and promoting AI initiatives. This study provides an in-depth understanding of how AI adoption functions as a practice-based initiative for establishing new design, development and implementation practices. Organizations identify AI-enabled opportunities and address barriers through management practices that span technological, organizational and environmental dimensions. Specifically, the technological dimension defines enablers for the design process; the organizational dimension outlines implementation phases; and the environmental dimension offers guidelines for networking and collaboration with external stakeholders and regulatory compliance. Accordingly, the value drivers and barriers of AI adoption are closely linked to these management practices (Figure 1). In line with the TOE framework (DePietro *et al.*, 1990), the drivers and barriers of AI adoption correspond to the technology, organization and environment dimensions. This multidimensionality makes the expansion of AI adoption from pilot projects to large-scale organizational practices a complex undertaking.

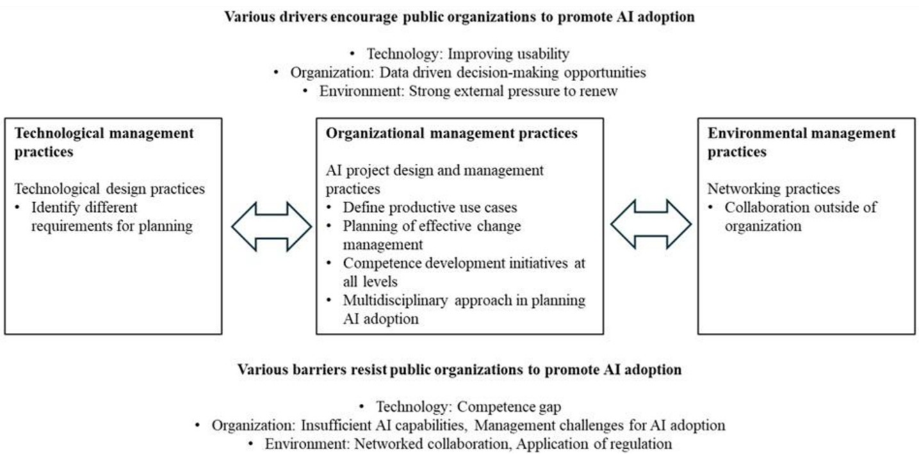

Figure 1. The conceptual framework for promoting artificial intelligence adoption in public sector organizations

Source: Created by the author; main TOE categories adapted from DePietro *et al.* (1990)

This study reveals that various management practices for boosting AI adoption can be crystallized into technological design practices, AI project design and management practices and networking practices. Technical design practices focus mainly on requirement specification – a critical decision-making phase for planning AI adoption. AI project design and management practices are associated with the use case selection, change management, competence development and multidisciplinary collaboration. Networking practices relate to stakeholder engagement and cooperation with other organizations. The results support the prior studies (Molin, 2024) that emphasize the role of cross-domain learning and ecosystem growth. Consistent with the findings of Hjaltalin and Sigurdarson (2024), this study emphasizes the importance of understanding the societal impacts of AI adoption. AI adoption is not merely an internal development project; it also encompasses broader environmental dimensions, ranging from the implementation of regulatory and security measures to the user experiences of citizens and other stakeholders.

The findings contribute to the TOE literature in the public sector (Defitri, *et al.*, 2020; Madaki *et al.*, 2023; Maragno *et al.*, 2023a) by proposing a framework for AI adoption management practices. Achieving large-scale and sustainable AI adoption requires organizational transformation at all levels. Managers must actively drive these changes both within their organizations and in external stakeholder environments. The rapid pace and complexity of effective AI implementation compel public sector leaders to revise their AI-related management practices. Aligning with prior research (Mikhaylov, Esteve and Campion, 2018; Campion *et al.*, 2022), this study highlights the importance of cross-organizational collaboration in AI adoption. The development of AI project design, management and networking practices is a long-term initiative, as organizations should continuously develop their employees' and stakeholders' capabilities. The development of basic AI capabilities, that is, AI literacy, should also focus on an environment where citizens and other stakeholders are end-users of AI-enhanced public services. A lack of shared understanding and knowledge transformation are major challenges in organizational development (Carlile, 2002, 2004), creating knowledge boundaries between different functions in AI adoption. Competence development practices and AI literacy programs promote a common understanding among all stakeholders (Alamäki *et al.*, 2024). Environmental drivers are associated with strong external pressure to innovate because of labor shortages, financial constraints and political pressure. These findings underscore the importance of environmental drivers, contributing to institutional theories (Delmas and Toffel, 2004), particularly studies on governmental, political and regulatory pressures. Regulatory pressure is especially relevant, as AI adoption is regulated in several countries. Political and financial pressures necessitate the continual development of public service effectiveness, while governmental pressure promotes e-governance initiatives.

The findings did not provide clear evidence that the results would vary across different types of AI applications. However, factors such as data sensitivity, AI regulation and the active involvement of citizens may influence the implementation of AI-related practices. The findings indicate that the nature of an organization is associated with the adoption of AI. Compared to government organizations or ministries, municipalities are multidisciplinary organizations with multiple functions. Government organizations and ministries have a more focused task area, leading to more concentrated data sources and higher data volumes. Consequently, the processes in cities that can be automated are more scattered and involve lower volumes compared to government organizations, which typically handle larger volumes within their specific sectors nationwide. The interview data suggests that cooperation between municipalities could help address resource shortages in developing dedicated AI solutions for specific needs.

5.2 Practical implications

This study highlights that effective and scalable AI adoption requires several management practices and cross-functional cooperation in organizations. Implementing the proposed framework requires the establishment of a multidisciplinary AI management team, which should first develop an AI roadmap outlining long-term development goals and actions. Although large-scale AI adoption in the public sector remains in its early stages, this study recommends initiating long-term, strategic AI adoption programs rather than isolated, technology-centric pilot projects. Collaboration and networking with other public administrations can significantly accelerate learning and help mobilize additional resources. Thus, public policymakers could use the results of this study to create AI strategies and practical guidelines for fostering inter-organizational AI management practices and collaboration in scaling AI initiatives across administrative sectors. Additionally, the results could be used to design training programs aimed at increasing the AI literacy of public sector employees. Vocational and higher education organizations could benefit from this study in developing curricula for data and AI governance and management practices.

6. Limitations and future research

The basic limitation of this study is the relatively small target group and geographical limitation, which limit the generalizability of the findings. Additionally, the study did not focus on specific functions of the public sector but reviewed this phenomenon by interviewing key persons from different organization types who are all dealing with public sector services. Although this makes research data richer and the key principles of AI adoption did not significantly differ between organization types, it is, however, a limitation for a deeper understanding of a specific phenomenon. The findings primarily represent the situation in Finland, but the theoretical and practical implications can be cautiously applied to other countries. In future research, to minimize selection bias, different stakeholders of AI initiatives should be interviewed to ensure a richer diversity of perspectives. The testing of the proposed framework in different national contexts warrants further examination. Additionally, this study identified key management practices, yet AI adoption is a long-term process involving multiple stages. These stages warrant further investigation, particularly to understand typical trajectories in public sector digitalization. Moreover, the dynamic interplay between technological, organizational and environmental dimensions, and their varying emphasis across contexts, calls for additional research. Existing research on institutional, governmental, political and regulatory pressures influencing AI adoption remains limited, underscoring the need for further investigation, particularly as this study has identified multiple such pressures. Additionally, this study emphasizes the importance of examining the environmental dimensions of AI adoption. Future research should also make a clearer distinction between various AI solutions, as AI will soon be a natural part of almost all information systems.

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