Evaluating and Enhancing AI Readiness Models: Towards a Conceptual Framework for Public Administration

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Abstract: The rapid evolution of artificial intelligence (AI) technologies offers unprecedented opportunities for public administration to enhance efficiency, decision-making capabilities, and citizen prosperity. The potential of AI to revolutionise public services and governance is widely acknowledged, yet its successful adoption hinges on the readiness of public administration for AI integration at both organisational and national levels. As there is a lack of studies on AI readiness models in public administration, this review article aims to present a broad analysis of existing models and propose starting points for a comprehensive model of AI readiness in public administration. The objective is to identify core areas and elements essential for AI readiness and to evaluate the extent to which current models accommodate the diverse needs of public administration. The comprehensive literature review, according to the PRISMA protocol, includes a content analysis and qualitative coding of 29 relevant sources. The results reveal the key elements of public administration readiness for AI, both at the national and organisational levels. They also highlight elements that are not sufficiently considered in the existing models. Based on the results, a proposal for a comprehensive AI readiness model for public administration is presented. This includes elements at the national and organisational levels, both covering the three layers of public governance - internal operations, service delivery and policy-making. The findings are beneficial for both researchers and policymakers as they form the basis for further endeavours to develop a comprehensive framework for AI readiness in public administration.

Keywords: Artificial Intelligence, Public Administration, AI Readiness Models, Organisational Level, National Level, Literature Review

Introduction

Recent significant breakthroughs in the field of artificial intelligence (hereinafter AI) have been made possible by the rapid advances in computing power, the increasing availability of big data, and the development of new algorithms (Misuraca & Van Noordt, 2020) and have attracted the interest of governments across the world (Yeung, 2020; Fatima et al., 2020; Murko & Žabkar, 2024). AI comprises a set of techniques and subdisciplines such as machine learning, neural networks, natural language processing, computer vision, deep learning, etc. (Dwivedi et al., 2019; Murko et al., 2023a). The introduction of AI in government, at the overarching national level and the level of specific public organisations, opens up a wide range of unique opportunities, primarily found in three areas: (1) improving the internal operations of PA, (2) improving PA decision-making or policymaking, and (3) improving public service delivery (Samoili et al., 2020; Medaglia et al., 2021; Wirtz & Müller, 2019). Public sector and government organisations generate a lot of data through their processes, hence much potential for applying AI technologies (Dwivedi et al., 2019; Murko et al., 2023b). However, AI techniques alone cannot create value for the government and the public without having a unique blend of physical, human, organisational, etc. resources for successful adoption (Tomaževič et al., forthcoming 2024), which is dependent heavily on AI readiness (Fatima et al., 2022; Jöhnk et al., 2021; Mikalef & Gupta, 2021).

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Readiness, in general, is a willingness, condition or state of being prepared or ready for something (Cambridge Dictionary, 2024; Oxford English Dictionary, 2024; Merriam-Webster Dictionary, 2024). In this analysis, we focus on AI readiness at two levels: organisational and national. AI readiness refers to an organisation's or country's ability or preparedness to effectively implement AI technologies (Holmström, 2022). However, it differs significantly between the levels. For organisations, AI readiness focuses on internal capabilities such as, for example, technology infrastructure, employee skills, leadership support and strategic alignment with public service objectives and compliance with legal and ethical standards (Selten & Klievink, 2024; Tehrani et al., 2024). In contrast, national AI readiness encompasses a broader scope, evaluating a country's overall ecosystem, including policy frameworks, technological infrastructure, education systems, and public acceptance (Oxford Insights, 2023; Tortoise Media, 2024).

In this line of research, one comes across different concepts that are very closely related to AI readiness; they are synonymous, for example, AI preparedness and AI capability and there are also predecessors to AI, such as technology readiness/adoption, digital readiness, digital maturity, etc. While these concepts lay the foundational landscape for technological engagement, focusing specifically on AI readiness is crucial due to the unique capabilities and infrastructure demands of AI. AI differs from basic digitalisation primarily in its capacity for autonomous decision-making, prediction and learning from data. Digitalisation converts information into digital formats for easier management but does not enable systems to learn or make decisions. AI, especially through machine learning and deep learning, learns from data patterns and improves over time. Measuring AI readiness, therefore, goes beyond assessing digital capabilities to include evaluating computational resources, data governance, skilled personnel, and ethical frameworks. This is essential because AI requires advanced infrastructure and expertise to fully leverage its potential in predictive analytics, natural language processing, and other transformative technologies (Russell & Norvig, 2016).

Digital readiness sets the stage by emphasising the preparedness of entities to adopt digital innovations and can be defined as the state of the organisation or country being prepared for digitalisation (Nasution et al., 2018; Soomro et al., 2020). Soomro et al. (2020) systematically reviewed digital readiness models that help organisations to self-assess their digital readiness. They reviewed 57 papers published from 2007 to 2019. 22 digital readiness models with 119 model dimensions have been explored, later clustered into four different themes: (a) Digital Systems and Infrastructure, (b) Digital Tools and Applications, (c) Digital Eco-system and Culture, and (d) Digital Agents and Skills (Soomro et al., 2020). On the organisational level, digital readiness and AI readiness align closely with technology adoption models like the diffusion of innovations (DOI) and the technology-organisation-environment (TOE) framework. The DOI theory explains the speed at which new technologies and ideas spread in organisations and how and why they spread (Oliveira & Martins, 2011), while the TOE framework describes three aspects of an organisation's context that influence the process of technology adoption: technological context (the technologies themselves), organisational context (the organisation's characteristics and resources), and environmental context (the industry, competitors, and regulatory climate) (Tornatzky & Fleischer, 1990).

Furthermore, AI readiness also overlaps with AI preparedness, as measured by the International Monetary Fund's AI Preparedness Index, which assesses readiness across several domains on the national level (Cazzaniga et al., 2024). Additionally, AI capability is also closely linked to readiness and involves leveraging organisational resources to utilise AI effectively (Mikalef et al., 2019; Mikalef & Gupta, 2021; Chowdhury et al., 2023). Similarly, AI maturity models, tools used to define the degree of 'readiness' to take advantage of AI (Saari et al., 2019; Alsheibani et al., 2019) have been systematically reviewed by Sadiq et al. (2021). These concepts collectively underscore the multifaceted and interlinked nature of AI readiness, capability, and maturity essential for successful AI integration in public administration.

Despite the extensive exploration of foundational concepts, to the best of our knowledge, systematic reviews specifically focusing on AI readiness models at the organisational and national levels remain unexamined. While existing literature features examples of AI readiness models or indices, a comprehensive review that evaluates these models across various sectors and compares the measurement dimensions is lacking. This paper aims to identify key studies on AI readiness at both organisational and national levels. It seeks to ascertain whether these models allow for generalised measurement across different sectors or are tailored to particular industries with the main research question: What is the scope of readiness models in the AI domain?

The remainder of the paper is structured as follows: Section 2 describes the materials and methods applied in this study, outlining the systematic approach used for data collection and analysis. Section 3 presents the results of the analysis and a discussion, offering a comprehensive evaluation of the existing AI readiness models. Section 5 concludes the paper, summarising the main findings and discussing the implications for future research and practice in the field of AI readiness.

2 Methodology

To accomplish the study's research objectives, we conducted a systematic literature review as an adequate, comprehensive, transparent and replicable way of identifying, selecting and analysing scientific literature regarding our subject of interest (Fink, 2007; Page et al., 2021). The search was conducted between February and April 2024 by applying the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Moher et al., 2009). The PRISMA procedure entails four phases: (1) identification, (2) screening, (3) eligibility, and (4) inclusion (Knobloch et al., 2011). During the identification phase, the scope of relevant studies was established in line with our research questions:

RQ1: What is the scope of readiness models in the AI domain?

RQ2: Do the models allow for generalised measurement across different sectors?

The scientific literature and reports on artificial intelligence readiness research were extracted from Scopus, Web of Science, and Google Scholar. At the organisational level, Scopus returned 57 documents and WoS 29, indicating a robust initial pool of research material. Moreover, in an additional test-search, 6 more articles from Google Scholar were added to the database, which were not included in the previous Scopus and WoS searches. However, for the national level, the search was conducted through Google Scholar from the ground up, with indices and reports being added progressively during the search. The search queries used in the advanced document search included keywords related to artificial intelligence and readiness, including synonymous or closely related concepts such as capability, capacity, and maturity.

After examining the content of the searched documents (the second PRISMA stage) certain papers were removed for not being related (the third and fourth PRISMA stages). This led to 24 documents being identified as relevant to the study of AI readiness on the organisational level and five indices for the national level.

Figure 1: Flowchart of determining the database in Scopus, WoS and Google Scholar

General limitations for Scopus, WoS and Google Scholar
- Document type: articles, conference papers, books, indices and reports
- Language: English
- Period: not limited
- Keyword search: AI readiness/preparedness/maturity/capacity/capability
- Search field: All subject areas
- Result: 95 documents found for the org. level (Scopus, Wos & Google Scholar) & 5 for the national level (Google Scholar)

↓

Manual examination
- Checking and screening the content
- Deleting unrelated documents

↓

Final database
24 documents organisational level and 5 documents national level

Source: own analysis

The complete versions of the identified literature were retrieved and stored using NVivo 14, a software program for qualitative and mixed-methods research. This software allowed us to code the key elements based on the research framework while reading the identified literature. The coding system enabled us to link similar ideas from different articles, identify contradictions in arguments, compare (dis)similarities, and build a structured overview of identified elements regarding AI readiness, as presented in the following section.

3 Results and discussion

3.1 Organisational level

In the search for AI readiness models at the organisational level, 24 suitable sources were identified, which are listed in Table 1. When deciding on the suitability of the model for analysis, its relevance to the definition of AI readiness and the research questions of this study was crucial, regardless of the mere name of the model. AI readiness at the organisational level requires an appropriate framework for the elements that influence AI readiness. As suggested by Tehrani et al. (2024), Alter's (2013) work system framework is a particularly appropriate basis for categorising the diverse and fragmented notions of AI readiness and developing a multidimensional construct for AI readiness, and we therefore adopted this framework for analysing the models in Table 1.

Alter's (2013) framework for work systems describes each work system in terms of nine essential elements, including participants, information, technologies, processes, products/services, customers, strategies, environment and infrastructure. In this framework, processes are activities and workflows within the system that detail how tasks are performed and managed to deliver the system's offering to customers. Participants include all people who interact with the system, including IT users and nonusers. Information refers to the data and knowledge that is used, created or processed within the work system, ranging from raw data to processed information and knowledge. Technologies are tools, hardware and software used by the participants of the work system and also by automated agents. The product/service element represents the goods or services that the work system produces or delivers to customers, including the design, development, production and delivery processes associated with the tangible or intangible products or services. Customers are the individuals or organisations that receive or benefit from the products or services produced by the work system. The environment includes the broader context in which the work system operates, e.g. external factors such as regulations, market conditions and competitors that influence and interact with the work system. Infrastructure refers to the human, technical and other essential resources required to support and be utilised by the work system. Strategy encompasses the overarching goals, objectives and plans that guide the operation and decision-making of the work system. (Alter, 2013; Tehrani et al., 2024).

Table 1: Comparison of the models according to the elements of AI readiness at organisational level

No.	Model/ framework	Source	Processes	Participants	Information	Technologies	Product/service	Customers	Environment	Infrastructure	Strategies
General models											
1	Organizational AI readiness	Jöhnk et al. (2021)	x		x	x		x		x	x
2	Organizational readiness for dig. transformation	Lokuge et al. (2019)	x		x	x	x	x			x
3	Organizational AI readiness	Youssef et al. (2023)		x	x					x	x
4	Extended TOE	Alsheibani et al. (2018)		x		x		x		x	x
5	AI readiness for dig. transformation	Holmström (2022)	x		x	x				x	x
6	Technology, organization, people (TOP)	Tursunbayeva and Gal (2024)	x	x	x	x		x			
7	Functionality, availability, complexity, cost (FACC)	Dasgupta and Wendler (2019)	x	x		x	x		x	x	x
Business sector models											
8	Digital organizational readiness	Machado et al. (2021)	x		x	x					x
9	AI capability	Mikalef and Gupta (2021)	x	x	x	x				x	x
10	Extended TOE	Najdawi (2020)	x	x		x		x	x		
11	TOE + Diffusion of innovations (DOI)	Nguyen et al. (2022)	x	x		x		x	x	x	
12	Business AI readiness	Nortje and Grobbelaar (2020)	x	x	x	x	x			x	x
13	Extended and deepened TOE	Pumplun et al. (2019)	x	x	x	x		x	x	x	
14	Eight dimensions of AI readiness	Tehrani et al. (2024)	x	x	x	x		x	x	x	
15	Extended TOE	Yang et al. (2024)	x			x	x	x	x	x	x
16	Organizational AI readiness	Aboelmaged, (2014)		x		x		x		x	

17	Technology acceptance model (TAM)+TOE	Chatterjee et al. (2021)	x		x	x	x		x		
18	Technology, organization, environment (TOE)	Gupta et al. (2022)	x	x		x			x	x	
19	Perceived characteristics innovating (PCI)	Issa et al. (2022)		x	x	x				x	x
Public administration models											
20	TOE	Madan and Ashok (2023)	x	x		x		x	x		
21	AI capability in government	Mikalef et al. (2022)	x	x	x	x		x	x		x
22	TOE	Neumann et al. (2024)	x	x		x		x	x		
23	Extended TOE	Pechtor and Basl (2023)	x		x	x	x	x	x	x	
24	AI readiness for government	Deloitte (2020)	x	x	x	x			x		x

Source: own analysis

The models presented in Table 1 cover several elements of AI readiness in organisations, indicating a multidimensional nature of this phenomenon. Almost all (23) models analysed include the element of technology, processes (20) and participants (17) are also very important. On the other hand, products/services (6), strategies (13) and environment (13) are the least present in the models analysed. Looking at the individual models, the models that contain 7 elements each are the most comprehensive. Among the general models, there is one by Dasgupta and Wendler (2019) and there are four such business models (Nortje & Grobbelaar, 2020; Pumplun et al., 2019; Tehrani et al., 2024; Yang et al., 2024. Among the models dealing with AI readiness in public administration, such models include Mikalef et al. (2022) and Pechtor and Basl (2023).

In relation to the groups of models, general models are found to cover fewer elements than business models and public administration models, which cover most of them, suggesting that the specialisation of the model in relation to the area of AI readiness it explores contributes to the comprehensiveness of the model. Although the general models focus less on processes compared to the other two groups of models, they do cover the element of strategic aspects of AI readiness that are missing in the more specialised models. General models also focus less on the element of environment, which is present in all models dealing with AI readiness in public administration. This is a reflection of the legal, ethical and political frameworks that govern the adoption of AI in public organisations (Deloitte, 2020; Pechtor & Basl, 2023). In the models dealing with AI readiness in public administration, a lack of elements related to product/service, infrastructure and strategies is identified. As Nortje and Grobbelaar (2020) emphasise, the identification of these services in business promotes process mapping, which could serve as an important tool for a more effective and efficient implementation of AI in business processes. Services and products should also be improved in public administration. Although costs and benefits are considered, the priority is on trialling new technologies and prioritising public value over cost savings (Pechtor & Basl, 2023). Furthermore, the proper establishment of an AI infrastructure and strategic planning in public administration is not just about adopting new technology. It is about fundamentally changing organisational capabilities to improve responsiveness, efficiency and public trust. In this context, it is critical for public administration to understand how AI readiness in organisations impacts public value creation and the transformation of government processes (Van Noordt & Tangi, 2023).

3.2 National level

Our review of AI readiness models on the national level identified five distinct indices, each measuring AI readiness but differing in focus and methodology. The Government AI Readiness Index by Oxford Insights (2023) assesses the preparedness of 193 countries to deploy AI in public services, using 39 indicators across three main pillars: Government, Technology Sector, and Data & Infrastructure. The Global AI Index by Tortoise Media (2024), covering 62 countries, benchmarks national levels of AI investment, innovation, and implementation across seven sub-pillars: Talent, Infrastructure, Operating Environment, Research, Development, Government Strategy and Commercial. Additionally, two indices focus on self-assessment by countries. UNESCO's Readiness Assessment Methodology (RAM) (UNESCO, 2023) helps nations evaluate their AI preparedness across five dimensions: Legal and Regulatory, Social and Cultural, Economic, Scientific and Educational, and Technological and Infrastructural, incorporating both qualitative and quantitative indicators. The International Monetary Fund's index (Cazzaniga et al., 2024) can help countries self-assess their level of preparedness for AI adoption. It draws from historical technology adoption literature to focus on foundational elements like digital infrastructure and human capital, as well as second-generation elements such as innovation and regulation. Lastly, the 2024 Artificial Intelligence Index Report from Stanford Institute (2024) for Human-Centered AI tracks a broad spectrum of AI-related data, from technical progress to policy measures, distinguishing itself from other indices by its comprehensive tracking of AI data rather than country readiness. This report is recognised globally for providing insights into AI's impact on society; for example, OECD.AI (n.d.) Policy Observatory lists the AI index by Stanford Institute (2024) in their Catalogue of Tools & Metrics for Trustworthy AI. Each of these indices contributes uniquely to understanding national AI readiness, with varying emphases on assessment areas and methodologies.

Initially, we categorised the diverse aspects covered by each index, subsequently reorganising them into specifically defined categories (see Table 2) for a structured analysis. These categories include Policy and Governance, Infrastructure, Human Capital and Skills, Innovation and Development, Social and Cultural Context, Economic Factors, and Data. It is important to note that these models often encapsulate multiple dimensions within a single category. Our comparative analysis focused on examining what each model measures and how it does so within these defined categories.

Starting with the first category, **Policy and governance**, a common thread among indices is the assessment of national AI strategies, reflecting a global consensus on the importance of having a strategic approach to AI. However, the depth and breadth of what is measured under the policy and governance vary significantly. For example, Oxford Insights (2023) and UNESCO (2023) adopt a broader governance perspective, incorporating ethical, legal, and operational considerations, while the IMF (Cazzaniga et al., 2024) and Tortoise Media (2024) focus more narrowly on legal adaptability and strategic execution, respectively. The Tortoise Index's emphasis on measurable targets and dedicated government bodies presents a practical, implementation-focused perspective. The inclusion of governance principles varies notably across AI readiness indices, reflecting distinct priorities. Oxford Insights (2023) and the IMF (Cazzaniga et al., 2024) both emphasise government effectiveness. Oxford Insights (2023) extends this by also incorporating regulatory quality and accountability, offering a holistic view of governance readiness for AI, unlike the IMF (Cazzaniga et al., 2024), which focuses solely on the adaptability of legal frameworks and government effectiveness, while Tortoise Media (2024) does not consider any governance principle.

When it comes to the **Data** category, Oxford Insights (2023) is the only index that categorises 'Data' as a separate dimension, explicitly addressing both data availability and representativeness, which highlights the importance of accessible and inclusive data infrastructure for AI readiness. UNESCO

(2023) takes a legalistic approach, incorporating data governance under its legal dimension, underscoring the integral relationship between legal structures and data management for AI. In contrast, Tortoise Media (2024) includes data aspects under 'Operating Environment', and notably, the IMF (Cazzaniga et al., 2024) does not specifically address data, which might limit its assessment scope given the centrality of data in AI development.

Table 2: Comparison of the models according to the elements of AI readiness at the national level

CATEGORY	**Oxford Insights** Government AI readiness index	**UNESCO** The Readiness Assesment methodology	**Stanford Institute** AI index	**IMF** AI Prepardness Index	**Tortoise Media** The Global AI Index
Policy and governance	Vision, Governance and ethics, Adaptability	Legal dimension	Policy and governance, Responsible AI	Regulation and ethics	Government strategy
Infrastructure	Digital capacity, Infrastructure	Technological and infrastructural dimension	Technical performance	Digital infrastructure	Infrastructure, Operating Environment
Human capital and skills	Human capital	/	Education	Human capital and labour market policies	Talent
Innovation and Development	Innovation capacity	Scientific and Educational dimension	Research and development, Science and medicine	Innovation	Research, Development
Social and Cultural Context	/	Social and Cultural dimension	Diversity, Public opinion	/	/
Economic Factors	Maturity	Economic dimensions	Economy	Economic integration	Commercial
Data	Data availability, Data representativeness	/	/	/	/

Source: own analysis, adapted by Oxford Insights (2023), UNESCO (2023), Stanford Institute (2024), Cazzaniga et al. (2024) and Tortoise Media (2024).

In the realm of AI readiness indices, the **Human Capital and Skills** category is pivotal, reflecting the emphasis on educational and professional competencies essential for advancing AI technologies. The indices illustrate varied emphases on educational outputs, labour market dynamics, and practical skills relevant to the digital and AI sectors. Each index brings a unique lens; Oxford Insights (2023) looks at broad educational outputs and inclusivity. IMF (Cazzaniga et al., 2024) provides a detailed view of educational quality coupled with labour market dynamics. Tortoise Media (2024) focuses on current practical skills and community engagement in AI-related platforms. Stanford Institute (2024) emphasises structured education specifically tailored to AI and computing from the foundational levels upward.

Despite the common goal of measuring **Innovation and development** in AI, the indices approach this with different emphases. Oxford Insights (2023) and IMF (Cazzaniga et al., 2024) focus on the financial and regulatory aspects of innovation. UNESCO (2023) places a significant emphasis on the intersection of education and innovation, suggesting that knowledge dissemination and ethical considerations are vital. Tortoise Media (2024) and Stanford Institute (2024) provide a more detailed analysis of research impact and practical applications, with Tortoise Media (2024) also looking at how AI advancements penetrate through academia and industry.

The **Social and Cultural** category is exclusively addressed by UNESCO (2023) and Stanford Institute (2024) within their AI readiness indices, each taking a different approach to encapsulating the societal and cultural dimensions of AI development and integration. UNESCO (2023) adopts a holistic view, suggesting that AI readiness is not only about technological capability but also about ensuring that AI development is integrated into a broader social context that supports diversity, public health, environmental sustainability, and cultural enrichment. Stanford Institute (2024) focuses on the educational and perceptual aspects of AI, indicating that societal acceptance and diversity in AI education and discourse are important indicators of readiness. These indices reflect an understanding that measuring AI readiness for countries requires consideration of factors beyond economic and technological realms. It is crucial to include variables that address deeper societal layers, such as cultural norms, public opinion, and social policies, to fully assess a nation's preparedness for AI integration and development.

The **Economic factors** in AI readiness indices highlight different dimensions crucial for evaluating a nation's preparedness for AI. Oxford Insights (2023) emphasises market capacity within the AI and tech sectors. UNESCO (2023) assesses economic structures supporting technology integration, such as labour markets and overall investments. IMF (Cazzaniga et al., 2024) targets economic openness and global integration using metrics like tariff rates and capital mobility. Tortoise Media (2024) examines the commercial dynamics within the AI industry, including business engagement and startup activity. Stanford Institute (2024) covers broader economic impacts, including jobs, investment, and automation. Each index uses a set of tailored economic indicators to provide insights into various economic readiness aspects, from market dynamics and structural supports to global integration and industry-specific activities.

The indices reveal a broad understanding of **Infrastructure** that includes both physical (such as internet access and telecommunications) and soft components (like government policies and e-commerce readiness), each crucial for different aspects of AI readiness. Oxford Insights (2023) and Tortoise Media (2024) provide a comprehensive look at both digital capabilities and physical tech infrastructure, highlighting the advanced technological assets necessary for AI development, while IMF (Cazzaniga et al., 2024) includes also foundational infrastructure. UNESCO (2023) takes a slightly different approach by incorporating the quality of infrastructure and statistical capabilities, which are vital for the data-driven nature of AI technologies. IMF (Cazzaniga et al., 2024) highlights the economic aspects of infrastructure as well. These varying focuses reflect each index's perspective on what constitutes infrastructure readiness for AI, showing that readiness is not only about having the latest technology but also involves having a supportive environment that includes secure, accessible, and efficient infrastructure.

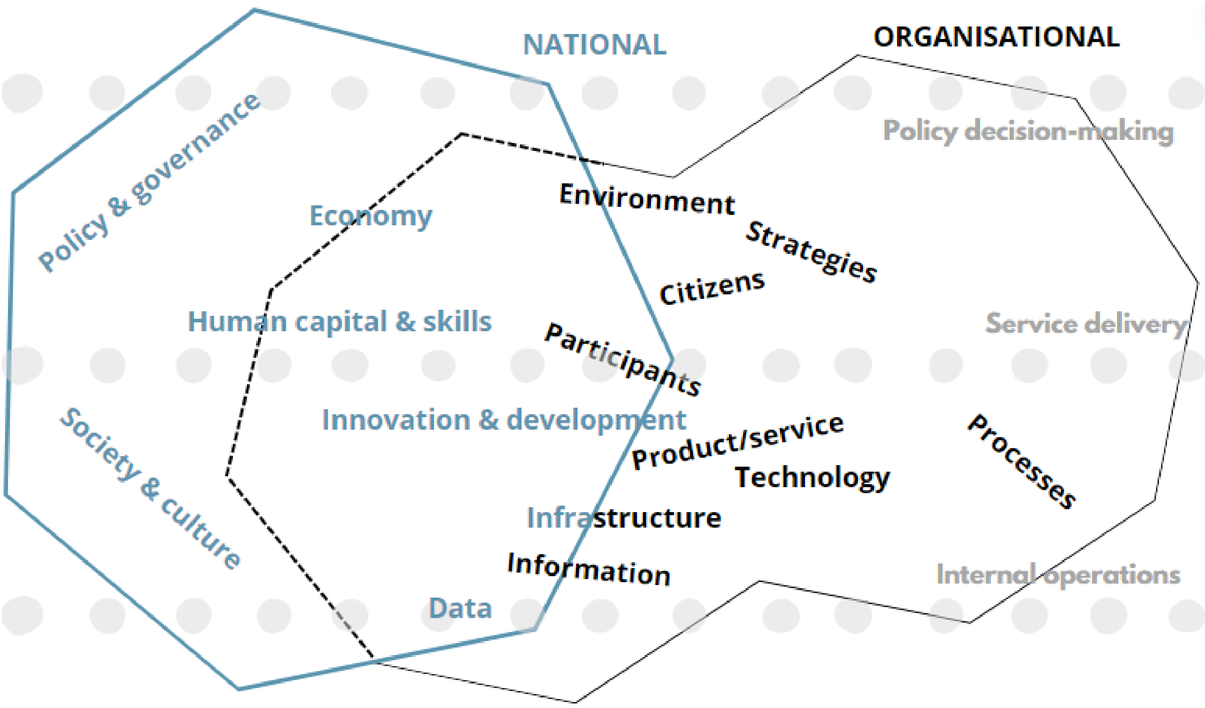
Finally, as discussed in the previous chapter, AI readiness overlaps with broader concepts of digital preparedness and maturity, signifying a natural progression in digital readiness models. The research by van Noordt and Tangi (2023) highlights the strong complementarity between historical eGovernment developments and a country's ability to deploy AI technologies effectively. This connection underlines the importance of considering established digital readiness models such as the Digital Economy and Society Index (DESI) (European Commission, 2023) when evaluating AI readiness.

The DESI (European Commission, 2023) and AI readiness indices share common focus areas such as human capital, connectivity, and digital technology integration but differ significantly in their specificity and objectives. While DESI provides a comprehensive overview of digital economy metrics across the EU, tailored to inform policy within the framework of the European Commission's Digital Decade targets, AI readiness indices are more narrowly focused on assessing specific elements that influence a country's preparedness for AI, including AI talent availability, data aspects, legal and ethical frameworks and technological infrastructure for AI development.

3.3 Towards AI readiness model for public administration

Based on the analysis of AI readiness at both national and organisational levels, we propose a comprehensive AI readiness model for public administration, as shown in Figure 2. Economic factors at the national level intersect with citizens, the external environment and the strategies at the organisational level and influence product/service consumption and external operating conditions (Madan & Ashok, 2023; Najdawi, 2020; UNESCO, 2023). Human capital and skills at the national level overlap with participants at the organisational level and include all individuals in organisations who interact with the system (Oxford Insights, 2023; Tehrani et al., 2024). Innovation and development at the national level overlaps with technologies and product/service development at the organisational level and includes the tools used and the innovation cycle from conception to deployment (Stanford Institute, 2024; Yang et al., 2024). National-level data corresponds to organisational information, including all data and knowledge used, created or processed (Issa et al., 2022; Oxford Insights, 2023). Finally, infrastructure is an important overlapping element between the national and organisational levels of AI readiness, with the national focusing on the physical and digital facilities that are essential for AI technologies and organisations focusing on the necessary human, technical and other resources Mikalef & Gupta, 2021; Nortje & Grobbelaar, 2020; Tortoise Media, 2024).

Figure 2: Proposed AI readiness model for public administration



Source: own analysis, partly adapted by Alter, 2013; Tangi et al., 2024

On the other hand, policy and governance as well as society and culture at the national level and processes at the organisational level are very specific elements that do not directly overlap due to their unique focuses and spheres of influence. The policy and governance element includes regulations and administrative frameworks that are generally broader in scope and applicable across sectors, as opposed to specific organisational strategies that determine the objectives and operational approaches of individual entities (Deloitte, 2020; Madan & Ashok, 2023). Similarly, societal and cultural contexts influence general public attitudes and norms that do not directly correlate with internal organisational processes tailored to specific operational needs. In the context of public administration organisations, these distinctions are critical as they navigate between broad government mandates and internal efficiencies and strive to align detailed operational strategies with broader societal expectations and the political environment to create significant public value (Van Noordt & Tangi, 2023).

Both the governmental and organisational levels of AI readiness in public administration operate at three layers of public governance. According to Tangi et al. (2024) (cf. Samoili et al., 2020; Medaglia et al., 2021; Wirtz & Müller, 2019) this involves internal operations (optimisation of processes), the provision of public services to citizens (service delivery) and decision-making at the level of public policy formulation. A comprehensive model of AI readiness for public administration must therefore include elements at national and organisational level that influence AI readiness at all three layers mentioned.

Conclusion

This review paper addresses the notable research gap in studies of AI readiness models in public administration. It provides a thorough examination of existing models at national and organisational levels and proposes foundations for a detailed and comprehensive AI readiness framework tailored to public administration. The review of 24 relevant sources at the organisational level shows that elements of technology, processes and participants are frequently included in AI readiness models, while products/services, strategies and the environment are less frequently addressed. The analysis suggests that public administration models generally cover more elements than general or business models, emphasising the importance of adapting models to specific contexts to enhance their comprehensiveness and applicability. The need for improved product/service elements and strategic planning in public administration is highlighted, underlining the role of AI in transforming organisational capabilities and enhancing public trust and efficiency.

Our review of national-level AI readiness models has highlighted the diversity in scope and methodological approach among five identified indices. Each index assesses preparedness across several categories. Our analytical framework involved categorising the diverse aspects covered by each index and then conducting a detailed comparative analysis within these categories to understand how different models measure and interpret AI readiness. Notably, while all indices provide valuable insights into various facets of AI readiness, they vary considerably in their emphasis on different categories. For example, while the Oxford Insights (2023) and UNESCO (2023) indices provide a broad view encompassing governance, technology, and data infrastructure, others, like the IMF and Tortoise Media (2024), focus more on economic integration and commercial dynamics. Stanford's index (Stanford Institute, 2024) stands out by tracking a wide spectrum of AI-related data, which is crucial for understanding the broader impact of AI on society.

Moreover, our analysis underscores a significant gap in the emphasis on Data as a separate category. Despite its critical importance as the lifeblood of AI, where machine learning models rely heavily on data quality, quantity, and data spaces, this category is not consistently highlighted across all indices. This oversight suggests a need for a more pronounced focus on data-related metrics to better capture the nuances of AI readiness. Similar goes to the realm of Social and Cultural Context; only a few indices, such as UNESCO (2023) and Stanford Institute (2024), specifically address these aspects, indicating an underrepresentation of social factors in AI readiness assessments. This gap points to the necessity for more holistic approaches that integrate societal impacts and cultural dimensions to fully understand AI readiness.

The proposed AI readiness model for public administration incorporates elements from both the national and organisational levels and integrates their unique contributions to promote AI readiness. Economic factors, human capital, innovation and infrastructure at the national level are directly linked to organisational processes such as service delivery, use of technology and interaction between stakeholders. Policy and governance as well as societal and cultural influences that have an impact at the national level do not directly intersect with organisational processes that are tailored to specific operational needs. This comprehensive approach aims to ensure that public administration can effectively integrate AI to enhance internal operations, optimise service delivery and support informed policy making by aligning detailed operational strategies with broader societal expectations and government frameworks.

This paper has some limitations that should be noted. Methodologically, it is based on a literature review conducted according to the PRISMA protocol. It is possible that, despite their best efforts, the authors have not considered all relevant sources in the field. As the paper represents the initial proposal for a model of public administration readiness for AI, it would be beneficial for further analyses to engage more sophisticated methodological approaches that would contribute to the verification and further development of the model. Nonetheless, the paper's findings contribute to existing scientific knowledge on public administration AI readiness and provide researchers and policymakers with initial concepts for the future development of those models that will help create greater public value in public services for all stakeholders.

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