ANALYSIS OF SUITABLE FRAMEWORKS FOR ARTIFICIAL INTELLIGENCE ADOPTION IN THE PUBLIC SECTOR

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Abstract

Modern management and digitalization are gaining momentum in the public sector. Governments and municipalities are trying to catch up to the private sector, where the adoption of Artificial Intelligence (AI) is further advanced. Research about AI in the public field is still in the early stages, but publications have increased in the last few years. This paper analyzes the current literature regarding the adoption of AI in the public sector. The goal is to evaluate if there are suitable frameworks that help public institutions introduce, build, and run AI applications. To this goal, articles are evaluated how much the existing frameworks support the adoption AI process.

1. Introduction

The adoption of artificial intelligence (AI) applications is moving fast in the public sector and seems to be very beneficial for creating public value (Misuraca et al., 2020). However, the research about AI's adoption, use, and impacts is heavily skewed towards the private sector. A recent literature review showed that from 1142 articles, only 59 cover the specific application of AI in the public sector (van Noordt & Misuraca, 2020a). Nevertheless, the uptake of AI in public administration is now an essential topic in states' political agendas worldwide and especially in the EU (van Noordt et al., 2020). The challenges for the authorities are manifold and consist of the topics like the need for governance, transparency, data collection, and prevention of discrimination (van Noordt & Misuraca, 2020b). The introduction and adoption of AI bring various challenges that fall into the following groups: social, economic, ethical, political, legal, organizational, data-related, and technological (Sun & Medaglia, 2019). While the social, ethical, and political challenges belong to the broad field of AI governance, organizational and technical aspects can be covered by frameworks that help organizations tackle these issues.

There are many different definitions of AI, based primarily on what is regarded as intelligence. Due to the constant development of new capabilities that AI can achieve, those definitions continue to develop further (Misra et al., 2020). Also, the expectations toward AI are often still unclear (Nordström, 2021). For this article, we choose the definition of (Wirtz et al., 2019), which is based on a literature review and unifies several other definitions: "AI refers to the capability of a computer system to show humanlike intelligent behavior characterized by certain core competencies, including perception, understanding, action, and learning". Going further, the term AI application is defined as "the integration of AI technology into a computer application field with human-computer interaction and data interaction". However, this is still just a snapshot of what is currently viewed as AI or AI applications; this might change over time. This change in the perception of AI is referred to as the so-called "AI effect" (McCorduck, 2004). This effect describes technologies described as AI in the past that are not called AI today because society got used to them – so the current classification might be invalid in 5 – 10 years (Misuraca et al., 2020).

While AI is now regarded as general-purpose technology (European Commission. Joint Research Centre., 2020), few researchers concentrate on concrete frameworks that help adopt artificial intelligence (Alsheibani et al., 2020). This paper aims to research the literature about AI in the public sector for existing frameworks. Secondly, these frameworks should be assessed if and how they can be used or modified to support agile AI adoption in the public sector. This leads to two following questions:

Q1: Can suitable frameworks be found in the literature, especially in the area of AI in the public sector

Q2: How can the existing framework contribute to the agile adoption of AI in the public sector with concrete guidelines and fields of action

The goal is to examine which frameworks, or at least artifacts, can be used to develop an agile adoption approach. The available articles are graded from this point of view; the grade is not meant to measure quality.

This paper should help give guidance regarding AI adoption in the public sector, particularly about the current state of available frameworks. It should also identify further research needs to develop an agile approach for adopting AI in the public sector.

2. Research Method and Evaluation

Critical factors for the adoption of AI in the public sector are subject matter knowledge, organizational structures, and a methodical approach (Wirtz et al., 2019). Unfortunately, limited resources and know-how are, together with budget restrictions, the common barriers to adopting new technologies in public institutions (van Noordt & Misuraca, 2020b). Therefore, a framework should offer structured guidance for introducing artificial intelligence to help institutions overcome these barriers (Bauer, 2020). Guidelines might include assessing the AI readiness, recommendations for different levels of the institution's hierarchy, and concrete directions to navigate the adoption process. In practice, it is also essential to maintain the AI application throughout the whole lifecycle, which means that the framework should cover more than only the introduction of a prototype (Sorgenfrei et al., 2014). Therefore, this paper suggests a list of requirements used to assess the existing frameworks in the literature (Table 1).

The search was conducted through Scopus and WOS with the search terms "ai AND public sector" and "artificial intelligence AND public sector" in the time range of 2018 to 2022. Due to the small number of results, the search was also extended to Google Scholar. Other keyword combinations were tried but led mostly to irrelevant results, e.g. including the health sector or AI solutions for Covid-19-related challenges. The titles and abstracts were screened if the papers were eligible for further analysis. One criterion was that only academic papers were included, and the time range was set to the past five years. As the next step, the papers were reviewed for frameworks.

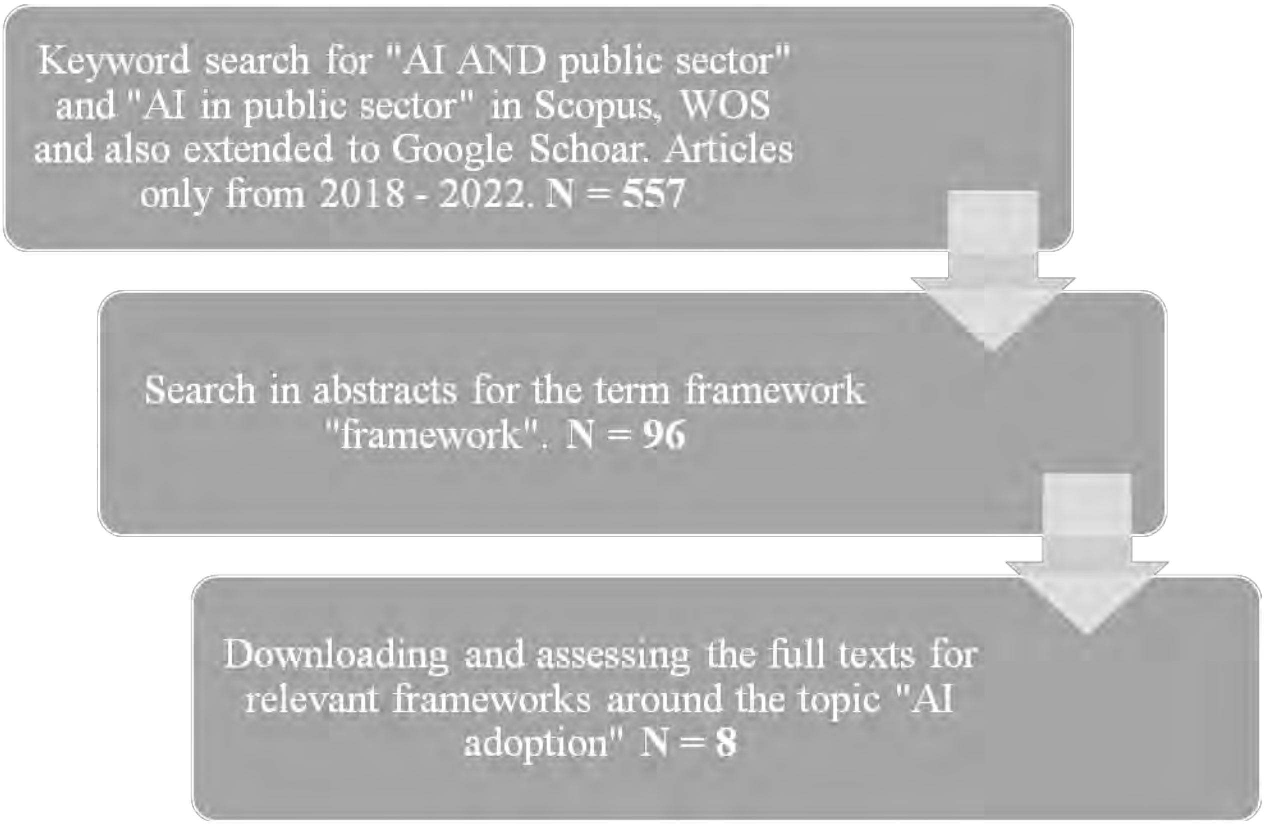

Figure 1 - Selection process of the relevant articles. Source: authors

Eight papers presented different kinds of frameworks related to AI in the public sector and were further examined. The frameworks were assessed by using several attributes. First was the coverage of the AI application lifecycle in the public sector (Levy et al., 2021) to check how broad the method is. The lifecycle describes six steps from idea through the production stage to dismantlement. Because this cycle focuses mainly on purchased third-party solutions, the "procurement" step was extended by "build the solution" to consider if AI applications are built in-house.

A framework for AI adoption should cover as much of the lifecycle as possible to ensure that the focus is not only on rapid prototyping but also on productive deployment and evaluation.

Another interesting aspect is whether the proposed approach is very general or offers concrete steps and fields of action. Frameworks can then facilitate access to AI solutions and reduce the need for technical knowledge (Bauer, 2020). It is also essential that the framework addresses different layers of abstraction (Sun & Medaglia, 2019). An example of a multi-level structure is the macro, meso, and micro model of Veale and Brass (Veale & Brass, 2019). Studies from other sectors showed that agile approaches might be a better fit for developing and adopting AI (Kruse et al., 2019). The trend towards agile development and management is now increasing in the public sector, following the agile movement in the private sector (Mergel et al., 2018). Agility should not be limited only to the development phase but should also be extended to deployment and maintenance (Ruf et al., 2021). These methods are derived from the DevOps movement and are now the focus of research as MLOps (Mäkinen et al., 2021). Another evaluation metric is whether the frameworks assess the different grades of AI readiness (Peretz-Andersson et al., 2021). Lastly, technology adoption and technological-organizational aspects should be considered because this might be a crucial aspect of AI's successful, productive usage. Also, the acceptance and confidence in the decision made by AI should be regarded (Chong et al., 2022). Therefore, an user acceptance model like UTAUT2 (Unified Theory of Acceptance and Use of Technology) (Cabrera-Sánchez et al., 2021) for user acceptance and TOE (Technology–Organization–Environment Framework) or DOI (Diffusion of Innovation) for adoption in organizations (Schaefer et al., 2021) should be somehow incorporated into the framework.

Table 1 - Weighted requirements for AI adoption frameworks; Source: author

Requirement	Weight	Description
R1: Coverage of the AI lifecycle	10%	Is the AI lifecycle considered in the framework?
R2: Concrete steps and fields of action	20%	Does the framework offer concrete steps in fields of action on how to adopt AI? Can the framework be used as a guideline?
R3: Granularity on multiple levels	20%	Is there a multi-level model (macro, meso, micro) that offers various forms of granularity?
R4: Agile aspects (e.g., MLOps)	25%	Were agile development principles considered in the framework, for example, MLOps?
R5: Consider AI maturity	10%	Is the framework adaptive to different levels of AI maturity?
R6: Incorporation of other methods (e.g., UTAUT2, DOI, TOM)	15%	Does the framework incorporate standard models for technology adoption like TOE or user acceptance models, e.g., UTAUT2?

The attributes were accordingly weighted to emphasize the aspects of agility, granularity, and field of action. In total, these weights sum up to 100%, the most emphasis is on the requirements R2 – R4. Because there are already several frameworks to determine the AI readiness of organizations, its weight is relatively low.

3. Findings and evaluation results

In total, eight articles were identified suggesting frameworks in the realm of AI in the public sector. The presented frameworks cover different aspects of artificial intelligence in the public sector. The variety ranges from prevention of discrimination, assessing the impact of AI, or even multi-layer conceptual frameworks.

Each framework was evaluated according to the given requirements. The fulfillment of each requirement was rated on a scale from one to five, with a score of five being the highest grade for fulfilling the requirement ultimately or delivering additional aspects in that area. A score of one means that the aspect is not covered at all. The emphasis was on agile aspects, concrete steps, and multi-level usage to ensure that the framework is oriented towards practical use.

Table 2 - Results of the assessment; Source: authors

Name	R1	R2	R3	R4	R5	R6	Weighted Scale
(Makasi et al. 2021)	4	5	4	1	1	1	2.7
(Misuraca and Viscusi 2020)	3	3	5	1	4	1	2.7
(van Noordt and Misuraca 2020a)	4	3	4	1	4	1	2.6
(Wirtz and Müller 2019)	4	2	5	1	3	1	2.5
(Buhmann and Fieseler 2022)	5	3	4	1	1	1	2.4
(Kankanhalli et al. 2019)	2	2	2	1	1	1	1.5
(Yfantis and Ntalianis 2020)	2	4	1	1	1	1	1.5
(C. Weyerer and F. Langer 2019)	2	1	2	1	1	1	1.3

Requirement R1 evaluated how much the AI application lifecycle is considered. Learnings from other sectors like healthcare show, that the attention to the whole lifecycle is currently underrated (Jackson et al., 2019). Several frameworks use parts of the AI lifecycle like design, development, and deployment (Buhmann and Fieseler 2022), whereas Van Noordt and Misuraca focus on the adoption steps in general. Wirtz and Müller presented cycles and adoption processes at different organizational and technical layers. The other papers are more specialized on distinct aspects and less oriented towards a specific AI application lifecycle. Thus, their framework concentrates mainly on the factors influencing AI adoption and the resulting outcomes.

The second requirement, R2, was derived from Q2, highlighting the need for practical advice. Almost all articles tend to be conceptual, whereas (Yfantis & Ntalianis, 2020) offer a more tangible solution based on game theory. This approach is not very common in practice and might be challenging to apply in public sector institutions. The most concrete steps are presented by Makasi et al. because the fields of action are tightly coupled to the ITIL (Information Technology Infrastructure Library) framework.

In hierarchical organizations like they can be found in the public sector (Pūraitė et al., 2020), it might be helpful to cover different levels of abstraction. The grade for requirement R3 reflects if the framework supports this or not. Two articles (Wirtz and Müller 2019 and Misuraca and Viscusi 2020) introduce this multi-level approach that can be used or extended for a future agile framework. Misuraca and Viscusi use macro, meso, and micro as system levels, while Wirtz and Müller introduced policy, application, functional and technical layers. Depending on the perspective, both models are suitable as a base for another framework.

In order to foster trust in AI applications, openness is a crucial aspect (Bostrom, 2017). Openness can be achieved using an agile approach combined with transparency principles (Zieni et al., 2021). The idea of MLOps (Machine Learning Development and Operations or ML DevOps) or other agile practices was not mentioned in any framework. Because the implementation of AI applications is heavily data-driven, AI projects could similarly benefit from using agile methods like Big Data Analytics (BDA) projects. There the use of agile is already partially established and recognized as beneficial (Grady et al., 2017). Several newer papers show, that the use of agile methods in Machine Learning (ML) projects can improve the project outcomes in terms of failure rate and duration (Ranawana & Karunananda, 2021; Uysal, 2022). The lack of presence of agile methodologies in the existing frameworks can indicate that further research is needed in that field and was covered by requirement R4.

Public sector institutions often show low AI readiness (Mutawa & Rashid, 2020), which should also be considered in an adoption framework. This is indicated by requirement R5. Since there are already existing methods to assess readiness (Holmstrom, 2021), this requirement has the lowest weight. The papers from Misuraca et al. and van Noordt discuss the necessary prerequisites to adopt AI, which implies that they presume a minimum level of readiness.

Frameworks like TOE or DOI help better understand the technology adoption process (Alsheibani et al., 2018). Also, user acceptance plays an important role and can be recognized with models like UTAUT2 (Gansser & Reich, 2021). Requirement R6 evaluates whether one of these existing methods was considered in the frameworks. None of these models were mentioned, which might be another field for future research regarding the public sector.

4. Conclusion and future work

This paper aims to answer research questions Q1 and Q2 about the availability of frameworks for AI adoption in the public sector. First, the literature was scanned for articles about AI in public institutions. The resulting 96 papers were analyzed to whether they present a framework that might support the adoption process. The relatively small number of articles and the recent publication dates indicate that the research about AI in the public sector, especially the adoption, is still in the early stages.

Q1: Even if the total number of eight identified frameworks is small, Q1 can be answered with yes. **Q2:** Regarding Q2, some frameworks contribute to the adoption of AI in the public sector, but the top scores (2.7) indicate that the existing frameworks still lack essential support for certain aspects. Primarily requirements R4 and R6 are not supported at all, whereas R5 is at least supported by three out of four of the best-rated frameworks. This shows that agile aspects and existing models for technology adoption need to be incorporated with the already existing work. This would then result in a higher score (four and above), representing an improved framework for AI adoption in the public sector with some practical relevance.

The number of existing frameworks for the public sector is relatively small, and they differ in focus and field of application. Those covering the AI adoption process are more on the conceptual side of the spectrum; frameworks helping to identify concrete fields of action are still scarce. Another conclusion could be that the review process should be repeated to see how the research develops in that area

Newer approaches like MLOps are not yet covered in the public sector research. These models may be going to be included within the following years. Also, models covering technology adoption on organizational levels like TOE or DOI are not represented in the AI research of the public sector. The same is true for user acceptance models like UTAUT2. Another underrepresented area is the coverage of the AI application lifecycle. Only two papers describe such a lifecycle so far (De Silva & Alahakoon, 2021; Levy et al., 2021).

Because applications are typically purchased for 5+ years in the public sector, the maintenance and life cycle play an essential role. This is an area that should be researched further to help the public IT have a long-term perspective on the adoption of AI. The research about AI in the private sector is already more advanced, and there these trends started to emerge in the last two years. Therefore, it is also a finding that there is still much potential for research in this area.

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