Developing competences for Artificial Intelligence in the Public Sector: The AI4Gov Canvas

Gianluca Carlo Misuraca [a*], *Rony* Medaglia [b], *Claudio* Feijoo [c], *Marzia* Mortati [d], *Colin* van Noordt [e]

[a] Department of Design, Polytechnic University of Milan, Milan, Italy, gianlucacarlo.misuraca@polimi.it

[b] Department of Digitalization, Copenhagen Business School, Frederiksberg, Denmark

[c] Technical University of Madrid, Madrid, Spain

[d] Department of Design, Polytechnic University of Milan, Milan, Italy

[e] KU Leuven, Leuven, Belgium

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Abstract. This article introduces the AI4Gov Canvas, an evidence-based framework designed to identify and develop the competences needed by individuals working with artificial intelligence (AI) in the public sector. Recognising the need for functional specialist profiles in AI management, use and implementation within public administrations, we address the challenge of combining a variety of domains, such as technology, management and design, and policy, ethical and legal expertise.

The AI4Gov Canvas was developed through a three-step process of competence identification, clustering, and validation, involving a review of research and grey literature, expert interviews (N=5), and an online survey (N=54). It is structured around three dimensions: technology, management and design, and policy/legal/ethical, with each dimension further categorized into three levels of abstraction: meta-competences, governance competences, and operational competences.

The Canvas serves as a practical tool for mapping existing competences, identifying training needs, and designing functional specialist profiles that balance competence importance with the difficulty of obtaining them. We provide concrete examples of how the Canvas can be used to create personas, such as the "TechnoSteward" and the "Policy Sentinel", which highlight the framework's ability to guide the development of realistic and multi-disciplinary competence profiles. We conclude by outlining lessons learnt and future steps.

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1. Introduction

Artificial intelligence (AI) is becoming an increasingly vital technology for tackling social challenges and improving policymaking and public services. However, to successfully utilise these technologies, public administrations need to have the competences in their workforce to develop AI solutions, manage such initiatives, and ensure that they are used effectively.

The lack of a skilled workforce in AI is one of the critical challenges public administrations face: public managers often have limited expertise and lack competent figures to harness the benefits of AI technologies (Ahn & Chen, 2022; Neumann et al., 2022). While the lack of competencies in public administration plagues the effective deployment of other technologies as well (Zhang & Kimathi, 2022), they become crucial in avoiding irresponsible use of AI that may lead to harm. For instance, working with ethical frameworks requires different ways of working than merely having these frameworks (Fest et al., 2022). Public organisations are in need for functional specialist profiles on AI development and implementation with relevant competences.

Competences encompass key skills, expertise, and knowledge that are essential for various facets of developing and utilizing AI within the public sector. The European Centre for the Development of Vocational Training's defines competences as 'The ability to apply learning outcomes adequately in a defined context (education, work, personal or professional development)' (European Centre for the Development of Vocational Training, 2008, p. 47). This definition also specifies that 'competence is not limited to cognitive elements (involving the use of theory, concepts or tacit knowledge); it also encompasses functional aspects (involving technical skills) as well as interpersonal attributes (e.g. social or organisational skills) and ethical values' (European Centre for the Development of Vocational Training, 2008, p. 47).

Some existing frameworks on competences in a digital society have tackled the need to identify and categorize competences for relevant stakeholders. The Digital competence Framework (DigComp) (Vuorikari et al., 2022), for European citizens, and the Entrepreneurship competence Framework (EntreComp) (Bacigalupo et al., 2016), for enterprises, include general competences needed for personal development, social inclusion, active citizenship and employment, and transversal skills, such as entrepreneurship. While neither specifically focused on the public sector, nor on AI, they have paved the way for the global discourse on the need for identifying, building, and disseminating competences in the workforce of the future.

Researching competences for artificial intelligence (AI) in the public sector differs significantly from studying general digital competences due to the unique challenges and requirements associated with AI adoption in government contexts. AI competences in the public sector extend beyond technical skills, reflecting the need for compliance with regulatory frameworks like the EU AI Act and the broader societal impacts of AI implementation. These competences are also closely tied to governance practices that ensure effective deployment and continuous improvement of AI solutions, which are often hindered by rigid organizational structures and limited resources in public institutions. In contrast, research on general digital competences typically focuses on foundational skills for using digital tools and technologies, which are relevant across sectors but lack the specialized focus on governance, ethics, and public accountability required for AI in government settings (Hofmann & Ogonek, 2018).

The notable framework by the European Commission's Study on the development of a European framework for interoperability skills and competences in the public sector (EIFISC) (European Commission, 2021) is an example of zooming in on general competences related to digital transformation in the public sector. Scholarly studies so far have provided numerous empirical studies on general digitalization competences in the public sector (Edelmann et al., 2023; Hunnius & Schuppan, 2013; Mankevich et al., 2022; Ogonek et al., 2016), for example in relation to public middle managers (Roehl & Crompvoets, 2024), on digital leadership (Roman et al., 2018), and the context of smart cities (Tsoutsa & Lampropoulos, 2022) or developing countries (Hooda & Singla, 2020)

Only recently, the need for a specific framework on AI-related competences in the public sector has started to be discussed. The UNESCO framework "*Artificial Intelligence and Digital Transformation: Competences for Civil Servants* (Broadband Commission, 2022) has built the foundations for an in-depth understanding of the competence profiles of public servants that public organizations need when dealing with AI and is echoed in recent calls for further development of a comprehensive framework with the same focus (Misuraca et al., 2024).

However, key challenges emerge in the definition of an evidence-based framework that can be used as a practical tool for public managers engaged in AI projects. A first challenge rests in combining a large variety of domains that the adoption of AI in the public sector encompasses. These domains include technology expertise, such as software programming and Information Technology (IT) architecture designing; but also include managerial expertise, for example in leading AI teams; domain expertise, for example in combining AI and policy formulation; and ethical and legal expertise, for example in complying with national and supra-national regulatory guidelines (see, for instance, Mergel et al., 2024; Selten & Klievink, 2024; Medaglia et al. 2024).

A second challenge is that a single individual cannot realistically master all needed competences with equal proficiency (Misuraca & Rossel, 2023). The ideal competence profiles needed for individuals dealing with the opportunities and challenges of AI in the public sector are by necessity multi-disciplinary. On the one hand, in fact, public servants that are only knowledgeable on legal compliance practices, policymaking, and project management, for example, are ill-prepared to deal with AI initiatives, because they lack an understanding of the technical inner workings of AI systems and of their affordances. On the other hand, pure technologists who master "hard" skills in system design and programming, for example, lack the necessary insights to capture the value of such technologies in a public service context. While each competence domain is in high demand and essential to avoid common public AI project failures, it is not feasible for a single individual to have equally in-depth knowledge of the many relevant domains simultaneously.

To address these challenges, in this article we present the AI4Gov Canvas, an evidence-based framework to identify the competences required for a functional specialist in the management, implementation, and use of AI in public sector organizations.

The Canvas stems from the experience of the AI4Gov Master on AI for public services, a training programme co-funded by the European Union (EU) under the Connecting Europe Facility (CEF), designed and implemented to equip public managers with the competences needed to manage AI in the public sector. The Master was first offered in 2021-2022 and was awarded the European Digital Skills Award in the area of Upskilling in 2023.

2. Methodology

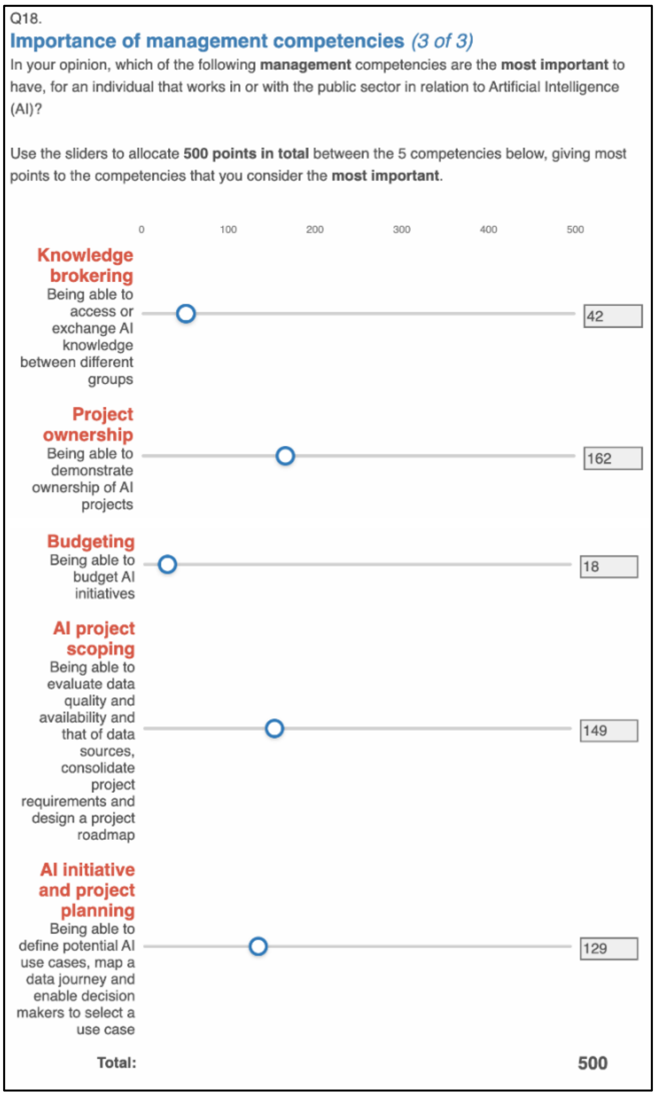
To develop a comprehensive framework of competences for the design, implementation, management, and use of AI in the public sector, we employed a three-step approach: competence identification, clustering, and validation. These steps build upon one another to generate a robust framework.

The first step, *competence identification*, aimed to gather relevant competences from existing knowledge on AI in the public sector. This involved a) a review of academic literature identified with a combination of a keyword search in research databases, and of a meta-review of published literature reviews on AI in the public sector (Reis et al., 2019; Sharma et al., 2020; Sousa et al., 2019; Wirtz et al., 2021, 2022; Zuiderwijk et al., 2021), to map competences highlighted in empirical studies (N=15); b) a review of policy and "grey" literature from think tanks, consultancy organizations, and public institutions, carried out through a snowball approach (N=5); and interviews with experts on AI in the public sector (N=5), recruited via the AI4Gov network. The outcome was a list of competences categorized into three dimensions: technology, managerial and design, and policy/legal/ethical competences.

The second step, *competence clustering*, focused on classifying these competences according to different levels of abstraction. Competences in fact range from abstract concepts such as attitudes (e.g., risk proclivity, user centricity) and general knowledge (e.g., foundational AI knowledge), to practical skills like data collection and budgeting. To systematically incorporate this range, the competences were classified into three levels: *meta-competences* (the most abstract), *governance competences*, and *operational competences* (the most practical). To validate and integrate this classification, a workshop with 20 public servants experienced in AI and digitalization in the public sector recruited through the AI4Gov network was held.

The final step, *competence validation*, assessed the relevance and difficulty of obtaining each competence. This step addressed the reality that not all competences are equally important or easy to acquire in practice, nor they are equally difficult to obtain. An online survey of experts among public sector organizations (N=54) was conducted, where participants ranked each competence in terms of perceived relevance and difficulty, using a constant-sum allocation method (Desarbo et al., 1995). The constant-sum allocation method nudged respondents to make mindful choices between survey items, thus avoiding the possibility that all competences are marked as equally important and/or equally difficult to obtain. The method has been fruitfully used in research literature to support the creation of competence frameworks, such as non-technical competences in business degrees and business graduates (Jackson & Chapman, 2012a; 2012b) and the value of smart manufacturing competences (Böhm et al., 2023). Using the Qualtrics software for online surveys, we designed items so that the respondents had to use sliders to allocate a limited number of points across each group of competences, to evaluate each of them in terms of importance, and of difficulty to obtain. The number of points for each group of competences equalled 100 points, times the number of competences in the group that the competence belongs to.

Figure 1 provides an example of how the constant-sum allocation method was presented in the online survey.


Q18.
Importance of management competencies *(3 of 3)*
In your opinion, which of the following **management** competencies are the **most important** to have, for an individual that works in or with the public sector in relation to Artificial Intelligence (AI)?

Use the sliders to allocate **500 points in total** between the 5 competencies below, giving most points to the competencies that you consider the **most important**.

0 100 200 300 400 500

Knowledge brokering Being able to access or exchange AI knowledge between different groups: 42

Project ownership Being able to demonstrate ownership of AI projects: 162

Budgeting Being able to budget AI initiatives: 18

AI project scoping Being able to evaluate data quality and availability and that of data sources, consolidate project requirements and design a project roadmap: 149

AI initiative and project planning Being able to define potential AI use cases, map a data journey and enable decision makers to select a use case: 129

Total: **500**

Fig. 1 – Constant-sum allocation method: example of a survey item.

The resulting data allowed us to define trade-offs when designing competence profiles that balance relevance and difficulty. This process ensures that the resulting competence framework reflects the practical constraints and priorities faced by public organizations in developing AI-related skills. As the outcome of this process, we created a comprehensive framework called the *AI4Gov Canvas*. This operational tool can be used by stakeholders to guide the development of AI competences in the public sector.

3. Results

The Annex to this article presents the list of all competences mapped, including a) the groupings in the three dimensions (management and design, technological, and policy, legal, and ethical) and in the three levels of abstraction (meta-competences, governance competences, and operational competences); b) the description of each competence; c) the coefficient of importance and coefficient of difficulty to obtain (μ) of each competence, derived from averaging the results of the online survey.

Results from the technology meta-competence group show that the most important competences are considered the foundational knowledge of AI (average score: 129) and data governance (average score: 124). This highlights the necessity for public sector professionals to have a solid understanding of AI principles and technologies to make informed decisions regarding AI integration. Coincidentally, these two competences are also considered the most difficult to obtain in the group (μ=116 and μ=169, respectively).

On the other hand, "awareness of fairness challenges" garnered an average score of 83, indicating that while respondents recognize the importance of fairness and bias mitigation in AI, they considered this technical competence not as important.

In comparing these values, it becomes evident that data-related skills and foundational AI knowledge are of paramount importance. While other competences, such as awareness of fairness challenges, technical design, technology inquisitiveness, and cultivating a data-oriented culture, are also valuable, their ranking provides a ground for prioritizing competences in building competence profiles.

It is noteworthy that some competences are considered highly relevant, yet they are also considered relatively easy to obtain. This is the case of "positive attitude towards AI" (μ=44) and "basic data literacy" (μ=78). Such competences are to be kept in mind, as they can be considered relatively "low-hanging fruits" when devising competence profiles for a Functional Specialist of AI in the public sector.

Results from the technology governance competence group show that competences in this group are considered easier to obtain. The most important competence, technical fairness risk mitigation, in fact, features a coefficient of difficulty to obtain very close to the baseline of 100. Other important competences that are considered relatively easy to obtain are "choice of machine learning techniques" (μ=95), and "choice of AI architecture" (μ=105).

Results from the technology operational competence group show that competences related to data collection and data quality assessment are considered the most important ones. Similarly to technology governance competences, these operational competences are also considered relatively easy to obtain. Understanding the fundamentals of machine learning, for instance, features a μ coefficient of 91, while being the third most importance technology operational competence.

Results from the management and design meta-competence group show that problem identification and framing, foresight, and user-centricity are not only the most important competences, but are also considered the hardest to obtain. These competences at a high level of abstraction represent the foundation of this cluster of competences for engaging with AI for public services.

Results from the management and design governance competence group also show that the most important competences are also the ones that are hardest to obtain. Change leadership (μ=118) and risk anticipation and mitigation (μ=116), in fact, feature a coefficient of difficulty to obtain that is well above the baseline. This pattern is also confirmed in the responses on the group of management and design operational competences. Competences that are considered the most important are also the ones that are considered the hardest to obtain. The competence of AI project scoping, for example, is very highly scored in terms of importance (153), and features one of the highest coefficients of difficulty to obtain of the entire list of competences (μ=143). On the other hand, the least important operational management competences of budgeting (μ=90) and of project ownership (μ=73) feature a much lower coefficient.

Results from the policy, legal and ethical meta-competence group show that critical technology assessment is considered the most important (133) and most difficult to obtain (μ=121) of this group of competences at a high level of abstraction. In general, all competences in this group feature a relatively high difficulty to obtain, except for the competence related to dissemination (μ=60).

The policy, legal and ethical governance group includes only four competences. Survey results show that AI procurement literacy is considered the most important competence of this group (108), while AI-compatible formulation is the hardest to obtain (μ=113).

Results from operational competence group in the policy, legal and ethical dimension show that understanding legal and ethical frameworks is considered the most important competence (115). On the other hand, the competence among these operational ones that is most difficult to obtain is specialized legal expertise (μ=121).

The diversity in importance ranking and difficulty in obtaining of each of these competences belonging to different dimensions and different levels of abstraction forms the basis for building a Functional Specialist Canvas. We present this framework in the next section.

4. The AI4Gov Canvas

The AI4Gov Canvas frames all competences identified and refined through the previous steps, clustered in the three dimensions of technology, management and design, and policy / legal / ethical. Each competence is also layered according to a level of abstraction, which increases as one gets closer to the centre: operational, governance, and meta-competence. The Canvas can be used as a spatial device to position each of the competences within the two dimensions of type of competence, and level of abstraction. Additionally, competences can be selected based on the degree of importance, and the coefficient of difficulty to obtain, derived from the results of the survey study. We illustrate an example of a possible use of the Canvas in Figure 2.

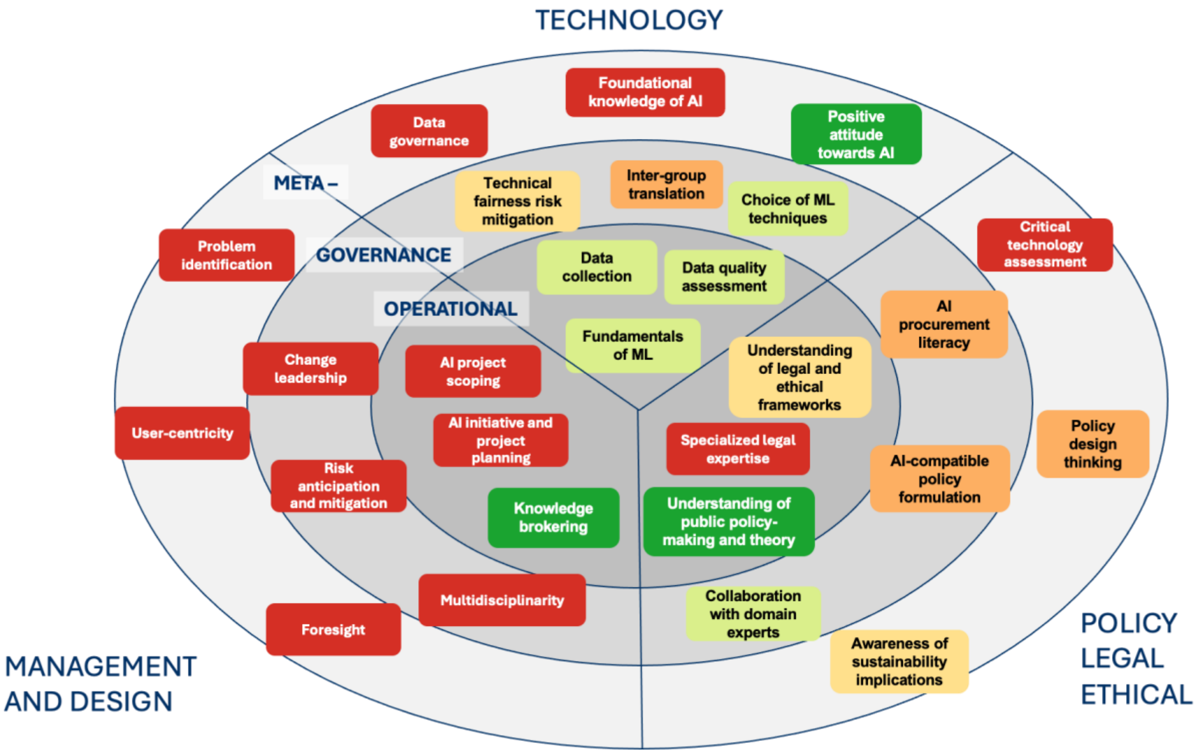


Fig. 2 - An illustration of the use of the AI4Gov Canvas.

In this example, we have mapped the three most important competences for each dimension and for each level of abstraction according to the average relevance score provided in the survey. Moreover, each competence is color-coded according to the average μ coefficient of difficulty obtained from the survey data, from vivid red (most difficult to obtain), to vivid green (least difficult to obtain).

Beyond the provided example, the canvas is developed to serve as a visual, flexible, and generative framework, rather than only a fixed assessment grid. Inspired by design research and public sector innovation practices, the use of the word *canvas* is deliberate and refers to a visual and structured co-design tool that facilitates reflection, discussion, and strategic alignment across stakeholders. The AI4Gov Canvas is not merely a static competence map; it is a generative framework that supports interactive and iterative dialogue about the conditions and capabilities necessary for a public sector organization to meaningfully engage with and govern AI. While existing tools may focus on business models or value creation, the AI4Gov Canvas is unique in its orientation toward public governance and its function as a reflective support for public sector institutions to explore their readiness and responsibilities when engaging with AI. The canvas format serves not only as an evidence-based mapping tool to assess competencies, but to stimulate critical discussion about the type of competence (technology, management and design, and policy /legal / ethical), its level of abstraction, its importance, and its difficulty to obtain. This in turn helps address the socio-technical, organizational, and political dimensions that shape AI governance. The AI4Gov Canvas is thus best understood as a sense-making tool: one that helps public sector teams explore the evolving capabilities they need to responsibly and strategically engage with AI, rather than providing prescriptive answers or benchmarking maturity levels. In this sense, it also provides a handy heuristic for tackling practical challenges in the governance of AI in the public sector.

For instance, the Canvas can be used to map the competences of a public manager, in order to precisely identify their area of strength and weaknesses against multiple dimensions (type of competences, level of abstraction, relevance, and difficulty to obtain). Such assessment can be used for purposes of benchmarking, both at individual and at organizational level of analysis; for rewarding public administration personnel; and for identifying training needs. Moreover, the Canvas can also be used to assess prospective public managers. This is the case of the use of the Canvas as a support tool in hiring processes. Candidates for a position in a public organization dealing with AI projects can be more objectively assessed against the multiple dimensions mentioned above.

Lastly, the Canvas lends itself to a *prescriptive* use. This goes beyond the *descriptive* approach that underpins the use of the Canvas for mapping competences, to include the use of the Canvas as a device to generate desired combinations of competences across multiple dimensions. This use of the Canvas allows for building of Functional Specialist profiles.

5. Designing functional specialist personas

The structure of the Canvas enables the bounded creation of Functional Specialist profiles. It does so by drawing on both the multiplicity of the dimensions it encompasses (type of competences, and levels of abstraction, relevance, and difficulty to obtain) but also, and most importantly, on the constraints provided by the coefficients associated to each competence.

These constraints are the feature that makes the AI4Gov Canvas stand out, when compared to existing similar competence frameworks – regardless of whether they are focused specifically on AI, or on general digital competences.

By setting a maximum value of both the score of importance and of the coefficient of difficulty to obtain that each competence has, users of the AI4Gov Canvas can better avoid devising lists of competences as mere "wish lists", or "dream profiles" that are not realistic. The AI4Gov Canvas, in fact, forces its users to make the necessary trade-offs between competences, even when devising profiles that are multi-disciplinary.

These trade-offs concern each of the dimensions that form the Canvas. With regards to the dimension of the *type* of competence: even for a functional specialist that is meant to possess competences across the technical, the management and design, and the policy / legal / ethical dimension, in which ones of these should they be stronger? With regards to the dimension of the level of abstraction of competence: should a desired functional specialist have mostly operational, governance, or meta-competences? With regards to the level of importance of each competence: should a desired functional specialist possess one very important competence, and multiple competences of much less importance? Or should they possess the largest possible number of averagely important competences? Finally, with regards to the difficulty of each competence: should a desired functional specialist possess one competence that is very difficult to obtain, and multiple competences that are much easier to obtain? Or should they possess the largest possible number of averagely difficult-to-obtain competences?

The AI4Gov Canvas allows to make informed decisions in devising functional specialist profiles for AI in the public sector. We will now turn to providing some concrete examples of how the Canvas can be used to create Functional Specialist personas.

5.1 Example 1: the TechnoSteward

Table 1 provides the details of an example of a competence profile created using the constraints of the AI4Gov Canvas. This example represents a Functional Specialist persona that features nine competences. In the Table, the competences are distributed across the three dimensions of type of competence (technology, management and design, and policy / legal / ethical) and the three levels of abstraction (operational, governance, and meta-competences) of the Canvas.

	Technology			**Management and design**			**Policy / legal / ethical**			**Total**	
		Imp.	*μ*		*Imp.*	*μ*		*Imp.*	*μ*	*Imp.*	*μ*
Operational	**AI-related software programming**	87	114	Knowledge brokering	89	72	Understanding of public policymaking and theory	97	77	273	263
Governance	**Inter-group translation**	120	113	Cross-team collaboration	101	97	Collaboration with domain experts	98	95	319	305
Meta-	**Data governance**	124	169	Data-supported decision-making	96	76	Dissemination	79	60	299	305
		331	396		286	245		274	232	**891**	**873**

Tab. 1 - Competences of the "TechnoSteward" functional specialist persona.

In this example, building a Functional Specialist profile corresponds to selecting nine competences that maximise the sum value of the level of importance of all competences combined (indicated as "Imp." in Table 1). Any competence can thus be chosen, with the constraint that the sum of the coefficient of difficulty to obtain (μ) of all the nine competences should not exceed the baseline difficulty to obtain of each competence (μ=100) multiplied by the number of competences in the profile (9 * μ100 = μ900).

The competences for this example profile have been selected within this constraint to include a particular focus on the technology dimension. Therefore, all three competences in the technology dimension have been chosen to have a very high coefficient of difficulty to obtain. These are (highlighted in bold type in Table 1): AI-related software programming (μ=114), inter-group translation (μ=120), and data governance (μ=124).

Conversely, in the other two dimensions (management and design, and policy / legal / ethical dimension), competences with low coefficients of difficulty have necessarily been selected. The three least difficult competences (highlighted in red in Table 9) are, in fact, knowledge brokering, in the management and design dimension (μ=72), and understanding of public policymaking and theory (μ=77) and dissemination (μ=60), in the policy / legal / ethical dimension.

For the rest of the competences, this technology-focused profile provides for selecting desired competences whose sum of the coefficients of difficulty is as close as possible to 900, but without exceeding it (μ=873); and for racking up as much value of importance as possible: in this case, Imp.=891.

Looking at the characteristics of this Functional Specialist competence profile, we label it as the persona of a "TechnoSteward". The TechnoSteward profile combines the technical prowess and the responsible stewardship needed for AI in the public sector. The TechnoSteward possesses a deep understanding of technology, including the hands-on competence of software programming related to AI, but also the ability to translate concepts from a bureaucratic language to a language that is understandable by users of AI public services, and to apply data governance practices. At the same time, the TechnoSteward can access or exchange AI knowledge between different groups, establish collaboration between teams, and make decisions based on data.

This persona embodies a technologist mindset, which is however also able to consider, to some extent, the implications of public policymaking and theory, to engage in dissemination, and to collaborate with experts from other domains. This combination of competences is not only cross-disciplinary but also, and most importantly, likely to be realistic, because it comprises of competences that are not all equally difficult to obtain. Figure 3 illustrates the competence profile of the TechnoSteward using the AI4Gov Canvas.

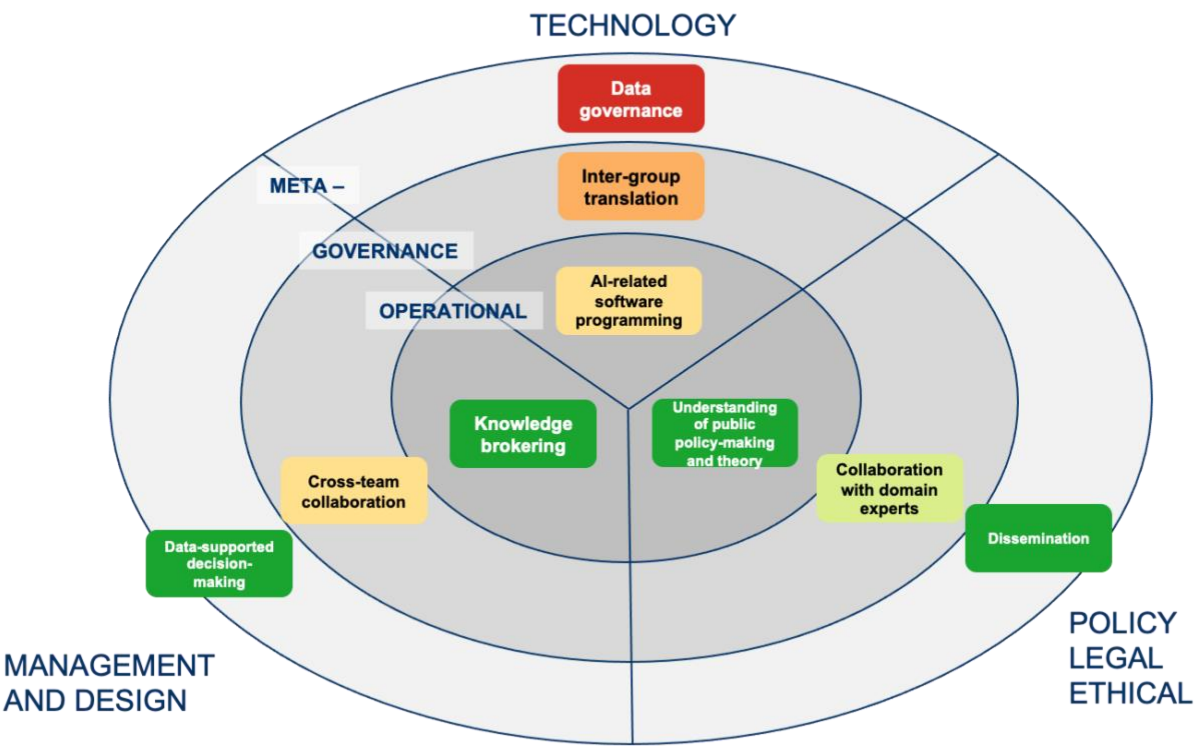


Fig. 3 - An illustration of the “TechnoSteward” competence profile.

5.2 Example 2: the Policy Sentinel

Using a similar approach, we showcase another exemplary profile that can be devised using the AI4Gov Functional Specialist Canvas.

This exemplary profile also combines nine competences in a persona that is realistically obtainable. We label this persona as the "Policy Sentinel", and illustrate its combination of competences in Table 2.

	Technology			Management and design			Policy / legal / ethical			Total	
		Imp.	*μ*		*Imp.*	*μ*		*Imp.*	*μ*	*Imp.*	*μ*
Operational	Data collection	136	89	Budgeting	84	90	**Specialized legal expertise**	98	121	*318*	*300*
Governance	Choice of machine learning techniques	100	95	Partnership development	103	100	**AI procurement literacy**	108	110	*311*	*305*
Meta-	Positive attitude towards AI	106	44	User-centricity	104	83	**Policy design**	113	111	*323*	*238*
		342	*228*		*291*	*273*		*319*	*342*	**952**	**843**

Tab. 2 - Competences of the "Policy Sentinel" functional specialist persona.

The competences for this example profile have also been selected within the constraint of a maximum of μ=900. However, the construction of this profile aims at having a special focus on the policy dimension. Therefore, all three competences in the policy / legal / ethical dimension have been chosen to have a very high coefficient of difficulty to obtain. These are (highlighted in bold type in Table 2): specialized legal expertise (μ=121), AI procurement literacy (μ=110), and policy design (μ=113).

On the other hand, in the other two dimensions (technology, management and design), competences with low coefficients of difficulty have necessarily been selected. The three least difficult competences (highlighted in red in Table 10) are, in fact, a positive attitude towards AI (μ=44), and data collection (μ=89), in the technology dimension, and user-centricity (μ=83), in the management and design dimension.

For the rest of the competences of this profile – whose sum of the coefficients of difficulty is as close as possible to 900, but without exceeding it (μ=843) – the Policy Sentinel encapsulates the persona's expertise in AI policy development, coupled with some relevant management and also some technological competences. "Sentinel" evokes a sense of watchfulness, indicating their role in safeguarding public interests and ensuring responsible AI governance. This persona is adept at navigating the regulatory landscape and shaping policies that strike a balance between innovation and policy and compliance considerations.

Figure 4 illustrates the competence profile of the Policy Sentinel using the AI4Gov Canvas.

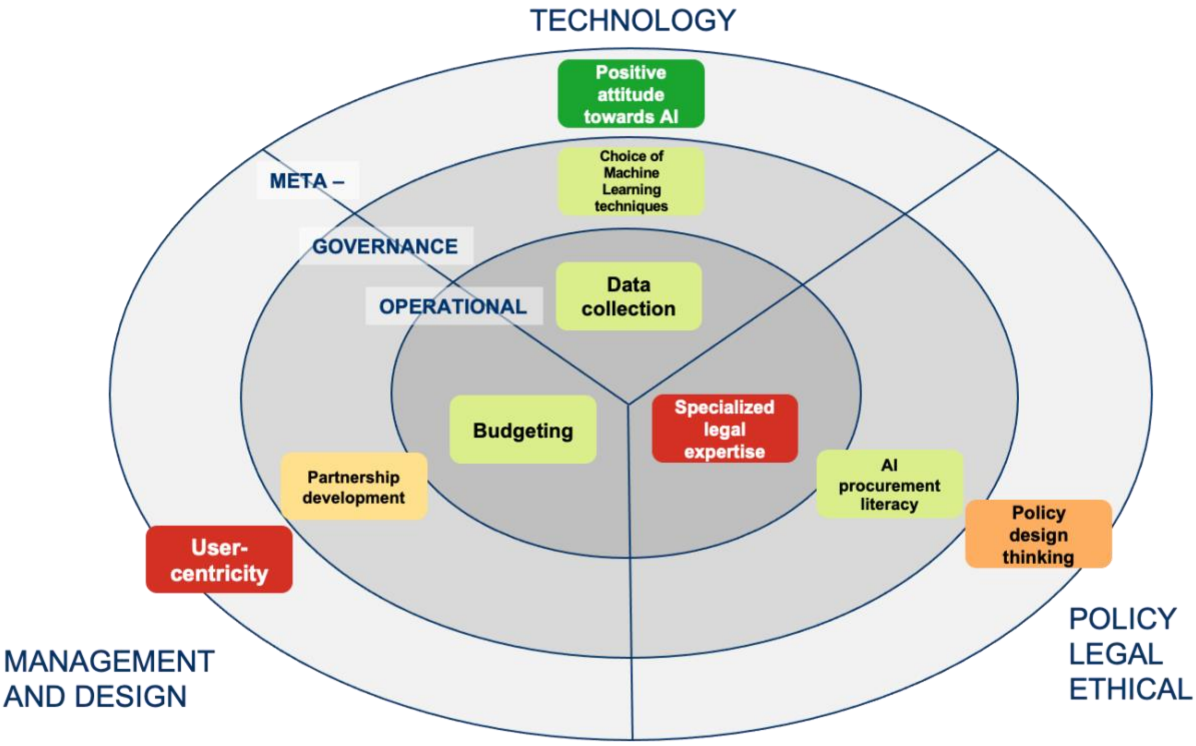


Fig. 4 - An illustration of the "Policy Sentinel" competence profile.

The Policy Sentinel features an in-depth understanding of the AI policy landscape, with specialized legal expertise, familiarity with the practices of procuring AI, and adopting a design thinking approach for devising and implementing AI policies in an iterative and user-centered way. But this persona is also able to budget, to develop partnerships, and to grasp technological dilemmas, such as choosing the right type of machine learning techniques needed in a specific situation.

Being generated within the constraints of the AI4Gov Canvas, this blend of competences spans various dimensions and is likely to be achievable, since it includes competences that vary in difficulty to acquire.

6. Lessons learned and next steps

Developing a competence framework for a Functional Specialist in AI for public services is crucial for ensuring that professionals in this domain have the necessary skills and expertise. However, it can be considered as a first step in the broader journey of investigating competence profiles for the future of AI in the public sector.

To continue developing the framework and to put it into fruitful use, we propose the following lines of action:

1) Refining / integrating the list of competences

This action involves further refining the list of competences required for AI specialists in the public sector. It may include reviewing industry standards, consulting experts, and considering specific job roles within the sector. Integration of competences should ensure that the framework covers all relevant skills and knowledge areas.

2) Soliciting feedback on clustering and levels of importance / difficulty to obtain

This action involves seeking further feedback from subject matter experts, practitioners, and stakeholders for validating the clustering of competences and determining their relative importance and difficulty to obtain. This feedback will help prioritize competences and create a more realistic framework. Moreover, it will help mitigating one of the limitations of the current version of the Canvas, which is the limited number of survey respondents on which its coefficients are based.

3) Soliciting feedback on the usability of the framework

Usability testing is vital to ensure that the competence framework is user-friendly. This action involves collecting feedback from potential users to identify any usability issues, such as unclear language, or confusing terminology, and make necessary adjustments. This testing should involve different user personas, including entry-level AI specialists, mid-career professionals, and senior leaders. Mechanisms for users to provide feedback on the framework's usability should be included, to collect and analyse user feedback and allow iterative improvements.

4) Identifying use cases for the framework

This action is concerned with systematically identifying various use cases for the AI4Gov Canvas. Given that competence frameworks are non-binding, users are not obligated to follow them rigidly. Instead, they are encouraged to apply them with flexibility, allowing for customization and adaptation to suit their specific needs (Bacigalupo, 2022).

Uses of the Canvas that should be further explored include:

- *Training and development*. The most immediate use of the Canvas can be experimented with in the educational programme of the AI4Gov Master on Artificial Intelligence in the Public Sector. The Canvas can guide the design of training and development programs for AI specialists. Within public organizations, the Canvas can be used to ensure that employees receive the necessary training to engage with AI.
- *Self-assessment.* The tool can serve as a self-assessment platform, allowing public managers to evaluate their current competences, identify areas for improvement, and set personal development goals.
- *Career development.* public managers can use the framework to plan their career trajectories and identify the competences needed for advancement in their roles.
- *Recruitment and hiring.* Public sector organizations can utilize the framework as a reference when recruiting AI specialists. The Canvas can help in creating job descriptions, evaluating candidates, and aligning hiring practices with competence requirements.
- *Performance evaluation.* Managers and supervisors can use the framework to assess the skills and competences of their team members, facilitating more informed performance evaluations.
- *Benchmarking and reporting.* The tool can support the creation of reports and benchmarks to help public organizations track the overall competence level of their workforce and to identify areas where further investment is needed.

5) Integrating with existing frameworks

This action focuses on developing compatibility and integration with existing competence frameworks in the field of AI competences, such as those from national governments and international organizations. This integration can enhance the credibility and usefulness of the framework and reduce redundancy. For example, an immediate possibility for integration of the AI4Gov Canvas is with the UNESCO framework "*Artificial Intelligence and Digital Transformation: Competences for Civil Servants* (Broadband Commission, 2022), as also suggested in Misuraca *et al.* (2024). The alignment with the UNESCO framework would allow for the extension of the scope of the AI4Gov Canvas to a global horizon, beyond the one of Europe. The integration between the two frameworks could be based on the complementarity between the focus that the AI4Gov Canvas has on *individual* competences, and the focus of the UNESCO framework on *organizational* capabilities.

6) Guideline for an ecosystem of digital talent in AI, data spaces and digital transformation of the public sector

Finally, the authors have also used the AI4Gov Canvas as the foundation of the four-year AI4Gov-Accelerate project (2025-2029), funded by the Digital Europe Programme of the European Commission, that seeks to strengthen public administrations by enhancing their ability to attract digital talent and by fostering an educational ecosystem primed for innovation in AI, data spaces, and digital governance transformation. The AI4Gov Canvas has shaped the three key components – AI4Gov-X, AI4Scale, and AI4Engine – that collectively serve as core pillars of this project. First, the AI4Gov-X educational platform formalizes the knowledge base through a master program complemented by micro-credentials and extracurricular training, empowering participants with the skills required by rapidly evolving digital transformations where the AI4Gov Canvas will help participants to select their learning path. The AI4Scale sandbox then extends these learnings into practice by offering a collaborative environment where AI applications can be deployed, tested, and incubated, thus bridging academia, industry, and the public sector and again completing the practical skills addressed in the AI4Gov Canvas. Last, the AI4Engine innovation mapping – in the shape of an AI agent – is expected to serve as new input for the evolution of the AI4Gov Canvas by identifying emerging trends, and best practices on a global scale. By bringing these three elements together, AI4Gov Canvas not only cultivates individual competencies but also provides guidelines for human-centric AI-based public services.

7. Conclusion

As public organizations face the challenges of designing, implementing, and managing AI applications, the need for equipping public servants with the relevant competences becomes increasingly pressing. Given the specificity of artificial intelligence and its benefits and risks, the definition of competences needs to be not only as focussed and as granular as possible, but also grounded in empirical data. Our proposal, the AI4Gov Canvas, is an attempt to establish a data-driven competence framework that not only draws on an analysis of existing research and policy documents, but that also grounds it claims on empirical data from relevant actors involved in AI projects.

We hope that the framework can serve both as a tool for conceptualizing AI competences in the public sector; but also as a practical instrument that practitioners can use in strategic and tactical decisions related to the adoption of AI in the public sector.

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Appendix A

Technology competences

Level of abstraction	*Competence label*	*Description*	*Coefficient of importance*	*Coefficient of difficulty to obtain (μ)*
Meta-competences	Foundational knowledge of AI	Being able to understand the fundamentals of AI at the conceptual level	129	116
	Data governance	Being able to apply data governance practices	124	169
	Positive attitude towards AI	Being able to have a positive attitude towards AI technologies in the public sector	106	44
	Basic data literacy	Being able to understand the basics of data	95	78
	Technical design	Being able to approach innovation of AI technology in an iterative and user-centered way	91	93
	Technology inquisitiveness	Being able and willing to keep learning on new developments in AI	86	109
	Data-oriented culture	Being able to think of data as central in the activity of a public manager	86	102
	Awareness of fairness challenges	Being able to be aware of challenges to fairness in the use of AI technologies	83	89
Governance competences	Technical fairness risk mitigation	Being able to assess fairness risks of AI and to mitigate these risks through technical instruments	126	105
	Inter-group translation	Being able to translate concepts from a bureaucratic language to a language that is understandable by users of AI public services	120	113
	Choice of machine learning techniques	Being able to know when to use a certain algorithm, tool, and library in specific situation	100	95

Level of abstraction	*Competence label*	*Description*	*Coefficient of importance*	*Coefficient of difficulty to obtain (μ)*
	Choice of AI architecture	Being able to know when and how use which AI architecture and why (e.g., cloud infrastructure)	97	105
	Compliance with AI technical standards	Being able to adhere to and develop AI based on ethical and legal technical standards	95	97
	Re-use of AI-related components	Being able to reuse AI-related components from other sources during the development of AI solutions	91	107
	Data sharing	Being able to share data for AI-related purposes	70	78
Operational competences	Data collection	Being able to collect data for AI-related purposes	136	89
	Data quality assessment	Being able to assess the quality of data for AI-related purposes	133	90
	Understanding the fundamentals of machine learning	Being able to understand key objectives and applications of machine learning	133	91
	Understanding of causal analysis and decision theory	Being able to understand cause and effect relationships and being aware of decision theory related to data science practice	111	105
	AI-related software programming	Being able to use relevant programming languages for the development of AI, such as Python and R	87	114
	Database management	Being able to conduct data and database management effectively	83	107
	Understanding of computer vision and Natural Language Processing	Being able to understand AI computer vision and natural language processing	73	111
	Understanding of applied maths	Being able to understand and use applied mathematics	43	93

Management and design competences

Level of abstraction	*Competence label*	*Competence description*	*Coefficient of importance*	*Coefficient of difficulty to obtain (μ)*
Meta-competences	Problem identification and framing	Being able to identify and distinguish between different types of problems that require either data science or another approach	130	124
	Foresight	Being able to anticipate future needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs	106	121
	User-centricity	Being able and willing to collaborate with users of AI digital services and valuing their feedback	104	83
	Leadership	Being able to lead to support AI initiatives	100	96
	Data-supported decision-making	Being able to make decisions based on data	96	76
	AI benefits understanding	Being able to understand the benefits of AI	90	83
	Risk proclivity	Being able to take risks in pursuing AI projects	89	107
	Digital-by-design thinking	Being able to think digital first in thinking of new AI services, policy, and practices	85	109
Governance competences	Change leadership	Being able to identify opportunities to improve the organisation and overcome structural and institutional obstacles to change	119	118
	Risk anticipation and mitigation	Being able to anticipate and mitigate risks of AI (e.g., privacy, security and ethical)	114	116
	Multidisciplinarity	Being able to blend traditional public service skills with modern digital skills	104	93

Level of abstraction	*Competence label*	*Competence description*	*Coefficient of importance*	*Coefficient of difficulty to obtain (μ)*
	Partnership development	Being able to develop partnerships, define opportunities for AI projects and define collaboration systems for new AI projects	103	100
	Cross-team collaboration	Being able to collaborate with different teams and organizations to pursue AI projects	101	97
	Project management style evaluation	Being able to identify and distinguish between different types of problems that require either data science or another approach	88	85
	Choice to delegate to AI	Being able to consider relevant factors in deciding whether to delegate a public service or a process to AI	71	91
Operational competences	AI project scoping	Being able to evaluate data quality and availability and that of data sources, consolidate project requirements and design a project roadmap	153	143
	AI initiative and project planning	Being able to define potential AI use cases, map a data journey and enable decision makers to select a use case	106	121
	Knowledge brokering	Being able to access or exchange AI knowledge between different groups	89	72
	Budgeting	Being able to budget AI initiatives	84	90
	Project ownership	Being able to demonstrate ownership of AI projects	67	73

Policy, legal, and ethical competences

Level of abstraction	*Competence label*	*Competence description*	*Coefficient of importance*	*Coefficient of difficulty to obtain (μ)*
Meta-competences	Critical technology assessment	Being able to understand the limitations of data-driven technologies and choose whether to focus on augmenting experts rather than replacing them	133	121
	Policy design	Being able to approach AI policymaking in an iterative and user-centered way	113	111
	Awareness of sustainability implications	Being able to be aware of implications of AI on environmental sustainability	98	99
	Dissemination	Being able to communicate AI initiatives	79	60
	Empathy	Being able to have an empathetic approach in implementing AI, identifying the needs, wants, and objectives of end users and other stakeholders	77	109
Governance competences	AI procurement literacy	Being able to set up and manage tender contracts on AI in a way that is compatible with public interest values	108	110
	AI-compatible policy formulation	Being able to formulate policy questions as questions that can be answered by AI techniques	104	113
	Collaboration with domain experts	Being able to work together with domain experts from varying professional backgrounds	98	95
	Collaboration with AI ethicists	Being able to work with specialised ethicists who provide legal and ethical assessments on AI	90	82
Operational competences	Understanding of legal and ethical frameworks	Being able to understand and be aware of relevant legal and ethical frameworks on AI	115	96

Level of abstraction	*Competence label*	*Competence description*	*Coefficient of importance*	*Coefficient of difficulty to obtain (μ)*
	Specialized legal expertise	Being able to utilise specialised legal expertise such as on data rights, intellectual property, licensing, relevant, and domain-specific legislation	98	121
	Understanding of public policy making and theory	Being able to understand policymaking processes, governance, and public management theory and practices	97	77
	Auditing	Being able to apply auditing techniques to ensure compliance with design, performance, and liability standards	91	106