

An Artificial Intelligence Maturity Model for the Public Sector: A Design Science Approach

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Abstract: This article presents the development of an artificial intelligence maturity model (AIMM), specifically tailored for public sector organizations to assess their readiness for AI adoption. Using design science methodology, the research synthesizes insights from academic literature and expert consultations to propose a comprehensive AIMM. Through iterative development and expert feedback, the study refines a model that categorizes AI maturity across eight dimensions. The model's validity is assessed through expert evaluations and questionnaires, confirming its relevance and utility in guiding public organizations toward effective AI adoption. This research contributes to the theoretical and practical understanding of AI implementation in the public sector, addressing unique challenges such as procurement models, legal compliance, and organizational capabilities.

Keywords: *AIMM, artificial intelligence, design science, maturity model, public sector*

1. Introduction

In recent years, many governments and public administrations have attempted to introduce artificial intelligence (AI) projects to seek efficiency and effectiveness, but AI projects are notoriously difficult to implement, requiring a high level of various elements to align in the organization for the implementation to be successful (van Noordt & Misuraca, 2022a; 2022b; Dreyling *et al.*, 2021). Public administrations are implementing projects, however with varying levels of success. The difficulty is that AI is an inherently complex technology (Jöhnk, Weißert & Wyrski, 2021) that requires, among other things, organizational support, leadership buy-in, and strong technical and data science competence (Fukas *et al.*, 2021). Artificial intelligence maturity models (AIMM) are meant to give organizations a tool through which they can evaluate the organization's maturity when it comes to AI technologies (Sadiq *et al.*, 2021), to adopt, implement, and run a particular AI project.

While AI expansion is relatively new, the technology itself is not. The nature of the technology presents many potential problems in society (Wirtz, Weyerer & Sturm, 2020). Challenges in the adoption of AI in the public sector include not only the success or failure of projects but broad concepts like data and privacy, and AI bias, which governments must reckon with if they choose to adopt AI technologies to improve government services (Zuiderwijk, Chen & Salem, 2021; Wirtz, Weyerer & Geyer, 2019; Dreyling *et al.*, 2023).

This research originates from discussions with practitioners in the field of AI who have experience in consulting with government entities, which revealed an anecdotal problem. In the private sector, there are many consultancies who go into a customer's site to ensure that relevant and necessary pre-requirements for an AI project are present. In addition, private sector organizations have the ultimate way of measuring the potential success or failure of a project in an institutionally relevant way—they conduct a cost-benefit analysis projection. On the other hand, in the public sector not only is this measure not a holistic or appropriate one, but many organizations procure AI pilots (van Noordt & Misuraca, 2022a) without knowing whether any of the factors necessary to succeed are present in the organization. In the academic literature, a search for thorough AI maturity models (AIMMs) reveals no thoroughly investigated and validated AIMMs for use in the public sector, which acknowledges the differences in goals and procurement models between the public sector and private sector.

To this end, this paper investigates the following research question: How would public sector organizations assess the maturity of their organization to adopt AI enablement for digital public services? To answer this question, the researchers used a design science methodology to propose and validate an artifact that serves as an AI maturity model for the public sector. Initial research was conducted by collecting and analyzing academic and gray literature on the topic of AI maturity models. Initial requirements for the creation of the artifact are gathered from the literature and interviews with public sector representatives. The researchers created an initial version of the AI maturity model and then iterated three times on and validated it with experts in the field until the artifact was validated.

The AI maturity model for the public sector and this article both contribute to the academic literature and to the field by offering a maturity model for public sector organizations seeking to adopt AI by giving them a way to assess their organization and see where they can improve the capabilities to have a better potential for a successful AI implementation that adheres to legal, ethical, and security guidelines.

2. Theory

2.1 AI adoption in the public sector

Since the introduction of e-government and digitalization, governments have been trying to use information and communication technologies (ICTs) to improve services and digital governance (Tskhadadze, 2024). A growing body of work discusses the use of AI in the public sector, including studies mentioning implementations of AI in government across the EU (van Noordt & Misuraca, 2022a) and the US federal government (Engstrom & Ho, 2021). In the EU, AI Watch surveys hundreds of public authorities that have at least initiated AI-related projects. Potential uses for AI in the public sector are currently being conceived from public administrations optimizing bus routes (Hong, Kim & Park, 2018) to researchers proposing machine-learning (ML) systems to simplify legal language for citizens (Üveges, 2022).

Public authorities are seeking to adopt AI technologies to be able to claim gains in efficiency and effectiveness that the technology can enable by furthering the capability of digital solutions to solve longstanding problems (Ramiro Troitiño, 2022). Growing technological competence can have the potential to increase overall economic well-being (Stavytskyy *et al.*, 2019). At

the same time, digital public services are not something that have improved at the rate of other measurable factors, according to the Digital Economy and Society Index (DESI) (Masoura & Malefaki, 2024).

When implementing AI in the context of public organizations, there are many potential challenges, including social, legal, and technical ones (Dreyling *et al.*, 2021; Holmström, 2022). The majority of the projects implemented are chatbots or other ways of communicating with the government (van Noordt & Misuraca, 2022b). There are questions about data protection and the efficacy of legislation like the General Data Protection Regulation (GDPR) (Kesa & Kerikmäe, 2020). It is debatable whether the technology truly contributes to efficiency and effectiveness gains or simply alters the distribution of the channels through which humans contact the government. Other types of implementations include AI uses in back-office processes (Mehr, 2017). In the US, for example, a legal team that handles disability claims developed machine-learning tools to be able to process similar cases in bulk. In this way, the judge deciding the cases would be able to study fewer relevant legal codes in a day and also avoid task switching between types of cases (Engstrom & Ho, 2021). The increase in research on the topic and the practical number of cases indicate that AI use is on the uptake in governments.

2.2 Digital transformation

Digital transformations (DT) are shifts in the organization due to the adoption of a technology that causes iterative and self-impacting changes (Mergel, Edelmann & Haug, 2019). This means that once a technology is adopted it may impact the structure or communication of the organization. The adoption of AI does not in and of itself mean that there will be a large-scale digital transformation in the organization.

During digital transformation, it is important for an organization to adapt to external and internal pressures (Vial, 2021). This can also be the cause of DT. One important factor to consider in this process is the idea that the technology and organization can have mutual and reinforcing impacts. The organizational structure and competencies within the organization have an impact on how the technology is adopted within the organization. And once the technology is integrated, it further impacts the organizational operations and structure of the organization itself.

Organizations and institutions have a number of stakeholders and phenomena that they must reconcile in order to accomplish a digital transformation and

derive productivity value from the technology adopted (Hinings, Genehuber & Greenwood, 2018; Brynjolfsson & Hitt, 2000). The strategy and systems adopted should reflect the opinions of the stakeholders in the organization. AI technologies, because of the potential of an intelligent system to learn in an exponential way, make it worth considering the impacts upon the organization as well as what secondary and tertiary processes will have to be put into place to maximize the utility of the technology (Brynjolfsson & McAfee, 2014). Especially when considering modifying the channels through which humans are able to access government services, many social, legal, and technical questions must be considered.

Digital transformations are known to often be a response to external and internal forces (Vial, 2021; Mergel, Edelmann & Haug, 2019). It is reasonable to believe that recent developments with large language models (LLMs) and the proliferation of their use in general availability may currently be pushing the level of awareness to the populace in a way that previous iterations of technology diffusion caused firms and governments to initiate the digital transformation process. The digital transformation process can be informative in considering the elements of what can make a successful AI adoption because it is organizationally a digital transformation with additional complexity added.

For example, the trends in how these transformations take place and have a feedback effect across the organization are valid in AI-related transformations. One of the key points in the literature shows the importance of competences, strategy, and culture (Mergel, Edelmann & Haug, 2019; Vial, 2021). In the AI adoption process these play an outsized role because the outcome of the project depends so much on the technical talent. Even in an organization that plans to adopt the technology provided by a for profit company through public private partnership, the public personnel need to be able to understand enough from a technical perspective to ensure that the product will do what is promised by the sales team (Labanava *et al.*, 2022). In addition, because the public sector has laws, norms, and expectations of trust, security, privacy, and data protection, the public entity would typically be expected to ensure that all of these criteria are met to a reasonable level of public expectation and legal compliance. This is key to ensuring that the AI is developed and implemented in accordance with public value perspective (PVP), detailed by Moore (1995) and expanded upon by Benington (2011), Williams and Shearer (2011), and Pang, Lee and DeLone (2014), to show the need for public authorities to use their skills to explore “new opportunities in public value creation” (Lemmik, 2024).

The complexity of digital transformation, combined with the difficulty of managing, implementing, and maintaining AI systems, has led to a variety of maturity models based around various facets of AI (Sadiq *et al.*, 2021; Fukas *et al.*, 2021). These maturity models are designed for sector-specific applications like auditing and Industry 4.0. None of them directly address the needs of the public sector as it pertains to how the unique position of stewardship that governments have in relation to their populace affects the motivations for and execution of AI adoption (van Noordt & Misuraca, 2022b; Dreyling *et al.*, 2021).

3. Methodology

Design science methodology, as one of the main aspects of information systems research, is a way of informing the creation and evaluation of new artifacts that can be used by both business and technical practitioners in the field.

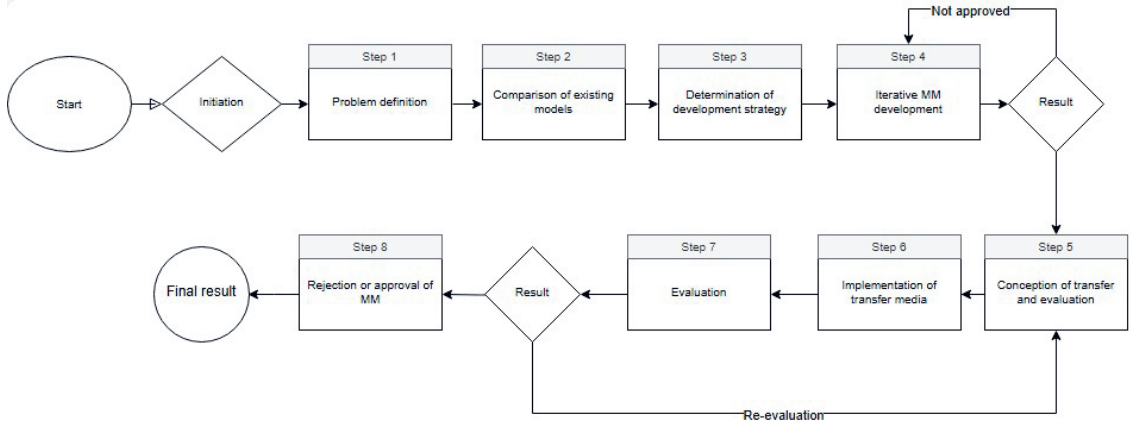
According to Hevner *et al.* (2004, p. 83) there are seven design science guidelines: design an artifact, problem relevance, design evaluation, research contributions, research rigor, design as a search process, and communication of research.

Becker, Knackstedt and Pöppelbuß (2009) built upon the design science guidelines in information systems, proposed by Hevner *et al.* (2004), to create a framework specifically for the creation of maturity models in research. This study suggests a framework for adapting existing maturity models to a new application, while following Hevner's principles.

To assemble the design, the researchers conducted a review of academic and grey literature. In building the artifact for this contribution, it was important for the authors to ensure that previous work in the academic and private sectors were considered and integrated into the initial research that would build the instrument from which expert user feedback would be garnered. A thematic analysis of the papers of the surveyed literature informed the search process. The grey and academic literature were assembled into a computer-assisted qualitative data analysis software (CAQDAS). The researchers then coded the documents according to the elements that might be relevant to the AI maturity model framework that answers the research

questions in this paper. The coding schema was inductive and focused on elements and the atomic parts which comprised these elements.

Figure 1. Design science steps.



Source: Hevner *et al.*, 2004; Becker, Knackstedt & Pöppelbuß, 2009;
Alsheiabni *et al.*, 2019.

This aided in steps one, two, and three. Then, during user requirements elicitation, the sample selection was chosen for people with expertise in participating in AI-related projects. During research on AI-related DT in government, the researchers asked interviewees about the ways that public sector entities evaluate AI maturity. These ten interviews with 7 individuals, carried out over the course of 2023, provide the empirical basis for understanding public administration requirements for an AIMM. The interviewees confirmed the lack of processes of engaging cross-functional teams to measure the ability of the organization to adopt the AI technology or the presence of prerequisites for the technology like data or existing tools (Dreyling, Tammet & Pappel, 2024). Understanding how to adapt the MM for a new purpose is key to Becker's work (2009). Through a qualitative analysis, the interviews revealed the need to expand the current AIMMs to fit the public sector application of an AIMM. A snowball sampling method was used, in line with sampling recommendations (Creswell, 2017) for situations where specific skills are required or when the target group for sampling is narrow. After the interviews and literature informed the broad requirements for categories and levels, the researchers began step four.

3.1 Build and results

The artifact was constructed in the format of existing maturity models (Fukas *et al.*, 2022; Sadiq *et al.*, 2021), following the guidelines of Becker, Knackstedt and Pöppelbuß (2009) for repurposing existing maturity models for new applications. The team established the relevant categories that must be addressed for the use in question. Then the levels were determined through considering the relevant literature and iterating with expert feedback. Similarly to the contribution of Fukas *et al.* (2022), the authors decided to follow the level structure of the capability maturity model integration (CMMI), because it is a standard practice for those in the field and one seen in academic maturity models as well (Sadiq *et al.*, 2021; Warsinske *et al.*, 2019). In the search process, the categories that the research team, interviewees, and literature agreed were relevant to the maturity model were collected and collated into a list of categories and elements.

After developing the concepts that needed to be added to make the AIMM relevant for the public sector, the team commenced step five, involving the transfer and evaluation metrics, and step six to implement the transfer.

3.2 Artifact meta-attributes and validation

The artifact was assembled with the categories and appropriate levels based on a combination of the literature review and expert feedback. The AIMM has eight categories that consist of “technology and tools,” “data,” “people and competences,” “organization and processes,” “leadership and strategy,” “financial,” “law, ethics, and trust,” and “security and privacy.” The levels are based on CMMI (Warsinske *et al.*, 2019) and go from level one to five—initial, assessing, determined, managed, and optimized.

The validation was continued until the primary metric was satisfied in step eight. This particular maturity model’s primary metric was whether it suited the purposes of an AI maturity model for the public sector. The question was posed to experts was: “Does this AI maturity model for the public sector adequately function for its proposed purpose of helping public sector entities evaluate their maturity for developing, implementing, and managing artificial intelligence?”

Step seven was to validate the artifact. Because of the transfer concept, the team did three rounds of iteration on the AIMM, and levels associated with it. The first iteration involved interviews with two experts who had

experience with AI implementation and the public sector to gather feedback on the first version of the AIMM. Then, the second iteration consisted of a further validation with four experts from the public sector. Ultimately, the team decided to do another iteration to improve the level definitions for the AIMM. For this, a questionnaire with the final iteration of the AIMM and levels was sent to twelve experts with experience in the public sector and AI implementation.

4. Artifact

4.1 Artifact creation

AI is a technology that is not as simple as a “set it and forget it” system; instead, it operates in a system which requires that data be processed and have potential-bias related effects. The adoption merits consideration of the effects across many areas that may take place. This means that public entities adopting AI have the obligation to consider the adoption in a manner that is more deliberate than private sector offerings of the same technology.

To this end, the researchers conducted a search for previous academic work on “readiness assessments,” “feasibility studies,” and “maturity models” related to AI implementation in organizations. Then the AI maturity model search was expanded to understand the first principles of AI maturity models. The largest AI maturity model systematic literature review was produced by Sadiq *et al.* (2021). Furthermore, private sector expertise was considered useful because much of the consultancy work is driven by private companies rather than academic works on the same topic. Due to this relevance, the search for gray literature on AI readiness assessments narrowed to the public sector clients to get an indication of what specific issues and focuses the large consultancies saw when public sector entities attempt to adopt AI.

Each category in the maturity model has levels associated with it. The schema for levels of maturity, and the associated definitions of these levels, is derived from the CMMI institute’s maturity levels. This schema has been used in many maturity models and, more importantly, provides a practical and understandable roadmap for organizations seeking to improve their maturity (Sadiq *et al.*, 2021; Becker, Knackstedt & Pöppelbuß, 2009; Fukas *et al.*, 2021). The one presented in Fukas *et al.* (2021) is used to determine some of the categories and the use of the CMMI level structure. However, the AIMM in Fukas *et al.* (2021) was originally intended for use with private

Figure 2. Artificial intelligence maturity model for the public sector.



sector auditing organizations. Because of this, the team decided to use the inspiration but change many of the metrics and determine which additional categories would be beneficial. In addition, the levels in Fukas *et al.*, (2021) are very brief and it was deemed useful to have more practically descriptive items for the officials in the public sector. For example, the budget category and the concept of return on investment was removed and replaced with concepts that are more relevant to the public sector. In addition, products and services was removed in favor of an added security and privacy category to bring in some of the concepts outlined in Das, Bala and Mishra (2023).

The tables below indicate the categories and definitions of their levels. Each level was determined from a combination of interviewees' responses and the academic literature, applied to the guidelines provided by Warsinske *et al.* (2019) as they pertain to the levels of organizational maturity in the CMMI framework.

Table 1. Maturity levels: Technology

Initial (1.1)	Organization is exploring specific AI opportunities and related technologies; it has no access to specialized AI technological solutions (even if it has invested in related technologies, such as DevOps, robotic process automation, or advanced analytics), nor has it partnered with anyone outside the organization to obtain such solutions.
Assessing (1.2)	There is a good understanding—through Proof of Concept or piloting—of technological needs of an AI initiative; experiments are conducted on personal computers or ad-hoc private, hybrid, or secure public cloud-based environments; there is an agreement on collaboration with a technology partner to support the implementation of AI initiative; AI model training still occurs manually, without automated resource management.
Determined (1.3)	Organization moves from the piloting phase to the implementation phase based on a chosen AI technology; infrastructure is used to harness GPU power beyond personal computers and ad-hoc deployments; technical controls are established to facilitate human oversight and incorporate explainability features outlined by AI governance practices for production deployment.
Managed (1.4)	There is a technology architecture that allows for cost-effective scaling of existing AI models and streamlined deployment of new models; deployment architecture is formalized; AI solutions are deployed from one business process area to others (e.g., through code reuse); there is the capability to manage AI technology within the organization through understanding of requirements, need for flexibility and scaling, which are also covered by technology policies (if technology is managed in-house; otherwise this capability is obtained through a partner organization).
Optimized (1.5)	There is the capability to provide continuous technical support for continuous monitoring (implementing techniques for monitoring AI models in operational environments) and retraining of AI solutions; AI deployment architecture becomes standardized and efficient, aligning with the organization's strategic objectives; new use cases drive technological advancements; AI is leveraged to manage technology infrastructure automatically (possibly through a partner organization), optimizing resource provisioning and enabling innovative use cases.

Table 2. Maturity levels: Data

Initial (2.1)	Raw data beginning to be prepared for AI modelling; some analysis of what data is needed to train the AI model.
Assessing (2.2)	Data for AI modelling is collected, but there may be biases in the information, or it may be incomplete; data is not cleaned and validated and/or properly structured for AI modelling.
Determined (2.3)	Data is compatible with analytics techniques and AI models; data inconsistencies are eliminated, and data is standardized and prepared; data is used for AI modelling but only for particular applications. External data sources are tested and able to be used with preprocessing.
Managed (2.4)	Standardized data resources are made available across the organization; data quality is consistently monitored and improved through data audits with the view to improve existing or deploying new AI models; a significant number of employees have participated in a formal data literacy or proficiency program.
Optimized (2.5)	Data needs for creating new AI applications are proactively considered and data drives new services; AI applications are constantly improved by providing more or improved data and responding to changing needs and technology.

Table 3. Maturity levels: People and competencies

Initial (3.1)	Some employees have an understanding of the AI possibilities, but these skill sets are ad hoc in random parts of the organization; there is no formal expertise in data science or AI.
Assessing (3.2)	External resources have been hired or otherwise regularly consulted; some employees in the organization are familiar with AI possibilities and have tried to build real use cases on that; there is an understanding in the organization that AI skills are needed, but no systematic approach to their development has been introduced.
Determined (3.3)	Some forms of training on AI have been provided to a sizeable number of employees, either through internal or external training or as on-the-job support; data scientist(s) have been employed or a designated resource for data analytics has been assigned to deploy AI use cases, but on a project basis; external sources may be consulted, but the leading role for working on AI use cases is within the organization.

Managed (3.4)	AI competencies are defined and consistently developed throughout the organization to prepare a sizeable number of employees for AI deployment and employees comprehend and contribute to the organization's AI vision; administrative positions are dedicated to supporting AI solution development efforts and building AI competence.
Optimized (3.5)	The organization employs leading AI competencies that are also consulted by external parties; AI expertise is fully integrated into every major business unit; constant innovation and improvement take place with organization's own resources responding to needs and technological changes.

Table 4. Maturity levels: Organization and processes

Initial (4.1)	There is a basic approach to AI solution development and AI information collection, neither are there defined processes behind the first attempts to explore AI use cases; momentum is building but no formally assigned AI sponsor or champion is designated to mature AI capability and tools.
Assessing (4.2)	Initiated AI projects have project-level processes and procedures; solutions are decentralized; refining and testing hypotheses regarding potential AI solutions for business problems takes place through trials and Proof of Concepts; AI champions and teams have been established; evaluation of tools and standards is being considered; cultural change has been addressed.
Determined (4.3)	Organization-wide approaches are documented for AI projects; there is a common approach for introducing AI initiatives and standardized process of AI delivery; AI project teams are capturing metrics and documenting best practices and tools to achieve outcomes, although it may not yet be systematic across the organization; AI governance and promotion of AI culture are in place, distinguishing between AI development and maintenance; senior leadership takes a more active role in sponsoring change.
Managed (4.4)	AI initiatives follow policy, governance, and technical standards; AI project teams are capturing metrics and documenting best practices and tools to achieve outcomes across the organization; leadership makes decisions by analyzing data against defined and captured metrics.

Optimized (4.5)	Organization has broken down silos to integrate data and resources more effectively; best practices and lessons learned from all AI projects are captured to share with each other; leadership is updating policies and procedures by analyzing data against defined and captured metrics to optimize organization-wide impact and create more public value.
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Table 5. Maturity levels: Leadership and strategy

Initial (5,1)	Organizational leadership has perceived the initial need to explore the possibilities of AI; there may have been an attempt to develop an AI use case in the organization; there is no AI strategy and the direction for AI is unclear.
Assessing (5.2)	Leadership supports experimenting with AI and is interested in the results without a commitment to act; there are no goals for AI although the AI project-level objectives are in place. AI strategy takes shape through the analysis of various AI project-level experiences in the organization.
Determined (5.3)	Leadership recognizes and supports the opportunities of AI orally, with resources and actions; there is a collaboration between public organizations driven by the need to find common solutions to common problems through AI; there is an AI strategy with objectives in place signifying a commitment to its deployment in the entire organization.
Managed (5.4)	AI strategy has become more comprehensive with an emphasis on safety, mandates and accountability, performance metrics, and maintainability of AI models over time; AI strategy aligns with broader organizational strategies.
Optimized (5.5)	AI is a core part of the organization’s vision and AI permeates the entire organization and its business operations; there are regular discussions at the management level on the effectiveness of the AI strategy, its value and future, and its capacity to innovate constantly.

Table 6. Maturity levels: Financing

Initial (6.1)	Sufficient funding to cover AI pilot, or the funding is external to the organization.
Assessing (6.2)	There is project-based funding for AI in the phase of experimentation, but not for its deployment.
Determined (6.3)	There is an understanding what is the financial effect of deploying AI projects (financial goals, costs, and benefits); AI projects are managed with clear project-level financial controls; funding of AI projects is through organization's development budget competing with other innovations.
Managed (6.4)	There is an understanding of the baseline cost of the business area where the AI project will be introduced; a portfolio management plan guides investments into AI; a dedicated AI budget exists.
Optimized (6.5)	Unified budgeting schemes and indicators encompass both business and AI technology domains; there is a long-term perspective on the financing needs of the AI tools in use and on their return on investment and the financing is stable.

Table 7. Maturity levels: Law, ethics, and trust

Initial (7.1)	Legal, ethical, and trust considerations for AI are not addressed beyond the regular data privacy and protection aspects.
Assessing (7.2)	Awareness about the legal, ethical, and trust considerations is developing, but approaches are incomplete and taken at the project level.
Determined (7.3)	Legal, ethical, and trust considerations are an integral part of every AI project; AI risk assessment is carried out for each AI project before its launch; there is a formal procedure to collect feedback from stakeholders on any issues related to legality, ethics, or trust in the AI system; there is no formal standard yet with what AI projects should comply with.
Managed (7.4)	The organization checks compliance with formalized AI-related standards through an organization-wide formalized mechanism before the launch of every AI project; compliance is also monitored throughout the AI implementation phase.

Optimized (7.5)	There is an automated and continuously improving legal, ethical, and trust compliance process, which is optimized to the organization’s needs, with a flexible system that continuously improves and adapts to legal and ethical changes in the AI landscape and the situation on the ground.
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Table 8. Maturity levels: Security and privacy

Initial (8.1)	Organization and/or AI-related data and privacy security policies are rudimentary in the organization causing unregulated security and information storage and exchange.
Assessing (8.2)	Organization begins to integrate AI-related specificities into the organization data and privacy security policies for controlled security and information exchange; checking of AI systems to ensure that private data does not get presented to users.
Determined (8.3)	Defined and implemented organization data and privacy security policies and processes (including specific AI-related aspects) for digital data exchange are in place, ensuring that no private data is released on the part of AI systems; qualitative security risk management implemented in AI projects and beginning research into quantitative risk management.
Managed (8.4)	Implementation and monitoring of organization-wide AI-specific privacy and data security policies and processes are in place based on standards and testing, ensuring safety and secure digital data exchange, no private data leakage from AI systems; quantitative cyber risk management processes implemented at AI project level.
Optimized (8.5)	Continuous improvement and optimization of organization-wide organizational and privacy and data security policies and processes are in place based on standards and measurement of trends; regular auditing of AI systems for private data leaks; regular quantitative cyber risk management with mitigating actions is widely enforced across the organization.

4.2 Artifact evaluation

For the initial evaluation, as defined in the methodology, feedback was garnered from four experts with experience in the public sector, with two of them also having academic and consulting experience. The final artifact was presented via a questionnaire to confirm the levels and maturity model. All four experts responded in the affirmative to the step eight heuristic of whether the experts believe the maturity model functions for its intended purpose. However, two of the experts thought that it did not meet its intended purpose. One believed that it was too complicated and weighty for an organization to implement. The other felt that the language used in the levels led them to believe that it was geared toward the private sector. More clearly defined levels are a benefit in that not many of the maturity models have them. Fukas *et al.* (2021) created a contribution that actually defined the levels. In their systematic literature review, which represents the body of work on academic maturity models until that year, Sadiq *et al.* (2021) did not define levels in any explicit way. However, it also creates a challenge: the comments from the two experts who did not think the AIMM was ideal revolved around the specific language and the cumbersome nature of evaluating the levels. The AIMM does what it purports to do. But this does not mean that it will work for every situation. The necessity to have multiple versions, possibly one that is a lightweight checklist for public authorities and another that is the expanded version contained in this paper would be an option to relieve this challenge. This would be a way to popularize the results according to step six in Hevner (2004) and would go beyond the primary methods through which the AIMMs discussed in Sadiq *et al.* (2021) and found in the literature have historically done.

5. Summary and outlook

The AIMM presented in this article is holistic in that it includes many categories that are relevant to the AI maturity of entities of the public sector. However, this becomes a challenge in that the response rate of many of the potential respondents the questionnaire to validate the final artifact was around 50%. In addition, although the team garnered feedback from personnel from seven different countries throughout the validation process, it is still feasible to get a different result given a different group of experts participating in the validation process. Future work would include

conducting an evaluation of an organization and then getting feedback on both the maturity model and the process. Lemmik (2024) conducted design science research of a self-evaluation method to operationalize this maturity model with a government authority. However, one challenge is that it was not possible to conduct research that provided value to the organization through a live process that engages cross-functional teams to ensure that all the relevant functions and personnel were able to contribute to the knowledge base to give a proper evaluation and be educated on the areas in which the administration can improved.

Other future work could also potentially involve publishing the AIMM and the accompanying documentation as a web application that is available to other public administrations to conduct these sessions and allow for feedback to the researchers.

The concepts and levels of these categories can be discussed among the entire cross-functional team to ensure that maturity levels are satisfactory prior to the procurement or beginning of the project and, more importantly, that everyone in the organization has cohesion in terms of the goals and expectations of the project. Ultimately, the results of this maturity model and its evaluation show that it is a difficult task to please all stakeholders when it comes to the idea of implementing AI in the public sector. From the discussions with the interviewees in the validation of the maturity model, it became apparent that the majority of public institutions are on level one or two in the categories of the maturity model. This article contributes to the knowledge in the field by proposing an academic maturity model for use in the public sector adoption of AI. This will hopefully raise the awareness of public authorities as to what organizational maturity in relation to AI adoption can be and provide a method to build a roadmap for their public administration and thereby improve the potential of a successful AI implementation that adds to public value.

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