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Exploring artificial intelligence adoption in public organizations: a comparative case study

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ABSTRACT
Despite the enormous potential of artificial intelligence (AI), many public organizations struggle to adopt this technology. Simultaneously, empirical research on what determines successful AI adoption in public settings remains scarce. Using the technology organization environment (TOE) framework, we address this gap with a comparative case study of eight Swiss public organizations. Our findings suggest that the importance of technological and organizational factors varies depending on the organization's stage in the adoption process, whereas environmental factors are generally less critical. Accordingly, this study advances our theoretical understanding of the specificities of AI adoption in public organizations throughout the different adoption stages.

KEYWORDS Artificial intelligence; AI; public organizations; public administration; technology adoption; TOE framework

1 Introduction

Whether and how new technologies subsumed under artificial intelligence (AI) could be used in public organizations has been much debated in recent years. While there is justified scepticism and fear that governments using AI may become too technocratic (Janssen and Kuk 2016), jeopardize privacy (Maciejewski 2017), reinforce inequalities, and even threaten democracy (Eubanks 2017; O'Neil 2016), it has also been pointed out that AI offers a plethora of opportunities for the public sector.

Thanks to the availability and use of large data sets and transactional data[1] and hardware developments, governments could realize new goals (Ulnicane et al. 2021; Margetts and Dorobantu 2019; Hitz-Gamper, Neumann, and Stürmer 2019), such as better decision-making and forecasting, improved communication between government and citizens, personalized public services, reduced administrative burdens (Androutsopoulou et al. 2019; Margetts and Dorobantu 2019), a generally better quality of public services, and improved public value creation (Bullock 2019; Wang, Teo, and Janssen 2021). A number of AI application areas have been identified, such as knowledge management, process automation, conversational

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agents and assistants, predictive analytics, fraud and threat detection, resource allocation, and supporting expert tasks (Mehr, Ash, and Fellow 2017; Wirtz, Weyerer, and Geyer 2019). Unsurprisingly, public organizations are increasingly considering adopting AI technologies (Sun and Medaglia 2019) and have started to issue policy documents about the use of AI (Ulnicane et al. 2021). However, while in certain early-adopter countries (e.g. the US or the UK), the use of AI in the public sector is increasing, there are many public organizations where productive applications remain rare (Mikalef et al. 2021; Oxford Insights 2020; Margetts and Dorobantu 2019; Wirtz and Müller 2019). AI in government is often at an experimental stage (Margetts and Dorobantu 2019), or traditional automation solutions are wrongly labelled 'AI'.

Even if the body of research about AI in the public sector has been growing recently (Sousa et al. 2019), empirical studies in public sector settings are scarce (Campion et al. 2020; Sun and Medaglia 2019). Some notable exceptions have studied the role of AI in administrative discretion and transparency (Ahonen and Erkkilä 2020; Bovens and Zouridis 2002; Justin, Young, and Wang 2020; Criado, Valero, and Villodre 2020; de Boer and Raaphorst 2021; Peeters, Giest, and Grimmelikhuijsen 2020), organizational changes caused by introducing AI in predictive policing (Meijer, Lorenz, and Wessels 2021), chief information officer perceptions and expectations of AI in the public sector (Criado et al. 2020), public value creation through AI (Wang, Teo, and Janssen 2021), and the application of AI in a pandemic (Cheng et al. 2021). However, only a handful of empirical studies exist on determinants of successful AI adoption within public organizations (Campion et al. 2020; Chen, Ling, and Chen 2021; Schaefer et al. 2021; Sun and Medaglia 2019; Wang, Zhang, and Zhao 2020). Given that AI is a highly complex, general-purpose technology with many new potential application areas (Jöhnk, Weißert, and Wyrtki), we believe that the lack of research on the mechanisms of AI adoption constitutes a significant research gap. Particularly, empirical evidence is needed about the specific challenges and facilitating factors in the adoption process of AI projects in public sector practice (Wirtz, Langer, and Fenner 2021) to bridge theoretical considerations about AI usage and practical implementation.

This study addresses this gap by empirically analysing the adoption process of AI initiatives in eight different public organizations in Switzerland. It takes an interdisciplinary approach, connecting streams of research in Public Administration and Information Systems. Using the AI-adapted technology organization environment (TOE) framework by Pumplun, Tauchert, and Heidt (2019) as a theoretical basis, our research question is: *What are the technological, organizational, and environmental factors that facilitate or hamper the adoption of projects involving AI technologies in public organizations?* Given the limited previous empirical research on this topic, we have used an exploratory qualitative research design to gain in-depth insights. This study's main contribution is to better understand the sector-specific challenges and favourable factors when public organizations adopt AI technologies. As we see adoption as an ongoing process instead of a single point in time, we extend existing theory by introducing a time dimension, allowing us to formulate propositions about which factors are most relevant at each of three consecutive stages ('assessing', 'determined', 'managed') in the adoption process. As such, our study heeds the calls for 'research focusing on the wide variety of aspects involved in the phenomenon of AI adoption in the public sector' (Sun and Medaglia 2019, 379) and for a 'distinctive approach to AI in the public sector' (Criado et al. 2020).

2 Theory

2.1 AI in the public sector

There is no universally accepted definition of AI (Wirtz, Weyerer, and Geyer 2019). AI may be understood as machines or computer systems that think and act humanly by performing tasks that commonly require human intelligence (e.g. decision-making and learning) or that think and act rationally by focusing on logic and carefully considering all options (e.g. finding the best solution to a problem) (Russell and Norvig 2021). In a specific area, AI might outperform humans, but it is 'unable to autonomously solve problems in other areas' (Kaplan and Haenlein 2019), so is understood as 'weak AI' (Wamba et al. 2021, 2). Others argue that AI will develop abilities that surpass human intelligence (Kaplan and Haenlein 2019) and 'will [...] supplant us as the dominant species on the Earth' (Bundy 2017, 285), which is known as AI singularity or 'conscious/ self-aware AI' (Kaplan and Haenlein 2019, 16). In this study, we lean towards the understanding of 'weak AI' to argue that 'AI applies advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions' (Gartner 2021). Thereby, AI systems 'correctly interpret external data [,] [...] learn from such data, and [...] use those learnings to achieve specific goals and tasks through flexible adaptation [...]' (Kaplan and Haenlein 2019, 15). One aspect that is inevitably connected to AI is the access rights to the data and data ownership (Martens 2018). Legal instruments such as data protection laws form the basis to regulate data access and data ownership (Martens 2018).

Despite the growing debate, the actual diffusion of AI in public sector practice remains low, particularly compared to private sector companies (Mikalef et al. 2021; Wirtz and Müller 2019; Wirtz, Weyerer, and Geyer 2019). Challenges to adopting AI in public organizations stem from factors more prevalent in the public context: (i) a lack of technical staff to introduce and assess new technologies, (ii) the risk of potential erroneous use of AI (e.g. security risks, privacy concerns), (iii) the need to guarantee transparency in the context of AI, (iv) moral dilemmas such as when to use AI, and (v) ethical considerations, (e.g. non-discrimination of citizens) (Margetts and Dorobantu 2019).

Nevertheless, research on AI and closely related fields in the public sector has grown recently (Sousa et al. 2019; Wirtz, Langer, and Fenner 2021). To date, most studies have involved the *what* and *why* when discussing possible applications and advantages or disadvantages of AI. Many of these studies are conceptual in nature (e.g. Agarwal 2018; Androutsopoulou et al. 2019; Bullock 2019; Criado and Ramon Gil-Garcia 2019; Kankanhalli, Charalabidis, and Mellouli 2019; Meijer and Wessels 2019; Peeters and Schuilenburg 2018; Pencheva, Esteve, and Jankin Mikhaylov 2020; Wirtz and Müller 2019; Young, Bullock, and Lecy 2019; Newman, Mintrom, and O'Neill 2022). For instance, Pencheva, Esteve, and Jankin Mikhaylov (2020), Criado and Ramon Gil-Garcia (2019), Wirtz, Weyerer, and Geyer (2019), and Wirtz, Langer, and Fenner (2021) reviewed the literature on big data and AI in the public sector, identifying key themes and applications such as efficiency and process automation, legitimacy, accountability, cost savings, fraud detection, decision-making, knowledge management, digital agents, improved policy analysis and evaluation, and new transformative business models. Criado and Ramon Gil-Garcia (2019) and Wang, Teo, and Janssen (2021) emphasized the need and the mechanisms for public value creation through AI, while Pencheva, Esteve, and Jankin Mikhaylov (2020) called for research supporting practitioners by answering relevant questions about AI in public organizations. Medaglia, Gil-Garcia, and Pardo (2021, 1) invited researchers to focus on 'governance of AI, trustworthy AI, impact assessment methodologies, and data governance'. Similarly, Wirtz, Langer, and Fenner (2021) called for a better balance in research methodologies and studies focusing on creating new government structures due to AI. Agarwal (2018) outlined the challenges public administrations face given AI's radical changes. Arguing that many of the current processes in government may soon become irrelevant, he stressed the 'need to lay the groundwork for governments to rethink how they will be able to best serve their constituents' (Agarwal 2018, 917). Peeters and Schuilenburg (2018) and Meijer and Wessels (2019) critically discussed algorithmic tools in predictive policing and justice against the lack of empirical research and questions regarding the role of human judgement, accountability, and transparency. Relatedly, several studies (Bovens and Zouridis 2002; Bullock 2019; Justin, Young, and Wang 2020; de Boer and Raaphorst 2021; Young, Bullock, and Lecy 2019) discussed how AI systems affect street-level bureaucrat discretion, arguing that the context determined whether to use artificial or human discretion. The former offers improvements in scalability, cost-efficiency, and quality, while concerns regarding equity, manageability, transparency, and political feasibility remain. Although caution is necessary when utilizing AI in governance to prevent 'administrative evil', Bullock (2019, 9) argued that both humans and algorithms may make imperfect choices.

Several studies have focused on challenges and risks of AI, such as privacy, legal, and ethical issues (Bannister and Connolly 2020; Janssen and Kuk 2016; Wirtz, Weyerer, and Geyer 2019), which mainly address questions of *what* and *why (not)*. In light of the negative consequences of faulty AI for society, these studies are of high normative and practical relevance (see De la Garza (2020) for the example of the Michigan MiDAS system that wrongly accused citizens of tax fraud). Janssen and Kuk (2016) discussed the limitations and challenges of AI in governance, stating that with autonomous algorithms, there are issues with accountability, bias and discrimination, embedded political orientations, and other undesirable practices. Newman, Mintrom, and O'Neill (2022) argued that instead of relieving administrative burdens, AI reinforces bureaucratic structures. Kernaghan (2014) recommended the development of an ethics regime for robot applications in public organizations and evaluated the need for regulation. Wirtz, Weyerer, and Geyer (2019) outlined different applications and the associated challenges of AI in law and regulations, ethics, societal issues, and technology implementation in public organizations, while Sun and Medaglia (2019) analysed how different stakeholders perceive the challenges of applying AI in public healthcare, proposing some guidelines for the governance of AI adoption in the public sector. Lastly, Eubanks (2017) as well as Alon-Barkat and Busuioc (2022) explored how automated decision-making in public services may negatively impact already disadvantaged groups and reinforce existing biases, while Bannister and Connolly (2020) provided a taxonomy of decision-making algorithms in public organizations that help control the risk of introducing such biases.

Other studies focus on *how* AI should be used by analysing processes and strategies for the implementation and modes of AI technologies. Chen, Ling, and Chen (2021) used the TOE framework to study the adoption of AI in Chinese state-owned companies. They found that the innovation's compatibility with adopter needs, the new approach's relative advantage, complexity, managerial support, government involvement, vendor partnership, and organizational capability all support adoption. By drawing on the TOE framework, Mikalef et al. (2021) examined contributing factors to AI capability-building in public organizations based on data from German, Norwegian, and Finnish municipalities. The most important factors were perceived financial cost, organizational innovativeness, governmental pressure, government incentives, and regulatory support. In contrast, perceived public pressure and the perceived value of AI solutions were less influential. Wang, Zhang, and Zhao (2020) used empirical evidence from Chinese government chatbot projects to explore determinants of AI adoption. They found that pressure and readiness factors play varying roles in the pre- and post-adoption stages and that 'pressure can encourage local governments to implement chatbots' (Wang, Zhang, and Zhao 2020, 1). Kankanhalli, Charalabidis, and Mellouli (2019) conceptually identified multiple challenges in adopting AI technologies in the public sector and called for more domain-specific studies on the implementation and evaluation of AI systems, challenges and quick-wins, and studies expanding methods and theories. In semi-structured interviews with German municipalities, Schaefer et al. (2021) analysed perceived challenges to AI adoption from a public employee perspective, identifying factors such as technical compatibility, skills, costs, strategic alignment, government pressure, and innovativeness. Campion et al. (2020) focused on inter-organizational collaborations in AI adoption. The greatest challenges in such collaborations include data sharing concerns, insufficient data understanding, and lack of motivation. Wirtz and Müller (2019) formulated an integrated AI framework for public management, including layers for public AI policy and regulation, applications and services, functions, and technology infrastructure, aiming to better understand the ideal embedment of AI systems into administrative procedures. Similarly, Androutsopoulou et al. (2019) suggested a model and technical system based on natural language processing for improving communication between governments and citizens. Finally, Desouza, Dawson, and Chenok (2020) provided reflections on issues that public organizations face when adopting AI, structured along the dimensions of data, technology, organization, and environment – including for instance, complexity in stakeholder management, public value creation, transparency requirements, and due oversight.

2.2 IT innovation adoption

AI adoption is an example of IT innovation adoption – a process that results in an outcome that is new to the adopting organization, such as the introduction and use of a technology, product, process, or practice (Hameed, Counsell, and Swift 2012, 359; Damanpour and Schneider 2009) and that involves productively 'using computer hardware and software applications to support operations, management, and decision making' (Thong and Yap 1995, 431). In public sector innovation, outcomes can typically be new processes, new products, a new positioning of an existing product or service, or even new paradigms (Bason 2018). The ultimate purpose of adopting innovations is often to increase organizational performance (Hameed, Counsell, and Swift 2012), but in public contexts, it is also about creating societal value (Ulnicane et al. 2021), making processes more efficient and better tailored to citizen needs (Newman, Mintrom, and O'Neill 2022), or designing new policies to solve societal problems and introducing and delivering new services and platforms to users (e.g. for citizen collaboration) (Chen, Walker, and Sawhney 2020; Walker 2007).

Studying IT innovation adoption mechanisms at the individual and organizational level has a long tradition in information systems research (Lai 2017; Oliveira and Martins 2011). Over time, the field has developed numerous widely used theoretical models, such as the technology acceptance model (TAM) (Davis 1989), the diffusion of innovation (DOI) theory (Rogers 1995), the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Davis, and Davis 2003), and the TOE framework (Tornatzky, Fleischer, and Chakrabarti 1990) – all used to explain different kinds of technology adoption (see e.g. Oliveira and Martins 2011; Ma 2014; Mergel and Bretschneider 2013; Grimmelikhuijsen and Feeney 2017; Demlehner and Laumer 2020; Nam et al. 2020).

Compared to other IT innovations, AI is a general-purpose technology with 'high implementation complexity [. . .] which differentiates it from other digital technologies that are typically easy-to-use and easy-to-deploy' (Jöhnk, Weißert, and Wyrtki 2021, 6), such as social media use (Mergel and Bretschneider 2015). Furthermore, the adoption of AI requires concerted and sustained efforts across different organizational units or with external parties, especially between IT and expert units in the AI application area, and significant changes in strategic direction, resources, knowledge, culture, and data (Jöhnk, Weißert, and Wyrtki 2021), highlighting the need for a theoretical framework that considers not only technological but also organizational and environmental factors.

2.3 The TOE framework

Contrary to other technology adoption frameworks that view adoption from an individual point of view (e.g. TAM or UTAUT), TOE views technology adoption from an organizational perspective (Al Hadwer et al. 2021). It postulates that an organization's technological, organizational, and environmental context influences the technology adoption processes (Baker 2012) while not specifying particular influence factors (Aboelmaged 2014). Therefore, relevant factors for any specific research question must be defined based on previous studies and theoretical implications since '[d]ifferent types of innovations have different factors that influence their adoption' (Baker 2012, 236).

Several studies in public administration have used the TOE framework to study AI adoption (Chen, Ling, and Chen 2021; Desouza, Dawson, and Chenok 2020; Mikalef et al. 2021). Many other studies discussed above have investigated factors that can be assigned to technological, organizational, and environmental dimensions. The relative popularity of the TOE framework over other approaches might lie in the explicit emphasis on organizational and environmental factors – alongside the technological ones that tend to dominate in most other frameworks – and its focus on organizational rather than individual technology adoption.

Pumplun, Tauchert, and Heidt (2019) present an adaption of the TOE framework specifically geared towards AI that is grounded in earlier research, as the factors selected are reflected in many other studies (see e.g. Stenberg and Nilsson 2020). Their framework includes the technological items *relative advantage of the AI solution over the conventional technology* and *compatibility with existing business processes* and the *business case*. While a relative advantage implies improvement potential and increases the chances of adopting a new technology (Greenhalgh et al. 2004), the mechanisms behind the factor compatibility mainly pertain to complications in the interplay with existing systems, whereby lack of compatibility leads to hesitation regarding a new technology (Alsheibani et al. 2020). In the organizational dimension, the framework includes *culture* (namely *top management support), change management*, and *innovative culture, organizational size, financial and human resources, data availability and quality*, and *organizational structure*. AI adoption often needs far-reaching changes in organizational structures and culture for employees and clients to accept the innovation and significant organizational resources (e.g. skills and quality data) to develop AI solutions in cross-functional teams (Jöhnk, Weißert, and Wyrtki). The fact that public organizations frequently struggle with radical organizational and cultural changes underscores their importance (Mergel, Ganapati, and Whitford 2020). The framework further includes the environmental items *competitive pressure, government regulations (GDPR and employee councils), industry requirements*, and *customer readiness*. Government regulations[2] and other public sector-specific requirements tend to be important in public organizations and their consideration may hinder the adoption of new technologies. While there is usually less competitive pressure to adopt new technologies in the public sector, customer readiness and citizen expectations may still create pressure on public organizations.

Based on our own experience working with public sector organizations using AI technologies and on frameworks by Jöhnk, Weißert, and Wyrtki () and Schaefer et al. (2021), we added the items *AI strategy, collaboration*, and *origin of project initiation* to the organizational factors of the framework (see Table 1). The availability of an AI strategy is proposed by Jöhnk, Weißert, and Wyrtki () to influence AI adoption, and in AI projects, it is common for organizations to work together with external partners (Chatterjee et al. 2021). Therefore, factors like collaboration and initiation need to be considered. To simplify matters, we removed the sub-dimensions of the government regulations (GDPR and employee council) in the environmental factors as they seemed too specific and of limited relevance in the Swiss context. At the time of data collection, the Swiss equivalent of the GDPR had not yet entered into force (Guirguis et al. 2021), while employee councils are not as widespread in Switzerland as in other countries (Ziltener and Gabathuler 2018).

2.4 Assessing the AI maturity level

To assess the AI maturity levels in our study, we draw on Alsheiabni, Cheung, and Messom (2019), who integrated different levels of AI adoption in an organization (see Table 2). IT innovation adoption rarely refers to one single point in time but is a process (Hameed, Counsell, and Swift 2012). Therefore, introducing a time dimension to measure the degree of innovation adoption is necessary to assess whether an innovation can be integrated into daily practice (Hameed, Counsell, and Swift 2012). Alsheiabni, Cheung, and Messom (2019) differentiated between five levels. At the *initial* level, minimal functions based on AI exist, and there are no detailed plans to use AI. At the *assessing* level, experimentation with AI technologies has begun, and the organization is looking for possible applications. At the *determined* level, some advanced AI projects have moved beyond the experimental phase, and the infrastructure requirements for larger-scale implementations are identified. At the *managed* level, the necessary processes for organization-wide, large-scale AI applications are defined. Finally, at the *optimize* level, the organization has the infrastructure and architecture suitable for large-scale AI applications.

Table 1. The TOE factors investigated in this study based on Pumplun, Tauchert, and Heidt (2019).

Dimension	Factors	Explanation
Technology	Relative advantage	The advantage of AI technology compared to conventional technology.
	Compatibility: with business processes and business case	Compatibility of the AI solution with existing business processes and the underlying business case.
Organization	Culture: Top management support, strategy, change management and innovative culture	Cultural aspects that influence AI adoption, like management support, change management efforts, and a general innovative culture within the organization.
	Organizational size	An organization's size.
	Resources: Budget, employees, and data	Availability of financial and human resources and high-quality data as a basis for AI solutions.
	Organizational structure: Project structure, collaboration, and initiation	An organization's structure regarding the project, collaboration with internal and external partners and the question of who initiates an AI project (internal or external initiation).
Environment	Competitive pressure	The external pressure on an organization to launch AI projects.
	Government regulations	Government rules and regulations influencing AI adoption (e.g. data protection legislation).
	Industry requirements	The requirements of an industry that influence AI adoption – in our case, public sector requirements.
	Customer readiness	Readiness of customers and citizens for AI solutions by public organizations.

Table 2. Maturity levels and according AI function based on Alsheiabni, Cheung, and Messom (2019, 51).

Level	AI functions
Initial	Very limited or no AI function, and the organization has no plans to use AI.
Assessing	Discovery of AI technology.
Determined	AI project is at an advanced stage; determination of infrastructure needed to further implement AI.
Managed	Certain AI processes are defined throughout the organization. Preparation of large-scale AI application.
Optimize	Full AI infrastructure is ready for large-scale AI application.

3 Methodology

This study uses a qualitative multiple case study research design, suitable for cases where previous research findings are insufficient for formulating concrete hypotheses and where more general research questions guide the investigation (Yin 2018). Furthermore, analysing multiple cases produces more robust results (Yin 2018).

3.1 Case selection and data collection

The cases (organizations) identified help answer our research question about identifying technological, organizational, and environmental factors that facilitate or hamper AI adoption in public organizations. We limited our case selection to Swiss public organizations for several reasons. First, Switzerland ranks average among developed countries in the *Government AI Readiness Index* – an index based on 33 indicators across 10 dimensions (vision, governance and ethics, digital capacity, adaptability, size, innovation capacity, human capital, infrastructure, data availability, and data representativeness) ranking governments on how ready they are to implement AI in the delivery of public services (Oxford Insights 2020, 4). It is also close to average in the latest *European country benchmar*k of how many (automated) public services are offered online (European Commission 2020). This suggests that Switzerland is broadly representative of countries and public organizations in other developed countries. Second, we strove to keep factors outside the organizations – such as national policies – as constant as possible since we are interested in organizational AI adoption processes.

Three main criteria guided our case selection. Initially, we included cases based on their organizational type (as innovation adoption in the public sector is usually associated with organizational characteristics) (Melitski, Gavin, and Gavin 2010), and considered including ministries, public agencies and state-owned enterprises. Second, we sought to include cases from different tiers of Swiss government (local, regional, and national) to capture the specific conditions in each tier. While federal government organizations are generally more centralized, local government in Switzerland possesses a high level of autonomy, allowing for decentralized innovation (Mueller 2011). State-owned companies, however, balance state-ownership with autonomy (Rentsch and Finger 2015). In case selection, we sought an equilibrium between the different state levels and legal structures and as a final requirement, chose organizations working on at least one AI-based project.

Eight cases fulfilled all the criteria, and 17 interview partners were identified based on their affiliation with the respective AI project (see Table 3). Where possible, we interviewed multiple individuals per case to triangulate perspectives. Data collection through qualitative semi-structured interviews took place between August 2020 and

Table 3. Case description.

Case	A	B	C	D	E	F	G	H
State-level	National				Regional		Local	
Legal structure	State-owned enterprise		Ministry		Agency		Municipal administration	
Market situation	Partial market environment				Monopoly environment			
Employees	>30,000	>60,000	>1,000	>4,000	>400	>20	>5,000	>200
N° of AI projects studied	3	2	1	3	2	1	1	1
Type of task performed with AI	Optimization of disposition and scheduling of operations assets.	Optimization of resource allocation in an internal service and voice recognition for customer service.	Optimization of people allocation.	Digitalization of services, business process optimization, and solutions for specific business tasks,	Service delivery through conversational agent and automatization of customer service provision,	Service delivery through conversational agent.	Service delivery through conversational agent.	Service delivery through conversational agent.
N° of interviews	3	2	2	3	2	3	1	1
Roles of interviewees	(a) Internal project lead (b) Internal project lead (c) Internal project lead	(a) Internal innovation manager (b) Internal project lead	(a) Internal project lead (b) Internal government modernization expert	(a) Internal programme lead (b) Internal project lead (c) External project lead (public organization)	(a) Internal programme lead (b) Internal project lead	(a) Internal project lead (b) External project lead (private company) (c) Internal IT expert	(a) Internal project lead	(a) External project lead (private company)

July 2021. The video call-based interviews lasted about one hour and were structured using a theory-based questionnaire with open-ended questions to gain explorative insights (see 3.3).

3.2 Case description

Our cases differ in the state level, legal structure, market situation, and size (see Table 3). Cases A and B are state-owned enterprises at the national tier of government in a partial market environment with tens of thousands of employees. Cases C and D represent ministries at the national tier of government with over 1,000 (Case C) and over 4,000 employees (Case D). In Cases E and F, the organizations are agencies at the regional level with over 400 and over 20 employees, respectively. Cases G and H are local municipal administrations, G being a larger municipality with over 5,000 employees while H has 200. Cases C to H operate in a monopoly environment.

The cases differ in the number of AI projects considered in this study, ranging from one (Cases C, F, G, & H), over two (Cases B & E) to three projects (Cases A & D). Furthermore, the cases vary regarding the task that is AI-assisted. In six projects of the four cases (A, B, C, & D), the task performed is an optimization task. In four other projects and cases (E, F, G, & H), the task is service delivery through a conversational agent (chatbot) (Cases E, F, G, & H). In the remaining projects, the tasks are voice recognition for customer service (Case B), digitalization of services and solutions for specific business tasks (Case D), and automatization of customer service delivery (Case E).

We included both the internal perspective of organizational representatives and the external perspective of project partners to gain a more profound view on the cases we studied, and all interviewees were directly involved in their respective AI projects. Overall, we interviewed nine internal project leads, three external project leads, two programme leads, one expert in government modernization (internal), and one IT expert (internal).

3.3 Questionnaire and operationalization

The questionnaire contained six sections (see Appendix A in supplementary). First, we introduced the interviewees to the subject and study context without revealing any information that could have influenced their answers. To understand the AI projects and assess the degree of AI adoption in the cases, the second block contained questions regarding the AI project. Blocks three to five were dedicated to the TOE framework dimensions as outlined in Section 2.3 (see Table 1 for the dimensions and factors), translated into open-ended questions. We enquired about the relative advantage of AI technology compared to conventional technology and compatibility with existing business processes (technological factors). Culture, organizational size, resources, and organizational structure were the concepts of interest regarding the organizational factors. We also studied competitive pressure, government regulations, industry requirements, and customer readiness (environmental factors). The questionnaire ended with an outro section.

3.4 Data coding and analytical method

The interviews were recorded, transcribed, and coded using maxQDA qualitative analysis software; coding followed the deductive category assignment method (Mayring 2014). The category system was theoretically deduced from the extended TOE framework by Pumplun, Tauchert, and Heidt (2019) (see Appendix B in supplementary: coding scheme, incl. anchor samples). In the coding process, we included an inductive component to the analysis by adding further codes for recurrent patterns in the data. In total, we defined 24 codes and 505 codings. For consistency, coding was conducted by one researcher and cross-checked by another.

4 Results

4.1 AI maturity level

First, we assessed the degree of AI adoption (see Table 4) by asking the interviewees about the starting point of their AI projects. The earliest project was launched in 2012 (Case A). Some projects started in 2017 (Cases A, B, & C), some in 2018 (Cases E & F), but most projects began in 2019 (Cases B, D, F, & H). Considering that the projects are comparatively young, it is unsurprising that in five cases, it is unclear if the projects will be able to reach their goals. Two projects have achieved their goals and two have not. The number of AI projects per case also differed. Cases A and B had a comparably high number of projects (Case A: ~50, B: ~100) ranging from early proofs of concepts to fully operational projects. In contrast, the projects studied in Cases C, F, G, and H were the only AI projects in their respective organizations. In Cases C and H, the projects were still in their pilot phases, while in Cases F and G, the solutions were already productive. Thus far, Case E has two projects with an AI component (both productive), while Case D has implemented around ten AI projects and pilot projects.

This information allowed us to align the cases along the levels proposed by Alsheiabni, Cheung, and Messom (2019, 51) introduced in Section 2.4 above. Cases C, F, G, and H are in the AI technology's discovery stage and belong to the *assessing level*. Cases D and E are characterized by at least one AI project at an advanced stage with the determination of infrastructure needed to implement AI further, representing the *determined level*. Cases A and B were assigned to the *managed level*, as they displayed defined AI processes throughout the organization (see Table 4).

The degree of AI adoption somewhat coincides with the organizational form, state-level and organization size. Large state-owned companies constitute the managed level, while one national ministry and a local agency are assigned to the determined level. The assessing level consists of the local administrations together with one national ministry and one cantonal agency. On the assessing level, three organizations described the introduction of a conversational agent, while the organizations on the managed level tackle more complex optimization problems.

4.2 Technological factors

Following the TOE framework, we assessed the role of technological factors for AI adoption (see Table C1 in supplementary: structured overview incl. anchor samples). The first factor we examined was the relative advantage of AI compared to

Table 4. Degree of AI adoption.

Case	A	B	C	D	E	F	G	H
Project start	2012; 2017	2017; 2019	2017	2019	2018	2019	2018	2019
Goal attainment	n.a.	Yes; n.a.	n.a.	n.a.	Yes	No	No	n.a.
N° of AI projects	~50	~100	1	~10	2	1	1	1
Status	Full range	Full range	Pilot phase	Full range	Productive	Productive	Productive	Pilot phase
Level+	Managed	Managed	Assessing	Determined	Determined	Assessing	Assessing	Assessing

Note: +*Levels according to* Alsheiabni, Cheung, and Messom (2019, *51)* conventional technology. Our findings reveal two ways for public organizations to approach AI solutions – top-down through strategic initiatives or bottom-up for technological reasons, the latter being more frequent in our cases. Usually, AI technologies are chosen because conventional technologies are not suited to solving existing problems:

'[N]o one has solved this problem yet. [. . .] It then turned out that [it] was more complex to solve than assumed. [. . .]. That's when it occurred to us that deep learning could be helpful because the scalability is different with neural networks'. (Case A, Interview a)

For many of the projects, there was no initial intention of solving the problem with AI:

'At first, we did not start with the intention of using AI [. . .]. The intelligent component was only added in the course of the project when we could no longer achieve our goal with conventional technology'. (Case B, interview d)

In some of the analysed cases, however, the public organizations actively prepared for a future enhanced by AI technologies (e.g. hiring specialists and aligning the data infrastructure and the data strategy to this goal), representing a top-down approach.

When asked if the AI solution impacted existing business processes, results were mixed. While interference with current processes was actively avoided in some cases, most felt no impact on existing processes.

'At the moment, I'm not interested in internal processes. [. . .]' (Case A, interview c)

Some cases were actively prepared for the adaptation of processes. Here, integration into existing processes was a critical success factor for AI adoption:

'Implementing something into existing processes is not easy. Implementing AI requires different prerequisites: [. . .] high-quality data, the right infrastructure, [. . .] the right APIs in place, etc. This can easily kill the business case of any AI component'. (Case B, interview e)

4.3 Organizational factors

According to the TOE framework, organizational culture is a crucial factor (see Table C2 in supplementary). When asked about top management support, all but one respondent emphasized its importance for AI adoption (e.g. through guaranteed funding, internal support, and clearing resistances).

When asked about active change management measurements (e.g. actively addressing fears about AI), some interviewees reported that these were important for overcoming resistance from various stakeholders like management, employees, and end-users. Resistance can stem from a lack of understandability and explainability of the AI solution (e.g. workers not understanding how an AI prioritizes their work, which they would like to know). Since AI projects often disrupt daily routines, it seems essential to actively address these concerns.

'We are in the middle of a big transformation process. [. . .] From a leadership point of view, we address this process with a great focus on our employees. Only if the employees are happy can customers be satisfied'. (Case E, interview k)

As another cultural dimension, innovation culture also plays a role in AI adoption, and most interviewees stated that agile project management methods and a culture that tolerates some failure would support AI adoption.

As a last cultural dimension, interviewees were asked if their organization possessed an AI strategy. While in some organizations had strategic documents promoting and regulating the use of AI, others did not – and the AI projects emerged from a technological rather than strategic considerations.

We also noticed additional cultural aspects beyond the pre-defined coding scheme. First, while operating with publicly funded mandates, risk-avoiding behaviour might pose a challenge to AI adoption. Due to their novel character, AI projects are often associated with risks:

'We are operating in an administrative context [and a politically sensitive terrain] where one is concerned with limiting risks'. (Case C, interview f)

Other organizational factors like project size were considered next. The largest organizations in our study were also the most mature regarding AI adoption. However, we cannot substantiate the general assumption that the larger the organization, the greater its maturity. We also assessed available resources regarding the budgets, employees, data, and the remaining organizational dimensions (project structure, collaboration, and initiation) (see Table C3 in supplementary). Unsurprisingly, interviewees stated that lack of funds could hinder AI projects, although some met these economic challenges by seeking other internal or external funding sources. Financing was also reported to influence the form of collaboration with external partners. In situations with a clear investment by the organization that is related to an expected outcome, collaboration was closer. In situations without funding of the partner, collaboration tended to be more fluid.

Access to data was not generally reported as challenging. Despite significant variations among the cases, we could not identify an ideal project size in terms of employee numbers. What was striking was the importance of mutual understanding between employees and external partners. Similarly, in one case, technological knowledge was promoted through internal events where employees presented their work to interested colleagues. Each case we examined had at least one partner and emphasized the importance of some technological understanding among employees involved in the projects. Partners provided knowledge that is not otherwise present. The initiative to collaborate could come from a project partner or the organization. Partners were either public or private service providers or universities, and while collaboration with academic partners was relatively informal, working with service providers was usually regulated by contracts. The external service providers were mainly small and highly specialized companies (with a few exceptions). Despite this, collaboration was no guarantee for success, as one case reported. Generally, our respondents said it was helpful to have a lean project organization that allowed goal-orientated evolution:

'Fortunately, there was no need to set up a large project organization [. . .]. Otherwise, the project would probably not have succeeded so quickly'. (Case F, interview m)

During coding, we identified further patterns in the data – the communication and intrinsic motivation of project members and the interviewees' organizational affiliation and proximity to the units affected by a solution seem important for AI adoption:

'Usually, acceptance increases the further away you are from the affected units. These units might not accept the solution, although it is supported by management'. (Case A, interview c)

4.4 Environmental factors

To assess competitive pressure, we asked whether there were similar projects in comparable organizations (see Table C4 in supplementary); in some cases, the solution was unique, while in others similar solutions already existed elsewhere. Although public organizations are not in competitive market environments, one organization was actively preparing for potential future scenarios:

'We expect the pressure to increase, although we are not currently in a competitive situation'. (Case E, interview k)

Data protection was frequently mentioned as a regulatory challenge since any potential threat might put a project on hold. Another factor was the unclear application of regulations. As multiple interviewees stated, particularly in digital matters, federal or cantonal law often leaves room for interpretation, making AI project compliance challenging.

We also asked how operating in the public context influenced AI projects. Access to financial and human resources were often cited as issues. Budgeting processes in the public context are usually rigid, and planned budgets restrict innovative and spontaneous projects. Both the access to existing IT personnel and recruiting new employees is stated to be challenging. Recruiting can be difficult because public organizations have the reputation of not being particularly innovative. Existing resources are often unavailable long-term and cannot be used for unplanned AI projects:

'Most of the IT resources have already been planned for years for the digitalization of our core processes. This does not leave many resources for [. . .] innovation projects, which inhibits our innovative capacity'. (Case C, interview f)

A further characteristic of the public sector seems to be the project management method. While many digital projects use agile practices, public organizations often insist on traditional project management that lack the necessary trial-and-error cycles for AI solutions. As one interviewee explained:

'In the beginning, the difficulties were that our agile approach was rejected, arguing that this was not possible within the federal government and that we had to work with [a traditional project methodology] instead'. (Case D, interview h)

The interviewees did not name any other industry particularities, and some did not feel like there were any at all, suggesting that industry requirements were little relevant for AI adoption in the cases.

Lastly, we asked our interviewees about customer readiness. While customer feedback was not evident in some cases and therefore it is hard to judge the customer readiness, none of the interviewees perceived customer readiness as an issue, although some emphasized its importance.

4.5 Aggregation of the findings by AI maturity level

When contrasting the findings against the different maturity levels described in Section 4.1, differences in the importance of the individual factors depending on the organization's maturity level became apparent (see Table 5). While for organizations on the assessing level, *technological* factors are generally of medium importance, they are more critical for organizations on the determined and managed levels. The exception is 'business processes', which is of low relevance for organizations at all levels.

Table 5. Findings aggregated by AI maturity level.

Dimension	Factor	Assessing Level (Cases C, F, G, & H)	Determined Level (Cases D & E)	Managed Level (Cases A & B)
Technological Factors	Relative advantage	Medium	High	High
	Business case	Medium	High	High
	Business processes	Low	Low	Low
Organizational Factors	Top management support	Medium	High	High
	Change management	Low	High	Low
	Innovation capacity	Low	Medium	Medium
	Strategic alignment	Low	High	Low
	Organization size	Low	Low	Low
	Budget	Low	High	Medium
	Employees	Low	High	Low
	Data	Medium	Medium	Medium
	Project structure	High	Medium	Medium
	Collaboration	High	High	High
	Initiation	Medium	Low	Medium
	Communication	Low	Medium	Medium
	Organizational affiliation	n.a.	n.a.	High
	Intrinsic motivation	High	Medium	Medium
Environmental Factors	Competitive pressure	Medium	Low	Low
	Government regulations	Low	Medium	Low
	Industry requirements	Low	Low	Low
	Customer readiness	Low	High	Low

For organizations at the assessing level, ‘project structure’, ‘collaboration’, and ‘intrinsic motivation’ are critical *organizational* factors. Twice as many factors were rated as particularly important in organizations at the determined level – ‘top management support’, ‘change management’, ‘strategic alignment’, ‘budget’, ‘employees’, and ‘collaboration’, while organizations at the managed level emphasized ‘top management support’, ‘collaboration’, and ‘organizational affiliation’.

Overall, we found none of the *environmental* factors to be highly relevant. Only the organizations at the determined level reported an influence of customer readiness on AI adoption.

5 Discussion

This study explores factors that facilitate or hinder the adoption of AI projects in public organizations. Our analysis is structured according to an AI-specific adaptation of the TOE framework (Pumplun, Tauchert, and Heidt 2019). By considering its dimensions separately for different levels of AI maturity (Alsheiabni, Cheung, and Messom 2019), we have expanded this framework, which is the essential theoretical contribution of this study. As illustrated above, this enables us to provide more nuanced insights by capturing shifts in the importance of various factors of the TOE framework across different levels of experience with AI technology in public organizations.

For organizations with low AI maturity (on the assessing level), a pattern emerges across all cases, indicating that these organizations are mainly concerned with administrative issues, such as finding the best way to launch the projects and attracting intrinsically motivated staff and the right partners. Through the lens of the resource-based view theory (Barney 2001), this can be explained: At this early stage of an area that may be of future strategic importance, the organization seeks to acquire the necessary initial resources and capabilities and creates an appropriate organizational structure to deploy them (Kraaijenbrink, Spender, and Groen 2010). Despite their lack of experience, three out of four cases successfully implemented AI-based conversational agents with the help of external partners, confirming that despite low AI maturity, successful adoption of stand-alone and comparatively simple AI solutions is possible. The fourth case is still in the process of implementing a more complex people allocation AI project assisted by an external partner. This underscores the importance of finding partners possessing the resources and skills the public organization lacks (Desouza, Dawson, and Chenok 2020).

However, not all forms of collaboration may be equally likely to succeed in public settings. In the smart city context and drawing on agency and stewardship theory, Neumann et al. (2019) found that collaborations based on stewardship, aligned interests, and mostly voluntary are more likely to produce public value-oriented results than profit-oriented, mandate-based, agency-type collaborations. However, in three out of four cases at the assessing level, the cooperation was based on mandates, indicating a risk that external partners may be more interested in financial reward than outcome (Davis, Schoorman, and Donaldson 1997). The need to rally intrinsically motivated staff behind the projects is also crucial at this level, as it is often individual innovative forerunners who initiate the projects, indicating the importance of public service motivation (Ritz, Brewer, and Neumann 2016). These findings lead us to the following theoretical proposition:

Proposition 1: Organizations that are relatively inexperienced in AI technologies depend on motivated staff and external partners to implement the AI project. Less complex AI applications such as conversational agents often serve as an exploratory application of AI in such organizations.

For organizations with intermediate AI maturity (at the determined level), we observe a shift in the pattern of relevant factors compared to organizations with low AI maturity. Technological factors, in particular, become more relevant. The AI projects at this level address key challenges within the organizations (e.g. automating processes, optimizing workflows), increasing the importance of the relative advantage of AI and its relevance to the business case (Hofmann et al. 2020). However, this simultaneously increases complexity and requires more profound internal knowledge, which is presumably why we observe a tendency towards less dependency on external partners and more insourcing or back-sourcing (Moe et al. 2014) in this group.

Within the organizational factors, importance shifts towards cultural and resource-related factors, including top management support, change management, strategic alignment, budgeting, and employees – all of which are elements of strategic management (Ansoff et al. 2019) – while collaboration remains an important but less decisive factor. Therefore, our results support previous studies emphasizing the importance of strategic management in AI adoption, particularly at the determined level, since management can provide resources and deal with resistance to change (e.g. Alsheiabni, Cheung, and Messom 2019; Pumplun, Tauchert, and Heidt 2019). This finding is in line with resource-based view theory in the public sector context, which postulates that for initiatives with the potential to improve the organization's performance and enhance public value, it is vital for management to allocate the necessary resources (Bryson, Ackermann, and Eden 2007). Environmental factors remain relatively unimportant, except for customer readiness. In line with Carrasco et al. (2019), our results for organizations on this level illustrate that the customer perspective is relevant for AI adoption. Success will depend on whether internal or external customers are willing or able to use the new AI-enabled services: 'public services are best conceptualised as service systems in which users co-produce and co-design' as 'public services are subject to public scrutiny' (Laitinen, Kinder, and Stenvall 2018, 58). This is also underscored by agile practices that emphasize customer centricity (Mergel, Ganapati, and Whitford 2020) in the adoption processes in the analysed cases, as agility allows organizations to respond faster to citizen needs (Chatfield and Reddick 2018). Another important factor influencing citizen acceptance is understandability and explainability – explainable and understandable AI systems help to create transparency, decipher causalities, strengthen trust in unbiased and fair systems, and increase security (Hagras 2018).

Our findings for organizations on the determined level lead us to the following theoretical proposition:

Proposition 2: Organizations with intermediate experience with AI technologies require substantial strategical management support to allocate key resources to move beyond the exploratory stage. As AI applications begin to address core business functions and complexity rises, a greater share of implementation is done internally, and the customer perspective gains importance.

Compared to organizations at the determined level, we notice no shift in the importance of technological factors in organizations with higher AI maturity (at the managed level). As the number of AI projects and their complexity increase, we observe a gradual intra-organizational diffusion of AI technology (cf. de Vries, Tummers, and Bekkers 2018). Interestingly, both cases on the managed level are larger state-owned enterprises that partially operate in market environments, suggesting that such companies may be frontrunners within the public sector (cf. Neumann et al. 2019). Technological innovations typically happen in stages (Mergel and Bretschneider 2013), with innovators leading the way (Rogers 1983). If early adopters introduce AI projects, other public organizations might mimic their behaviour (March and Olsen 1989). The relatively low relevance of existing processes is surprising and contrary to earlier findings (Alsheibani et al. 2020). Our respondents were possibly aware of the potential influence of existing processes, but able to avoid complex integration (Hasselbring 2000) or maybe this aspect would still gain importance at the optimized level of AI maturity (Alsheiabni, Cheung, and Messom 2019). Organizational factors appear to be less critical at this level, possibly because the required resource allocation and organization takes place in earlier stages, except for top management support and collaboration, which remain vital. In these cases, significant internal resources are available to develop AI solutions, even if partnerships are still used for complex challenges. Additionally, organizational affiliation – which refers to potential conflicts between the organizational units developing and using the AI solutions – is more important. As AI becomes more widespread, issues such as the 'not-invented-here syndrome' (Antons and Piller 2015) and technology acceptance issues (Marangunić and Granić 2015) may become more relevant. Again, we find little evidence of the relevance of environmental factors at this level, leading us to the following theoretical proposition:

Proposition 3: More AI-experienced organizations may be viewed as inspiring early adopters by other public organizations. State-owned enterprises may play a significant role in this, as they often possess more innovation resources than other public organizations and can develop complex AI solutions in-house. However, with the intra-organizational diffusion of AI, resistance may increase.

While ethical aspects of AI have recently received much scholarly attention, surprisingly, none of our respondents mentioned ethics in the unstructured parts of the interview. Given the inherent dangers of the reinforcement of inequalities (Eubanks 2017) and threats to democracy (O'Neil 2016), we consider it imperative for public administrators to proactively ensure their AI applications safeguard public values such as efficiency, fairness, accountability, transparency, and human responsiveness (Schiff, Jackson Schiff, and Pierson 2021). Specific ethical concerns such as biases in AI-driven decision-making are already noticeable in the political arena (Manyika, Silberg, and Presten 2019); however, '[g]overnance of emerging technologies is a highly complex endeavour' (Ulnicane et al. 2021, 85). We anticipate that regulations and a closer monitoring of AI initiatives in the public sphere will be introduced soon (Desouza, Dawson, and Chenok 2020; Sun and Medaglia 2019; Wirtz, Weyerer, and Geyer 2019), leading to an increased influence of these factors on AI adoption, as has been the case with social media regulations (Mergel 2015).

Strengths and Limitations of the Study

One strength of this study has been to use exploratory qualitative methods to deepen our understanding of the nascent and important topic of AI adoption in the public sector and offer insights into different factors when public organizations adopt AI. A second strength is understanding AI adoption as a process and distinguishing between different adoption stages. Our interdisciplinary approach, connecting public administration and information systems research, is the third strength. Lastly, as this study focuses on *how* best to implement AI, our findings, theoretical contributions, and propositions support practitioners by answering relevant questions about the use of AI in public organizations, heeding the call by Pencheva, Esteve, and Jankin Mikhaylov (2020).

This study also has its limitations. For example, all cases were Swiss and we did not distinguish between different types of AI applications in the public sector, thereby impeding broader generalization, especially beyond Switzerland and other developed countries. Future studies on AI adoption should focus more on differences between organizations in various nations (see Mikalef et al. 2021), between whole nations as in the case of e-government (Lee, Chang, and Stokes Berry 2011), and consider AI adoption from an individual citizen perspective (see also Wirtz, Langer, and Fenner 2021). Furthermore, our results reflect the views of those involved in the projects and therefore constitute a form of self-assessment.

Subsequent research might focus on long-term evaluations involving more stakeholders and striving for more generalizable results. Since our study deliberately focuses on adoption factors of AI in the public sector, it does not consider further the application risks within the public sector (Eubanks 2017; Janssen and Kuk 2016; Maciejewski 2017; O'Neil 2016), nor does it discuss the question of how public organizations might deal with algorithmic transparency (Giest et al. 2020).

6 Conclusion

AI could be described as a double-edged sword for the public sector. It has excellent potential to improve the inner workings of public organizations as well as some key outcomes such as the quality of public services and public value creation. Conversely, AI implementation is more complex than other IT innovations, and many public organizations face sector-specific obstacles. Against this backdrop, the present study supports the call for more research on drivers and hindering factors of AI adoption – shedding light on different factors and extending the TOE framework by adding a time dimension to observe different stages of organizational AI maturity.

Despite this, public organizations should never lose sight of the broader implications of AI technology, such as fairness and accountability. Lastly, AI should be adopted for the right reasons, as one of our interviewees succinctly summarized:

'AI is a means to solve previously unsolved problems, not for solving problems you first have to create'. (Case A, interview c)

Notes

1. See Pencheva, Esteve, and Jankin Mikhaylov (2020) for a review of literature about big data in the public sector.
2. In the case of public organizations, government regulations could also be seen as an organizational factor. To be in line with previous research, we chose keep this classification as an environmental factor.
3. The citations from the interviews are labelled by a-h depending on which interview they originated in, according to Table 3: Case description

Disclosure statement

No potential conflict of interest was reported by the author(s).

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